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Sustainable Low-Carbon Isolated Island Electricity Systems - Policy and Investment Impacts Assessed Using System Dynamics

George Jr. S Matthew

A thesis submitted in partial fulfilment of the requirements for the degree of
Doctor of Philosophy



School of Engineering and Innovation
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Milton Keynes, United Kingdom

July 2017

I dedicate this work to....

My wife Neicia Baptiste-Matthew. Thank you for your support, love and understanding throughout this process.

My mother, Judy Brathwaite, for your unwavering support and strength, even during the time of the loss of our family home.

My immediate family, Georgina Matthew-Philbert, Jael Brathwaite, Jenielle Brathwaite, Jamar Brathwaite and Michael Brathwaite.

“Because we don't think about future generations, they will never forget us”

- Henrik Tikkanen

DECLARATION

This dissertation is the result of my own work and includes nothing, which is the outcome of work done in collaboration except where specifically indicated in the text. The work presented in this thesis is an original contribution and has not been previously submitted, in part or whole, to any university or institution for any degree, diploma, or other qualification. Parts of this thesis have appeared in the following peer-reviewed publications:

1. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. (2014) 'Simulating the development and utilization of autonomous smart grid systems using system dynamics', in PhD Colloquium at the 31st International Conference of the System Dynamics Society. Delft, Netherlands.
2. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. (2015) 'Insights into the Thermal Generation Futures of Isolated Island Electricity Systems Using System Dynamics', in 32nd International Conference of the System Dynamics Society. Cambridge, MA. Available at: <http://www.systemdynamics.org/conferences/2015/proceed/index.html>
3. Matthew, G. J., (2015) 'System Dynamics and Future ICT- enabled Electricity Networks', Presentation at the 15th International Conference on Technology, Policy and Innovation. Milton Keynes, UK.
4. Matthew, G. J., Nuttall, W. J., Mestel, B., Dooley, L. and Ferrão, P. M. (2016) 'Renewable integration in island electricity systems - a system dynamics assessment', *Advances in Intelligent Systems and Computing*, 426, pp. 107–119. doi: 10.1007/978-3-319-29643-2_8.
5. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. S. (2017) 'A dynamic simulation of low-carbon policy influences on endogenous electricity demand in an isolated island system', *Energy Policy*, 109, pp. 121–131. doi: 10.1016/j.enpol.2017.06.060.

ABSTRACT

This thesis presents a novel System Dynamics (SD) policy and investment analysis framework for future low-carbon electricity systems, using an electrically isolated island system as its case study. Current electricity systems are undergoing a long-term transition towards reduced fossil fuel use, primarily driven by high fuel costs, environmental concerns and the desire for energy security. These systems are facing a number of evolving policy drivers: most notably, current attempts to pursue higher levels of renewable energy sources, greater energy efficiency and other supporting technologies. Emerging challenges are shaping the low-carbon objectives of future electricity systems and the ensuing implications for future policy and investment decisions. This thesis presents a number of critical policy recommendations allied with longer-term investment observations, evolving from the nexus between the environmental and energy security concerns of an island-based electricity system.

Island systems such as São Miguel, are small enough to be understood while being large enough to reveal highly complex structures and inherent time and spatial interactions within and between social, economic and technical factors. It is argued that a systematic SD-based approach can reveal possible system structure trajectories, with such insights assisting the understanding of overall sustainability while recognising emergent challenges and behaviours.

The thesis shows that learning-by-doing renewables cost reductions exists but are not very significant in island electricity systems. Additionally, it shows that setting low-carbon policy targets is beneficial for emissions reductions, but meeting these targets too early is either inefficient or impractical if targets are unrealistic. Critical evaluations of endogenous electricity demand growth and the system capacity margin are provided, which highlights consequential policy challenges for island-based systems. The most important and influential low-carbon agendas giving endogenous impacts on electricity demand are elaborated. The thesis also confirms that more effective policies, for sustained renewables uptake and improved investor decision-making for the generation mix, can be achieved. Insights distilled from smaller electricity systems can help frame the outlook of larger systems.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABM	Agent-Based Modelling
BAU	Business as usual
CLD	Causal loop diagram
CO ₂	Carbon Di-Oxide
DER-CAM	Distributed Energy Resources Customer Adoption Model
DP	Dynamic Programming
EDA	Electricidade dos Açores
EPPAM	Electric Utility Policy and Planning Analysis Modelling
ERSE	Entidade Reguladora dos Serviços Energéticos
ETI	Energy Transition Initiative
EU	European Union
EV	Electric Vehicles
FACTS	Flexible AC Transmission Systems
FALCON	Flexible Approaches for Low Carbon Optimised Networks
GDP	Gross Domestic Product
GEEREF	Global Energy Efficiency and Renewable Energy Fund
GHG	Greenhouse Gas
GSGF	Global Smart Grid Federation
HOMER	Hybrid Optimization of Multiple Energy Resources
HVDC	High Voltage Direct Current

ICT	Information and Communication Technology
IEA	International Energy Agency
IED	Intelligent Electronic Devices
IT	Information Technology
IRENA	International Renewable Energy Agency
IRP	Integrated Resource Planning
KM	Kilo-meter
kW	Kilo-watt
LCOE	Levelised Cost of Electricity
LEAP	Long range Energy Alternatives Planning System
LP	Linear Programming
MAE	Mean Absolute Error
M	Mean
MCMC	Markov Chain Monte Carlo
MIP	Mixed-Integer Programming
MIT	Massachusetts Institute of Technology
MSE	Mean Square Error
NIST	National Institute of Standards and Technology
NLP	Non-Linear Programming
PMU	Phasor Measurement Units
SD	System Dynamics

SDS	System Dynamics Society
SFD	Stock and flow diagrams
SIM	Scenario Investment Model
T-21	Threshold-21
TIMES MARKAL	The Integrated Markal-Efom System
UK	United Kingdom
UNDP	United Nations Development Program
UNF	United Nations Foundation
UNFCCC	United Nations Framework Convention on Climate Change
UPFC	United Power Flow Controllers
US DoE	United States Department of Energy
USA	United States of America
WAM	Wide Area Monitoring
WAsP	Wien Automatic System Planning Package
WILMAR	Wind Integration in Liberalized Markets

Chapter 1. Introduction

Electricity consumption is considered as the key link between economic growth, social equality and environmental sustainability (UNF, 2013). This assumption relies heavily on the intuition that human development and the quality of life are dependent on the continuous abundance and economic supply of energy for electricity production (Gómez Expósito, Conejo and Cañizares, 2009). The ensuing debate that surrounds the relationships between the provision of electricity and economic growth has intensified. There is a range of tremendous beneficial impacts that electricity can have on the livelihoods of humans. According to the former United Nations Secretary-General, Ban Ki-moon, the growth that has freed millions of people from poverty is associated with an increase in electricity emissions and unwanted environmental effects. However, in the literature, Barnes (2007) claims that access to electricity is a necessary, but not sufficient, condition for economic development. The need for sustainable development should involve secure and self-sufficient means to achieve it. The following section distilled these arguments in providing the background for this thesis.

1.1 Background

Current research suggests that there is a need for electricity to be embedded in today's modern societal structures to promote economic development, however, there is an overreliance on its consumption (IRENA, 2015; European Commission, 2016). Concurrently, more than 1.2 billion people worldwide have no access to electricity, and a further 1 billion only have intermittent access (UNF, 2013). According to UNF (2013), some 3 billion people - almost half of humanity are without access to modern energy services, relying on traditional biomass for cooking and heating. This problem is evident in poorer and less developed countries and as a means of solving such an issue,

there are calls from global bodies for united commitments which can attract global attention to the importance of electricity (UNF, 2013; GEEREF, 2016; UNFCCC, 2016). Incentives have been created for countries worldwide to improve and expand their electricity systems using environmental (climate change) friendly sources, while seeking to achieve reliable energy for all.

The use of low-carbon energy sources, energy efficiency and other resources (UNF, 2013; Islands Energy Program, 2016) are able to provide electricity systems with the tools needed for sustainable energy. In line with this shift and according to UNF (2013), key objectives to be met by 2030 include doubling the rate of energy efficiency improvement and the share of renewable energy in the global energy mix. This solution set will satisfy the desires of an electricity-rich society and provide a starting ground for the globally less fortunate. Consequentially, it has been suggested that the pursuit of low-carbon renewable sources will tackle the common challenges of high energy prices, energy security concerns from the import dependency of fossil fuel generation sources and the related excessive carbon emissions (Weisser, 2004b; Foxon, 2013; IRENA, 2013; European Commission, 2016; UNFCCC, 2016). This use of renewables will improve access to modern energy services, and at the same time enhance the sustainability attributes and resilience of the electricity supply (UNF, 2013).

In this respect, electricity systems are currently undergoing a transition. This transition should represent the objective to satisfy increased electricity consumption (3.4% average growth rate of worldwide electricity consumption since 1974 as derived by IEA (2016)) whilst ensuring compliance with steep decarbonisation targets (UNFCCC, 2016). The future electricity demand dictates an increasing need for uninterrupted supply for the global population (IEA, 2016) coupled with meeting global climate change objectives (European Commission, 2016) and tackling the overreliance on fossil fuels (Islands Energy Program, 2016). Future electricity systems will thus be diverse, dynamic and evolving low-carbon integrated systems. According to (MIT, 2011), even though the majority of current electricity systems are not broken, emerging challenges from such a transition, if not met, could substantially degrade the system's reliability and efficiency in the

future. Interestingly, the energy sector has experienced multiple transitions, namely from wood to coal, oil and gas (Naill, 1992; Jacobsson and Johnson, 2000), so a further natural progression to low-carbon electricity systems is viewed as both tolerable and achievable (MIT, 2011).

It has also been established that electricity systems are already experiencing a parallel evolution from the traditional centralised fossil-based generation set-up to a predominately decentralised low-carbon architecture (Vallvé, 2013; Islands Energy Program, 2016). With an evolution timeline that is considered to be a gradual increase to using renewable technologies that can be deployed within the near future or already being deployed (US DoE, 2004). Alternatively, there can exist a substantially accelerated timetable to the fully transitioned low-carbon electricity system - a system that is remarkable in its complexity and impressive in its scope (US DoE, 2004). In both cases, new types of electricity systems will emerge, such as low-carbon and smarter systems enabled by pervasive *Information Communication Technology* (ICT) with bidirectional communications and power exchange between suppliers and consumers (Bompard *et al.*, 2012).

These systems are not to be limited to a diverse set of dynamic, distributed energy suppliers, they should connect smart users (responsive, energy efficient, and variable) to sustainable energy sources. Many challenges and opportunities arise with the development of these systems and services. Moreover, there is evidence that public policies and a variety of technological and economic changes will alter both the demand and supply of electricity from these systems (MIT, 2011). However, such changes represent a key means for the de-carbonisation and decentralisation of the present electricity system (Bompard *et al.*, 2012; Islands Energy Program, 2016). Implementation includes operational and architectural factors, with the need for newer policies and renewed investment strategies for producing, delivering, storing, and consuming electricity. If regulatory policies and the technologies employed in the electricity system do not change, it will be difficult to maintain acceptable reliability and sustainability (MIT, 2011).

Traditional fossil-based electricity systems are embodied with high amounts of multi-level interactions (Geels and Schot, 2007; Chappin, 2011). The accompanying complex dynamics are not only from the technical and physical aspects of the system but also from the numerous socio-economic systems interacting with it (Geels, 2002; Chappin, 2011). According to (Foxon, 2011; Bompard *et al.*, 2012), future low-carbon electricity systems will be even more complex than traditional fossil-based electricity systems. Specifically, the physical, social and economic entities of transitioning low-carbon systems will have an increase in varied and diverse interrelationships and interactions (Chappin, 2011; Bompard *et al.*, 2012). Some of these interactions and complexities are inherently tied to the environmental and energy security concerns of these low-carbon transitioning systems. Therefore, stakeholders, especially governments and energy companies, will have to capture the trade-offs between these complexities and the potential long-term benefits pursued. Hence, there is a further need to adapt behaviours to ensure that an evolution to the low-carbon electricity system design and implementation goals can be achieved. These objectives should be coupled with the broader political and cultural policy considerations of the system.

One key approach to determine the behaviours, goals and attitudes within complex systems is to acknowledge that the inherent system structure leads to these behaviours and guides the interactions found within it. The patterns of behaviours (sequences of events) and not random events, signal the existence of the underlying system structure (NWEI, 2016). A focus on the random events occurring within the system will be futile for understanding the system and for developing proactive solutions for these systems. However, by looking at the patterns of events, feedback systems thinking, can lead to the necessary proactive solutions that have a high leverage to influence the system (Sterman, 2000).

Hence, it is useful to understand the structure of the transitioning low-carbon electricity system to achieve the required system design and output solutions. This understanding will emerge from the social, technical and economic interactions of the key entities and drivers within the system. Therefore, the need to address environmental and energy security concerns (of fossil fuel import

dependency) of these systems using a feedback systems thinking approach will prove beneficial. Implications from the nexus of environmental and energy security concerns for an isolated and bounded system can reveal important and useful proactive solutions for transitioning low-carbon electricity system. Additionally, insights into future emerging challenges and plausible solutions for policy and investments within these systems can be distilled. The next section provides the motivation for the approach taken in this thesis.

1.2 Motivation

Policy makers worldwide are attempting to reduce the emission of harmful greenhouse gases produced during electricity generation, while simultaneously either preserving or enhancing energy security. This challenge is compounded by the desire to achieve the required changes without greatly increasing economic costs which would risk an erosion of national economic competitiveness. Resultantly, future electricity systems are facing emerging policy drivers to pursue high levels of renewable energy sources, energy efficiency and other supporting technologies. Emerging challenges from these policies will shape the low-carbon outcomes, and impacts, and the future of these electricity systems.

The use of energy policies involved have traditionally relied on the “energy trilemma” of costs (energy equity/affordability), environmental concerns and security of supply issues, illustrated in Figure 1.1a (Nuttall, 2013; World Energy Council, 2016). These factors remain and are key to the policy and investment decisions taken within the evolving systems. However, the focus on specific aspects of the energy policy trilemma will be better articulated within the context of the structure of the electricity system considered. In addition the overall organisational and management structure of the transitioning complexities involved for the system is important, as is the long-term consequences of how these structural factors might influence the energy related behaviours and challenges of such low-carbon electricity systems. These long-term views are critical for ensuring

the viability of the system (Sterman, 2000). A clearer picture can hence be framed of the planning and policy-shaping framework of these systems.

However, most studies into electricity systems have focused only on the electricity system purpose and functionality such as grid balancing (Lalor, 2005; Ekanayake *et al.*, 2012; Momoh, 2012; Ilic, Xie and Liu, 2013). A variety of large-scale, event-oriented optimisation and econometric simulations are employed. There are other studies that argue that the physical grid is merely one system in a “system of systems” and more suitable methods need to be adopted (Dyner, 1996; Jordan, 2013). According to Bompard *et al.* (2012), in-depth analysis of the complete socio-techno-economic “system of systems” is of much more benefit to stakeholders. A complex system view method is advocated to understand the system implications and to propose feasible solutions to include suitable policy agendas.

In general, there are many systems view and complexity science methodologies available including complex network theory, agent-based strategies, *system dynamics* (SD), game theory and multi-scale modelling (Forrester, 1961; Macal and North, 2006; Bompard *et al.*, 2012; Owlia and Dastkhan, 2012). Of these methods, SD has emerged as a suitable candidate for capturing the key salient features of the system (Sterman, 2000; Jordan, 2013). The need for incorporating social and economic factors as opposed to just considering the technical and physical details of the electricity system are key to the SD modelling approach by allowing the delayed policy effects necessary for understanding the policy implications to be captured. In addition, the characteristics of the electricity demand endogenously evolving from low-carbon policies can be studied and the relevant energy policy trilemma critically evaluated using SD.

For larger electricity systems such as in a country or continent, the challenge involves even higher levels of complexity of the inherent system components interaction (Bompard *et al.*, 2012). The larger the system the more interactions that exist and hence the more difficult it is to understand and to model. Dyner, (1996) elucidate the idea of simple models, acknowledging that while higher

levels of complexity exist in larger systems, a more pragmatic option is to consider a smaller, but nevertheless complete, autonomous electricity systems. Interestingly, this approach can be done for the electricity systems of islands that are small enough to be understood, but large enough to reveal highly complex structures and interactions (in both time and space) between social, economic and technical factors.

Transitioning island electricity systems have less complexity and are simpler because of their smaller size and scale. In addition, they might, due to this smaller scale face some low-carbon transitioning challenges such as increasing the uptake of higher levels of renewables earlier than larger interconnected networks (Eurelectric, 2012). Hence, these island systems can and has been used as testbeds for deriving a valuable understanding of the critical issues that might exist (Eurelectric, 2012; Islands Energy Program, 2016). Indeed, the modelling and analysis of such testbeds can provide useful insights not only for other island networks but also for the larger global electricity systems that exist. However, greater reformulations of the models would be required if they are to be extended to larger, interconnected electricity systems, such as in the USA, UK and Europe. Conversely, isolated island systems can be left behind in the evolving low-carbon electricity transitioning process and thus might adopt strategies from bigger interconnected systems (Eurelectric, 2012). Although this is true for most isolated island systems, there is a growing interest into programs, which use small island systems as testbeds for low-carbon transitions. Realistically, the economic and technical viability can be best appreciated for its contextual simplicity due to factors such as non-liberalised markets and single electric utilities that have monopolistic power purchase agreements, simplifying the policy context of these systems.

Energy policy, in general, addresses a particularly complex and complicated socio-technical set of problems. The importance of the issues involved motivates researchers to attempt to gain insight and understanding the system complexity can make modelling approaches difficult and prone to error. Those risks should not necessarily deter, but they do require care from the outset in order

that they are mitigated. The research presented in this thesis has been developed with an acute awareness of these issues and it has led to a series of decisions concerning methods and project scope.

These include:

- To use an established modelling approach well suited to complex socio-technical systems.
- To consider a territory sufficiently large to manifest key issues, but sufficiently small to be tractable.
- To have a case study in which some elements of the system complexity are attenuated (e.g. no local retail price formation for the electricity tariffs)

Over the last twenty years there has been a growing recognition around the world that energy policy combines three distinct, vital and often competing elements (World Energy Council, 2016). These elements can be broadly summarised as energy economics, energy security and environmental protection, and illustrated in Figure 1.1. Various formulations of these concerns have been explored (Foxon, 2013; ICE, 2015) and the concerns have evolved with time. In the 1990s policy attention on energy economics focussed on building liberalised markets so as to improve energy affordability, but arguably the focus has shifted in recent years to be more on the end than the means – i.e. to emphasise energy affordability more explicitly.

It is trivial for policy-makers to put in place measures to enhance one or even two of these competing considerations. In particular, fossil fuels are favoured when attempting to meet a pair of goals such as cost and security of supply. For example, electricity generation from coal has tended to be attractive in respect to its cost (affordability) and availability (security) but it suffers from very poor environmental characteristics (greenhouse gas emissions). Constructing policies for all three dimensions is extremely difficult and generally requires a portfolio of technologies and fuels. It is noted that energy policy and policymakers attempts to reconcile these three difficult challenges leads to the description of the three competing elements as the “energy trilemma” a

deliberate play on the word dilemma – in that case a difficult choice between two alternatives. According to ICE (2015), measures cannot be considered in isolation and probably all types of energy technology, including energy efficiency has a role to play. This assertion emphasise the fact that the “energy policy trilemma” is not an absolute trilemma, as the solution appears not to lie in correctly making a single difficult choice, but rather in combining a set of difficult choices into a compromise solution taking the form of a portfolio of technologies.

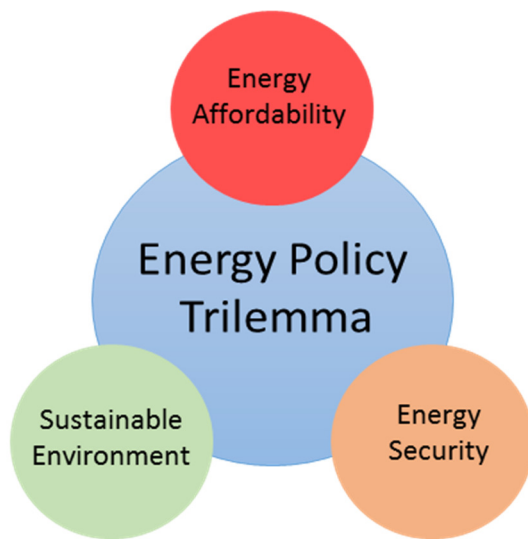


Figure 1.1 Illustration of the Energy Trilemma (adapted from World Energy Council, 2016)

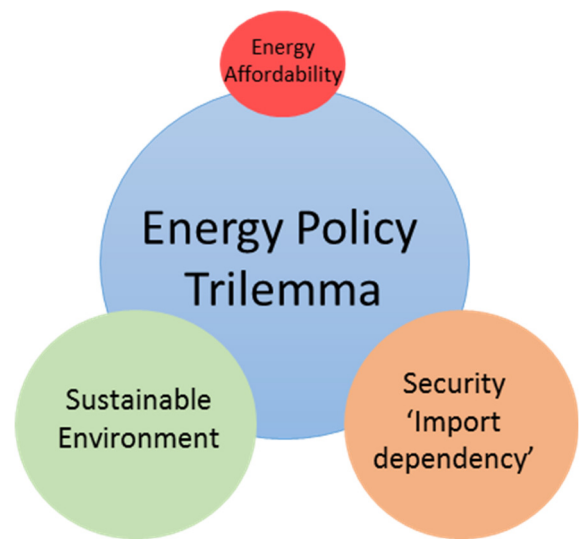


Figure 1.2 Illustration of the Energy Trilemma Simplification used for this Thesis

Noting the characteristics of transitioning island electricity systems and the need to minimise risks associated with excessive system complexity, a territory was selected for this research work where local retail price formation for electricity tariffs does not occur (EDA, 2008). This greatly simplifies one aspect of the energy trilemma (Economics/Affordability) for the research presented here. The revised emphasis is illustrated schematically in figure 1.2, where the issues of energy affordability are diminished as they are essentially reduce to considerations of cost minimisation (technologies, fuels and energy waste) as unit revenues are essentially fixed. In addition, the focus on the security of supply (availability) from the import of fossil fuels and the environmental concerns for climate change are given the emphasised.

For the reasons outlined above the research has been focussed on one particular isolated island territory, São Miguel in the Açores. The considerations in respect of this territory may be summarised as follows:

- It is part of Portugal, the European Union, and is economically developed.
- It is of sufficient size and complexity to emulate the attributes of larger systems.
- It has neither electrical connections to any other island nor to the mainland.
- While the island has some political autonomy, electricity tariffs are not set locally but are determined administratively in Lisbon, so the electricity system on the island is not economically isolated (EDA, 2008).

In addition, the research takes a whole systems approach to understanding the structure of the complex evolving low-carbon electricity systems using the SD approach. More details of the case study are provided in Section 3.5.

1.3 Research Questions and Objectives

From the discussions in the previous sections, the following overarching research question was framed:

What does the convergence of environmental and energy security concerns imply for small isolated electricity systems?

The main hypothesis for this work is that current electricity systems are in a low-carbon transition with numerous policy drivers. These drivers are based on the need to lower environmental impacts from carbon emissions and to also ensure sustainable electricity supply. Inherently, there are many emerging challenges and behaviours that require a systematic approach to understanding. This understanding might facilitate beneficial policy and investment decisions appropriate for such systems. Interestingly, the challenges for policies and long-term investment decisions are more readily revealed within smaller and isolated electricity systems.

Considering the energy policy trilemma, for isolated island systems such as São Miguel the concept of electricity price formation related to the electricity tariffs and affordability can be largely ignored and replaced by long-term overnight investment electricity cost. Hence, the energy policy trilemma as shown in Figure 1.1, for the purpose of this work, is revised to reflect the structure shown in Figure 1.2. With this assertion and the fact that the energy security aspects of the island system is centred on low (fossil fuel) import dependency the research does not focus on the whole energy policy trilemma shown in Figure 1.1. In essence, the contextual simplification puts the focus on the nexus between the environmental and energy security (fossil fuel dependency) concerns of the island system. This thesis has the potential to provide an insightful approach for mitigating the emerging policy and investment challenges and behaviour issues of low-carbon-transitioning island systems. Issues include sustaining the uptake and increasing the amounts of renewables, ensuring energy security (fossil fuel import independence), and understanding useful strategies that can improve investment decision-making for the electricity generation capacity mix. Critical policy recommendations allied with long-term investment observations, as influenced by these environmental and energy security concerns, can hence be revealed.

The following four research sub-questions address particular aspects within the scope of this thesis:

1. *How are fossil-fuel-based island systems influenced by electricity demand and capacity margin standards?*

This sub-question provides some context for the in-depth analysis of the requirements of this thesis. By asking this question, the aim is to explore in detail the fossil fuel investments and policy structure (prior to low-carbon) for isolated electricity systems. As a first step, a simple (assuming) fossil fuel only model of the island system is built. In addressing this sub-question the effects of exogenously determined electricity demand and existing capacity margins (RAE, 2013) of the system are examined. The capacity margin as defined in the literature is a percentage, which gives the level by which available installed electricity generation capacity exceeds the peak electricity demand within

the system. This is formulated as $\frac{\text{total available capacity} - \text{peak demand}}{\text{peak demand}} * 100$. According to RAE, (2013) the capacity margin is also referred to as the reserve margin, the stipulated excess capacity in time of peak demand. It is assumed that the electricity demand and the existing capacity margins can guide the long-term direction of the electricity system. Hence, the use of electricity industry standards for capacity margins and relevant demand growth is simulated to see impacts, if any, on the long-term investments made within a fossil-fuel-based isolated island system. Based on these outputs, the existing capacity investments and policy challenges for the system in the absence of low-carbon transitioning can be established.

2. How effective are low-carbon policy targets within a small isolated island electricity system?

It is argued in the previous sections that current electricity systems are pursuing large amounts of renewables driven by concerns for environmental and energy security (ie. to reduce fossil fuel import dependency). This sub-question seeks to uncover the low-carbon policy evolution. The main aim here is to verify that low-carbon policy goals are useful and can be improved for investment decisions for the capacity mix within the nexus of the environmental and energy security concerns of the system. Based on the local *learning-by-doing*¹ affordability of renewable technologies, together with environmentally driven goal-seeking policies, the effectiveness for increased renewable capacity investments and the carbon emissions impacts within the system are articulated.

3. How is electricity demand endogenously influenced by low-carbon policies, and what are the long-term implications on isolated islands?

To uncover the challenges of an environmental and energy security driven policy agenda, consideration of the impact on demand is needed. An endogenous view of the demand gives a better understanding of the internally generated challenges and opportunities presented. The

¹ Learning-by-doing is considered as the cost reductions achieved from increased experience of the locals (eg. engineers) with the new technologies. Explained further in Section 4.2.2.

impacts of key policy factors such as low-carbon policies for *electric vehicles* (EV), energy efficiency and other demand influences should affect the electricity demand of the system. The usual methods for modelling low-carbon electricity transitions and by extension long-term *Integrated Resource Planning* (IRP) are done with an exogenous demand forecast for electricity demand (HOMER; PLEXOS; TIMES MARKAL) and are unable to capture an endogenous effect of the electricity demand. Therefore they are unable to elucidate the long-term effects on the demand, as influenced by low-carbon policies. Explorations of the impacts of low-carbon policies on the endogenous demand of the island system are examined using a range of scenarios.

4. *How can energy policy and investor decision-making be improved by system dynamics insights?*

This sub-question integrates the outputs from the previous three sub-questions. It is proposed that the endogenous demand, the low-carbon policy targets and the investment structure of the low-carbon transitioning island system will provide insights into the appropriateness of long-term investments. The question provides an understanding of how the long-term affordability (using the levelised cost of electricity (LCOE) (NREL, 2016) as an overnight cost basis) and not electricity tariffs as an endogenous consequence of capacity investments for islands such as São Miguel. A methodological framework based on the four sub-questions is developed to guide energy-policy and investor decision making. This allows for the understanding of a stable/improved generation mix of renewables and other technology portfolios that are effective for environmental and energy security concerns.

1.4 Contributions

As described earlier, a key consideration when approaching the research of this SD study is the need to manage the complexity and minimise the risk of inaccurate and disproportionate modelling focus. The smaller, simpler and more tightly bounded systems are hence more attractive in such terms. The step-by-step approach taken for this thesis was to construct a series of distinct and

constrained models. The research started with the simplest of these models and progressed to consider issues of greater scale and complexity. Once each of these models had been developed and tested they assumed the status of system sub-models as they were combined to form a 'complete' synthesis model. That holistic analysis is presented in Chapter 6, but each of the intermediate sub-models represents a study in its own right and they are sufficient, as stand-alone activities, to reveal powerful and interesting conclusions and contributions to the literature.

The key contributions of this thesis work are in the SD modelling and in the energy policy related to environmental and energy security concerns for low-carbon isolated electricity systems. A novel SD paradigm for transitioning low-carbon island electricity systems is developed to support policy goals, including notably, long-term capacity investments for increasing the uptake of renewables, and further reducing environmental impacts from the system. This is shown as a useful approach to uncover the desired endogenous implications of the system, from environmental and energy security driven policies. In addition, the approach provides policy guidance for improved decision-making for the long-term investment and integrated resource planning strategies that includes the generation mixes of island electricity systems.

Firstly, assuming a fossil-fuel only island system and using a simplistic model of such a system the key feedback effects related to the novel formulation of endogenous capacity margins are revealed. This simple preparatory model highlighted that the exogenously projected demand growth rate drives the system investments whilst the evolving capacity margin if adhered to by international (large system) standards will retard the long-term capacity investments of the system.

Secondly, the simple fossil-fuel model is extended to include the integration of renewables within the system. Low-carbon policy targets formulations allied with learning curves of renewables in island electricity systems are evaluated using this model. The research confirms that setting policy targets is indeed beneficial for emissions reductions, although meeting these targets too early can be inefficient or impractical if targets are unrealistic. However, in all cases considered the goals can

be eventually met. This means that there is great linkage to the policy goals of the system meriting critical evaluations. Hence, setting successful renewables targets should be further investigated for energy security and environmental concerns.

Thirdly the thesis presents a novel, detailed and endogenous electricity demand structure for transitioning low-carbon island electricity systems and proves that the long-term endogenous demand can be greatly influenced by low-carbon policies such as energy efficiency and *Electric Vehicles* (EV) promotion. Critical analysis reveals that energy efficiency is the more important and can act as a brute force solution useful for safeguarding the energy security of the system. EV electrification is not as influential but exhibits some interesting longer-term demand dynamics which can be interesting to policymakers for fulfilling their environmental and energy security objectives. Additionally, it was found that, for isolated island systems pursuing low-carbon objectives, it is the policy behaviour of the locals rather than externals that will make the key impact on future electricity demand.

Finally, the thesis integrates challenges that are most critical when considering transitioning low-carbon electricity systems. It confirms that effective policies, for sustained renewables uptake and improved investor decision-making for the generation mix, can be achieved. Electrification with EVs emerges as the prime candidate to sustain the uptake of renewables along with direct renewables policies. However, enhancing EVs increases the long-term electricity demand of the system, but it aids in deferring investments within the system in the shorter-term, unlike more direct renewables policies. Moreover, it is seen that in the long-term, investments in fossil generation is almost non-existent. However, some fossil-fuel based capacity stubbornly remains within the generation mix for frequency balancing. It is then interpreted that innovations in low-carbon frequency balancing generation can assist to further decrease the environmental effects while further enhancing the energy security (fossil fuel import independence) of the system. Additionally, it was observed that the right mix of low-carbon policies can mitigate the long-term uncertainty of a system impacted

by environmental and energy security concerns. This contribution assesses prospective solutions for the long-term investment strategies of emerging low-carbon island electricity systems.

1.5 Thesis Organisation

The thesis is organised as follows:

- **Chapter 2** presents a comprehensive literature review of the transitioning to low-carbon electricity systems. Specifications of the requirements and possible make-up of future low-carbon electricity systems is given together with the necessary technologies and applications that facilitate them. Chapter 2 also highlights the intrinsic complexity of these future systems and a critical review of the different modelling and research methodologies used to study them. Finally, the emerging characteristic challenges and behaviours embodied within policy and investment decisions of these low-carbon transitioning systems are provided.
- **Chapter 3** details the research methodology, and software modelling platform and case study system used in this thesis. It gives the rationale for choosing this methodology and the best practice for effectively modelling complex systems. Examples as applicable to this thesis work, such as the initial dynamic hypothesis are explained. In addition, an overview of the step-by-step approach employed for successfully conducting the research is shown.
- **Chapter 4** presents the two simple, separate initial sub-models. These two sub-models (fossil-fuel sub-model and renewables integration sub-model) address the first and second sub-questions of this thesis. The descriptions, validations and explanation of the use of the both sub-models are detailed within this chapter. The chapter provides comprehensive island-based scenarios that evaluate the findings. Work in this chapter has been published in (Matthew *et al.*, 2014, 2015, 2016).
- **Chapter 5** presents the third contribution. A sub-model used for characterising the endogenous demand within evolving low-carbon island electricity system driven by

environment and energy security concerns. It also analyses various policy scenarios for long-term endogenous electricity demand. Work from this chapter has been published in the journal *Energy Policy* (Matthew *et al.*, 2017).

- **Chapter 6** incorporates the sub-model structures developed in Chapters 4 and 5 to establish a more comprehensive model of the system to satisfy the fourth sub-question of this thesis. The model fully captures the necessary endogenous characteristics of the evolving low-carbon electricity system. Prospective long-term investment solutions and policy recommendations for improved decision-making within the nexus of environmental and energy security concerns are also developed from the scenarios and analysis.
- **Chapter 7** concludes the key findings and original contributions presented in this thesis. It provides some energy policy implications for isolated island systems and discusses the transferability of key thesis findings for larger interconnected electricity systems. In addition, some future research avenues created from this work are provided.

Chapter 2. Understanding the Complexity of Low-Carbon Electricity Systems

In the previous chapter, the advent of newer types of future electricity systems and their unavoidable complexity has been described. This dilemma is coupled with the desire to understand emerging challenges and behaviours within these systems. This chapter has three aims: 1) to specify the requirements for, and possible make-up of, future low-carbon electricity systems, 2) to highlight the intrinsic complexity and how this has been understood to date, and 3) to establish emerging characteristic challenges and behaviours embodied within policy and investment decisions. These are pivotal concepts inherent to electricity systems. They require improved understanding.

Noting numerous political and economic considerations and a myriad of end users, electricity systems are inherently large-scale socio-technical systems. They carry with them many economic implications to human society for development and for the overall well-being of individuals. Access, affordability, and availability of the production, delivery and consumption of electricity are provided by the grid system and entail a delicate balance of electricity supply and demand. Generally, electricity supply results from the management decisions made by power system operators for capacity investments, and to generate, transmit and distribute electricity throughout the grid network (MIT, 2011). On the other hand, demand arises from the complex decisions of numerous residents and industries connected to the grid. They consume electricity but in the future may be enabled also to produce electricity (MIT, 2011; Jordan, 2013). According to US DoE (2004), future low-carbon and smarter grids will apply currently available technologies, tools, and techniques to bring knowledge to power - knowledge capable of making the grid work far more efficiently and to be sustainable. However, despite such considerations and plans the present electricity system is set to move into an undetermined and uncharted territory. Hence, there is a

need to further understand the system before making changes to it, a vital approach needed for the key stakeholders.

“When you are confronted by any complex system, such as an urban centre or a hamster, with things about it, you are dissatisfied with and anxious to fix, you cannot just step in and set about fixing with much hope of helping. This realisation is one of the sore discouragements of this century ... You cannot meddle with one part of a complex system from the outside without the almost certain risk of setting off disastrous events that you hadn’t counted on in other remote parts. If you want to fix something you are obliged to first understand ... the whole system.”

-Lewis Thomas, 1974

This very useful advice provided some context for this work. Simplifications of the evolving low-carbon electricity system are warranted to clarify thinking and to improve understanding of the whole complex system. In addition, we elucidate useful insights into the socio-techno-economic “system of systems” complexity of the evolving low-carbon electricity system and seek to make visible inherent emerging challenges that are posed to policy and investment decisions.

2.1 Future Electricity Systems

Legacy electricity systems currently suffer from some of the key aspects of modern society such as rapid and evolving technological changes and pressures mainly driven by ICT influences. Together with ageing electricity network assets, and thermal and operational power network constraints such as CO₂ emissions, there are growing concerns about the sustainability and reliability of energy supply. The sustainability of these systems is heavily reliant on the unaffordability and availability of current fossil fuels for electricity production (Eurelectric, 2012; IEA, 2013). Also, in respect of the environment, there is a strong social urge to de-carbonise the present electricity system with increased shares of low-carbon energy sources (IRENA, 2014a; European Commission, 2016; UNFCCC, 2016). Furthermore, recent studies state that these issues motivate the development of smarter and/or low-carbon electricity systems (Ekanayake *et al.*, 2012; Momoh, 2012; Sawin,

Seyboth and Sverrisson, 2016). According to the authors, this development represents a means for de-carbonisation and decentralisation of present electricity systems and services. Therefore, it implies that existing and future electricity systems must adapt, and this provides an attractive basis for the exploitation of newer and improved electricity systems or smarter low-carbon grids (Momoh, 2012).

Consequently, this shift towards future electricity systems is not only influenced by the factors listed above. There is a diversity of emerging market players and end users appearing within such a system. They will lead the transformation from a centralised, producer-controlled network to one that is less centralised and more consumer-interactive. The resulting system would be a highly decentralised low-carbon energy system that can have two-way communication, and other enabling technologies and interoperability standards (MIT, 2011). According to US DoE (2004), society should prepare for a future electricity system that is cleaner, more efficient, reliable, resilient and responsive i.e. a smarter grid and/or smart grid system. Such systems are however not restricted to the distant future. Modern systems are already enabling this process of transition. Indeed, seeking such a system has influenced the present global trends, for the use of decentralised low-carbon energy sources (MIT, 2011; Sawin, Seyboth and Sverrisson, 2016). Renewable energy sources, such as wind, wave, and solar power are increasing. For example, over 25% of globally installed energy capacity in 2011 came from low-carbon sources i.e. renewables, nuclear (Madrigal and Stoft, 2012). In fact, renewable energy provided an estimated 19.2% of global final energy consumption [sic] in 2014, and the growth in renewable power capacity continued in 2015 (Sawin, Seyboth and Sverrisson, 2016). However, it is been observed that several of these energy sources are primarily variable in nature and present unpredictable effects, as they are integrated into a decentralised, diverse, dynamic and evolving integrated electricity system (Eurelectric, 2012; Ilic, Xie and Liu, 2013; IRENA, 2015). Although less variable low-carbon sources such as geothermal, run-of-river hydro and nuclear will have smaller effects on the physical system, they are either physically unavailable or suffer from social and political questions as in the case of nuclear. These alternatives

for low-carbon sources represent one of the key challenges of future electricity systems. (It is important to note here that the case study for this work has lots of prospects for, and is already endowed with geothermal and run-of-river renewable generation sources.) Furthermore, the required choice and integrated usage of various low-carbon sources are coupled with the distributed grid management, required data communication and automation sufficient for social consumer cooperation characterising the economic aspects of the future system. Momoh (2012), Ilic, Xie and Liu (2013), Ekanayake *et al.* (2012), give details of possible future electricity systems, and which are briefly summarised in the following section.

2.1.1 Outlooks for Future Low-carbon Electricity Systems

The literature highlights that there is no single agreed definition of future electricity systems, however; there are some key characteristics that must be satisfied. Future electricity systems must be observable, controllable, automated and fully integrated (Bompard *et al.*, 2012). According to Bompard *et al.* (2012), future electricity systems are smart electricity systems which can in turn, intelligently integrate the actions of all users connected to it - generators, consumers and those that do both (“prosumers”), in order to efficiently deliver sustainable, economic and secure electricity supply. Systems that can facilitate such requirements and behaviours can be low-carbon based and such systems are often referred to as smart grid electricity systems (US DoE, 2004; MIT, 2011; Ekanayake *et al.*, 2012; Momoh, 2012). According to US DoE (2004), two major timelines can be applied here. A smarter electricity system which offers valuable enabling technologies that can be deployed within the very near future or are already being deployed today, and the longer-term smart grid electricity system described above – which represents the future promise of an electricity system remarkable in its intelligence and impressive in its scope. Such systems are a decade or more from realisation (US DoE, 2004). The enabling technologies required to host such a system can be thought of as being a multi-technology mix of data collection, processing, and operational facilitation (MIT, 2011). Figure 2.1 gives a snapshot overview of the outlooks of future smart low-carbon electricity systems. All aspects of such a system are interconnected in order to provide the

necessary smart generation, transmission, distribution, consumption, and storage that entail a future smart grid electricity system which can deliver the anticipated positive benefits and general improvements to the daily lives of the global population.

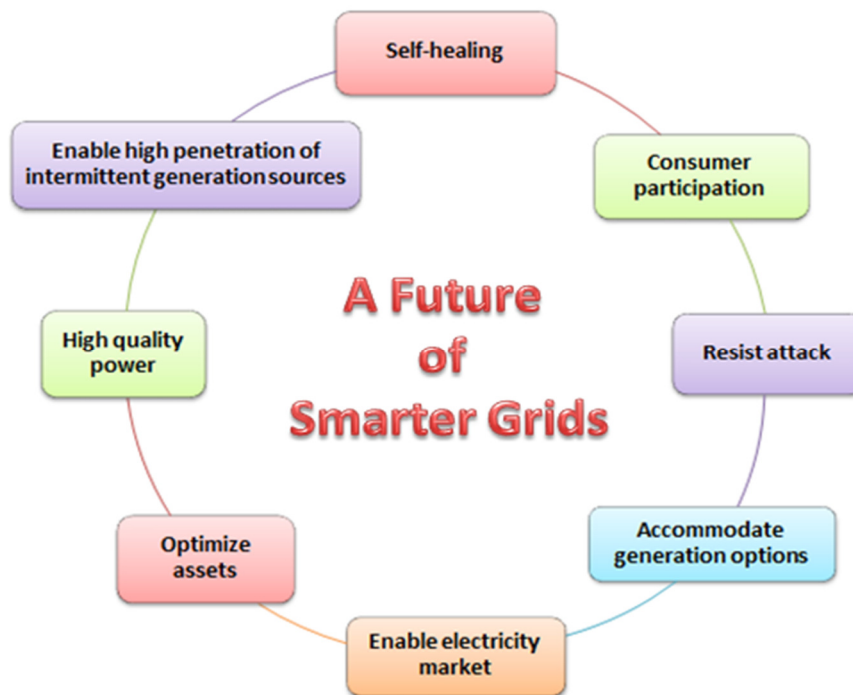


Figure 2.1 Outlook for Smart Low-Carbon Based Electricity Systems (adapted from Sauli Jäntti, 2014)

In due course, the electricity system may be equipped to meet present and future sustainability, reliability, flexibility and affordability needs (Chappin, 2011; IRENA, 2013, 2014a).

2.1.2 Context of Developing Sustainable Low-Carbon Electricity Systems

As described in the previous section and shown in Figure 2.1, the smart grid electricity system offers many interesting and beneficial outlooks for its stakeholders. This system can, and should, deliver enhanced energy security, reduced CO₂ emissions, improved grid asset utilisation, increased consumer participation, and be a more sustainable energy system for both present and future generations (MIT, 2011; Momoh, 2012). There is, however, no predefined roadmap of exactly how such a system should and will evolve. This research work focus on the transitioning of present systems into low-carbon electricity systems of today and the future, as they become the smarter

or smart grid electricity systems of the distant future. For this thesis, the evolution of low-carbon electricity systems is studied. These systems are the prelude to the smart grid (US DoE, 2004) and are dynamic, evolving and integrated electricity systems that can facilitate the options of distributed renewable generation, energy storage, electric vehicles and some form of load shifting/demand side management. Such factors represent what enables the development of low-carbon electricity systems without having the smart electricity system.

The underlying motivation for the expansion and development and, to an extent, the transitioning of legacy electrical power networks hinges on the concept of long-term power planning (Ford, 1997). Long-term power planning is also known as “capacity expansion planning” attempts to define the least-cost needed for capacity expansion that meets growing demand over a long-term horizon, of approximately 10 to 30 years (Jordan, 2013). According to details given by Jordan (2013), the costs incurred are typically the sum of the capital investments of newly constructed capacity and the ongoing system operational costs of meeting demand within the horizon of the system outlook. Typical decisions would include the timing of investment, the type of investment (fossil-fuels, nuclear, hydro, etc.), the size of newly constructed capacity, and the preferred mode of operation. These are all bounded within the long-term goals and ambitions for the system.

In addition, the development of any sustainable low-carbon electricity systems includes not only the technological advances of the technical and physical generation, transmission and distribution of the power grid system, but also the economies of the related energy markets, the surrounding ecological conditions and social behaviours of the stakeholders (Bompard *et al.*, 2012; Brinkman, 2015). Resultantly, the emerging electricity generation combines different types of new renewable sources together with legacy generation enabling incentives for appropriate investment decisions and for providing reasonable development and utilisation policies (MIT, 2011; Bruchon, 2013; IRENA, 2015). Furthermore, according to Bompard *et al.* (2012), there are inherent complexities

that will reveal emerging consumer, policy and sustainability challenges and behaviours for the transition into future low-carbon electricity systems.

A more detailed visual look at the complexity of the evolving low-carbon electricity systems is shown in Figure 2.2. It illustrates some of the modern enabling technologies such as ongoing power system enhancements, computational intelligence, environments and economies, low-cost communication and electronics, and interoperability standards that comprise the overarching aspects of future low-carbon based electricity systems.

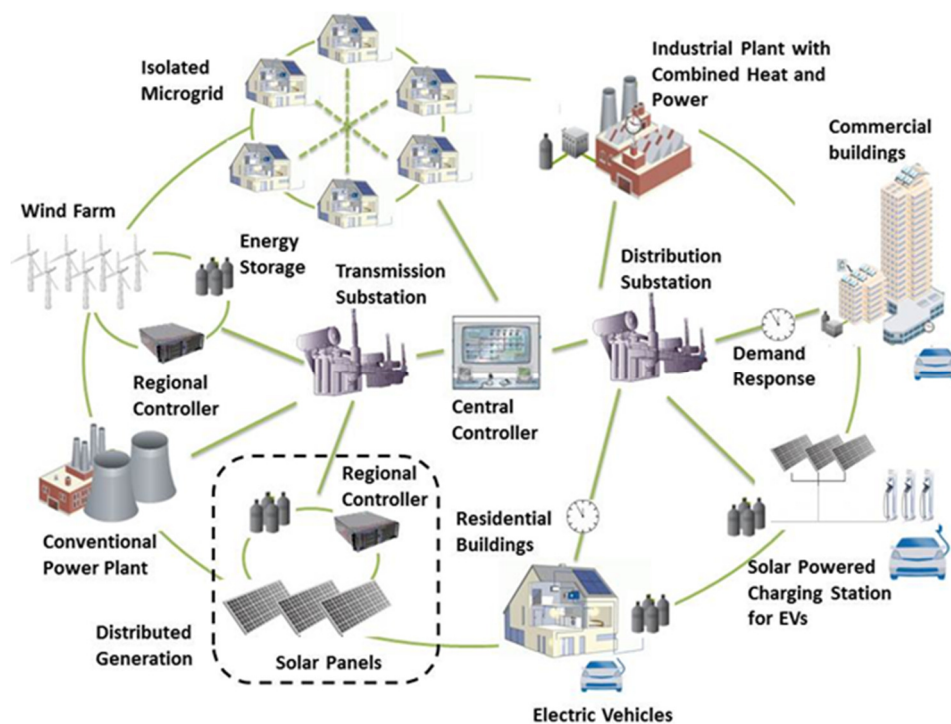


Figure 2.2 Evolving Complex Low-Carbon Electricity System Structure (Brown and Zhou, 2012)

Legacy electricity systems are indeed already complex, and as they transition into low-carbon systems they become even more complex due to increased distributed generation and more diverse consumer interactions. This increased complexity poses an even greater challenge to system planners and operators as they try to manage these systems (Dyner, 1996; Momoh, 2012).

2.2 Complex Systems

The emergence of complexity within systems can be seen as a daunting phenomenon that hinders proper understanding necessary for the management of such systems (Morecroft, 2007). Krohs and Kroes, (2009) states that complexity results from features of the system's parts that are qualitatively different to the emergent system properties they exhibit. Some systems are complex adaptive systems, which adapt as a whole and are self-organising. According to Bompard *et al.* (2012), the evolving low-carbon electricity system is a large-scale socio-techno-economic system characterised by distributed control and interactions of subsystems. Subsystems themselves are systems (Simon, 1973), and they interact on different levels. Chappin (2011) argues that complex systems can evolve because of the (inter) action of all actors involved, and each actor can only partially influence the path of the transitioning system. The need for capturing multi-level interactions necessary for insights into future pathways of technological transitioning systems was highlighted in Geels (2002). As the transition to future low-carbon electricity systems occurs, the added complexity of the changing components or subsystems interactions on different levels signals this need for improved understanding of the system. Foxon (2011), in looking at the transition to a sustainable low-carbon economy, highlighted that the elucidation of the causal influences relating to the evolutionary dynamics in each subsystem is key to achieve the necessary insights. These insights are akin to the role of system design and control. Since this evolution of the system reveal temporal and spatial complexities which are not intrinsic to the system design and control (Sterman, 2000). Furthermore, the overall organisational management structures of all those complexities within the system are important and necessitate in-depth studies.

2.2.1 Systems View vs Event-based Thinking

Complex system thinking is synonymous with the concept of a systems view approach, with thinking in systems originating from the 1950s (Dijkema, 2004; Bekebrede, 2010). Many different perspectives on systems thinking have developed over time (Chappin, 2011), however, as highlighted by Forrester (1961) the key is to understanding the structure of the system and

capturing counter-intuitive behaviours. Behaviours that may be motivated by a desire to solve a problem but often make it worse, creating unanticipated side effects and provoking reactions by others seeking to restore the balance that is upset (Chyong, 2014). Furthermore, the structure of the system creates behaviour (Goodman, 1997; Sterman, 2000; Morecroft, 2007). System thinking can help in redesigning the structure (Sterman, 2000; Chappin, 2011). Goodman (1997) in his iceberg framework shown in Figure 2.3 points to the fact that the events (what happened) and patterns (what has been happening) are defined by the interactions creating this behaviour, which is the underlying system structure.

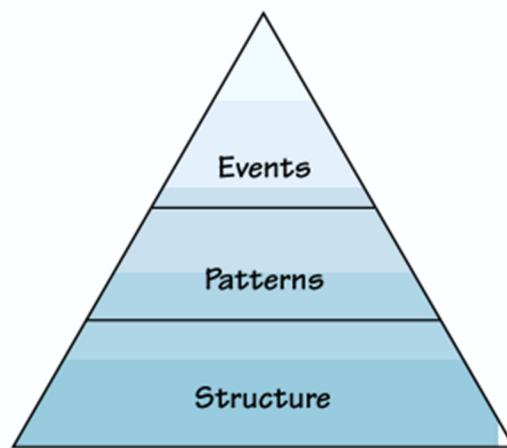


Figure 2.3 Iceberg Framework for Systems Thinking (Goodman, 1997)

System view thinking highlights circular causality, that is, the feedbacks between and amongst actors and entities within the system. According to Sterman (2000), the problems and their solutions are intertwined and problems are a consequence of the cumulative effect of previous decisions and actions. Such circular thinking gives rise to and improved understanding of otherwise perplexing phenomena, as the network of cause and effect that lies behind them are revealed (Chyong, 2014).

Alternatively, the use of an event-oriented thinking is generally not as fruitful as systems thinking. This type of thinking focuses on the events, which is at the top of the framework shown in Figure 2.3. Event-based thinking provides limited understanding because typically this thinking style is

linear: from problem-as-event to solution-as-fix. This leads it to be pragmatic, action oriented and often myopic (Chyong, 2014). Since the problems, that it addresses are usually sporadic and stem from uncontrollable events external to the origination of the symptoms. This type of thinking can assist in having a quick fix towards a temporary solution but generally will not provide a good long-term solution.

Resultantly, a focus on event-based thinking leads to a reactive solution that is not very influential in the long-term, whilst feedback systems-thinking provides proactive solutions that have a greater impact (Sterman, 2000; Morecroft, 2007; Martinez-moyano and Richardson, 2013; SDS, 2014). By mapping the feedback paths and casual relationships within the system using the mental models of the system (Forrester, 1961; Goodman, 1997), this allows for an understanding of the structure and in turn, the behaviours generated. This understanding assists in redesigning the structure of the system to minimise problems and elicit hidden long-term consequences. Our chosen method of a systems view approach is important, and not inconsistent with our focus on modelling the key underlining feedbacks and relations. The next section highlights the use of modelling in both legacy and future complex electricity systems.

2.2.2 Complex Electricity Systems Modelling

Large-scale socio-technical systems, such as a transitioning electricity infrastructure, are increasingly becoming more complex in nature (Chappin, 2011; MIT, 2011; Bompard *et al.*, 2012). It would be beneficial to understand them, and hence to solve problems and in turn to inform decision making. According to Chyong (2014), an approach to the use of reactive solutions by observing the sporadic event-type problems that arise, prove to be less influential than proactive solutions based on understanding the system structure. Also, Dyer (1996) argues that an abstraction of reality can be useful, thus models and modelling are of utmost importance to the planning process of electricity systems. In fact, the use of models for understanding complex electricity systems is widely observed in the literature.

For example, legacy electricity systems use a method known as “traditional planning” in which a centralised coordinator is responsible for operational decisions, real-time control and monitoring of the electricity system. However, with future low-carbon electricity systems being distributed and decentralised the models for these systems should have more autonomic characteristics. Nevertheless, centralised planning models such as *Integrated Resource Planning* (IRP) can still aid in various contexts and situations. However, the use of optimisation approaches for system expansion with electricity markets as imperfect, oligopolistic markets using sequential game theory are examples of situations where centralised models do not work well (Jordan, 2013).

Modelling of complex systems (such as an evolving low-carbon electricity system) can prove beneficial not just for understanding the system, but also for informing the decision-making within the system. Many different types of modelling mechanism have been utilised over the past few decades especially in the area of capacity generation expansion (i.e. increasing electrification) as a means of development and for enhanced utilisation of these systems. However, with these models, the uncertainty increases with the number of possible solution futures, and all the decisions are taken sequentially (Centeno, 2009). Jordan (2013), argues that additional features should be incorporated into these models, making the decision problem even more complex. Non-linear relationships can arise in both the objective function of the amount of capacity needed and the financial and time constraints considered. This will influence the set of possible solutions that can exist for the model. Concurrently, while it is mathematically attractive to have an optimal long-term (20 or more years) plan, it is rarely, if ever, adhered to completely due to unforeseen changes both exogenous and endogenous along the way. Additionally, the traditional methods and models are solely driven by an event-based view of the electricity system planning (see Section 2.2.1). The most suitable modelling mechanism should be able to capture the uncertainties that exist over a long-term planning period, as can be done via systems view thinking.

Nevertheless, there is widespread use of mathematical methods such as *linear programming* (LP), *mixed-integer programming* (MIP), *dynamic programming* (DP) and *non-linear programming* (NLP)

to solve development and utilisation problems of modern and future electricity systems. The need for additional optimisation and heuristic solutions employed to tackle the high complexity and dimensionality of these problems resonates with these mathematical methods. Some of the optimisation and heuristic methodologies are stochastic programming, simulation techniques, genetic algorithms, *system dynamics (SD)*, *agent-based modelling (ABM)*, Monte Carlo simulation, probabilistic simulation, decision theory, game theory, scenario analysis, multi-criteria techniques and real options (Centeno, 2009). All of these above mentioned methodologies prove to be useful for modelling different aspects of electricity systems for which they are most effective. These different aspects include capacity expansion investments and improving the decision making of the system such as grid balancing or energy policy analysis (Dyner, 1996; Lalor, 2005; Dimitrovski, Ford and Tomsovic, 2007; Ilic, Xie and Liu, 2013).

Of the methods mentioned above, stochastic programming, simulation techniques, genetic algorithms and Monte Carlo simulation are all focused on optimisation of the system for a specific variable/s requirement/s and are event-based approaches. Whilst, probabilistic simulation, decision theory, game theory, scenario analysis, multi-criteria techniques and real options are not focused on optimisation of the system variable, they nevertheless do not possess a whole systems view approach. However, agent-based modelling (Macal and North, 2006) and SD can give a good representation of the real world systems using a whole systems view approach and are highly capable of incorporating all of the necessary uncertainties that exist within the system. Agent-based modelling focuses on individual actions of all entities within the system whilst SD is about the understanding of how all entities in a system interact with each other (Harrison, Thiel and Jones, 2016), giving the system structure desired in Section 2.2.1. The agent-based method makes use of a bottom-up approach in which each individual active entity within the system is characterised by rules and allowed to interact with other entities. The global behaviour of the system then emerges as a result of interactions of the individual behaviours and not the complete system structure. According to Rafferty (2010), agent-based modelling is computationally expensive and can ally itself

to either the holistic or reductionist viewpoints of the system. SD only allows for the system view required and is not a computationally expensive technique (Sterman, 2000). Hence, within this thesis, SD has a greater appeal than agent-based modelling, and more support for this is presented in Sections 2.2.4 and 3.1.

In summary, four categories of planning models are observed in this section similar to the observations of (Owlia and Dastkhan, 2012). These are econometric models such as LP that have low precision generally because of considering low details. Then there are energy equilibrium models such as genetic algorithms that also has a low level of details. Thirdly, there are optimisation models which utilise mathematical modelling techniques such as MIP. These models have a high level of details but suffer from the fact they are event-oriented and cannot investigate the dynamics of the system. Finally, there are simulation models such as system dynamics, which can include all-important features such as high level of details, precision, and flexibility and most importantly are able to investigate and analyse the dynamics of the system. The next section provides context to the desired shift for better modelling of present and future electricity systems.

2.2.3 Improving Modelling Methodologies for Future Electricity Systems

The wide range of methods used for modelling legacy electricity systems, highlighted and summarised in Section 2.2.2, will most likely continue to be useful for future low-carbon electricity systems. However, according to Jordan (2013) and Steel (2008), a key problem exists, which is that the electricity demand and total costs are usually assumed to be exogenous to these planning models. They argue that understanding and making the best of the development and utilisation of future electricity systems will rely heavily on a more endogenous view of electricity demand load (Meier and Chatterjee, 1987; Jordan, 2013), and some other emerging characteristics that are not yet apparent or included. Their arguments are in line with the systems view, the approach of understanding the structure of the system and has brought to light the needed shift in rationalising policy and planning models within the energy sector. According to Jordan (2013), this shift involves the creation of integrated tools incorporating the salient features of the various countries of the

electricity systems being modelled. These range from conventional methods to those that capture physical and economic laws. The following, Table 2.1 lists a variety of salient social, economic and technical factors that can be of interest to electricity system modellers. Observations from developing countries may offer insights and understanding for the problems facing more developed economies, such as São Miguel (our case study).

rural - urban divide	decentralised supply options
reliance on traditional energy (biomass, firewood)	prevalence of inequity and poverty
informal sector activities (barter, in-kind payments)	technological change
technology diversity (ability to leapfrog)	technology diffusion
transition to modern energy (increased consumption pattern and rising energy intensity due to modernization, urbanisation, employment demand)	sector reform/structural change and competition in emerging liberalised markets
spatial difference and divergence in consumption/ disaggregated demand by income and location	environmental implications of energy use (sustainability)
low data availability for modelling	long-term uncertainties
economic growth and corresponding energy implications	demand-side options
energy shortage/poor performance of utilities	the financial status of utilities
low energy access and rates of electrification	resource depletion
institutional issues like corruption	

Table 2.1 Listing of salient features not commonly included within energy models for developing countries (adapted from Jordan, 2013)

In line with this, the literature contains a very rich collection of electricity modelling studies that include physical and technical details of the electricity system together with some form of salient

characteristics. This literature set includes pioneering energy-modelling programs such as (“WAsP – the Wind Atlas Analysis and Application Program”) used for bankable wind resource assessment and siting of wind turbines and wind farms. (“LEAP - Long range Energy Alternatives Planning System” used widely as a software tool for energy policy analysis and climate change mitigation assessments. Whilst (“TIMES MARKAL - the Integrated Markal-Efom System”) does multi-year investment optimisations of the system and can also test a series of policy options. These tools have long been used to assist with energy and electricity system optimisation and capacity expansion planning. Although widely used, they do not fully capture a wide range of salient features of the electricity system nor have endogenous demand. From these many electricity systems modelling methodologies, and those highlighted in Section 2.2.2., only a limited number can capture the salient features needed to understand fully the evolving complex “system of systems”. Furthermore, to understand complex socio-techno-economic systems, such as an evolving low-carbon electricity system, it is best to use a mechanism that can utilise a whole-systems view in order to capture endogenous interactions and also to account for the most salient features of the system. The above-mentioned techniques LEAP, TIMES MARKAL and WAsP, and others such as *Hybrid Optimization of Multiple Energy Resources* (HOMER), *Distributed Energy Resources Customer Adoption Model* (DER-CAM) and Energy Exemplar (PLEXOS) are also generally based on single or multi-objective optimisation mainly seeking to optimise the system using the event-based approach. However, these newer methods such as HOMER and PLEXOS are commonly used for assisting the energy transition IRP process (HOMER, 2017; PLEXOS, 2017). The action oriented guide, Islands Playbook energy transition initiative (ETI) is also used for assisting the energy transition IRP process (ETI, 2017). These advances for comprehensive modelling are good but they are unable to capture the key causal relationships within the system. Also, they lack the feedback structures, inertia, and delays that can be accounted for in the real system and captured using a systems view approach. Furthermore, as shown in the previous section, SD is highlighted to be more suitable than agent-based modelling as the desired whole systems approach for this thesis. We are

aware that ABM is a widely used method which leaves an opportunity for the use of SD for this thesis work. Additional reasons not listed before includes the expertise needed for this research project and the high level of confidence given by prior use of the SD method for electricity systems modelling. This thesis gives interesting insights into the structure of the evolving complex low-carbon electricity system for providing more influential long-term solutions to emerging policy and investment behaviours within the system. The current use of SD for electricity systems modelling and further discussions concerning the reasons for the choice of this methodology may be seen in the following section and Section 3.1, respectively.

2.2.4 System Dynamics and Electricity Systems

At the same time, SD modelling has been used for strategic energy planning and related policy analysis for more than thirty-five years and can efficiently provide a basis for a well-documented, understandable, and concise representation of complex electricity systems (Dyner, 1996; Ford, 2008; Steel, 2008). By definition, SD is a whole-systems approach, based on theories of non-linear dynamics and feedback control, which are used to represent, and understand, the structure and dynamics of complex systems (Sterman, 2000). It was developed in the 1950s by Jay Forrester (Forrester, 1961) and has been used extensively from the early 1970s up until today. Many pioneering models such as Roger Naill's FOSSIL2 were used to simulate and inform oil and natural gas policies in the United States during the 1970s and 1980s (Naill, 1992). In a parallel fashion, Andrew Ford developed the ELECTRIC1 model which was used to analyse the future of the US electric power industry (Ford, 1975). This work was the first in a series of SD electric utility models known as the EPPAM models, adaptations of which were useful in formulating the COAL2 and FOSSIL2 models, along with IDEAS and its evolved Energy2020 (Systematic Solutions Inc, 2014) counterpart. Similar to these models are two currently available open web-based SD based models, C-ROADS used for global climate policy analysis (Climate Interactive, 2014a). And its extension EnROADS is useful for linking global energy, to economic and public policy, and climate policy analysis (Climate Interactive, 2014b). These models are important in managing energy and environmental

resources and continue to be influential in shaping the decisions of many policy makers worldwide (Dyner, 1996; Ford, 2010; Jordan, 2013; POLES, 2016).

In terms of other aspects, it is seen in the literature that SD studies have addressed many problems in the electricity industry. Numerous such models can be found in the literature each highlighting different aspects of energy policy or electric power grid systems (Arango *et al.*, 2002; Ford, 2010; Caravajal, Arango and Arango, 2011). The effects of external agents on utility performance, the financial performance of utilities, the effects of energy conservation practices on utility performance and deregulation in both the UK and US electric power industries are also highlighted (Radzicki and Taylor, 1997). It is claimed that these insights can be attributed to the ability of SD for representing rapidly changing, deregulated utility markets with high uncertainty and risk (Dyner and Larsen, 2001). Additionally, the elicitation of the impact of market structures, power, and competition, uncertainties on capacity investments, technology mix and cost to consumers are all efficiently captured (Sanchez *et al.*, 2007; Jordan, 2013). These models are all targeted to assess macro-level policy analysis by capturing multiple feedbacks, delays, and the behaviours of stakeholders such as utilities/power companies, consumers, and governments (Jordan, 2013).

In the area of markets and transportation, two concise detailed review of SD modelling over the past few decades is provided in Teufel, Miller and Genoese (2013) and Shepherd (2014). These articles show the appropriateness of using SD for these types of electricity system models based on the fact that qualitative aspects and salient features can be easily incorporated to reflect more realistic behaviours and system structures. Shepherd (2014) gave a comprehensive review of SD models applied in the field of transportation. According to Teufel, Miller and Genoese (2013), three trends for the use of SD were highlighted. Ranging from SD being used on its own to being complemented in conjunction with other methodologies such as decision trees, game theoretic approaches, and real options theory. Examples of these combinations include the use of embedded game theory to simulate generation expansion in the context of security of supply mechanisms based on long-term auctions (Rodilla *et al.*, 2011). There is also the successful combination of SD

with optimisation methods for simulating power plant construction in the Western Electricity Coordinating Council while capturing detailed power grid transmission operation (Dimitrovski, Ford and Tomsovic, 2007).

In a paper by Arango *et al.* (2002), a model was developed for the estimation of cash flows and other financial indicators of capacity expansion within the Colombian energy market. The authors modelled the costing of endogenous electricity market prices without considering the relative installed capacity investments existing within the system. Deregulated electricity markets as a catalyst for capacity expansion were also explored by others (Vogstad, 2004; Jaeger, Schmidt and Karl, 2009). In addition, more highly detailed and new market design models are emerging based on green electricity certificate markets, distributed integration of renewable energy sources, carbon policy incentives and taxation, and the use of newer types of energy storage mechanisms (Ford, Vogstad and Flynn, 2007; Ford, 2008, 2010; Rooney, Kazantzis and Nuttall, 2013; Robalino-Lopez, Mena-Nieto and Garcia-Ramos, 2014). In Bildik *et al.* (2015), the SD approach was applied to understand the diffusion of a new technology, namely wind power. The authors showed the extent to which SD captures the underlying mechanisms of the diffusion process and applied this as a comparative study for the large interconnected energy systems of California and the Netherlands.

Furthermore, stochastic variable distributions and related methods such as applying *Markov Chain Monte Carlo* (MCMC) simulations within SD modelling for calibration and sensitivity testing were observed in some studies (Sterman, 2000; Chyong Chi, Nuttall and Reiner, 2009; Pierson and Sterman, 2013). In addition, SD combination with scenario planning Lindgren and Bandhold (2009) can be seen in Connors *et al.* (2002) and other similar works. These works have helped reinforced the concept that there is significant relevance for the use of SD as a methodology for the evolving low-carbon electricity system analysis.

With a focus on transitioning low-carbon electricity systems, the work of Black (2005) was highlighted as an initial detailed and insightful SD model of these evolving systems. The author

studied the US power grid deregulated market focusing on demand response technology adoption. Black (2005) formulated his model with endogenous demand load and accounted for its impact on the demand side management of the electricity system, a useful formulation that is applied in this thesis. Collins *et al.* (2013) produced an SD-aided study using an approach of disaggregated demand and supply for their analysis of electricity system planning. The authors incorporated load seasonality and technology operations into the generation capacity expansion problem using exogenous energy demand and supply. Other studies including Steel (2008), Jordan (2013) and like with Black (2005) suggest that endogenous demand dynamics cannot be ignored, being intrinsically tied to the structure of the system. Jordan (2013) focused on the aggregated endogenous demand dynamics to study electricity capacity expansion. Previously, Steel (2008) looked at aggregated endogenous demand dynamics and the effect of consumer decisions on electricity grid reliability, energy resources depletion and electricity tariffs. Both the modelling efforts of Jordan (2013) and Steel (2008) were targeted to large-scale electricity grid networks in developing countries. Our focus is on a small-scale grid within a developed, isolated territory.

This collection of literature points to the benefits provided by SD as a basis for understanding the emerging challenges and opportunities of an evolving low-carbon electricity system. The literature reveals the mature and rich history of SD for modelling electricity systems. The combinational use of SD with other methodologies was also highlighted. In addition, the importance of endogenous electricity demand in electricity systems became apparent in this section. The following section provides an overview of the major strides worldwide towards testing and studying evolving low-carbon electricity systems. Additionally, the particular role that SD can play is highlighted.

2.3 Studies of Evolving Low-Carbon Electricity Systems

As noted in Section 2.1.2 we focus on the transitioning of modern electricity systems into low-carbon futures. A future of low-carbon systems sits within the scope of smart/er grid systems with low-carbon objectives, noting enabling technologies and applications as shown in Figure 2.1. The evolving low-carbon electricity system is a step in the pursuit of the smart grid. There is a great

amount of literature devoted to low-carbon projects for electricity systems worldwide (Botelho, 2013; Ilic, Xie and Liu, 2013; Vallvé, 2013; IRENA, 2014a; Sawin, Seyboth and Sverrisson, 2016). Additionally, numerous projects of evolving low-carbon systems are continually appearing around the world. IRENA (2014) gives detail of over twenty-five low-carbon projects from islands and countries in the African and Indian Ocean, Mediterranean Sea, Caribbean and Pacific. These projects are mainly wind farms, solar farms and the use of energy efficiency and EVs for enhancing the energy security of the system and reducing their dependence on fossil fuels. According to the Islands Energy Program (2016), projects of this kind will create a blueprint that can be replicated in other isolated economies and possibly on other larger systems. In continental countries, low-carbon projects are also on the rise (IEA, 2013; Sawin, Seyboth and Sverrisson, 2016). For example, projects such as Low Carbon London and *Flexible Approaches for Low Carbon Optimised Networks* (FALCON) are pursuing the trialling of a series of low-carbon techniques such demand side management, in addition to developing new tools for modelling evolving low-carbon electricity systems. Sawin, Seyboth and Sverrisson (2016) highlights “the year 2015 was an extraordinary one for renewable energy, with the largest global capacity additions seen to date, although challenges remain.....” The authors also noted that the vast majority of countries worldwide have low-carbon, renewable energy supporting policies in place at the end of 2015. It was also observed by Vallvé (2013) that isolated island or remote areas can be an ideal testing grounds for mature low-carbon technologies. Since these low-carbon generation technologies can complement each other and can be matched in different ways to the electricity demand. This also implies that these systems are at the forefront of the innovative use of storage and load management techniques (Vallvé, 2013). Additionally, the development of micro-grid studies such as on Jeju Island, South Korea and in Hachinohe, Japan is noted. Micro-grid demonstration projects are examples of the recent trialling of autonomous low-carbon electricity systems. This current trend of projects and trials on smaller or less complex power grid systems (such as these previously mentioned micro-grids), parts of cities and/or on islands

resonates as a major theme for the development of low-carbon electricity systems and have also motivated this thesis work.

2.3.1 Isolated and Interconnected Electricity Systems

As seen in the previous section, it leads to say that stakeholders worldwide are attempting to pursue low-carbon electricity systems and to preserve or enhance energy security. This affords the opportunity to study such evolving systems. For large electricity systems, such as for a major country or continent, the inherent system complexities present an intractable challenge (MIT, 2011; Bompard *et al.*, 2012), so a more pragmatic option is to consider a smaller, but nevertheless complete, autonomous electricity system as a case study. Furthermore, there is growing evidence that it is important to understand how smaller semi-autonomous systems become sustainable and hence to extend considerations to larger interconnected networks (Ilic, Xie and Liu, 2013; Vallvé, 2013). As a result, smaller systems offer an ideal test bed to investigate the transitioning of the low-carbon electricity system (Eurelectric, 2012; Ilic, Xie and Liu, 2013; Vallvé, 2013; Islands Energy Program, 2016). We do this in the hope of testing easily managed and useful solutions.

In addition, isolated island systems differ from larger scale interconnected systems in that they generally do not endogenously develop new technologies. This is true even in the case of equivalent high levels of prosperity. Isolated island systems lack size complexity and are too small for effective internal economic competition when considering more sustainable future pathways (Eurelectric, 2012). Market isolation is often physical in origin. Islands also do not usually have the local price formation of electricity tariffs, hence these tariffs can be modelled as an exogenous variable, (largely) independent of local economic conditions. In addition, energy provision for island systems has historically been dominated by a dependency on imported heavy fuel oil and diesel, which means that such an energy system (and indeed the island's economic growth) have been strongly linked to fossil fuel prices (Eurelectric, 2012; IRENA, 2014a; Islands Energy Program, 2016). This system also has limited scale for cheaper fossil fuel generation options such as coal and natural gas (IRENA, 2014a). The literature suggests that typical small island consumers and stakeholders have

no power to influence fuel prices as they are exogenous to the island. This is true even when the island is linked politically to a larger developed country (EDA, 2008; ERSE, 2012, 2014). The impetus for low-carbon objectives, while remaining flexible and reducing the dependency on expensive oil imports has created a strong economic incentive to change the system's status quo (Eurelectric, 2012). Resultantly, island systems have represented an attractive focus for research of this type, not merely because of the tractable system size, but also because of the inherent economic and policy simplicity arising from their constitutional framework.

The previous section highlights the fact that small island systems have been studied extensively in the past decade as “living laboratories” for sustainable energy solutions, eg. Açores, Caribbean and Pacific islands (MIT-Portugal, 2013; IRENA, 2014b; Islands Energy Program, 2016). This has led to a rich repository of available data useful for electricity system modelling. Prior studies provide an interesting context to the type and quality of data available. For example, Weisser (2004) examined the main economic and technological obstacles for incorporating renewables within small island systems, while Parness (2007), Pina, Silva and Ferrão (2012) and Ilic, Xie and Liu (2013) studied testbed systems for electricity grid balancing and unit commitment optimisation. By acknowledging the differentiated dynamics and the lower levels of complexity in such systems, the results of these studies can be transferred to other island electricity systems and also extended to larger interconnected systems. Albeit, the additional inherent issues of fossil fuel on island systems (Vallvé, 2013; Islands Energy Program, 2016) is native only to island systems and this fact will have to be accounted for when transferring lessons learned to larger systems. The next section highlights some relevant modelling of low-carbon electricity systems on islands, along with some perspectives for the use of SD.

2.3.2 Modelling Low-Carbon Electricity Systems on Islands

The core focus of this section is to provide greater detail into studies of low-carbon island electricity systems. (Eurelectric, 2012; MIT-Portugal, 2013; Vallvé, 2013; IRENA, 2014a; Chmiel and

Bhattacharyya, 2015) give tremendous insights into a host of projects explored for future electricity systems using islands as “living laboratories” for the testing of future electricity system solutions. These major projects have driven and supported the growing interest of researchers keen to use island systems as case studies for improved understanding. Of these studies, highlighted above, are some that are of key relevance to this thesis. One such example is the work of Pina, Silva and Ferrão (2012), where the authors made use of the island of Flores in the Açores, characterised by high renewable energy penetration. They developed a TIMES MARKAL model with exogenous electricity demand growth. These authors sought optimal solutions for the energy system design and management, in the face of different possible exogenous evolutions of electricity demand. They also analysed the impact of demand-side management options, such as energy efficiency measures and dynamic demand response, to show that load shifting strategies can delay new investments while rendering the current investments on renewable resources more economically viable.

A different model of similar emphasis is an energy storage study on small isolated islands, also in the Açores, by Cross-Call (2013). A least-cost unit commitment model analysis was applied in order to determine the expected cost savings from introducing energy storage into existing electricity grid networks. The study highlighted some challenges and identified potential cost savings arising from energy storage within an evolving low-carbon electricity system. Similar to this is the work of Silva (2013) who employed multi-criteria decision methods to compare energy storage and other planning options for sustainable development within an island. Additionally, Parness (2007), made use of an economic dispatch and unit commitment model to explore environmental sustainability options on São Miguel in the Açores, giving attention to the optimal charging strategies for EVs, as needed to reduce electricity and transportation costs and to minimise CO₂ emissions. Of similar scope, Baptista *et al.* (2009) made use of the island of São Miguel to assess the impact of introducing EVs, applying a short-term discrete scenario-based life-cycle approach, quantifying the impact of EVs on the electricity demand and the CO₂ emissions.

Other works such as Critz, Busche and Connors (2013) used the *Wind Integration in Liberalized Markets* (WILMAR) model, balancing supply and demand on an hourly basis to model the Hawaii Island's electricity unit commitment scheme, with and without, demand response. That study used exogenous demand and treated demand response as a fully shift-able resource constrained by capacity and operational costs. Bruchon (2013) adopted the same model to study the island of Cyprus, in order to explore the potential of demand response programmes for integrating renewables into the electricity system from an hourly unit commitment perspective using stochastic optimisation. Perez and Real (2008) explored the creation of a European-type integrated electricity market within a small and isolated island group, the Canary Islands. These authors sought to understand better the challenges in creating such a market. Their results show that the designs of both the vertical industrial structure and the electricity grid operator (and its attributes) are key determinants of the successful operation of such an electrical system. In addition, the use of HOMER and PLEXOS to support IRP within the context of isolated island systems is used for such transitioning systems.

Collectively, the majority of these studies do not account for endogenous demand dynamics of the system but rather include the use of exogenous demand growth. They are also mainly stochastic optimisation models operated with the purpose of balancing short-term grid mismatch and/or investments. As shown in Section 2.2.3, modelling the salient features, such as the endogenous demand dynamics and longer-term system factors, can give useful insights into the long-term evolution of the electricity system. The use of SD is anticipated to help with capturing these details. However, for such small island contexts, the use of SD is very limited. In addition and in particular, the number of long-term investment and resource planning models is very limited. We posit this is because of a tendency of previous research work to focus on short-term policy and design requirements for small island systems, hence lacking exposure to the already used systems thinking best practice occurring in larger systems.

As mentioned above, the availability of SD studies in regard to small island electricity systems is limited. One study (Balnac, Bokhoree and Bassi, 2009) made use of a tool called Threshold-21 (T21) which applies SD to policy making in an integrated manner. The study provided a T21 electrical power sector model of the isolated islands of Mauritius. Although supply and demand load were endogenous to the model it assumed a least-cost-first rule when allocating demand to predominately fossil-fuel generating sets. According to the authors, the study allowed for a better understanding of Mauritius' power sector and provided an initial structure for an electrical power grid model with scope for improvements. This adds merit to the use of SD for understanding low-carbon island electricity systems. To the best of this author's knowledge, there does not exist any other literature targeted to SD modelling of isolated low-carbon electricity systems on islands, apart from our own works (Matthew *et al.*, 2014, 2015, 2016, 2017).

The research work that is undertaken in this thesis differentiates from Balnac, Bokhoree and Bassi (2009) in that the focus is not only modelling the dynamics of the physical and technical electricity system interactions, but also endogenous demand load, renewable resources, and key socio-economic aspects. Our intention is to give stakeholders insights into the emerging long-term characteristics of the system, leading to more informed policy decisions for satisfying the evolving demand and the required low-carbon objectives in general. The next section highlights a brief background to emerging policy and investment challenges for transitioning low-carbon electricity systems.

2.4 Emerging Policy and Investment Challenges

In general, complex infrastructure systems are evolutionary, and they exhibit path dependence and lock-in (Chappin, 2011). Chappin, (2011) argues that options for these systems in the future are shaped by current choices, just as the current options are shaped by past influences. According to Herder *et al.* (2008) and Nikolic (2009), the systems that are observed today were not designed as such, but they evolved to their present state. Often, infrastructures become outdated and hence might not be able to perform the tasks they were intended to do. Moreover, the system may not

be able meet future needs such as sustainability and affordability. In the case of the low-carbon electricity system transition, this drives the push for new public policy which in turn increases the complexity of the system due to changes in the physical aspects of the system (Chappin, 2011). These changes may be realised after some delay in time for policy implementation. However, the perceptions of the key stakeholder's may change during this time and the system may now be tied into an unwanted direction. Actor dynamics (Chappin, 2011), multi-level interactions (Geels and Schot, 2007) and co-evolutionary process (Foxon, 2011) all play an important role in the desired transitioning of the system. In short, the transition of the low-carbon electricity system is a property of the transition time, combining the influences and interactions (feedbacks) of the actors and policies with the required technical system. Inherent to this is the policy uncertainty and the drive for improved/different infrastructures.

2.4.1 Role of Policy for Low-Carbon Electricity Systems

Low-carbon electricity system transition is a paradigm shift from one state to another, guided by the roles of the actors within the system. The emergence of various new types of public policies can be seen as a guide to achieve the desired system. However, as these policies are being acted upon there might emerge newer and different types of interactions and system feedbacks. Furthermore, policies can possibly drive further complexities within the system which can in-turn, and over time, evolve into uncontrollable challenges for the sustainability and usefulness of the system. According to Chappin (2011), electricity policy can influence emerging challenges and behaviours within this system since it forces changes to the technical components. These changes can then influence the perceptions and preferences of the other social and economic actors in the system. The electricity policies have inherent challenges which will appear over the long-term evolution of the system. This is compounded by the stakeholder's desire to achieve the required changes without greatly increasing economic costs that would risk an erosion of the sustainability and/or energy security of future low-carbon electricity system.

2.4.2 System Investment Implications

As noted in the previous sub-section, the policy aspects of the emerging low-carbon electricity system have influences on the complexities that arise in the system. There will also be inherent changes needed in the technical components of the emerging electricity system. In general, the investments needed within these transitioning systems are determined by the improvements or changes needed in the physical infrastructures. The need for increasing amounts of low-carbon electricity generation militates against new fossil fuel generation and possibly even nullifies previous investments. These changes also require an understanding of the most suitable investments needed to achieve a sustainable system. The synergy between the policies enforced by the evolving system and the investment decisions taken inexorably ties one to the other, however, they can both equally leverage influences on each other.

For example, apart from direct costs implications (IRENA, 2013; Vallvé, 2013), there are other emerging issues such as possibly poor reliability and availability of the renewables versus the benefits of sustainability and economic stability (MIT, 2011; IRENA, 2014a). Most renewables, apart from geothermal, are variable depending on the time of day and weather which gives rise to concerns over the supply security of such systems (Hirth *et al.*, 2012; IRENA, 2014a). Barrett (2006) and Warren (2014) have highlighted some possible general solutions for low-carbon transition which include the building of new capacity (a costly venture due to the infrequent peak time usage they can command and small project sizes); increasing interconnections with other countries (an option which is restricted or unavailable for geographically isolated islands); developing and using large-scale energy storage technologies (an immature solution which is very expensive); location-dependent pumped hydro systems (not always feasible to build); and demand-side management (currently a theoretically rich, but so far practically limited solution).

Additionally, the demand within the transitioning system will evolve due to these low-carbon objectives and policies. EV adoptions can increase the demand within the system necessitating increased capacity investments, preferably, in renewables. Whilst, a focus on energy efficiency can

lower the long-term demand (IEA, 2013). The interactions between the causal influences from these and newer policies can shape the future investments within these systems. Low-carbon objectives and considerations give rise to the (added) investments that might be needed within such evolving system.

2.5 Summary

In this chapter, the context for transitioning low-carbon electricity systems has been explored together with some necessary tools for understanding these systems. In addition, many studies and research works have been presented that describe major strides made in modelling electricity systems. However, many of the key social, economic and technical drivers in the energy sector remain exogenous to most simulation models. The need to have endogenous demand and endogenous salient features were keenly pointed out by Jordan (2013), Steel (2008) and Black (2005). Steel (2008) formulated demand endogenously, but for a model that does not consider technical grid issues. Jordan (2013) followed suit with an endogenous demand model that has electrical power system physical and technical details but the model is focussed on only the capacity expansion of conventional fossil fuel electricity systems.

Furthermore, most studies are limited by their modelling tools and hence cannot provide for such endogenous features if the tool does not make it available. Recent modelling tools such as HOMER and DER-CAM are geared to specific low-carbon electricity system aspects and optimisation problems similar to the conventional TIMES MARKAL, WaSP and LEAP modelling tools. HOMER allows users to evaluate the economic and technical feasibility of a large number of technology options and to account for variations in technology costs and energy resource availability of hybrid renewable micro grids. It, however, lacks the social features of the system. DER-CAM, on the other hand, is an economic and environmental model of customer distributed energy resources adoption. But it lacks the social and technical features of the system.

In addition, the use of HOMER, PLEXOS and Islands Playbook *energy transition initiative* (ETI) for assisting a comprehensive energy transition IRP process have shown the need for a whole systems approach. These advances are good and can benefit from SD since they are unable to capture the necessary salient features and key endogenous features and causal relationships within the system.

SD brings the type of richness needed of a modelling methodology in order to capture the social, economic and technical features of an evolving low-carbon electricity system, the analysis needed to understand and learn from the system. Many useful SD works that undertake long-term policy analysis for both energy and environment systems has been seen in the literature. These works have helped shape the decisions made and consequently, the outlook of present-day energy and environment systems. With such a powerful tool, useful and beneficial insights into the future of low-carbon electricity systems can be achieved. In addition, the many pilot projects and trials seen in the literature present the opportunity for studying these systems and for testing solutions.

System view requirements for understanding and making better decisions in complex systems exist separate from event-based approaches also seen in the literature. In this context, SD can readily capture the structure and dynamics of complex systems, considering key feedbacks, delays, and inertia within the system. Also appearing in the literature as a contrastingly useful systems view approach is agent-based modelling which provides a different mechanism to modelling complex systems comprised of interacting autonomous agents. ABM is extremely well suited to problems with a highly spatial basis. However, the task considered in this work is essentially a long-term temporal challenge and, as such, is better suited to an SD approach. This work could later be linked to ABM models of the low-carbon transitions such as EV spatial charging models and even to IRP processes for isolated island systems.

Resultantly, after reviewing existing literature concerning state-of-the-art low-carbon electricity systems and models it is clear that there is no existing model that captures the evolving low-carbon electricity system in a holistic manner. This thesis, through the works presented in Chapters 3, 4, 5,

and 6 will detail the approach taken to model such a system and provide insights into emerging policy and investment challenges for the capacity resource planning of the low-carbon system transition. Detailed are the implications for smaller (a contextually simple island case study) electricity systems experiencing the convergence of environmental and energy security (import dependency) concerns for the low-carbon electricity transition effort. Chapter 3 will give the details of the SD method of study together with the modelling approach used in this study. Chapters 4, 5, 6, and 7 will then detail applications of the method, accounting for key endogenous behaviours and socio-techno-economic drivers. This study amounts to eliciting the key emerging challenges and behaviours of the evolving system. More details of the model development and approach for this thesis is given in the next chapter.

Chapter 3. Model Development and Research Methodology

This chapter gives an overview of the approach employed in the thesis, and the model development and formulation steps required for this research work. In addition key details of the case study system, São Miguel are given. The SD methodology was introduced in Sections 2.2 and 2.3 and revealed as a good candidate for the policy and investment analysis of a complex socio-techno-economic low-carbon electricity system. Sub-section 2.2.4 highlighted some of the pioneering SD studies together with their useful applications to energy, the environment and electricity systems. Additionally, some recent applications of SD in the context of evolving low-carbon electricity systems were shown in Section 2.3.2.

This chapter justifies the use of SD to provide complex system insights, together with policy analysis and investment implications, such as for those alluded to in Section 2.4. In addition, it addresses the relevant research gaps in the literature using SD as opposed to other competing event-based thinking methods and whole systems view methods for complex system modelling such as agent-based modelling. The relative weaknesses of agent-based modelling for a research work of this type were discussed in Sections 2.2.3 and 2.5. Mainly based on the fact that this method is much decentralised, considers spatial issues more than temporal issues and is more complex for the type of long-term analysis needed. Arguably, both methods can give similar insights but the SD method is inherently less complex. In fact, SD can account for key and interesting feedbacks within the system unlike agent-based modelling, discrete event modelling mechanisms, and other single and multi-objective optimisation methods utilised today. Description, details, validation and analysis steps of the SD methodology and model building approach used follow in the subsections of this chapter.

3.1 SD as a Viable Modelling Approach

SD is a computer-aided modelling approach to policy analysis and the understanding of complex systems. It is applicable to dynamic problems arising in complex social, managerial, economic, and ecological systems; interdependence, mutual interaction, information feedback, and circular causality can be analysed. SD provides the research community with a language to understand complex systems, and a method that encapsulates time lags to enhance learning in such systems. Sterman (2000) however cautions that while simulation models are necessary for effective learning in complex systems, they are not a one-stop cure for all problems that exist. Furthermore, the models developed must be able to mimic the real world well enough with the assumptions made and must be open to inspection, criticism and change. SD stands out as a pioneering modelling mechanism that gives a good representation of the real world electricity systems and is capable of incorporating the necessary uncertainties that exist within these systems (Dyner, 1996; Ford, 1997; Jordan, 2011).

The origins of this field, as stated in Section 2.2.4 was developed initially from the work of Jay W. Forrester (1918 - 2016). In his seminal book *Industrial Dynamics* (Forrester, 1961), he lays out the basis of the philosophy and methodology to be used within this field. SD has been extensively used not only for corporate and industrial problems but also to study the management of research and development, urban stagnation and decay, commodity cycles, economics, public policy, environmental studies, theory-building in social science, and other areas, including management (Sterman, 2000). SD emerged out of servomechanisms engineering, rather than general systems theory or cybernetics (SDS, 2014). SD is not an optimisation technique, but, by capturing a complex system's key feedback structures and important sources of inertia and delays, key endogeneities are often revealed which gives useful insights into the system structure and behaviours. This affords SD the capabilities to elucidate scenarios and reveal hitherto unexpected impacts and phenomena in response to policies (Morecroft, 2007).

Complex systems can be tightly coupled, non-linear, adaptive and history dependent (Chappin, 2011; Foxon, 2011). By using SD, it is possible to discover and represent the dynamics of the whole system in terms of the feedback processes, stock and flow structures, time delays, nonlinearities and accumulations (Sterman, 2000). It is believed that these system dynamics arise from the interactions of the complex and intertwined network feedbacks (loops) of the system entities/variables. Actually, all systems consist of causal relationships between system variables which can be either positive (+ve)/self-reinforcing or negative (-ve)/self-correcting/balancing feedbacks. The feedbacks between two variables of the system is a consequence of the *effect* and *cause*. In complex systems, *cause* and *effect* are distant in both time and space (the *effect* of a *cause* within the system can be delayed). SD is shown to be useful in efficiently capturing these delayed feedbacks, even those that typically have multiple loops with numerous time-delays, non-linearity and accumulations.

SD is useful because of its success in understanding the dynamics of complex systems (Forrester, 1987; Morecroft, 2007). According to SDS (2014), the most important conceptual tools and concepts of the SD methodology include feedback thinking, stocks and flow structures, feedback loop dominance, and endogeneity within the system. With a strong emphasis on these aspects, SD is able to help its users gain useful insights that are fruitful for policy analysis (Morecroft, 1988; Gary *et al.*, 2008; Bildik *et al.*, 2015). Feedback in a complex system is a key factor and the feedback concept is at the heart of the SD approach (Forrester, 1987; Sterman, 2000). Additionally, the concept of endogenous (internal to the system) change is also fundamental to the SD methodology. This helps dictate aspects of the model formulation - the complex system changes endogenously over time with exogenous (external to the system) triggers, but time itself is not seen as a cause of system responses (the system evolves over time, not because of time).

SDS (2014) highlights that by taking an endogenous view an SD model can expose the natural compensating tendencies in complex systems that conspire to defeat many policy initiatives. Hence, SD models should strive for endogeneity with an effort to uncover the sources of system

behaviours that exist within the structure of the system itself (SDS, 2014). In addition, SD can give the temporal resolution needed to facilitate discrete decisions and myriad operational details, but not miss the critical elements of policy structure and system behaviour (Chyong, 2014). Furthermore, with all of these representations, the complex transitioning low-carbon electricity system can be modelled using SD, to reveal the structure and behaviour of the system variables, and in turn the system. Thereby stakeholders are allowed the opportunity to understand these systems and to discover emerging challenges and behaviours. Furthermore, they can explore policy options and investment barriers and incentives, as the system evolves.

The concepts presented in this Section were applied to this research and there was an emphasis on the most accurate representations of key feedbacks of the evolving low-carbon electricity system. In addition, endogeneity of key variables was properly accounted for during development of the thesis models. This can be seen more clearly in Chapters 4, 5 and 6 as the SD models developed are made more comprehensive to capture the necessary key feedbacks and endogenous factors of the case study island system. The next section gives an overview of the development of an SD model with the important definitions and concepts necessary for producing SD models.

3.2 Development of an SD Model

To develop a model that is beneficial to stakeholders, an iterative process must be used with continual questioning, testing and refinement. In his comprehensive textbook, Sterman (2000) has outlined standard mechanisms for performing SD modelling. Broadly put, these steps are problem articulation, followed by the formulation of a dynamic hypothesis which utilises causal loop diagramming and stock and flow maps. Next is the formulation of the simulation model for behavioural relationships and decision rules followed by the testing phase with calibration and sensitivity analysis. The final step involves the policy design and evaluations.

Martinez-moyano and Richardson, (2013) recently elaborated on the conventions of Sterman (2000) pointing to approaches that can help improve the SD modelling techniques based on using

the opinions of a distinguished group of SD experts. In their proposal, shown in Figure 3.1, the authors recommended the addition of two later steps - model use implementation and dissemination, and the design of a learning strategy. These latter two steps are, however, better suited for a strictly client-based type modelling and not so appropriate for more academic studies. This research work made use of the best available SD techniques as recommended by Sterman (2000), Martinez-moyano and Richardson, (2013) and as highlighted in SDS (2014) together with the most beneficial policy analysis testing options as seen in the literature.

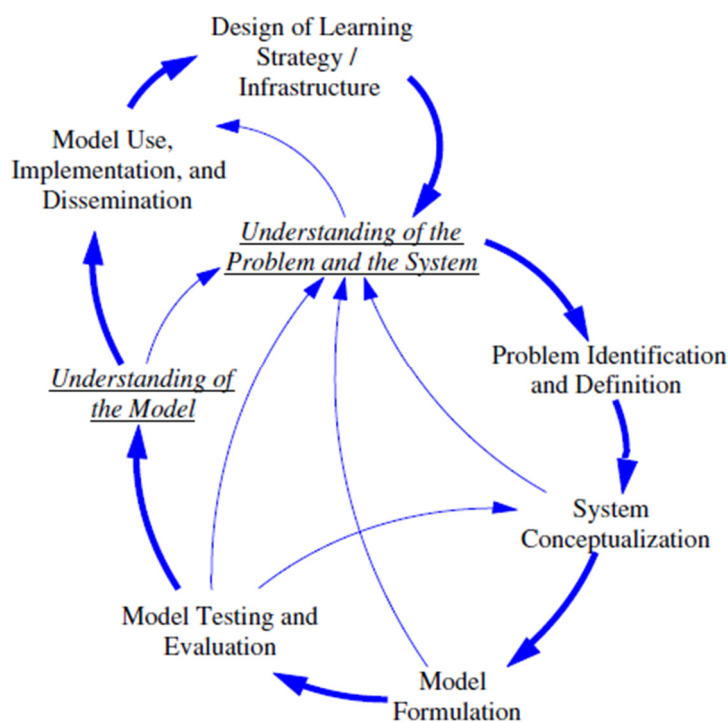


Figure 3.1 Overview of the SD modelling approach (adapted from Martinez-moyano and Richardson, (2013))

As seen in Figure 3.1, the process of modelling has many interconnected linkages which suggest that the modelling process can be considered alongside the dynamics of the system (Sterman, 2000). Hence, iterations comparing experiments in the virtual world of the model and experiments and learning in the real world of the problem is considered best practice for model development. This thesis captured all of the essentials of developing and using a good SD model. The following

subsections give details of the key aspects of the modelling process including terminologies and concepts native to SD, starting from an initial dynamic hypothesis.

3.2.1 Formulation of Dynamic Hypothesis and Model Boundary Selection

The necessary tools for the SD modelling process are the casual or feedback loops and the stock and flow diagrams, discussed in detail in Sections 3.2.2 and 3.2.3 respectively. Preceding this is the problem articulation/boundary selection and the dynamic hypothesis generation. According to Sterman (2000), the formulation of the dynamic hypothesis is a comprehensive process for the inclusion of an initial hypothesis of the problem and mapping of the feedback structures together with their endogenous focus. Hence, the conceptual and simulation model building process requires the problem to be defined dynamically, in terms of graphs over time. The developed model must account for an endogenous, behavioural view of the significant dynamics of the system, focusing on the characteristics of the system that generate or exacerbate the perceived problem/s. Figure 3.2 shows an example of a typical problem illustrating a variable graphed over time useful for the case study of this thesis. The figure shows the nominal dollar prices of fossil fuel for each of the years considered (it is noted here that the rate of inflation in São Miguel varied between -2% and 2% over the time period shown (SREA, 2016)).

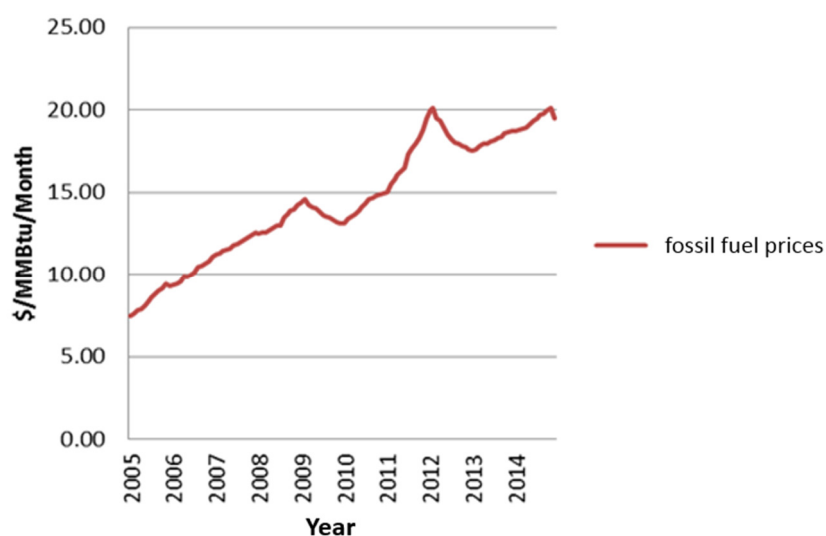


Figure 3.2 Graph of historical fossil fuel prices for São Miguel (Source: EDA (2016))

Confirmed from the figure is the issue of increasing fossil fuel prices over the last 15 years. It shows a trend in which the price of fossil fuel used for electricity production has tripled over the last 15 years. This trend is likely to continue into the future and lead to an energy affordability and security problem (Isle-pact, 2012). This problem is combined with the global desires of using less fossil fuel to aid in the mitigation of global warming and re-enforces the usage of more renewables for electricity production. A trend that is evident in the case study electricity system and depicted in the following figure.

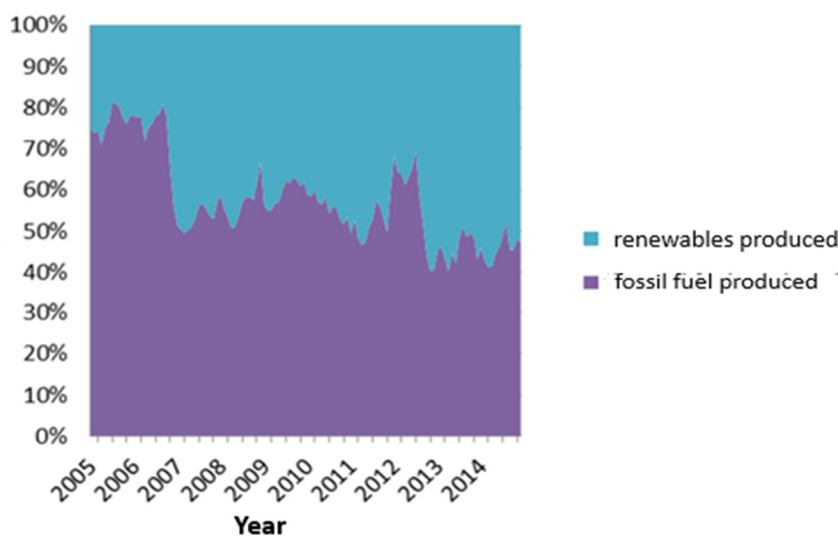


Figure 3.3 Graph of historical relative fossil fuel and renewables production (kWh) for São Miguel (Source: EDA (2016))

Figure 3.3 shows the historical trend of fossil fuel and low-carbon renewables usage in São Miguel. The figure shows that there was a significant drop in fossil fuel usage over the years 2005 to 2008, followed by a more gradual proportionate decline from the 2008 values until 2016. This indicates that the usage trend of fossil fuels and renewables experienced a drastic change but is now appearing to settle. These key variables of fossil fuel prices and the type of electricity generation sources used are good indicators of the general problem for low-carbon electricity systems. In this case study, and in most isolated island systems the price of fossil fuel is external to these systems and a small island without fossil fuel production sources cannot influence these prices. As a consequence high fossil fuel prices are a major problem for such systems and island governments

have long sought to free themselves of such problems (Weisser, 2004b; Vallvé, 2013). Hence, a choice of low-carbon renewables will help with the global warming issues and ensure the long-term electricity production security of the system (having import independence from fossil fuels), whilst the continued use of fossil fuels will have opposite effects.

Taking this into account, and considering the suggestions of Sterman (2000), the problem articulation of this thesis is centred on the fact that fossil fuels are becoming increasingly unaffordable for island systems that rely on these energy sources. Renewables can provide a solution, but it seems that the advent of high levels of renewables for electricity production is somewhat hindered, as evident in Figure 3.3. This represents a fact that there is a possible problem with the uptake of increasing amounts of renewables within low-carbon electricity systems. Hence this thesis explores policies for sustaining the uptake of renewables needed to ensure energy security (eliminate the dependence on imported fossil fuel for electricity generation) and to understand how this generation capacity mix may be stabilised.

To ensure an accurate representation of this problem, and of the boundaries, the model must be adequately defined. If the model boundary (Sterman, 2000 pg. 97) is too large then the model can be overly complicated. However, if the model boundary is too small then the model can miss important feedbacks and dynamics. Hence, an appropriate and suitable model boundary must be chosen. This is best done as an iterative process whilst examining the problem articulation. In addition, the time horizon required to understand the problem can guide how far into the future the model is extended. It should be able to capture delayed and indirect effects as the system unfolds over time. A suitably long enough time horizon is key for the understanding of the problem and for deciding the model boundary.

In the present case study, the time horizon was determined based on the longest delay of key variables and for capturing long-term trends within the system. The longest time delay for one such key variable are the low-carbon policies (investment goal completion timeline) which are usually

20 - 30 years in duration. In addition, 2050 is a key year for the timeline of low-carbon transitions based on important worldwide environmental and energy protocols and agreements. Consequentially, the chosen time horizon is 35 years (2015 - 2050) into the future with 10 years of history (2005 - 2015). Sterman (2000) used a model boundary chart in which he classified model variables as being endogenous (arising from within), exogenous (from outside) and excluded. In this thesis, short-term dynamics (hourly/daily) are widely ignored so variables such as grid frequency balancing and cash flows have been excluded from the model. Some key endogenous variables that have been used are the electricity demand, installed generation capacity for fossil fuel, renewables and energy storage, and adoption of electric vehicles. Key exogenous variables includes GDP and electricity tariffs. More details about the model boundary is shown for the specific sub-models of Chapters 4, 5 and 6.

The general dynamic hypothesis which emerges should be a working theory of how the characterised problem occurs (Sterman, 2000), as intuitively explained by the causal relationships that produce the observed system behaviour. Sterman (2000) also states that this hypothesis should be challenged throughout the modelling process. For this thesis, the initial working theory is that the system is driven by the need to lower CO₂ emissions and ensure sustainable electricity supply. Chapters 4, 5 and 6 will challenge this dynamic hypothesis as more causal relationships are discovered and explored. Subsections 3.2.2 and 3.2.3 introduce the necessary SD concepts for diagramming the feedback loops and physical (stock and flow) structures of the system being modelled. The initial working theory as a mental model diagram will be illustrated in the next subsection.

3.2.2 Causal Loop Diagrams (CLD)

It has been shown in Section 3.1 that causal or feedback loops exist in all complex systems and gives the *cause* and *effect* that determine the structure and behaviour of the system. *Causal loop diagrams* (CLDs) are flexible and useful tools for diagramming the system feedbacks and the mental models of the system structure. According to Sterman (2000), CLDs are simple maps for illustrating

the causal relationships among variables, visually represented by arrows from a *cause* to an *effect*. The arrows indicate either a positive (self-reinforcing) or negative (self-correcting or balancing) feedback between system variables. Reinforcing feedback loops are generated when there is an even number (possibly zero) of negative *cause* to *effect* relationships, whilst balancing feedback loops are generated when there are an odd number of these relationships. These loops are important to understand the feedback interactions within the system. Reinforcing loops produce growth and amplify these interactions, whilst balancing loops are counteracting and oppose the effects of the interacting variables.

A simple example of a reinforcing loop and a balancing loop, relevant to this thesis and illustrating the mental model of the initial dynamic hypothesis, is shown in Figure 3.4. There are three main interacting variables, namely, *low-carbon based capacity mix* (electricity generation mainly composed of renewable sources), *long-term effective supply* (a self-sufficient/sustainable electricity supply that is not dependent on fossil fuel imports) and *CO₂ emissions* (carbon-dioxide emissions from burning fossil fuels for electricity generation). The *energy security loop* (based on the concept of fossil fuel import independence) is reinforcing (denoted R) since *low-carbon based capacity mix* has a positive effect on the *long-term effective supply* which in turn has a positive effect back onto the *low-carbon based capacity mix*. This loop shows that if there is more *low-carbon based capacity* this will lead to more *long-term effective supply*, which will, in turn, lead to even more *low-carbon based capacity*. Given the structure of SD archetypes, if this loop operated independently, both the *low-carbon based capacity mix* and the *long-term effective supply* would typically change exponentially. This is mainly due to the fact that it is a positive reinforcing loop which will have an exponential archetype (Sterman, 2000).

On the other hand, the *low CO₂ emissions target loop* is balancing (denoted B), since *low-carbon based capacity mix* has a negative effect on the *CO₂ emissions* which then has a positive effect onto the *low-carbon based capacity mix*. This loop shows that increasing the *low-carbon based capacity*

mix this will lead to fewer *CO₂ emissions*, which will, in turn, lead to less *low-carbon based capacity mix* since it is reinforced by that later relationship. If this loop was operated independently, increases in the *low-carbon based capacity mix* will be counteracted and this variable would stabilise at some goal value. An SD archetype for this loop will be a goal-seeking archetype (Sterman, 2000). However, as these loops are interacting *the low-carbon based capacity mix* will be reinforced by the *energy security loop* and balanced by the *low CO₂ emissions target loop* leading to an eventual dynamic equilibrium. The SD archetype that will exist for this two loops interacting will be an S-shaped archetype (Sterman, 2000). This observation underpins the initial hypothesis of this case study of a low-carbon electricity system.

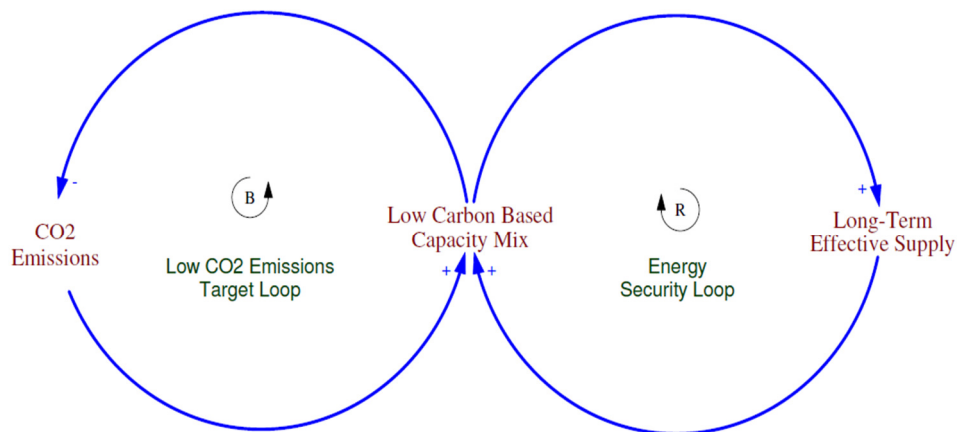


Figure 3.4 Example simple CLD diagram of the mental model of the low-carbon electricity system

3.2.3 Stock and Flow Diagrams (SFD)

As shown in the previous subsection, CLDs are useful to elucidate the feedback structure of a complex system. However, stock and flow diagrams focus on the physical structures within the system. *Stock and flow diagrams* (SFDs) track these physical structures such as the accumulations or measurable quantities of the system. In so doing, they characterise the state of the system, the sources of inertia and memory, and generate the quantifiable information upon which decisions

within the system are based. Stocks usually represents a noun and do not disappear if a time snap shot of the system is taken. Stocks usually decouples flows, create delays and hence can be said to have memory. Flows usually represents verbs and disappears if a time snap shot of the system is taken. Flows usually defines the change in the state of the stocks. Stocks and flows coexists and are mathematically defined for the system. The mathematical formulation requires detailed relationships between the different elements, for shaping a consistent basis, which often challenges and evolves the assumed mental model of how the system is thought to work. SFD diagramming gives the complete mathematical formulation of all aspects of the mental model.

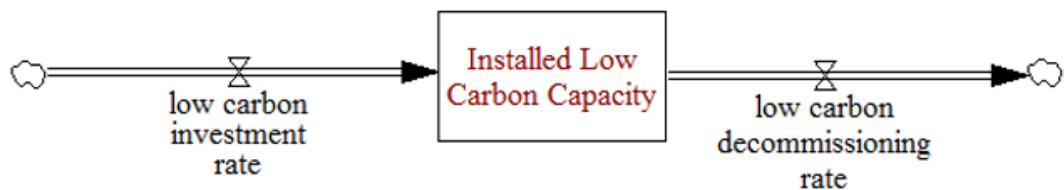


Figure 3.5 Example of a simple SFD diagram representing the low-carbon capacity mix

For example, as shown in Figure 3.5, the stock will be the measurable quantity of the *installed low-carbon capacity* and is illustrated as a box with arrows going into and out of it. The arrows represent the flows that influence the stock and reflects the rates at which this stock increase or decrease. The inflow is the *low-carbon investment rate* which is the rate at which the stock increases, whilst the outflow is the *low-carbon decommissioning rate* which is the rate at which the *installed low-carbon capacity* decreases. These flows can be nonlinear and operate at different rates that are dependent on other variables and/or link into the rest of the model. For example, the *CO₂ emissions* together with other variables can affect the inflow and/or outflow. Hence the casual relationships can be adequately expanded and be incorporated into the stocks and flows of the system. The clouds at the outer ends of the diagram represents the sources and sinks for the flows. Sources and sinks are assumed to have infinite capacity and do not restrict the flows to which they support. The source represent the stocks from which a flow originating from outside the boundary of the model

arises whilst a sink represent the stocks into which flows leaving the model boundary drains. Hence, in this example, *low-carbon investment rate* has infinity capacity and *low-carbon decommissioning rate* is not restricted from outside the model boundary.

Although the relationships between model variables are normally determined by simple mathematical equations, there is some interaction that might require a different approach such as the use of non-linear approximations or look-up tables. Key lookup tables and equations for this research are detailed in Appendix A. In addition, more details of this and other CLD and SFD diagramming conventions such as the resulting modes of dynamic behaviours can be found in Sterman (2000). The following section highlights the model testing approaches that are important for developing useful SD models.

3.3 Model Testing and Validation

It was seen in Section 2.2.4 that much work has been undertaken by SD pioneers to lay the foundation to validate any SD model. Moreover, a number of structural validity procedures are shown (Barlas, 1989; Qudrat-Ullah and Seong, 2010). This involves integration error testing to check that different integration methods do not give divergent results. Additionally, further validation includes defining the boundary adequacy of the model as discussed in Section 3.2.1, by defining what is exogenous to the model (and what is endogenous and separating these from what has been excluded from the model. Forrester (1968) made some statements which provide a solid basis for modelling versus other real system/experimental methods. Forrester (1968) stated that a model should be valid for its purpose but it may be irrelevant or wrong for some other purposes and that there is no universal standard to compare the validity of models constructed for different purposes. Generally, this gives the context and basis for the correct usage of an SD model. Additionally, it is asserted that validation is a process of establishing confidence in the soundness and usefulness of a model (Forrester and Senge, 1980; Forrester, 1987).

The models developed for this thesis were implemented using computer simulation software, in this case, Vensim (Ventana Systems, 2016). Vensim is a mature and a widely used SD modelling software environment. The software incorporates a mix of discrete difference equations and continuous differential or integral equations through a diagram capturing the SD stock and flow and causal feedback structures of the system. It has many built-in validation and sensitivity testing mechanisms for the model structure and parameters. Dimensional consistency and structural verification of the model are built into the modelling software (Sterman, 2000; Ventana Systems, 2016). Vensim package gives an error/warning and does not run accurately if the equations do not satisfy this level of consistency. Furthermore, coding errors and standardised model evaluation mechanisms such as sensitivity testing and reality checks come as standard with the software.

The coupled, nonlinear, first-order differential (or integral) equations for which simulation is easily accomplished within the simulation software is done by the partitioning of simulated time into discrete intervals and stepping through one time period at a time (Ventana Systems, 2016). The time period, a time-step of one month in the models for this thesis, are small enough to have no discernible effects on the pattern of dynamic behaviour exhibited by the model shown in Chapters 4, 5 and 6. The visualisation of the model behaviour served as a first step for the model validation, together with units' consistency testing of all the included formulae, and sensitivity and extreme condition testing of the mathematical formulations and assumptions within the model. The validation process for this work, and as seen in the literature (Sterman, 2000), was thought of as an integrated iterative process of the model building using the appropriate model validation data (entirely separate to the data used to run the model). This iterative process involves finding the most accurate conceptualization, mapping and formulation together with simulation and implementation of the modelling process. The developed SD models for this thesis underwent rigorous testing and model validation as required for all good SD models. Additionally, key variables used like electricity tariffs and consumption data were verified with EDA and with relevant global

data sources (Isle-pact, 2012; Ilic, Xie and Liu, 2013; Botelho, 2015; Nunes, 2015; EDA, 2016; European Commission, 2016).

Structure validity tests are also performed, with the use of direct comparisons of the model conformance to basic physical realities such as conservation laws and the realism of decision rules of the real system which increases the confidence in the model output. These tests usually with the inspection of the equations and model generated archetypes (structure-oriented behaviour curves) are important for the calibration of the model. Within this thesis, the behaviour of key variables such as the installed renewables capacity and fossil fuel capacity were assessed by measuring how accurately the model reproduces the behavioural patterns in the real system. This was achieved by comparing the outputs of the model with the historical output data of the real system. The base case of model simulation run was plotted and compared to the real historical data over the calibration timeline for the calibrated variables. This type of model calibration was achieved using the analytical and software methods such as the eyeball time paths (visualisation of the data) and other traditional statistical tests such as Theil statistics which breaks down the *mean square error* (MSE) source of errors in terms of the bias, unequal variation and covariation as in Sterman (2000) and Pierson and Sterman (2013). The historical model calibration time period used was 10 years (2005 – 2015) with the subsequent 35 years providing the future simulation period. All calibration tests were done using Vensim software based mechanisms and the respective detailed aspects are shown in Chapters 4, 5, 6.

Other model validations for the iterative model building include further extreme case testing, reality checks and sensitivity analysis. Sensitivity analysis required the varying of key model parameters such as the capacity factor of the renewables and monitoring the change in key model outputs such as the installed capacity mix. Extreme case testing involved the use of extreme values of assumptions such as no population to evaluate the model response for a reasonable behaviour such as no electricity demand. Sensitivity to the inclusion/exclusion of different policies and to high/low values of the initial GDP within the island system was also evaluated. Reality checks were

used for determining the usefulness of the model by using constraints such as a *no fossil generation capacity* to observe the model response is a reasonable one of *no monthly CO₂ emissions*. Relevant details of these tests are shown in the Appendix B1. All of these tests contribute to the model validation process and can confirm the usefulness of this model for understanding the evolving low-carbon electricity system and for providing policy implications for the systems. According to Radzicki and Taylor (1997), once a model is validated and equipped to understand system structure, it can then be used as a laboratory for testing policies aimed at altering system behaviour in desired ways. Approaches for the policy analysis and evaluation of the developed models are shown in the next sub-section.

3.4 Policy Analysis and Evaluation

To guarantee useful understanding and applicable policy insights many key variables and aspects of the developed models were first validated. Then, using the model, policy interventions and/or scenarios were examined that lead to various long-term system behaviours. Key decision variables such as the low-carbon policy targets and CO₂ emissions targets were carefully examined, along with indicators and uncertainties associated with the low-carbon electricity system renewables uptake problem, and given from the literature (Isle-pact, 2012; Botelho, 2015; Nunes, 2015; EDA, 2016). Different possible sets of decisions under different assumptions about the uncertainties were used to look for sensitivity (trade-offs/gaps) between the short-term and long-term behaviours, with the main goal being to understand the policy and investment implication within the system and to provide useful insights into the future of this evolving low-carbon electricity system.

According to Sterman (2000), the policy design process within a model is much more than tweaking the values of parameters, rather it is one of creating entirely new strategies and decision rules and making high-impact observations. Early sub-models explore the importance of existing policies and their impacts, whilst the later part of this thesis (Chapter 6) sheds light on investment decision

strategies useful for the long-term evolution of the low-carbon electricity system. Shown in the next section are key characteristics of the case study: an isolated island system.

3.5 Case Study - São Miguel

A desire for contextual simplicity motivates the choice of small island low-carbon electricity system for this work. The system used for this study was chosen since it is currently used as a testbed for sustainable energy solutions that emulates evolving low-carbon electricity systems, and it has no grid or market connectivity to other mainland systems, providing the simple context desired for conducting such a scope of study. It has been extensively studied for the last 8-9 years (Baptista *et al.*, 2009; Parness, 2011; Pina, Silva and Ferrão, 2012; Ilic, Xie and Liu, 2013; Silva, 2013) but not using the SD method. These prior studies have produced a large amount of data useful for the SD analysis. Prior studies have focused on São Miguel as a green island with a target of 50% renewables generation by 2020 with scope for other typical low-carbon aspects such as electric vehicle adoption and energy storage options (MIT-Portugal, 2013). These conditions definitely set the stage for the kind of challenges and opportunities an isolated low-carbon transitioning electricity system will likely face in the future.

São Miguel fits as a suitable case study for this work. It is part of the Açores archipelago of nine Portuguese islands about 1,500 km west of mainland Portugal in the Atlantic Ocean. It has a growing tourist economy and traditional sectors of fishing and farming, giving it the most diverse economy and energy needs of the nine Açores islands. The main electricity utility in São Miguel, *Electricidade dos Açores* (EDA), is a fully regulated utility alongside a few independent power producers which sell their electricity (less than 2% of total production) to the EDA utility (EDA, 2016). São Miguel's electricity system is stand-alone without any grid interconnections to other Azorean islands or to mainland Portugal. It is isolated in a technical, but not in a political and economic sense. The tariffs of electricity are determined from the mainland Portugal (EDA, 2008). Also embedded in the framework of this system is the political oversight from Portugal, since the Açores is an autonomous region integrated within the Portuguese Republic. The autonomous legislature dictates that the

Açores has its own governments and hence all decisions for the energy sector is done through the Regional Directorate for Energy which is tasked with the job of overseeing the promotion and execution of sustainable and environment-friendly low-carbon electricity systems in São Miguel. The Regional Directorate for Energy has all of the political control for enacting the necessary legislation within their power, such as clean energy goals. Retail tariffs however remain controlled at a national level (EDA, 2016).

According to EDA (2008), the existing on-island technical grid system structures are at a high standard similar to other developed systems. This system has capacity reserve margins above 30%, meaning that a significant amount of generation capacity is latent for much of the year. This is however required to maintain appropriate reliability and supply security (for reducing the risk of blackouts) in which adequate levels of redundancy of producing unit are installed (preference for several smaller units instead of one large generator). The annual electricity consumption grew by more than 3% a year for the 5 years prior to 2014 (ERSE, 2012, 2014) and future demand is expected to rise similarly. Furthermore, the *Gross Domestic Product* (GDP) on the island has grown by an average of 2% per year since 2005 (European Commission, 2016), signalling optimism for the electricity consumption growth forecast. Noting also that demand growth and tariffs for electricity are also expected to rise over the next few years (ERSE, 2012, 2014).

In this system, electricity consumption is allocated according to four different consumer types: residential, commercial services, industrial and public services (EDA, 2008, 2016). This is a typical characterisation similar to other well-developed systems. Statistics between 2005 and 2015 show that residential and commercial services make up \approx 30-35% of the total electricity consumption. Public services have a share of \approx 15% while for industry it is \approx 20%. Additionally, the total daily load duration curves have loads between 70 and 30 MW for the vast majority of hours in 2015 (EDA, 2016). This electricity system exemplifies a small developed isolated system that is at the cusp of low-carbon transition with inherent technical, social and economic complexities that are readily

identifiable and simpler than larger interconnected systems. The following section details the steps used for the modelling of the case study used in this thesis. It shows the approach taken to minimise the complexity and to obtain an efficient modelling of the system.

3.6 Modelling Approach and Summary

This chapter contains details of the efficient development of SD models and the modelling process. Also highlighted, are the key examples applicable and details of the case study for this thesis. Sterman (2000) cautioned that while there are certain key steps for modelling, it is not a cookbook procedure, but rather it is fundamentally a creative, disciplined, iterative and rigorous process. The approach used in this thesis is to develop multiple sub-models to emulate different aspects of the system and then to synthesise these sub-models into a single comprehensive model. A well-established approach was followed where greater in-depth learning can be achieved using an approach of smaller models to better demonstrate ab initio the dynamic behaviour of the system structure (Dyner, 1996; Shepherd, 2014).

The case study of this thesis work was initially analysed to assess whether it encompasses key drivers to the evolution of low-carbon electricity systems. Additionally, the process of scenario planning, as detailed in (Lindgren and Bandhold, 2009) was initially used to formulate different possible and probable paths of evolution of the case study island system. Subsequently, a mental model (as shown in Figure 3.4) was proposed to develop a theory of the behaviour of the system over time. This mental model was a direct consequence and driven by the fact that; CO₂ emissions and energy security (fossil fuel import independence) in the future will be a problem so more renewable and less fossil fuel generation is needed within the electricity system. Then, the system variables that are directly relevant to this problem statement were listed within the description of the different sub-models and these variables were determined to be endogenous, exogenous or excluded from the modelling process. Over the course of this process, and for the different sub-models some variables were added or dropped as needed in the mental model descriptions of Chapters 4, 5 and 6.

Three independent sub-models were developed over the course of this research work and then they were integrated into a single comprehensive model. The first sub-model developed was a fossil sub-model, which assumed an island system that has no renewables policy and accounts for endogenous fossil fuel capacity based on exogenous fossil fuel prices, electricity demand and renewables capacity. A mental model and the model formulation details were developed for this aspect of the system and are shown in Chapter 4. The second sub-model explored other aspects of the system for renewables integration into the system via (cost) learning curves. This sub-model accounted for endogenous renewables capacity, with exogenous electricity demand, renewables policy and fossil fuel capacity. The developed mental model and model formulation details of this sub-model are also shown in Chapter 4. Thirdly, the electricity demand sub-model was developed to capture the endogenous electricity demand within the system. Building on consumption factors such as economic growth, this sub-model emphasises aspects of low-carbon electricity policy factors such as electric vehicles and energy efficiency on the long-term demand. GDP and tourism growth were exogenous to this sub-model, whilst residential population and electric vehicles were endogenous. Details of the developed mental model and the model formulation details are shown in Chapter 5.

Finally, the three sub-models were synthesised into a comprehensive model which accounts for endogenous fossil fuel, renewables and energy storage capacities and electricity demand. The synthesised mental model, which captures the essence of Figure 3.4, but in much more detail along with the synthesised model formulations are explained in Chapter 6. It is important to note that the process of developing the sub-models and the final synthesised model was an iterative and lengthy process with numerous trial mental models in which many of those mental models were discarded. The feedback "loop" structures representative of the system were then studied and the resulting feedback loops were identified as reinforcing or balancing loops. The guiding concept is that the sub-models and the comprehensive model were built for their specified problem and purpose and they should provide an understanding of the system for this problem.

Figure 3.6 shows the subsystem architecture (Sterman, 2000 pg. 101) of the synthesised model. This figure illustrates the key aspects of the different sub-models of the synthesis model. As seen in the figure, the electricity tariff, GDP, tourist visits and technical specifications of electricity generation plants are not endogenous to the system in any of the sub-models and are external to the modelled system. Four key assumptions are made:

- (i) We assume that energy choices do not endogenously affect the GDP of São Miguel.
- (ii) We do not include the possibility of local technological innovation.
- (iii) We exclude the possibility that energy choices drive tourism growth.
- (iv) We assume that electricity tariffs charged in the island tends to be unaffected by system investment choices.

All four assumptions of these exogenous factors are contestable. However, others might seek to build upon this work by making some of these exogenous variables endogenous.

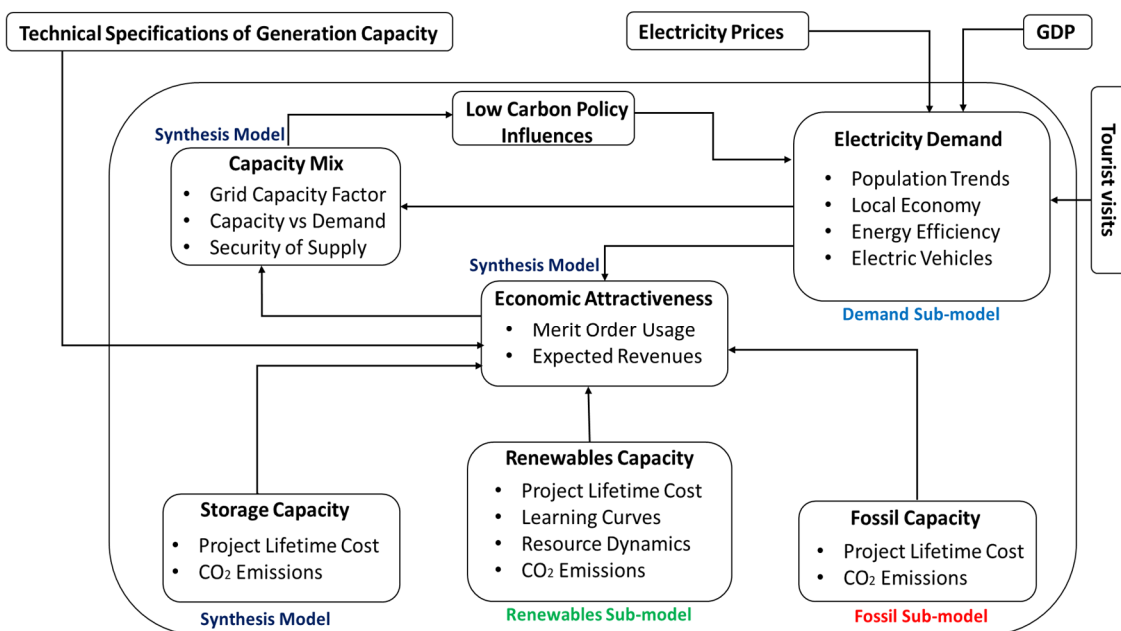


Figure 3.6 Overall subsystem architecture diagram for the low-carbon electricity system model

The parts labelled within the diagram will be detailed in the relevant chapters that address the sub-models individually. The next chapter will give the system structure for the fossil and renewables sub-models and the insights gained will be highlighted.

Chapter 4. Fossil Fuel Generation Futures and Renewables Integration in Island Electricity Systems

The contents of this chapter can be found in part or whole in the following peer-reviewed publications:

1. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. (2014) 'Simulating the development and utilization of autonomous smart grid systems using system dynamics', in PhD Colloquium at the 31st International Conference of the System Dynamics Society. Delft, Netherlands.
2. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. (2015) 'Insights into the Thermal Generation Futures of Isolated Island Electricity Systems Using System Dynamics', in 32nd International Conference of the System Dynamics Society. Cambridge, MA. Available at: <http://www.systemdynamics.org/conferences/2015/proceed/index.html>
3. Matthew, G. J., Nuttall, W. J., Mestel, B., Dooley, L. and Ferrão, P. M. (2016) 'Renewable integration in island electricity systems - a system dynamics assessment', *Advances in Intelligent Systems and Computing*, 426, pp. 107–119. doi: 10.1007/978-3-319-29643-2_8.

Following the modelling philosophy and research approach identified in Chapter 3, the initial sub-models for understanding fossil generation futures and the integration of renewables for the case study island system are explored in this chapter. As has been discussed in previous chapters, legacy electricity systems are transitioning into low-carbon renewables based systems which are more complex with greater multi-level interactions. To enhance the understanding of the policy and investment impacts on the future of these systems, the use of a whole systems view has been

advocated, specifically the holistic SD method. The initial dynamic hypothesis presented in section 3.2.1 was used as a guide for initially defining mental models of operation for a fossil fuel only based system and a fossil fuel based system that is integrating renewables for electricity production. Details of these two sub-models are presented in this chapter.

4.1 Overview

Today global production of electricity, particularly on island systems, is dominated by the combustion of fossil fuels. We must understand where we start from and it is suggested that a detailed analysis of the dynamics which surrounds just fossil fuel investments stands out as a necessary first step in understanding the whole system. The research firstly considers how the fossil fuel capacity additions in line with electricity demand growth and existing capacity margins affect the system's long-term stability. Long-term capacity planning based on only fossil fuel is not popular in the academic literature since progressive electricity systems are transitioning to low-carbon based sources whilst pursuing ambitious goals for renewable energy sources integration but it is vital one understands holistic paradigms first.

The fossil fuel sub-model presented in Section 4.2 of this chapter was developed for capturing endogenous causal relationships for the capacity margins and fossil fuel capacity long-term costing of a fossil fuel only generation based island electricity system. A separate sub-model, the renewables integration sub-model of Section 4.3 was developed to capture the endogenous causal relationships of the local learning curve cost experience of renewable technologies and the adoption of renewables from stipulated policy targets. The two sub-models are independent studies focused on different aspects of the system, however, key structures from both sub-models are used within the comprehensive synthesis model of chapter 6. This comprehensive synthesis model is achieved consistent with the initial dynamic hypothesis discussed in Chapter 3. This dynamics hypothesis is further challenged and considerations are given to a complete portfolio of endogeneity in order to answer the overarching research question.

The sub-models presented in this chapter were rigorously analysed in the context of research sub-question 1 (Section 1.2.2) concerning the significance of low-carbon policy targets within island electricity systems. It has been established that the effects of policy targets on the long-term investment decisions require better understanding (Weisser, 2004b). According to Weisser (2004), this policy target effects should assist policy makers to better shape generation mixes. Dyrer (1996), argued that IRP, the most widely used long-term capacity planning platform for small and developing countries, is myopic and not as insightful for addressing transitional policy issues as SD models can be. Moreover, relevant to this chapter and thesis, and as highlighted in Ford (1997), SD sub-models are especially useful for capacity expansion planning since they have the advantage of capturing the effects of time delays and endogenous feedbacks within the system. For example, Ford (1997) has provided valuable insights into the legacy electricity industry using the system characterisation of stocks of *capacity under construction*, and time delays for *construction* and *planning* within such systems. These all serve as key factors and inputs for capacity expansion in the fossil fuel and renewables sub-models of this thesis.

Reflecting a reality typical of island systems, these sub-models account endogenously for the key causal relationships of the system. They give some initial insights into the low-carbon policy effectiveness and capacity investment anatomy of the system. Firstly, assuming a fossil fuel only electricity system, the long-term capacity expansion outlooks of this system were studied. Subsequently, the significance of renewable targets for adoption and diffusion of renewable generation sources within the electricity system was evaluated. Thus, the initial supply side dynamics of the case study for capturing unintuitive and surprising opportunities with low-carbon policy and generation capacity investments was achieved. The next section presents the first of these two initial sub-models.

4.2 Fossil Fuel Generation Capacity Model

This section details the fossil fuel based system SD sub-model, which includes endogenous costing of capacity and capacity margins. The sub-model uses exogenous electricity demand and tariffs, and fossil fuel prices. The emphasis here is on endogeneity regarding the capacity investments of the system similar to previous studies seen in the literature (Ford, 1997; Collins *et al.*, 2013). However, it additionally includes an endogenous treatment of the capacity margin, unlike the other studies. This allows for the capture of detailed outlooks of the dynamics and investment decisions surrounding the fossil fuel capacity expansion of a system that is endogenously influenced by its capacity margin. Thus an in-depth understanding of the system structure and strategies that normally exist, and can exist, in the absence of renewables and other low-carbon enabling technologies is revealed.

4.2.1 Mental Model

The fossil fuel sub-model is based on the mental model feedback loop diagram detailed in Figure 4.1, which is adapted from Ford (1997), and accounts for, and explains, the delays (represented by double dashes on the arrows) and dynamics of fossil fuel capacity expansions in the absence of new low-carbon sources. The existing causal relationships are shown in the diagram as three balancing loops, each indicated by a letter *B*, and reflecting the key feedback structures of this system. Unlike Ford (1997) which has a “death spiral” for electricity tariffs and demand feedbacks, there is an endogenous *capacity margin loop* reinforcing the system. Additionally, the mental model diagram highlights a system that does not have any endogenous electricity tariffs, demand or fossil fuel prices. These variables are, however, derived from historical data and forecasts given for the system (ERSE, 2014; EDA, 2016).

The following table, Table 4.1, referred to as a model boundary chart (Sterman, 2000) summarises the scope of the model by listing the important endogenous and exogenous variables used for this sub-model, and the ones which have been deliberately excluded.

Endogenous	Exogenous	Excluded
Installed fossil fuel capacity	Electricity tariffs	Low-carbon policy targets
Revenues	Electricity demand	Renewables capacity targets
Fossil fuel investment rate	Fossil fuel prices	Cash flow constraints
Capacity margin	Capacity investment timeline	GDP changes
		Population changes

Table 4.1 Model boundary chart for the fossil fuel sub-model

Shown in Figure 4.1, the three balancing loops all interact at the *fossil capacity investments* and *fossil capacity installed*. The *capacity costing loop* (red loop) is being driven by the *electricity tariffs* and *fossil fuel prices* and has a balancing effect on the rate of *fossil capacity investments*, which after a time delay reinforces this effect on the *fossil capacity installed*. The key to this loop is the combined effects of the exogenous influences of the *electricity tariffs* and *fossil fuel prices* and the *fossil capacity costing* for balancing the amount of capacity that is installed. The more capacity that is installed, the more expensive it will be to produce electricity and simultaneously make capacity investments noting high fossil fuel prices (fossil fuel prices are always high for small island systems given the significant concerns for supply chain and transportation costs). Hence the installed capacity will be balanced. One other option that can occur in response is for the electricity tariffs (local price for electricity generation) to increase if it were endogenous to the system (a market structure can best dictate this). As noted before, isolated island electricity systems such as this case study typically do not have local price formation and rather use exogenously generated *electricity tariffs*, therefore the resulting installed capacity will be less responsive than might be expected in a market-based system with local price formation. Hence, in our case the capacity margin can fall despite economic indicators of a need for new capacity investments.

The *capacity construction loop* (red and brown mixed loop), at the centre of the figure, has a balancing effect on the *fossil capacity investments*, with this effect again being reinforced for the *fossil capacity installed*. This is an internal working loop which, as in Ford (1997), accounts for the delays necessary for new fossil fuel capacity to come online. Fossil fuel capacity will come online after a delay for project planning and construction and will only become a part of the installed capacity once commissioned.

Also shown is the *capacity margin loop* (green and red mixed loop) which again has a balancing effect on the *fossil capacity investments* and *fossil capacity installed*. If this loop operated on its own, as capacity is added to the system, the *capacity margin* would be higher and the *capacity forecast needs* would immediately decrease implying a less urgent need for more capacity. However, this loop is also influenced by the *electricity demand*, where higher exogenous *electricity demand* implies a higher *capacity forecast needs* and a lower than otherwise would be *capacity margin*. This lower endogenous *capacity margin* would then have a negative feedback influence on the *capacity forecast needs* which also reinforces the need for more capacity due to the *electricity demand*. And this, in turn, reinforces the fossil fuel investments and installations. In addition, it is important to note that the *electricity demand* would in a real world example be affected by other variables that are not accounted for within the boundary of this sub-model such as changes to population and GDP of the island. This is addressed in Chapter 5 where the *electricity demand* is made endogenous to the system.

This mental model hypothesis captures the whole system view of the effects of varying rates of exogenous electricity tariffs, demand and fossil fuel prices interactions for determining the endogenous fossil fuel capacity installations and capacity margin. In the long-term, for a system that consists of only fossil fuel capacity, this system is considered to be influenced mainly by the fossil fuel prices and the electricity tariffs. These key factors identified, will determine the extent to which investments in fossil fuel capacity are made.

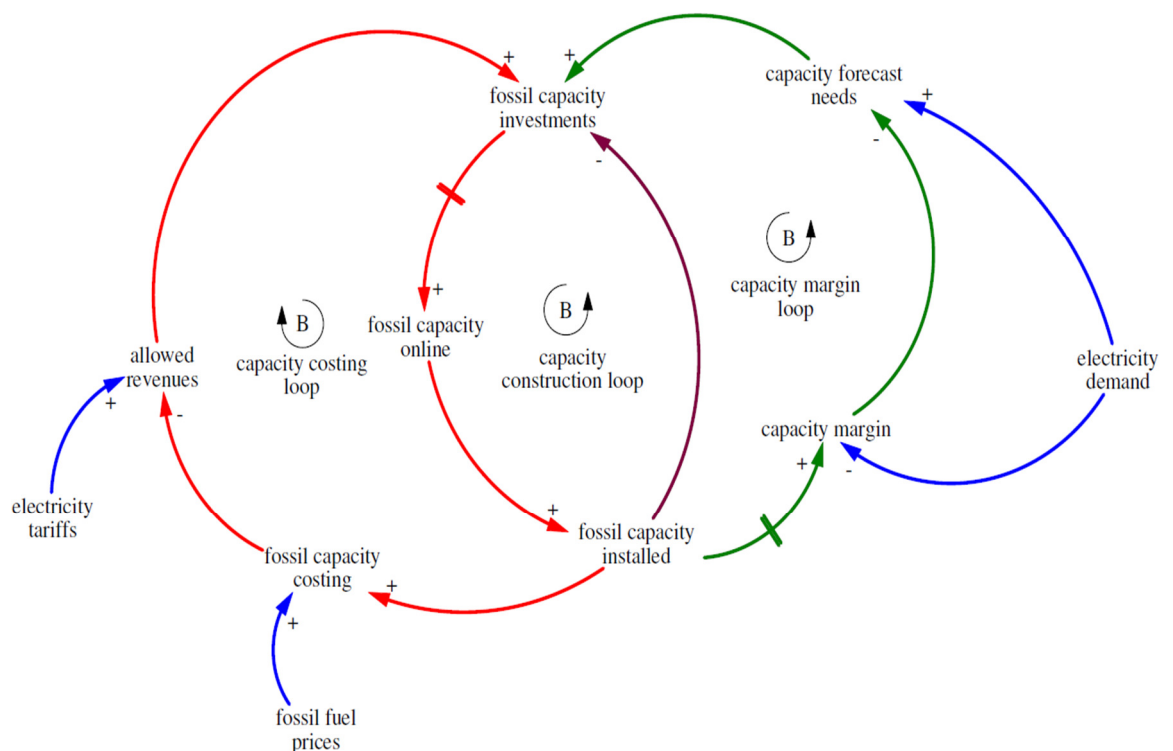


Figure 4.1 Mental model feedback diagram of the fossil fuel based island electricity system

Considering the case study of São Miguel, it is important to note that at model initiation, in 2005, the capacity margin was 30% (EDA, 2008), unlike larger systems which generally have capacity margins between 5 to 15% (IEA, 2010a). Additionally, the forecasted electricity demand is healthy (EDA, 2008; ERSE, 2014) for this system and it was seen that the operator within this system paid 40 - 65% more for fossil fuel used to generate electricity than the mainland Europe average (EDA, 2016). It is also expected that the electricity tariffs should increase in future, but this depends heavily on the mainland economy and resulting legislation (ERSE, 2014). This gave a case study system with high capacity margins, growing electricity demand and relatively high costs for generated electricity. By using these contextual characteristics and by challenging the mental model for the formulation of every important variable from Figure 4.1 a formal SD sub-model was developed for this case study. The key sub-model formulation is shown in the following section.

4.2.2 Model Formulation

The fossil fuel sub-model was derived and formulated from the mental model feedback loop diagram of Figure 4.1 and implemented using the Vensim software package. General stock management structures as applied for capacity expansion illustrated by Ford (1997) and Sterman (2000) were both used as a guide to the fossil fuel capacity expansion formulations of this system. The main mappings of the key stocks and flows within the system feedback structures are shown in Figure 4.2. The *capacity costing loop* is at the top of the simplified diagram and captures the financial influences of *cost per installed fossil fuel capacity*, *decommissioning cost* and the *allowed revenues* of the system. Also shown is the *capacity construction loop* which captures the normal fossil capacity investment cycle for putting this capacity online. At the lower half of the diagram is the *capacity margin loop*, which captures the influences of the installed fossil fuel capacity and the endogenous capacity margin.

Key stocks within this model are the *potential fossil fuel capacity* and the *installed fossil fuel capacity*². The growth of *potential fossil fuel capacity* depends on the *fossil fuel investment rate*, for the monthly time step Δt , which, in turn, is determined by the *allowed revenues* for investments, the forecasted total capacity needed and the capacity margin. The *allowed revenues* variable is defined as the difference in the expected revenues from electricity sales and the total costing incurred from electricity generation and decommissioning. Decommissioning of fossil fuel generation also incurs a cost (IEA, 2010a) and these aggregate costs were endogenously accounted for within the model. Hence, from the top half of the diagram, the total costing necessary to facilitate fossil fuel capacity expansion, and the requisite revenues that can upkeep this amount of installed capacity, were used to determine the financially stipulated investment rate of fossil fuel capacity. Within the lower half of the diagram is reflected the capacity margin and demand forecasted stipulated investment rates of fossil fuel capacity. Within the formulations, the demand

² The *potential fossil fuel capacity* is the capacity that are planned and not yet constructed whilst the *installed fossil fuel capacity* are the capacity that are built and online.

forecasted was determined from the exogenous values and forecasts, whilst the capacity margin was first determined as an initial value from the historical data of the exogenous demand and installed capacity of the system in January 2005, as given from EDA (2016). This was adopted, consistent with the literature, and based on the “derated” capacity margins as given in RAE (2013):

$$C_{margin} = \frac{capacity\ installed - peak\ demand}{peak\ demand} * 100, \text{ where } capacity\ installed \text{ is the installed fossil fuel}$$

capacity in MW, and *peak demand* is the highest demand in MW from January 2005 (EDA, 2016).

To model the capacity margin endogenously, the approach given in Sterman (2000) for goal adjustment was used, whereby $C_{margin\ needed}$, the rate of adjustment of the capacity margin

$$C_{margin} \text{ to a goal } C_{expected}, \text{ is given by } C_{margin\ needed} = \frac{C_{expected} - C_{margin}}{T_{capacity}}, \text{ where } T_{capacity} \text{ is the}$$

capacity margin adjustment period, and $C_{expected}$ was defined for the standard range of values as given in IEA (2010).

Some important dynamics from the stocks and flows of the model are the rate of change of installed fossil fuel capacity, $\Delta C_{fossil\ fuel} / \Delta t = F_0 - F_D$, where F_0 is the fossil fuel generation online rate and F_D is the decommissioning rate. Additionally, the rate of change of potential fossil fuel capacity, $\Delta C_{potential\ fossil} / \Delta t = F_I - F_O$, where F_I is the fossil fuel investment rate and F_O is the fossil fuel generation capacity online rate after construction. The investment rate F_I is a compound of several

$$\text{model variables: } F_I = \max\left(\frac{C_{DD}}{T_{fossil\ fuel}}, \frac{C_{DM}}{T_{fossil\ fuel}}, \frac{C_{DF}}{T_{fossil\ fuel}}, F_D\right)$$

where C_{DD} is the demand forecasted stipulated fossil fuel capacity needed; C_{DM} is capacity margin stipulated fossil fuel capacity needed; C_{DF} is the financially stipulated fossil fuel capacity needed; $T_{fossil\ fuel}$ is the fossil fuel capacity investment decision timeline. Investments within the system are made based on the capacity as defined from the maximum stipulated capacity needed of C_{DD} , C_{DM} and C_{DF} , in addition to replacing decommissioned capacity. The long-term dynamics surrounding the need for capacity given the capacity margin, demand forecasted capacity and financially driven capacity is examined for a range of electricity demand and capacity margin

scenarios. The electricity tariffs and fossil fuel prices were also adjusted within these scenarios as shown in the next section.

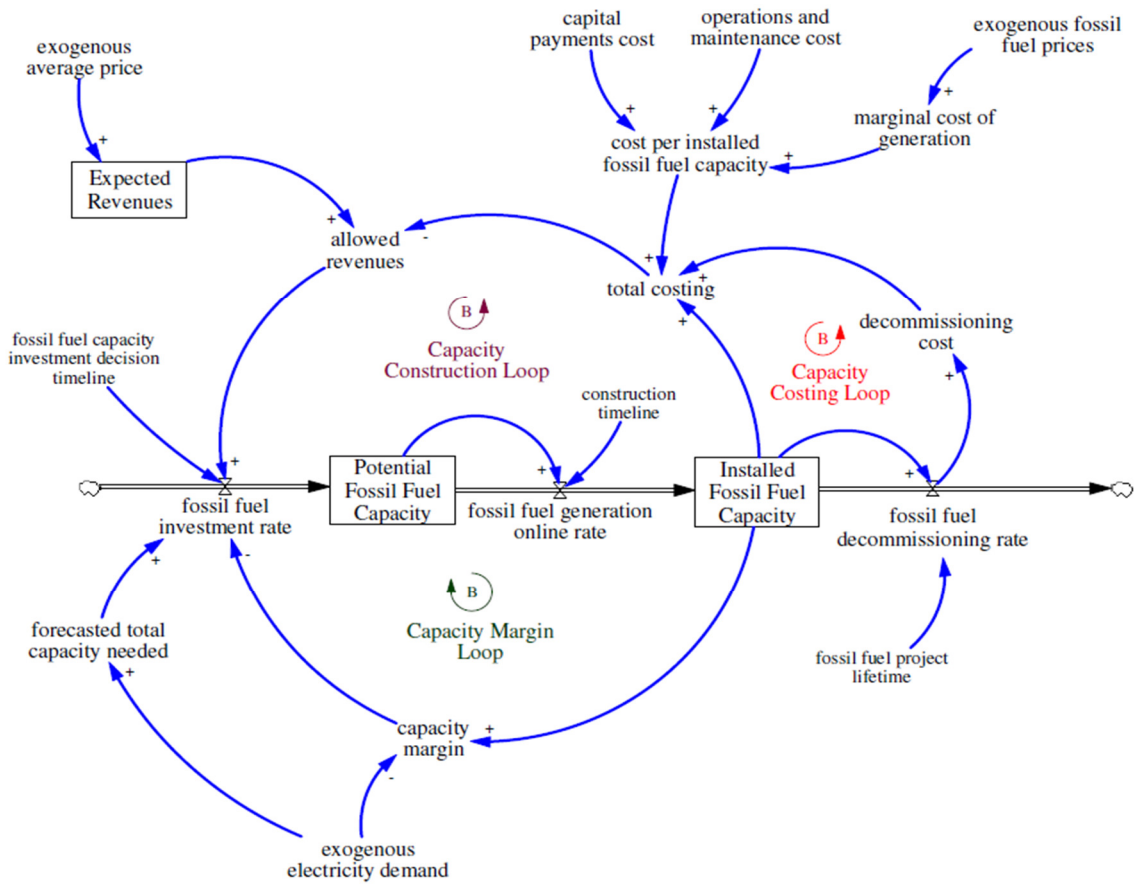


Figure 4.2 Simplified stock and flow diagram for the fossil fuel capacity model formulation

This developed sub-model captures the endogenous fossil fuel capacity expansion of the system whilst accounting for endogenous capacity margins and capacity costing. One of the key assumptions used in this sub-model is that the fossil fuel capacity accounts for all electricity generation within the system. This assumption seemed reasonable for an initial sub-model since the historical data of the fossil fuel capacity prominence (a ratio of the fossil fuel capacity to total generation capacity within the island) stood at over 75% in January 2005, shown in Figure 3.3 of Section 3.2.1.

As highlighted in Section 3.3, this sub-model underwent testing and validation checks common to SD model building. Reality checks on the installed fossil fuel capacity for total costing are done and structure validity testing of all formulations is performed. The model was simulated on a monthly

time step for 45 years as detailed in Section 3.3. Historical data from 2005 to 2015 of the exogenous variables listed in table 4.1 except the capacity investment timeline, which was fixed, were used for determining appropriate data extrapolations using the Vensim SMOOTH and FORECAST functions. These extrapolations were then compared and used as the respective exogenous inputs into the model. There were no direct comparisons of the installed fossil fuel capacity of this sub-model to the historical data of installed fossil fuel within this system since the real system has a fair share of renewables after 2007. However, the identified patterns of the long-term behaviour being exhibited by the simulated fossil fuel capacity give the useful elicitation required for this research work and for expanding the sub-model.

4.2.3 Evaluation and Analysis

Within the scope of this initial sub-model, the effects of the financial costing and capacity margin aspects in São Miguel are evaluated. Three main scenarios were used for the evaluations. In all scenarios, the initially installed fossil fuel capacity and initial potential fossil fuel capacity were obtained from the historical data of São Miguel, for the initial time of January 2005. The average present age of existing fossil fuel generators at this initial time was also used (EDA, 2016). The scenarios differ with regards to the exogenous electricity demand forecasted for the island system. The capacity margin is assumed to be 30% as is existent in this system (EDA, 2016).

Scenario descriptions

Reference scenario: This scenario considers the “business as usual” case and represents what is most strongly expected to occur under the current system. The electricity demand rate forecasts of 3% per annum increases, and the exogenous electricity tariffs and fossil fuel prices given from the extrapolated historical data were used for this scenario.

Below average demand scenario: This scenario reflects a lower than the forecasted electricity demand within the system of less than 3% per annum. This value is fixed at 1.5 % per annum. Electricity tariffs and the fossil fuel prices were set to be at a lower extrapolated trajectory over the

simulation time of the sub-model. A lower peak demand forecast of 1.5% per annum is also accounted for in this scenario.

Above average demand scenario: This scenario reflects a higher than the forecasted electricity demand within the system of more than 3% forecasted per annum. This value is fixed at 4.5% per annum. Electricity tariffs and the exogenous fossil fuel prices were set to be at a higher extrapolated trajectory over the simulation time of the sub-model. A growth in peak demand of 4.5% per annum is also accounted for within this scenario.

Scenario analysis

Figure 4.3 shows the monthly installed fossil fuel capacity of all three scenarios. This installed fossil fuel capacity appears to be stable until about 2017 in all three scenarios and then gradually rises for the rest of the simulation time up to about 200MW by 2050. The fossil fuel generation investments are reflected in the amount of new fossil fuel generation that is required to meet the needs of the island system. As expected the above average demand scenario has the highest growth whilst the below average scenario has the lowest. It is also observed here that the difference in the growth rates is reflective of the differing long-term positive impacts of the demand forecast on the installed fossil fuel in the island system.

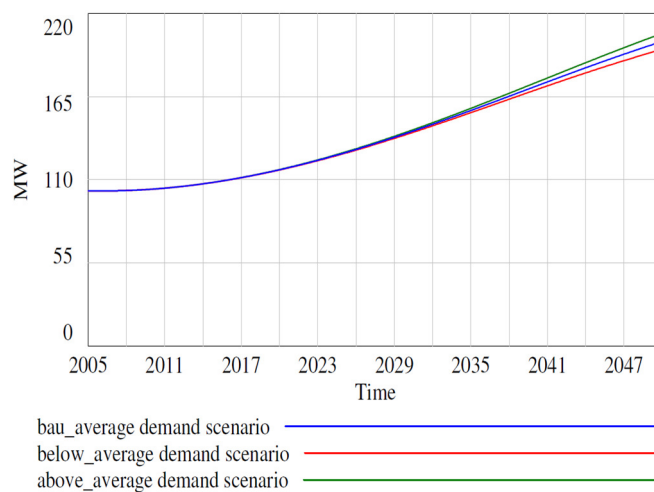


Figure 4.3 Installed fossil fuel capacity for below average demand, above average demand and the reference scenarios

Shown in Figure 4.4 are the results for scenario runs of the capacity margin together with the “business as usual” scenario. Using the “business as usual” reference scenario and changing the *capacity margin expected* given in Section 4.1 to reflect international industry standards of between 10% and 20% as given in IEA (2010), Figure 4.4 was generated. As one would expect there are smaller increases in the amount of installed fossil fuel capacity for meeting a 10% capacity margin (RAE, 2013), than for the reference scenario of the existing 30% capacity margin.

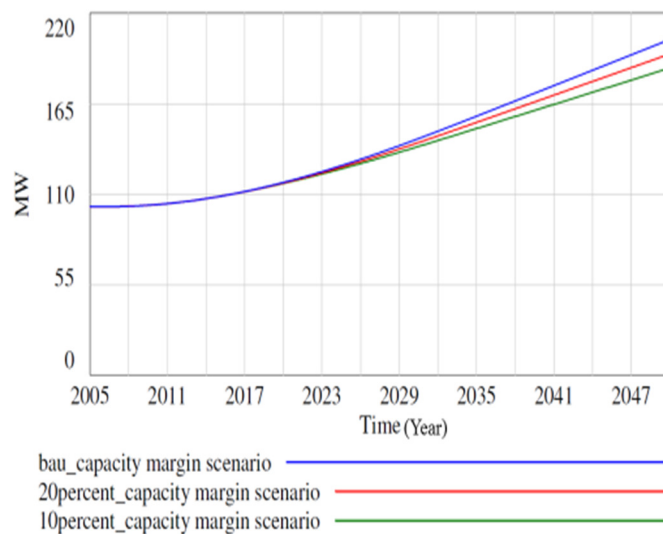


Figure 4.4 Installed fossil fuel capacity for 10 percent capacity margin, 20 percent capacity margin and the reference scenarios

The scenario runs give symmetrical results in the long-term implying that adhering to the capacity margin change (by removing or decommissioning fossil fuel generation) will lead to a proportional change in the installed fossil fuel capacity. It follows that adhering to a 10% international standard of capacity margin will have less increases in the long-term for the installed fossil fuel capacity from the reference scenario of approximately 30%. This would be a realistic option since there is a notable amount of installed generation capacity not presently in use (EDA, 2016), hence investment decisions that are not important for demand growth can be curtailed for this level of capacity margin. However, the issue of installed capacity redundancy needed for island systems should be

considered. Island systems generally require higher capacity margins (greater than 10%) to ensure their electricity supply redundancy and to avoid blackouts) (Weisser, 2004b; Botelho, 2015).

In addition, if the delay associated in perceiving the capacity margin or the capacity adjustment period, are longer, then the installed fossil fuel capacity and fossil fuel generations are also delayed in the long-term. A smaller delay, however, implies a lower amount of fossil fuel capacity installed and reduced unnecessary fossil fuel generation investments for the island during the simulation period. This is similar to Ford's (1997) conclusions on the lead time for capacity expansion projects to be shorter to ensure having enough financial basis for project completion and not over-investing in capacity in the long-term. We note here that large capacity margins in São Miguel are critical to the electricity system security (avoiding blackouts) but are not the desired driver for the fossil fuel generation capacity of the island system. However, the magnitude of the electricity demand forecast is a necessary driver for capacity expansion within the electricity system. Also, the allowed revenues and financial drivers within this system are not observed to have great impacts. This is to be expected because electricity tariffs are externally determined for the island system. The lack of financial impacts provides an opportunity for more economical generation mixes (to include different types of renewables) and for exploring the best options for integrating such low-carbon sources within such electricity systems.

Whilst undertaking an extensive review of renewable integration into island systems Weisser (2004) recommended that future models of such systems should incorporate both regulatory considerations and the dynamics of cost reduction learning from the experience of installed renewable sources, in order to evaluate comprehensively investment implications in the short, medium and long term. According to Weisser (2004), this is important to identifying the drivers and necessary investment and policy insights into a low-carbon optimised system. A sub-model for highlighting the integration of renewable energy sources within island electricity systems is presented in the next section.

4.3 Renewables Integration Capacity Model

An SD sub-model is here developed for investigating the effects of (local) emission reduction targets and learning curves on the integration of renewable generation sources³ within island electricity systems. Specifically, the sub-model highlights the low-carbon policy effectiveness for renewable capacity investment decisions. This is achieved by representing the endogenous interactions between the local renewable goal, the global influence of CO₂ emissions targets, and profitability constraining capacity investments (incorporating learning curve experience for cost reductions).

The sub-model adapts the learning curve implementation of Pruyt and Kwakkel (2011). These authors have studied the impact of learning curves on the cost of competing technologies in energy transitions. Their analysis is focused on solely the cost of the technologies and not the impact of emissions and low-carbon policy interactions with cost reduction learning. The more holistic approach presented here provides an opportunity for understanding the role of renewable targets whilst also considering the learning curve experience for installed renewables based on their decreasing cost from familiarity with the technologies driving enhanced profitability in the long-term. It also gauges the opportunities and challenges facing those making investment decisions regarding the integration of renewable sources in isolated island electricity systems.

4.3.1 Mental Model

The mental model feedback diagram shown in Figure 4.5 is used as the basis for this renewables integration study. The existing causal relationships are shown in the diagram as two balancing loops, indicated by letter *B* and one reinforcing loop indicated by the letter *R*. Together, they reflect the key feedback structures of the system. Similar to the fossil fuel sub-model of Section 4.2, this second sub-model does not endogenously account for the electricity demand and electricity tariffs. Moreover, fossil fuel prices are excluded from this sub-model. The key endogenous variables for

³ For this sub-model all renewables sources are considered as an aggregated representation of geothermal generation. Geothermal has a 80% share of renewables sources within the case study in 2015 (Botelho, 2016; EDA, 2016)

this sub-model are the installed renewables capacity, net CO₂ emissions and the renewables profitability based on cost reductions via learning. Additionally, there is no consideration for any long-term or short-term seasonal energy storage. A completed listing of the key variables of the model boundary chart, which summarizes the scope of this sub-model, is given in Table 4.2.

Endogenous	Exogenous	Excluded
Installed renewables capacity	Electricity tariffs	Capacity margin
Net CO ₂ Emissions	Electricity demand	Fossil fuel prices
Renewables investment rate	Low-carbon policy targets	Cash flow constraints
Renewables local learning costs	Capacity investment timeline	GDP changes
Renewables profitability	Fossil fuel generation supply	Population changes
	Government renewables subsidy	Energy Storage

Table 4.2 Model boundary chart for the renewables integration sub-model

As shown in Figure 4.5, the *renewables target locally influenced loop* (green and red mixed loop) is being influenced exogenously by the *local renewables target* and has a balancing effect on the amount of *planned renewables investment*. This is based on the shortfall of the amount needed to reach the *local renewables target*⁴. After a delay of construction and planning, this balancing effect is reinforced on the quantity of *renewables capacity installed* in the system.

The *globally-influenced CO₂ emissions target loop* (purple and red mixed loop) shows the balancing effects of the *renewables capacity installed* and *planned renewables investment* on the global emissions targets of the island system. Similar to the *renewables target locally influenced loop* this

⁴ The local renewables target is the amount of renewables agreed by the Açores for their island territories to pursue (EDA, 2008). São Miguel has the same renewables target as the rest of the Açores. Global CO₂ emissions targets are the emissions targets agreed to by the EU from the United Nations Framework Convention on Climate Change. These targets are given to the specific EU territories, such as Portugal which then gives it to the Açores and in turn São Miguel.

loop is also exogenously influenced by a target, but in this case, the target is stipulated from the European Union (EU) as the CO₂ emissions targets agreed for this territory. The shortfall of the amount needed to achieve this target balances the amount of *renewables capacity installed* in the system also after a delay for construction and planning.

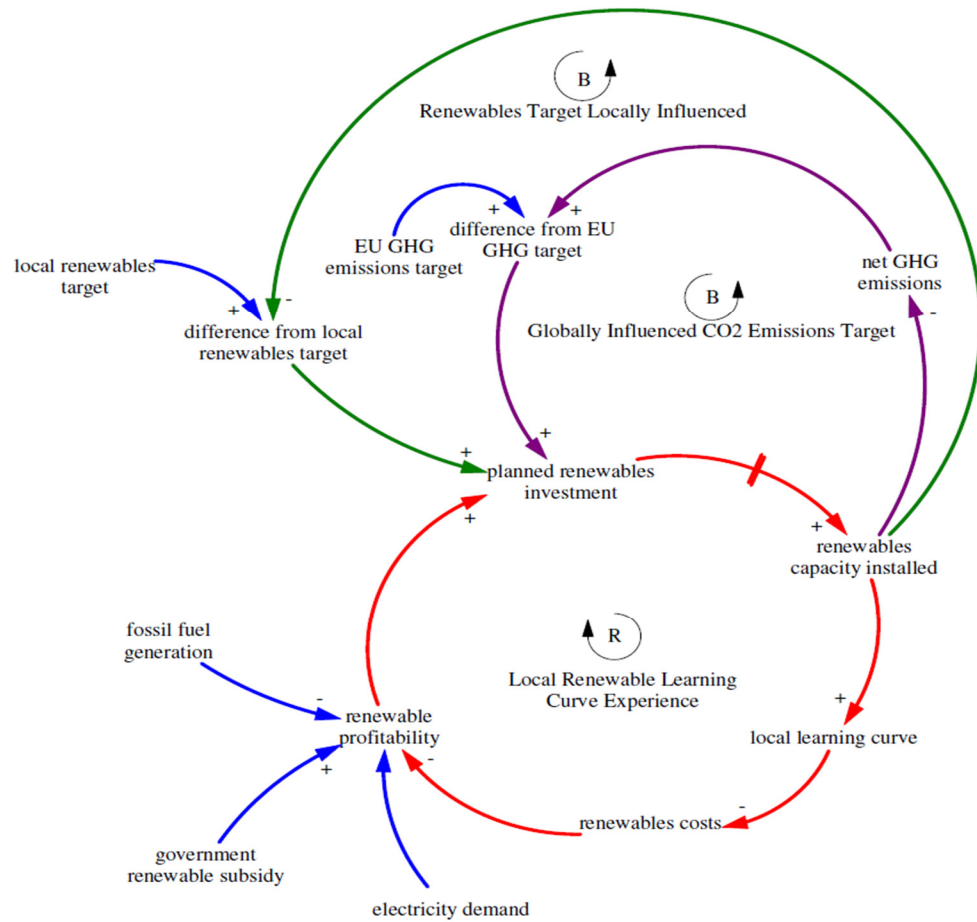


Figure 4.5 Overview of the key feedback structures related to renewable integration within the island electricity system

Also shown is the *local renewable learning curve experience loop* (red loop) which has a reinforcing effect on the *planned renewables investments* and, in turn, the *renewables capacity installed*. This loop captures the extent of cost reductions that accrue from the experience of installing renewables. These cost reductions are determined from the local stakeholder experiences with the installed renewables capacity (it is assumed that for every doubling of the already existing installed renewables there is a 10% cost reduction from the familiarity with these technologies in the island

system). This loop also captures the breakeven cost of renewable production capacity that is required for the system to be self-sufficient/sustainable.

These three loops are the key components underpinning the model's (and by extension the system's) structure, with their interactions being important for understanding the emerging characteristics of the long-term renewable integration within this island electricity system. The two balancing loops will restrict the installed renewables capacity within the system as their targets are met whilst, the reinforcing loop will encourage more renewables capacity as more installations lead to lower cost of renewables.

This sub-model, as with the previous sub-model of Section 4.2, is a long-timescale investment model using a monthly time-step. It is not a short-term grid balancing model. As such, this work is largely insulated from short-term issues of weather and renewables intermittency. In addition, the model crucially highlights a generic structure aggregating all renewable sources into a single entity. Later disaggregation will permit more accurate modelling, as the technological advancement with learning-curve cost reductions and long-term project lifetime profitability of the individual renewable sources can differ significantly. This mental model is then challenged for the formulation of the important variables for developing the formal SD sub-model of this section. This formal sub-model formulation is highlighted in the following section.

4.3.2 Model Formulation

As with the earlier fossil fuel model, this simulation model is implemented using the Vensim software package. The model has been derived from the mental model feedback causal loop diagram of Figure 4.5 and includes the stock and flow variables that capture the key system structure. The main mappings of these stocks and flows are detailed in Figure 4.6. The corresponding feedback structure loops of Figure 4.5 are also labelled within this diagram, including an additional loop useful for the model formulations, the *renewables capacity equilibrium loop*, which is synonymous to the *capacity construction loop* of Figure 4.1. The two loops at the top of

the diagram are responsible for capturing the influences of low-carbon targets and goals. The *globally influenced CO₂ emissions target loop* is driven by the installation of renewables which, in turn, reduces the amount of fossil fuel capacity used for electricity production. This reduction in fossil fuel electricity production reduces the amount needed to achieve the global target for CO₂ emissions leading to the need for fewer renewables capacity as the loop is iterated. Similarly, the *local renewables target loop* is driven by the installed renewables capacity, which, once increasing, reduces the amount of renewables needed to meet the renewables targets. Hence a lower renewables investment rate would result for this loop. The opposite would occur for the both loops if the *renewables capacity installed* were to decrease.

At the lower half of the diagram, are the *renewables capacity equilibrium loop* and the *local renewables experience loop* which are responsible for capturing the learning curve cost reduction effects of renewables capacity installations. The *local renewables experience loop* is driven by the current and all previous installations of renewables capacity over the long-term of the model. This brings to light an important set of considerations in renewable energy investments, which is, the relationship between unit cost and the scale of deployment. Such issues bring in the economic idea of “learning”, noted in Section 1.3 as the learning-by-doing (Weisser, 2004a, 2004b; Pruyt and Kwakkel, 2011) concept. In essence, the higher the accumulated renewables capacity installed, the lower will be the cost of new renewables capacity due to the local learning-by-doing. Learning-by-doing refers to the reduction of the cost of new renewables that comes solely from the experience/familiarity with the technologies. It is usually defined as the reduction in unit cost (typically total capital cost) that is achieved for each doubling of installed capacity (Sterman, 2000; Pruyt and Kwakkel, 2011). This cost reductions will increase the *renewables profitability* and reinforce the need for installing more renewables capacity. However, noting the unit size of today’s technologies and the relatively small scale of the island case study the opportunity for a significant number of doublings is small and hence learning-by-doing does not feature prominently in the results presented here, in Section 4.3.3.

At the same time, research and development should have the potential to reduce technology costs, but the likelihood and potential for this on such small isolated island are also generally non-significant. This can hence lead to the status of the Açores as an island system that risks a divergence from what might generally be expected by energy researchers globally. But it can reflect the further renewables cost reduction issues related to isolated island systems. The electricity generation technology mix deployed on São Miguel has been more conventional and in this research the assumption is made that the impact of the above described learning-by-research will be sufficiently small that it may be neglected.

The other loop in the lower half of the diagram, the *renewables capacity equilibrium loop* balances the *renewables profitability*, since the higher the *renewables capacity installed*, the expected revenues generated for each MW installed will be less. The unit maintenance costs thus rises with increased capacity due to the added usage and/maintenance of the installed capacity, hence a lower profitability for the renewables will occur. This loop is weaker and independent to the local learning-by-doing cost reductions and can be ignored if the renewable technology does not require maintenance (which is not the situation in the case study that has geothermal installations). Such smaller effects that might be of greater relative importance in larger territories can possibly be neglected in a small island system.

Also shown in Figure 4.6 are the key stocks of the *planned renewable investments*, the *installed renewable capacity* and the *cost per MW of new renewable capacity*. The growth of *planned investments* in renewable capacity depends on the flow of the *renewables investment rate*, which, in turn, is determined by the total capacity required to meet (i) forecasted demand load; (ii) the financial expectations of investors; and (iii) the CO₂ emissions and local renewable targets.

Mathematical details of the key formulations used in this sub-model are presented next, in addition, more details can be found in Appendix A1.

The cost reduction learning curve is modelled using the formulation given by Pruyt and Kwakkel (2011) for $C_{t+\Delta t} = C_t \left(\frac{X_{t+\Delta t}}{X_t} \right)^{-e}$, where C_t is the investment cost per MW at time t , X_t is the cumulative constructed capacity (including decommissions), and e is the learning curve parameter. The parameter $e = -\log_2(p)$, where p is the progress ratio with $0 \leq p \leq 1$. A *progress ratio* of 90% means that for each doubling of X_t there is a cost reduction of 10%. Similarly, a *progress ratio* of 80% means that for each doubling of X_t there is a cost reduction of 20%. Following (Sterman, 2000) pg. 338, this sub-model was tested with several realistic progress ratios. For the relationship of the progress ratio to the economic concept of learning-by-doing please see Pruyt and Kwakkel (2011) and Sterman (2000) pg. 338.

To model the influence of targets, the approach given in Sterman (2000) pg. 338 is used, whereby R , the rate of adjustment of a variable S to a target S_* , is given by $R = \frac{S_* - S}{T_A}$, where T_A is the adjustment period. This is used to define the CO₂ emissions and local renewables targets of the system. In the case of the CO₂ emissions, the reference target used is the base year value of 30% reduction (to 1990 values) and the initial CO₂ emissions value is used from January 2005. The adjustment time was determined by the scenarios implemented. For the local renewables target, the targets and adjustment times were determined by the implemented scenarios whilst the goal for installed renewables is used as a fraction of total installed fossil and renewables capacity in January 2005. Additional important dynamic components of the stock and flow structure of the model are the rate of change of installed renewable capacity, $\Delta C_{renewables}/\Delta t = R_O - R_D$, where R_O is the renewables online rate, R_D is the decommissioning rate of renewables and Δt is the monthly time step. Also, formulated is the rate of change of planned renewable investments, $\Delta C_{planned\ renewables}/\Delta t = R_I - R_C$, where R_I is the renewables investment rate and R_C is the rate of commencement of construction of new renewable capacity.

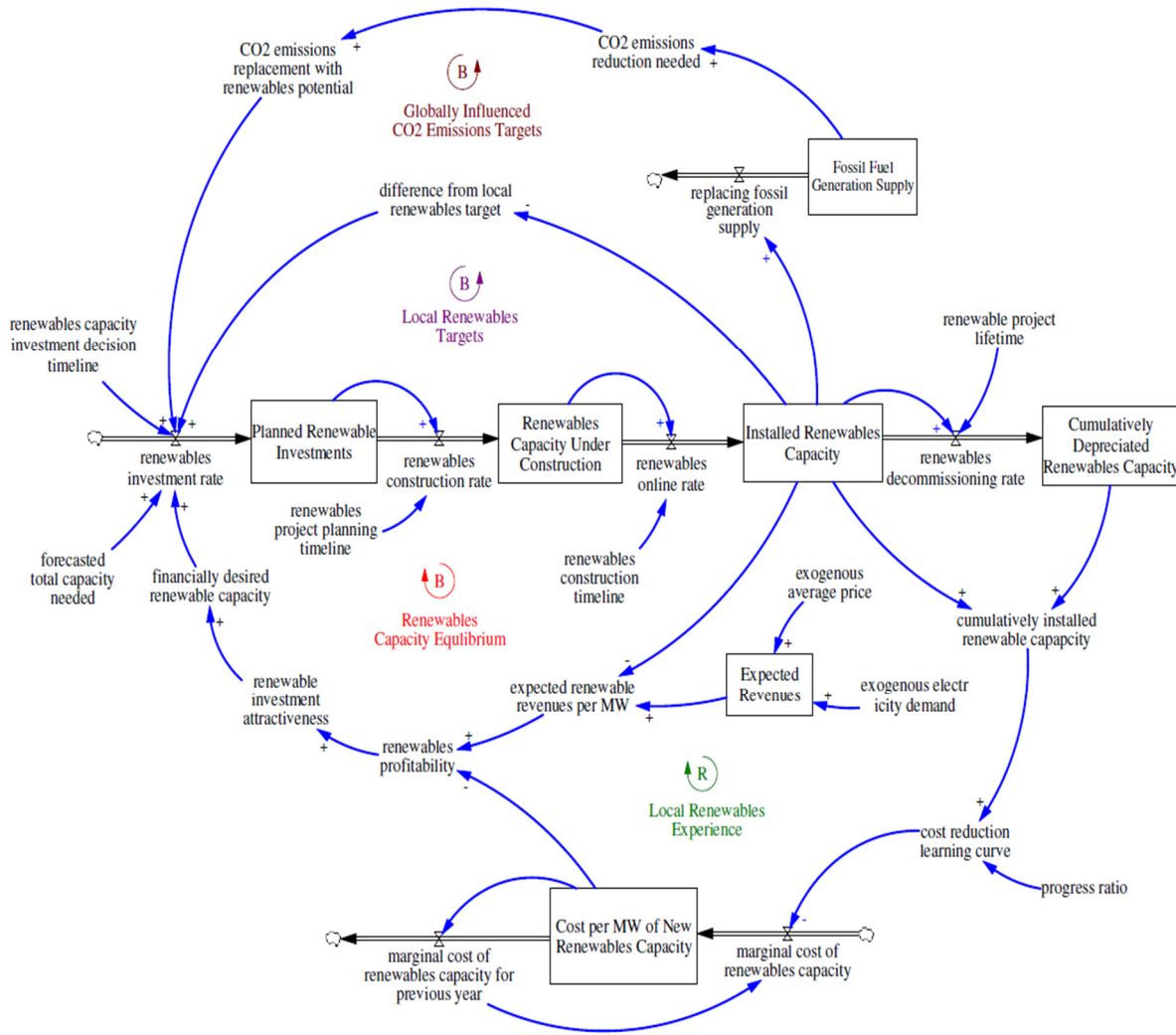


Figure 4.6 Simplified stock and flow diagram for the renewables integration model formulation

In addition the investment rate I is a compound of several model variables:

$$R_I = \max\left(\frac{C_F - C_{renewables}}{T_{renewables}}, \frac{C_{DF} - C_{renewables}}{T_{renewables}}, R_{LT}, R_{ET}\right) + R_D$$

where C_F is the forecasted demand load; C_I is the installed renewable capacity; C_{DF} is the financially desired renewable capacity; $T_{renewables}$ is the renewables capacity investment decision “time”; R_D is the rate of renewable capacity decommissioning; and R_{LT} and R_{ET} are, respectively, the rates of adjustment to the local renewables and CO₂ emissions targets, as described above. The financially desired renewable capacity $C_{DF} = A_R C_{renewables}$, where A_R is the investment attractiveness, which, following Black (2005), is modelled as a piecewise linear function of profitability.

Investments are made based on the low-carbon targets and local learning curve cost reduction capacity in addition to replacing decommissioned capacity. The long-term dynamics surrounding the policy push for renewables whilst considering the learning curves of the renewables is studied using a range of three scenarios. This study aims to include capturing the existing trends within the system for the diminishing usage of fossil fuel and increased installation of renewables. A phenomenon that is illustrated in Figure 3.3 and has been attributed to the national push within the island system for 75% renewable generation capacity by 2018 (Cross-Call, 2013).

One of the key assumptions of this model is that the installed renewables capacity will be used to replace the equivalent amount of fossil fuel electricity generation and not more aggressively to force their abandonment. This concept is captured in the *globally influenced emission target loop* of Figure 4.6. Consequently, and seen in Section 4.2, the island system has a very high amount of spare fossil fuel capacity, hence it will be unreasonable to assume that they will decommission huge amounts of these generation capacities immediately. Additionally, as highlighted above, the sub-model has a generic structure aggregating all renewable sources into a single entity, which reduces the accuracy of the delays from planning up to the commissioning of the installed renewables capacity due to differences with the lead time for geothermal compared to the time needed for the wind. For the wind, there can be a delay of 1-2 years whilst geothermal can take 3-4 years (IEA, 2010a). The values used within this sub-model implementation of 2-3 years is determined as an average of these times. This issue is however developed further in Chapter 6, where all the renewable sources are disaggregated.

To gain some insights into the long-term behaviour of the system structure and variables, the model has been simulated for the period 2005 - 2050. Both the calibration and simulation periods for this sub-model is used as defined in Section 3.2.1. The investment decisions for the renewable integration within the system have been observed and insights are given based on different renewable targets and CO₂ emissions policies. Additionally, as highlighted in Section 3.3 and also

done for Section 4.2, this sub-model underwent rigorous testing and validation checks. Structural validation of the model is achieved by comparing model outputs with historical output data of the real system for the endogenous installed renewable capacity. Results of the comparisons are highlighted in Figure 4.8. In addition, the historical data for 2005-2014 of the key exogenous variables listed in Table 4.2 such as the demand load and electricity tariffs, have been used to determine appropriate data extrapolations using the Vensim SMOOTH and FORECAST functions (Ventana Systems, 2016). The model is then used as detailed in the next section to analyze scenarios in which the rate of low-carbon policy influences on the rate of renewable integration is likely/not likely to be delayed, diluted, or defeated by unanticipated reactions and side effects.

4.3.3 Evaluation and Analysis

For this sub-model, the effects of the renewables targets and CO₂ emissions policy on the planned and installed renewable capacity within the system are evaluated. The embedded effects on the cost of renewable investments due to the cost-reduction from installation experience are also incorporated in the sub-model. In all scenarios, the initial planned renewable investments; installed renewable capacity and cost of renewable investments are obtained from the historical data of São Miguel, for the initial date of January 2005. Three different scenarios are used for evaluation, which varies according to the desired policies. The extrapolated input data for the exogenous electricity peak demand and tariffs of the system and the initial cost of renewable investments all remain the same in every scenario. The CO₂ emissions and renewable target policies are implemented as stated in Section 4.3.1, and by fitting the adjustment time and required goal to the desired policy.

Three Scenarios

Reference scenario: This scenario considers the “business as usual” case and represents the most likely outcome under a midterm goal of 30% reduced CO₂ emissions and 50% installed renewable capacity targets within the system by 2030.

Less-aggressive renewable scenario: This scenario features renewable policies that have a goal of 30% reduced CO₂ emissions and 50% installed renewable capacity targets within the system, by 2050.

Aggressive renewable scenario: This scenario represents the goal of 30% reduction in CO₂ emissions and 75% installed renewable capacity within the system by 2018.

Analysis

Figure 4.7 shows the observed trend for the planned renewable investments within the system. In all three scenarios, the initial state of the sub-model used the value of planned renewable investment to be zero MW, reflecting the reality of São Miguel in 2005. The monthly planned renewable investments peak just after the year 2011 for all scenarios and as expected the policy of 75% renewables by 2018 has a higher peak. After this peak, the trend appears to be a steep decline into a levelling off to around zero about the year 2035 for all three scenarios. The similarity of the three scenarios is partly a consequence of assuming the same demand growth in each case. However, results illustrate some similarities with the actually planned renewables in São Miguel in 2011 for 9MW wind capacity and 13MW geothermal capacity (Silva, 2013). Furthermore, it is expected that the renewables capacity will converge to meet the policy target as such, which is equivalent to archetypical s-shaped system dynamics behaviour where such convergences might be dependent on the system carrying capacity.

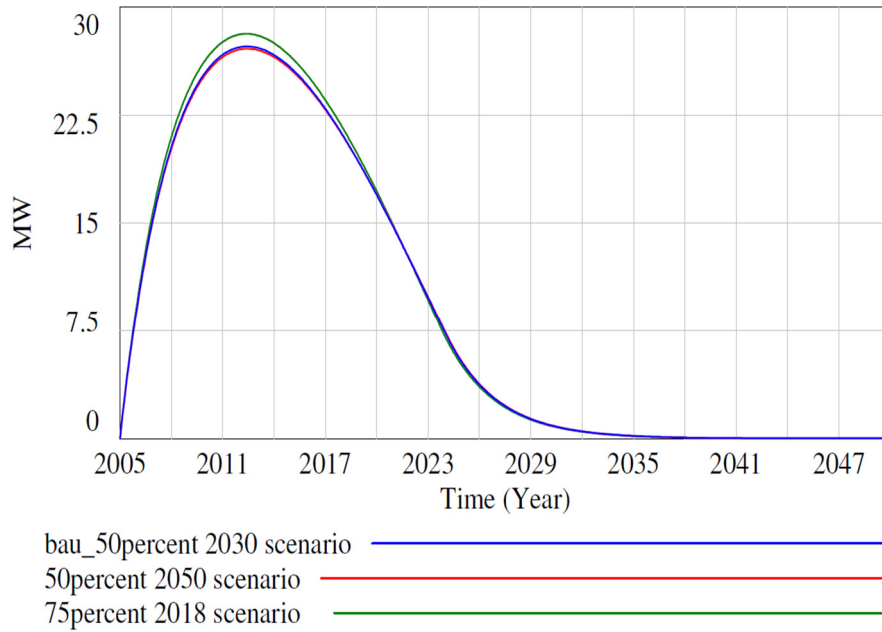


Figure 4.7 Planned renewable capacity investments for the three scenarios

Figure 4.8 shows the amount of installed renewable capacity for all three scenarios, which are also compared to the historical data of installed renewable capacity from 2005 to 2015 and the results of Ilic, Xie and Liu (2013) Chp. 20. All three of the scenarios reflect a similar amount of installed renewable capacity of about 39MW for 2015 in line with the real data. The calibration time of the model to account for the delays such as the capacity investment decision timelines are reasons why there was an initial deviation from the real data. However, the long-term trajectory of both the simulated model and the historical data tends to be correlated. Note, Ilić achieved similar results to the 100MW approximate value of installed capacity in 2028 using a stochastic dynamic programming method for long-term capacity planning in São Miguel. The visual confirmation of the simulation run to the historical data and the results of Ilic, Xie and Liu (2013) Chp. 20 adds value and some confidence in the validity of this modelling work. The aggressive 2018 renewable policy has an installation peak that occurs faster and is higher than the 2030 50% policy and the 2050 50% policy curves. However, the final capacity in 2050 does not differ by much and it is considered that this can be attributed to the electricity demand on the island (the carrying capacity for installations of the system).

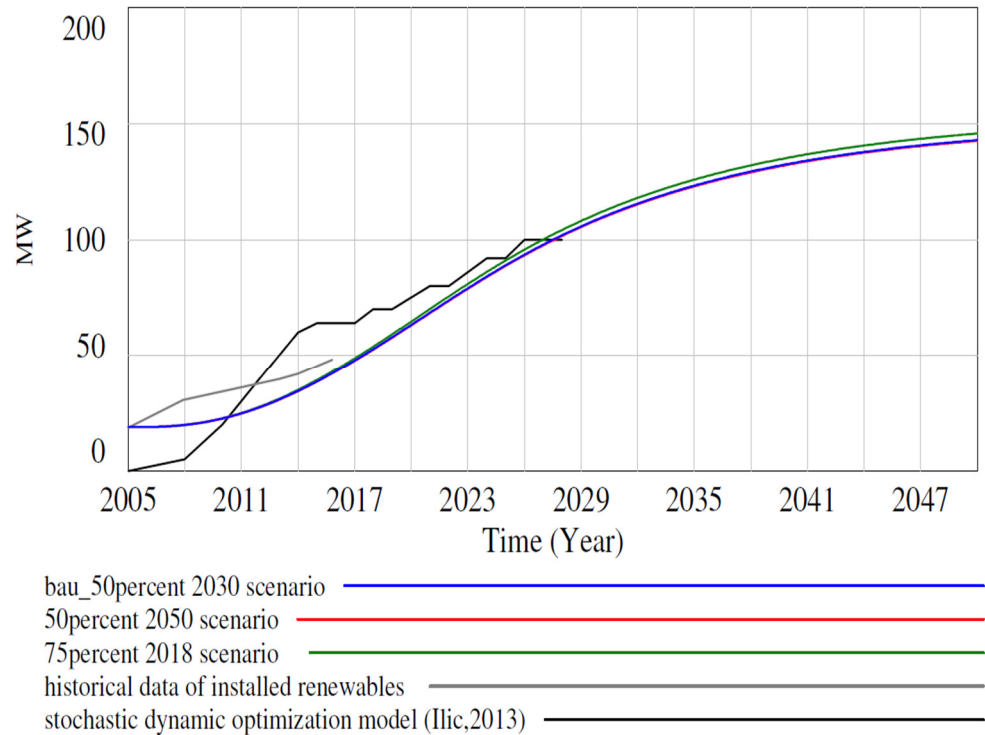


Figure 4.8 Installed renewables capacity. This thesis modelling (three Scenarios), real world data and independent modelling Ilic, Xie and Liu (2013) Chp. 20

Figure 4.9 highlights results for the cost reduction learning curve. This study uses a 90% *progress ratio* resulting in a 10% cost reduction on the initial cost price in 2005 for every doubling of the renewable capacity within the system. The new renewables overnight cost price for 2005 as given by IEA (2010) was used. By 2050, the cost of new renewable capacity is shown to decrease by approximately 25% in all three scenarios indicating that the learning experience of the renewable element within the island is not very high. The negligible difference between the aggressive policy and the other policies, even in the earlier years can be due to some constraints such as the demand forecast influences that are not endogenously accounted for within this sub-model. This will be developed later in the thesis. The corollary is that the learning-by-doing opportunity on such small islands is not very significant. Since such learning effects are typically measured in terms of the cost reductions that can be expected from a doubling of installed capacity. The small size of the island system evidently restricts the potential for large capacity growth and hence learning-by-doing.

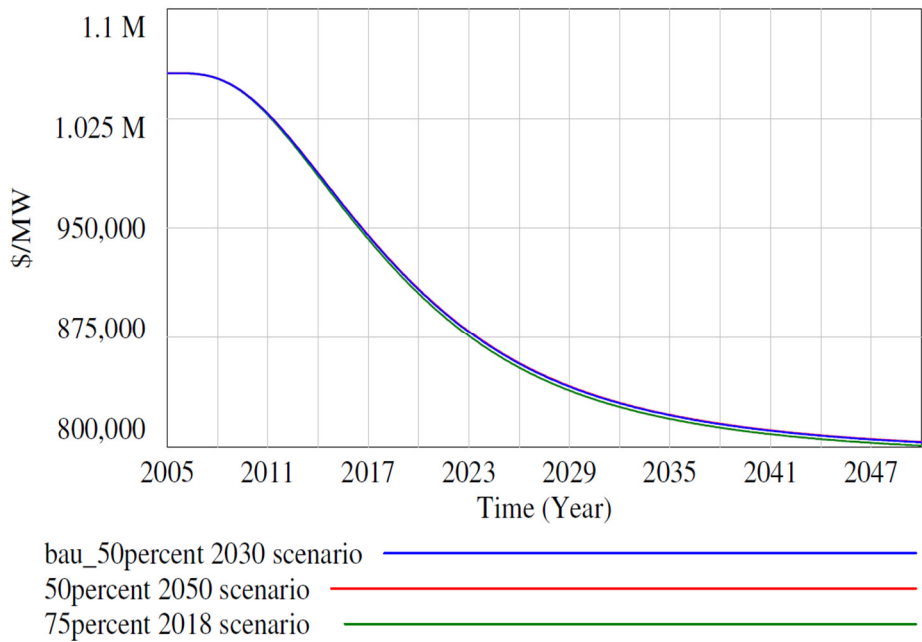


Figure 4.9 Costs per MW of capacity in three scenarios illustrating the effect of learning-by-doing

Figures 4.10 and 4.11 show how the deviation from the local renewable target and the renewable capacity needed for CO₂ emissions replacement influences the three scenarios respectively. In all cases, values are initially high then decrease in proportion to the aggressiveness of the associated policy. If stakeholders only considered these factors then there could be overly costly investments in the early years of the system. In Figure 4.10, both the reference “business as usual” and the less aggressive policies achieved their respective local renewable targets by about 2023. However, there are indications that the aggressive 75% 2018 policy appears to struggle. In that case, the simulated model achieved its target by about 2027. Hence, it can be asserted that the need to meet local installation targets are very influential and meeting the targets early is inefficient or a 75% target is simply too high. This can additionally be attributed to the carrying capacity of the system and the financial limitations attached to higher investments over a shorter time.

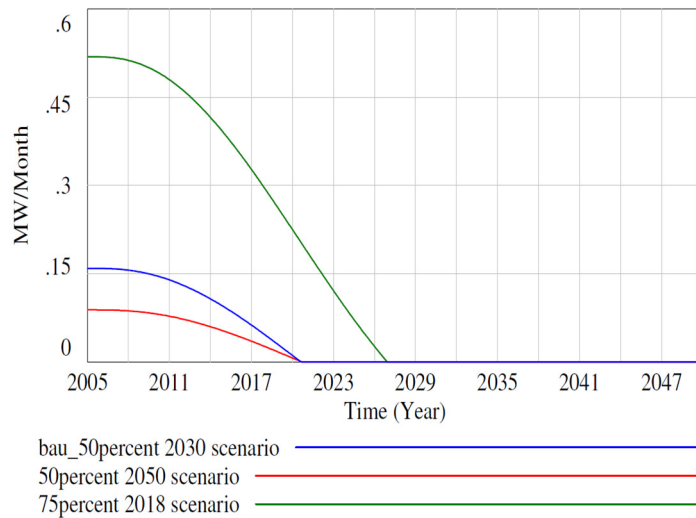


Figure 4.10 Deviation from the local renewable targets with policy in three scenarios

Shown in Figure 4.11 is the implication that a higher amount of renewables are needed on a monthly basis for the aggressive renewable scenario in order to achieve the EU influenced CO₂ emissions goals. However, with less aggressive goals this target is achieved about 1 year later than the more aggressive policy goals. This supports the idea that setting very high local installation targets for renewables capacity within an island electricity system is not productive. Conversely, it can be argued here though that failure to hit a high target can be more effective, in terms of driving renewables into the system, than setting very low targets.

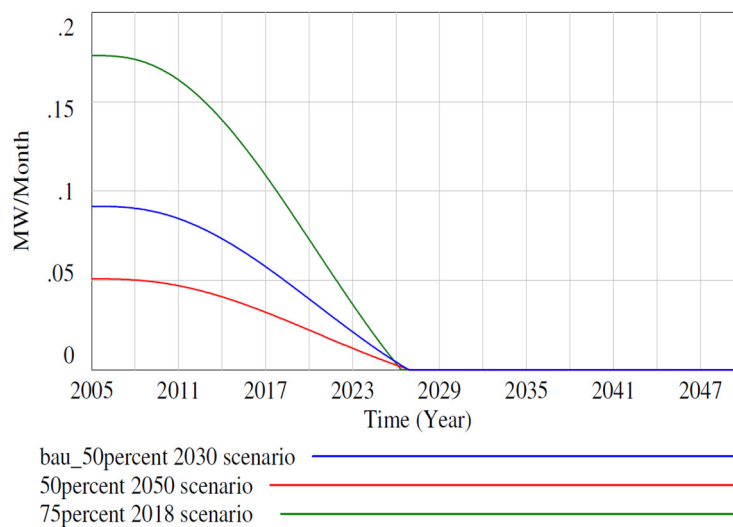


Figure 4.11 Convergence of renewable capacity replacement needed for CO₂ emissions targets with policy in three scenarios

Figure 4.12 illustrates the CO₂ emissions that are accumulated for the three scenarios. It is observed that the aggressive local renewables target was able to reduce the accumulated long-term CO₂ emissions by a larger margin than the other scenarios. This difference is only visible from around the year 2023 and is clearly of small importance. Both the less aggressive scenario and the reference scenarios have similar long-term impacts on the accumulated CO₂ emissions. This result gives some hope to the desire for having aggressive local renewables targets, however, the long-term implications for the whole system with this very small gain in reductions leave questions for concerns. A more comprehensive evaluation of the long-term CO₂ emissions of the different scenarios is done in Chapter 6 as these low-carbon policies are further analysed with long-term economic investment implications for the system.

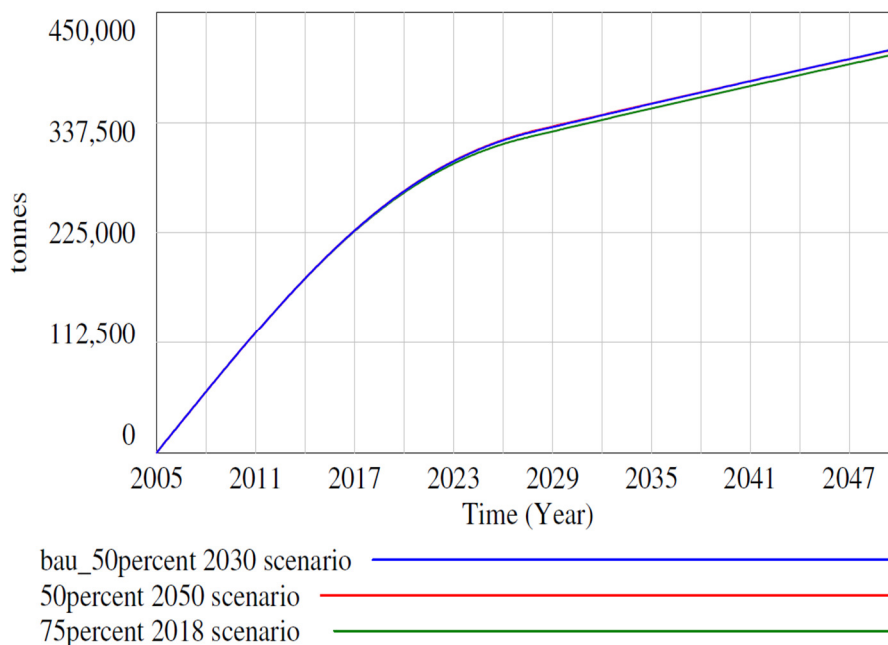


Figure 4.12 Accumulated CO₂ emissions in three scenarios

Observations emerging from this initial study is restricted in scope and may evolve further as other factors are made endogenous to the sub-model. One consideration that could greatly affect renewable generation is the effectiveness of energy storage. The special role of small reservoir hydropower installed capacity is noted in this regard. This is accounted for when the different renewable technologies are disaggregated in Chapter 6.

4.4 Conclusions

This chapter presents the initial contributions of this thesis for satisfying research sub-questions 1 and 2. Firstly, an initial sub-model of the isolated island electricity system of São Miguel assumed to have only fossil fuel generation is developed and analysed for research sub-question 1. Subsequently, research sub-question 2 is satisfied by an evaluation of renewables integration within the isolated electricity system under varying low-carbon policies to assess the effectiveness of these policies for long-term capacity investments.

The fossil fuel sub-model is used to analyse the dynamics surrounding the addition of new fossil fuel generation capacity to the system. Preliminary results and evaluations show that a focus on the capacity margin to international standards in this island does not significantly increase, but rather decreases the long-term fossil fuel investments and installed fossil fuel capacity. Additionally, the forecast for the demand growth is a key factor for driving the investments within this system, however financial incentives do not seem to impact the installed fossil fuel capacity and long-term profitability of the system. This can be attributed to the fact that the island system and the sub-model use variables, such as electricity tariffs and fuel prices, as exogenous inputs. Moreover, the exogenous tariffs and fossil fuel prices are an exogenous consequence of the capacity investments and operating cost of the system and are decided outside of the island system, therefore market incentives are non-existent. Hence, capacity investments in such a system are driven by the need for capacity and not by financial incentives. And the security of electricity supply for such a system is enhanced by careful inspection of the capacity margin and demand growth rate of the system.

The renewable integration sub-model is used to analyse the significance of low-carbon policies within isolated electricity systems. Key components of the model highlight the cost reduction due to local learning from renewables and the type of renewable policies employed. Results and evaluations suggest that setting renewables targets may not be very productive since meeting targets too early are inefficient or the targets are just too high. As shown in the results, in the long

run, the required renewable targets will be achieved eventually, even with less aggressive renewable policies. This implies that the financial health of the system can possibly be jeopardised due to higher investment costs needed over a short period of time trying to achieve aggressive targets. However, there can be acceptable increases in the installed renewables capacity for missed aggressive renewables targets. And there are some emissions reductions benefits by having more aggressive local renewables targets.

Concurrently, island systems typically suffer from a weaker innovation landscape and have limited opportunities for learning-by-doing (Jamasb, Nuttall and Pollitt, 2008). These realities combined with the preliminary results reported here suggest that island systems policy-makers should consider adopting a carefully-paced approach and should probably avoid establishing a world-leading position in innovation for renewables integration. That said, the small scale of island systems can lend themselves to experimentation and world-class opportunities from learning-by-research (Jamasb, Nuttall and Pollitt, 2008). In such situations, the island systems will be able to trial evolving renewable technologies via the research into these technologies within their systems. These initial ideas will be re-evaluated in the light of more holistic work within Chapters 5 and 6 of the thesis.

Concurrently, the insights distilled from these two sub-models show that there are benefits to be obtained from considering key feedbacks for various aspects of low-carbon electricity systems. It was assumed that in the fossil fuel sub-model that the capacity margin would play a major role for capacity investments but this was not seen within this island system. Additionally, it is noted that the cost reduction experience of renewables and the urgency for renewable integrations capacity targets are important, however, aggressive renewables policies do not appear to be very effective for these systems. These initial findings are a good starting point for understanding and steering the long-term generation mix and for providing the gaps needed for optimal investments in generation mixes of low-carbon electricity systems. The relevant follow on sub-model for achieving a higher level of endogeneity with electricity demand and energy efficiency is shown in the next

chapter. In that chapter, the objective is to focus on low-carbon enabling technologies such as electric vehicles and related factors and to model the electricity demand forecast as an endogenous component of the system.

Chapter 5. Low-carbon Policy Influences on Endogenous Electricity Demand

The contents of this chapter can be found in part or whole in the following peer-reviewed publication:

1. Matthew, G. J., Nuttall, W. J., Mestel, B. and Dooley, L. S. (2017) 'A dynamic simulation of low-carbon policy influences on endogenous electricity demand in an isolated island system', *Energy Policy*, 109, pp. 121–131. doi: 10.1016/j.enpol.2017.06.060.

Section 2.3.2 highlighted that the majority of previous island systems energy models have not considered endogenous demand dynamics and complexity. These models, however, have focused on the economic and/or technical provisions of electricity demand. In this chapter, electricity demand is made endogenous, since further endogeneity, as highlighted in Section 3.2 provides a better understanding of the system. The possible futures for electricity demand of the São Miguel case study are elucidated, thereby providing insights into the most important and influential energy policies that may impact upon long-term demand. These insights are obtained as consideration is given to the requisite low-carbon based policies in line with the initial hypothesis presented in Section 3.2.1. Furthermore, this chapter gives insights into the effects of these policies on the long-term behaviour of the modelled endogenous electricity demand within an evolving low-carbon island electricity system.

5.1 Overview

Emerging issues inherent to electricity systems pursuing low-carbon options are the nexus between reliability and availability of renewable energy, and the sustainability and economic affordability for meeting the evolving electricity demand. As highlighted in Sections 2.3.1 and 2.4.2, this is even

more challenging for island electricity systems because island systems are increasingly pursuing low-carbon policies as shown in Chapter 4 yet may be unable to make use of the mainland solutions suggested by Barrett (2006) and Warren (2014), as discussed in Section 2.4.2. These low-carbon pursuit issues are also highlighted in Eurelectric (2012) where the authors detailed an overview of a sustainable island energy future.

Small island electricity systems face great uncertainty in their demand with proportionally large daily and seasonal variations. A large difference in the night time demand versus the day time peak hours usually exists within such systems. For example, in São Miguel, consumption has a demand curve trough during the night, of approximately 40 - 50% of the peak daytime consumption (Isle-pact, 2012; EDA, 2016). These variations can be further enlarged by small changes in efficiency measures, economic activity and consumption patterns, in the absence of large system-balancing areas and smoothing effects. Concurrently, the large discrepancy between daytime and night time demand hinders the advent of more renewables, as otherwise favoured by the low-carbon agenda of these island systems. This is due to the fossil fuel generation needed for the peaking demand in the day and to stabilise the electricity system frequency throughout the night.

Recent studies have promoted the electrification of the global transportation sector as a means of adding further renewables capacity and enhancing the long-term security of the electricity supply (Kintner-Meyer, Schneider and Pratt, 2007; Aghaei *et al.*, 2016; Paterakis and Gibescu, 2016; Shokrzadeh and Bibeau, 2016). Current island electricity system research suggests that electrification of the transportation sector is important within these systems (Baptista *et al.*, 2009; Parness, 2011; Camus and Farias, 2012; Botelho, 2015). These authors highlight that the accelerated adoption of (*electric vehicles*) EV can facilitate the quick removal of fossil fuel generation in smaller isolated systems by matching the renewable-based supply with the EV demand. A policy favouring EV thus provides the opportunity to operate the vehicles principally on renewables that would have otherwise been curtailed when the demand load is low i.e., at night

time. While a minimal technical amount of fossil generation will be necessary to balance the frequency of the electricity system, the electricity produced by the renewables can be used to charge the EVs. The potential environmental benefits are significant including a diminished need for fossil fuel to run cars and power generators, thereby satisfying the low-carbon agenda whilst increasing the prospects of the security of the electricity supply to meet the long-term demand with more renewables.

In addition, energy efficiency mechanisms would typically reduce the electricity demand and ensure energy security in the future. Haney *et al.* (2010) postulate that low-carbon energy policies support a means of reduced electricity consumption through energy efficiency policies and demand-response/demand-side management mechanisms. Similarly, the International Energy Agency IEA (2008) identified a trend towards increasing energy efficiency measures as an essential element in overcoming the challenges facing the energy sector. While true for large interconnected systems, this has not been proven for small-island systems, where the focus is to maximise electrification, via the use of EVs, while minimising the curtailment of renewables capacity and increasing their economy-driven products (European Commission, 2013). On the other hand, economy-driven products such as tourism are asserted to be important for island systems and the new economic activities derived from these should increase the long-term demand load (IRENA, 2014b). Hence, there is a need for evolving low-carbon island electricity systems to explore the impacts on demand of changing economy-driven products such as tourism, EVs and also energy efficiency mechanisms. Implications for electricity demand are far reaching, and clarity is required to prioritise important policy decisions. The SD sub-model in this chapter defines the long-term endogenous demand of the island system. Assorted scenarios are critically analysed which emphasise, in turn, each of these policy drivers, and gauges which are the most important and interesting to policymakers for meeting the long-term electricity supply security and environmental concerns. Details of this sub-model are presented in the next section.

5.2 Endogenous Electricity Demand Model

The endogenous demand dynamics of the system have been captured using this SD sub-model. It has then been used for various scenarios, including energy efficiency, electrification and tourism, to identify the most important and influential of these policies as the island pursues environmental objectives and ameliorates electricity supply security concerns. The long-term trends of the simulated electricity demand under these current low-carbon objectives are assessed. This work is distinct from the contributions of Chapter 4, in that it details the system structure for the endogenous demand within the island system. This endogenous demand reflects causal relationships existing within the interactions of the existing system based on low-carbon policies unlike an exogenously defined extrapolation of demand as implemented in the sub-models of Chapter 4.

The electricity demand endogeneity is achieved by capturing the individual consumptions of the distinct consumer-types. Each sector of electricity consumption is modelled independently in its entirety and then all the sectors are aggregated to obtain the total system demand. For each of the consumer-type sectors, the local economic activity influences are modelled together with the dynamics of energy efficiency mechanisms and EV adoption. This sub-model adapts the log-linear model implementation Sterman (2000) pg. 526 to define the effect of local economic activity (GDP) on the electricity demand. And as noted in Chapter 3, the long-term monthly average of the endogenous demand is what is defined for this sub-model. In addition, the sub-model utilises the Bass diffusion model (Bass, 1969) for EV adoption policy implementations. Other key formulations are highlighted in Section 5.2.2. The next section provides an overview of the key demand-influenced feedback structures within the island system.

5.2.1 Mental Model

This sub-model is focused on the endogenous demand dynamics in the context of an isolated island with a degree of low-carbon policy autonomy. It is based on the mental model feedback loop

diagram shown in Figure 5.1. The existing causal relationships of the whole system are shown in the diagram as three main balancing loops. The main components highlighted by the causal loops are the detailed consumer-type sectors for electricity consumption and the electricity supply and energy storage aspects. The effects of GDP, tourism and population growth on the different consumer types are captured together with the energy efficiency and EV adoption policies. The key endogenous variable for this sub-model is the monthly average *net electricity demand*. Other endogenous variables are the number of *EV adopters* and the *supply capacity vs net demand mismatch*. Key exogenous variables are the GDP and the capacity investment portfolios⁵. The capacity investment portfolios are the aggregated renewables (aggregated similar to Section 4.3) and electricity storage portfolios and the fossil capacity portfolio which reflect the percentage of capacity required by these specific supply technology to satisfy the demand. Variables excluded from the model include the short-term grid balancing uncertainties, the capacity investment costs and electricity prices. The exogenous variables used were verified with EDA and with global data sources (Isle-pact, 2012; European Commission, 2013; Ilic, Xie and Liu, 2013; EDA, 2016).

The following model boundary chart, Table 5.1, summarises the scope of this sub-model by listing the key variables.

⁵ Capacity investment portfolios are based on the renewables, energy storage and fossil fuel generation. For example: the *renewable policy portfolio* is the desired amount of installed renewable generation sources as a percentage of the total installed supply capacity of the electricity system. This value has a direct impact on the installed renewables capacity and the electricity system is expected to converge to this fraction of total installed capacity during the model simulation. In this study the *renewable policy portfolio* is set at 45% of total supply capacity and is constant throughout the simulation. For this chapter the value of 45% is in line with the expected “business as usual” state of the system as given in the literature (EDA 2008).

Endogenous	Exogenous	Excluded
Net electricity demand	Overnight tourist stays	Capacity margin
Electric vehicle adopters	GDP changes	Fossil fuel prices
Electricity demand vs supply capacity mismatch	Low-carbon policy targets	Cash flow constraints
Day/night hourly demand imbalance	Storage, renewables and fossil fuel capacity investment portfolios	Electricity tariffs
	Day/night MIN MAX demand profile	Net CO ₂ emissions
	Average household size	External tourism adoption
	Capacity investment timeline	Differentiated renewables technologies
	Population changes	

Table 5.1 Model boundary chart for the endogenous demand sub-model

Shown in Figure 5.1, the balancing effect, *electric vehicles electrification loop* (green loop) is central to the system. This loop is influenced exogenously by the electricity supply capacity (for this demand model supply is an external input). The *electricity supply capacity* variable is driven by the *electricity storage, renewables and fossil generation capacities* which are in turn driven by their respective portfolios. The portfolio values have a direct impact on the generation capacity since the electricity system is expected to converge on this fraction of total installed capacity throughout the model simulation. For the purpose of this study, the storage and renewables capacity portfolios are initially fixed as a fraction of total capacity as evidenced from the specifics of the case study system. Hence they follow a fixed path across the years of the simulation. The electricity storage is linked to the renewables capacity portfolio which in turn influences the fossil fuel generation capacity portfolio.

The point of interaction of the electricity supply capacity with *electric vehicles electrification loop* is the *supply capacity vs. net demand mismatch*. This mismatch is desirable in the model as a value between 0 and 1. This variable is vital for checking that the system has the long-term supply to meet demand. For example, if the demand/supply capacity ratio (*supply capacity vs. net demand*

mismatch) is greater than 1 the supply is not sufficient to meet the demand, which is a worst case scenario for the system. The mismatch is reinforced by the electricity supply capacity, and, in turn, it reinforces the *electric vehicles adoption* and the *net electricity demand* within the system. The *net electricity demand*, however, has a balancing effect back onto the *supply capacity vs. net demand mismatch* variable.

Also interacting with the *electric vehicles electrification loop* is the *day-night imbalance loop* (black loop) which balances the *electric vehicles adoption* variable. If the day/night hourly demand imbalance is high then the incentive to adopt EVs is much higher than otherwise. This increase in EVs, however, balances the *day/night hourly demand imbalance*, closing this balancing loop.

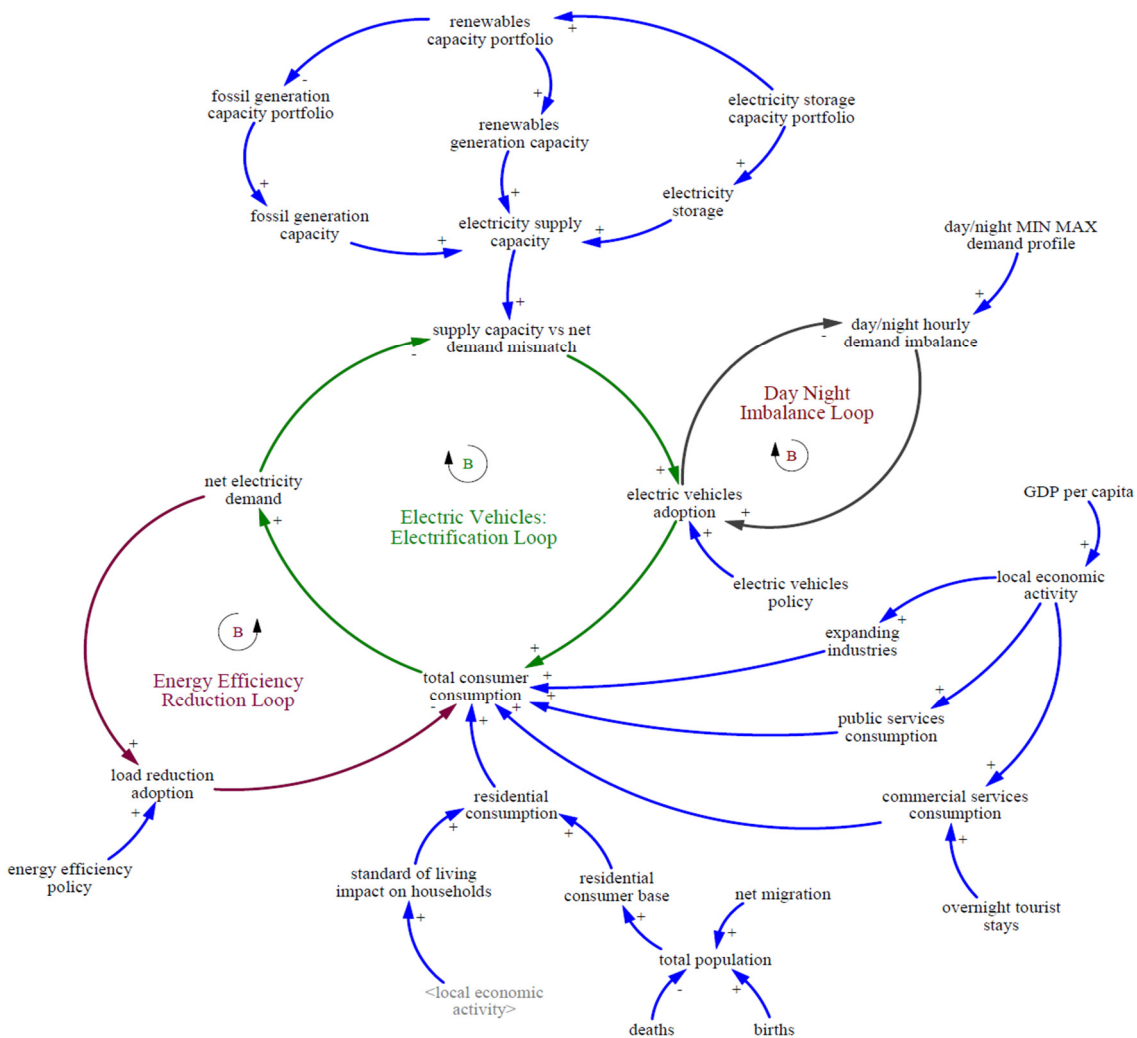


Figure 5.1 Mental model hypothesis of the key demand-driven components in the electricity system

Also shown is the *energy efficiency reduction loop* (purple loop) which captures the balancing effect of the energy efficiency measures on the endogenous electricity demand. The *net electricity demand* is influenced by the exogenous *energy efficiency policy* for the different consumption sectors of the system. This exogenous energy efficiency policy is implemented independently within the different sectors of the system. The net electricity demand within the system is a result of the endogenous *electric vehicles adoption* together with the energy efficiency influences for the residential, commercial, industrial, and public services consumer-types/sectors. These consumer-types are also tied to the exogenous (GDP influenced) local economic activity. In the case of the residential and commercial consumer types, there are additional exogenous influences from the *population* and *overnight tourist stays*, respectively.

The three loops highlighted, entail the key components for the endogenous demand of the evolving low-carbon system. The effect of GDP on the consumption is important since there are no market price formations associated with supply and demand dynamics within this system. Furthermore, this mental model is now used as a basis for the formulation of the important variables to develop the formal SD sub-model of this chapter. The formal sub-model general mathematical formulations are discussed in the next section, in addition, more details can be found in Appendix A2.

5.2.2 Model Formulation

The model is derived and formulated from the mental model feedback loop diagram of Figure 5.1 and implemented using the Vensim software package. The main mappings of the key stocks and flows of the endogenous demand are shown in the simplified model diagram, Figure 5.2. At the centre of the simplified model is the *avg total monthly consumer consumption*, which is the demand in MWh obtained by summing the demands from the different consumption sectors and the EV adoption. Each sector of electricity consumption is modelled independently in its entirety (which includes the energy efficiency policy implementations).

The influence of GDP on the consumption is modelled using the log-linear model implementation from Sterman (2000) (See Pg.527 for its derivation). This is done by considering a variable Y , which is the consumer-type sector consumption with its normal or reference value to be Y^* . When multiplied by the product of a nonlinear function of the variable X_i , for local economic effects, the relationship is formulated using the form:

Effect of X_i on $Y = \left(\frac{X_i}{X_i^*}\right)^{a_i}$, where $\left(\frac{X_i}{X_i^*}\right)$ is the nonlinear function of the normalised effect on Y and a_i is the elasticity of Y with respect to the normalized inputs (If $a_i = 0.5$, a 1% increase in X_i boosts Y by approximately 0.5%).

Using the simpler additive formulation for this expression, we get $Y = a_0 + a_1 \frac{X_1}{X_1^*}$ where a_0 is the base value for initial consumption of the various sectors (shown in Table 5.2) in the initial year, 2005, and a_1 is the elasticity (eg. Public Service Factor) used for the effect on Y and $\frac{X_1}{X_1^*}$ is $\frac{GDP}{reference\ GDP}$ (effect of local economic activity on consumption).

This formulation is implemented as an SD auxiliary variable for the respective consumer-type sectors shown in Figure 5.2. The values of a_1 for the respective consumer-type sectors were determined from Vensim payoff optimization for the simulated and historical data over the calibration time period of 2005 - 2016.

To model the influence of energy efficiency measures (the *energy efficiency reduction loop*), the approach given in Sterman (2000) is used, as previously defined in Section 4.3.1. This goal-seeking formulation is implemented individually for each consumer-type sector and is used to define the targeted energy usage reduction for the different sectors. The reference target for energy usage is a 6% consumption reduction from 2010 demand values by 2020 (Isle-pact, 2012; Nunes, 2015). Different desired target timelines such as by 2025 were implemented for the scenario analysis.

The size of the residential consumer-type, sector is derived from the population size resulting from the births, deaths, and migration within the system. This population size is formulated, as

$population = \int \frac{births+net\ immigration-deaths}{\Delta t} + Population_0$, where Δt is the monthly time step and $Population_0$ is the initial population in 2005. The resulting *avg no. of households* from this population is multiplied by the *avg consumption per household* to determine the *avg residential monthly consumption*. *Avg consumption per household* is defined from the *standard-of-living index* (World Bank, 2016) as a proxy for the electricity demand-growth per household, together with the given GDP implementation and the energy usage reduction target.

The public services consumer-type sector, *avg public services monthly consumption* is determined by the implementation of the GDP influences and the energy efficiency reduction as given above.

The commercial services consumer-type sector also captures the growth rate in monthly overnight tourist stays and the consumption per room per overnight stay. The growth rates observed from the historical data, SREA (2016), are used to determine the growth of *hotel based tourism* electricity use. For this flow, we have:

$\Delta hotel\ based\ tourism\ consumption / \Delta t = C_{room} * S_{overnight}$, where the variable C_{room} is the consumption per room per overnight stay, $S_{overnight}$ is the overnight room stays as given from the room stays fractional growth rate and Δt is considered as the monthly time step. In addition, as done previously, the GDP influences and the energy usage reduction for new commercial services consumption are implemented. Resultantly, the *avg commercial services monthly consumption* is determined as the summation of the inflows shown in Figure 5.2, which are the *hotel based tourism consumption*, the GDP influences and the energy usage reduction.

The industrial consumer-type sector captures the number of new industries as influenced by the exogenous GDP together with the GDP influences on the consumption of the existing industries. This relationship for the number of new industries, *new industrial businesses* is defined similarly to the GDP influences formulation given in paragraph two above. This GDP influences and the energy usage reduction for industrial business consumption is formulated to give the *avg consumption per industrial business*. Therefore, we have the variable for the *avg industrial business*

monthly consumption defined as follows: $avg\ industrial\ business\ monthly\ consumption = number\ of\ new\ industrial\ businesses * avg\ consumption\ per\ industrial\ business$

As seen in Figure 5.1 the *electric vehicle electrification loop* captures the contribution to total demand from EVs in collaboration with the *day-night imbalance loop*. The contribution to total demand from EVs is implemented with inputs from the EV policy, its enactment year and duration, and the travel consumption (assumed to be directly related to the EV grid charging needs) shown in Figure 5.2, and explained subsequently. Additionally, it is continuously verified that this desired number satisfies the long-term supply versus demand mismatch, and the short term day/night hourly demand imbalance.

The demand imbalance is determined from the pre-processing of the daily minimum and maximum demand (referred to as the *black box MIN MAX demand profiles* within the sub-model, Figure 5.2) of the hourly time-step data from the years 2012 - 2015 (Botelho, 2015). Using this hourly data from each month, the minimum and maximum hourly demand values are determined and the differences are calculated. The respective differences of the minimum and maximum demand for each month are then normalised using the maximum hourly demand occurring within that month. This is implemented as a pre-processing step prior to the model simulation and a normalised minimum/maximum profile is built from the 1095 data pairs (i.e. daily pairs spanning the three-year period, assuming 365 days per year). The data points are randomly chosen during simulations for determining the threshold amount of EVs necessary to handle the day/night hourly demand imbalance. Implementation details of the “black box” is given in Appendix C. The Bass (1969) diffusion model was used for the market-based EV adoption for the scenario analysis. The policy based EV adoption is implemented using the goal-seeking target approach given in Sterman (2000) pg. 276.

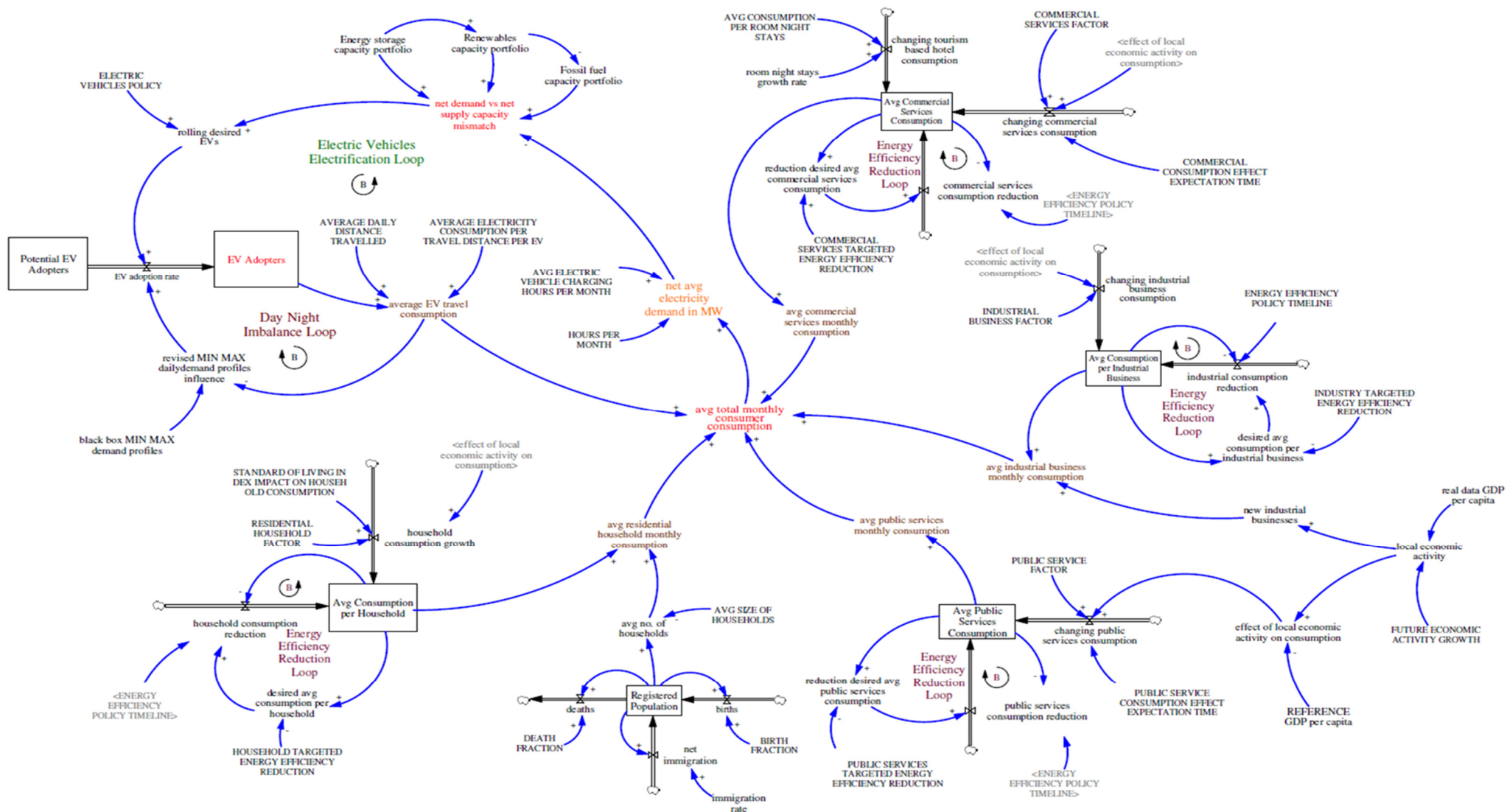


Figure 5.2 Simplified stock and flow diagram for the endogenous demand model formulation

The *avg EV monthly travel consumption* = $T_D * EVadopters * C_{EV}$ where T_D is the average daily distance travelled on the island (in Km), C_{EV} is the average consumption per distance travelled (Km) by EVs and $EVadopters$ is the number of EV adopters. For simplicity the EVs are assumed to be light-duty and charge once per day, during the off-peak night time periods for approximately 8-10 hours (which, given the geographical constraints of the island, is a reasonable assumption). Hence, the total demand in MW can be determined for the EVs from grid charging and added to the consumption in MW from the other consumer types within the system. We then have:

net demand vs supply capacity mismatch = C_D/C_S , where C_D is the demand capacity in MW from all consumer types and EVs and C_S is the installed supply capacity from renewables, fossil fuel and energy storage. If $\frac{C_D}{C_S} \leq 1$ there is no blackout and the supply can satisfy the demand, however if $C_D > C_S$ then the supply constraint is not met and this system will have blackouts.

The focus of this sub-model is to capture the electricity demand dynamics of the real system, therefore no emphasis is placed on the supply capacities, and supply capacity portfolios are chosen in line with the status quo for the different technologies. The portfolio values have a direct impact on the generation capacity since, in the absence of other drivers; the electricity system converges on this fraction of total installed capacity during the model simulation. For this study, the storage (0%) and renewables (45%) capacity portfolios are fixed as a fraction of total capacity, as determined by the specific case study (EDA, 2008). Hence they are held constant throughout the simulation. The capacity investments are however made endogenous to the system in Chapter 6. It is also observed that the model does not use the projected demand growth rate for the island but the GDP forecast is used as a proxy for determining the yearly increases in the absolute consumption of each consumer type. Finally, it is assumed that there are no cost considerations for new capacity builds or CO₂ emissions in this model, and that tourism growth is a totally exogenous entity and any influence by it on the GDP of the island system is neglected.

One constraint on the SD model is that it gives the average consumption and not the true peak demands and troughs for the various consumer types within the system. Consequently, the model does not account for the short-term hourly balancing of the grid system, although it does capture the demand-supply gaps for filling the night time low electricity demand periods. Full mathematical details of the key formulations used in this sub-model can be found in Appendix A2, on pg.224.

Sub-Model Validation

This sub-model was simulated, similarly to the sub-models of Chapter 4, on a monthly time-step over a 45-year time horizon from 2005 until 2050, with the goal of studying the average long-term endogenous electricity demand. Validation is a key part of building confidence in the sub-model. The methods given from Section 3.3 are used for testing and validation of this sub-model and some parts are highlighted here. One of the most intuitive tests of the model formulations is the use of the built-in Vensim error checking mechanisms. The Vensim package gives an error or flags up warnings (does not run accurately) if the equations do not satisfy a level of units consistency. Some extreme condition testing has also been completed. This includes sensitivity to the inclusion/exclusion of different policies and using low/high values of the reference GDP and a_1 , some of the parameters given in Section 5.2.2.

Finally, it has been checked that the new SD model emulates the real system accurately during the calibration period (2005 - 2016), by taking into consideration historical data, expert views from EDA and theoretical formulations. Within the calibration period (historical data), the patterns of behaviours being exhibited by important system variables should be mimicked by the model. For example, shown in Figure 5.3 is the plotted historical data of the monthly consumer demand from 2005 to mid-2016 (red curve), compared to the simulated average monthly demand (blue curve) over the same period.

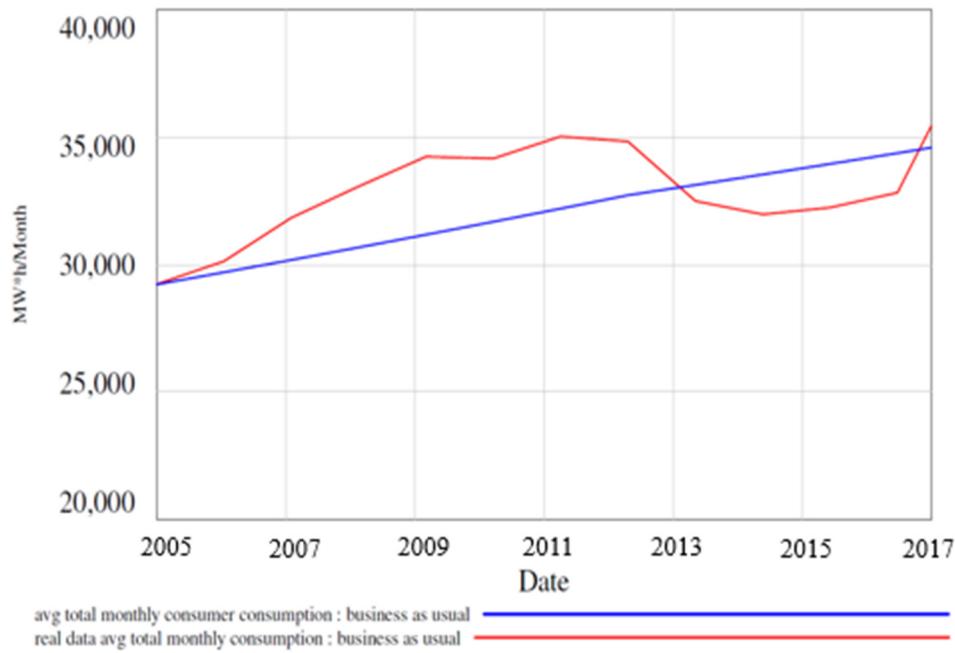


Figure 5.3 Fitness of base model output data to the real data

Visually, the simulated model output reflects the trend of historical data considering that the historical data are discrete monthly values whilst the model output is the average monthly value. In addition, a statistical measure of fit R^2 (which measures the covariance) was used together with the Theil inequality statistics to characterise the source of error for analytical comparisons (Sterman, 2000; Pierson and Sterman, 2013). For the data series shown in Figure 5.3, $R^2 = 25\%$ which indicates that the average monthly demand does not point-wise replicate the historical data as can be seen from Figure 5.3. However, this sub-model is designed to analyse the long-term behaviour that results from short-term monthly consumption movements, so point-by-point historical data scatter can be considered as noise. By using the Theil inequality statistics (Sterman, 2000), a method which decomposes the *mean square error* (MSE) into U^M (bias-unequal means of model and actual data), U^S (unequal variations) and U^C (unequal covariations), the sources of error between the simulated and historical data series can be determined. For Figure 5.3 data series, it is found that U^M is 0.12, U^S is 0 and U^C is 0.88 which suggests the error is concentrated in the unequal covariations. This implies that the model has the same mean and trends as the data, but differs from the data

point-wise. The model is then used as detailed in the next section to critically analyse the long-term demand trends of the simulated endogenous demand of the island system.

5.3 Policy Scenarios for Demand Dynamics

Three key system factors that influence energy-related policies are considered to generate plausible scenarios to critically evaluate the evolution of the endogenous electricity demand, namely: (i) energy efficiency (viewed as essential to ensure energy security in terms of fossil fuel import independence); (ii) tourism growth (since island systems are concerned about the impact on their electricity systems of an unforeseen influx of visitors); and (iii) electrification of the transport sector (light-duty EV) (since this is a focus of island systems for increasing the low-demand night time periods). These were chosen based on the literature, (Isle-pact, 2012; European Commission, 2013; Botelho, 2015; Nunes, 2015) because they are deemed to be potentially important drivers for the future of the evolving electricity system. In addition to these three scenarios, a baseline (business as usual) case has been included. This scenario considers the system in 2005 to mid-2016, together with the past and present policies and the current economic and social aspects. However, the existing renewables policy, which was enacted in mid-2008 to achieve approximately 75% renewable capacity by 2020, has been revised to 45%, based on the current rate of its installation (EDA, 2016). This value has been used for all scenarios in this chapter.

Scenario 1: Business as usual

The island population is determined by the current birth and death rates along with the GDP growth rate, both being extrapolated from the 2005 - 2016 data. The current policy for an island-wide, energy efficiency target of a 6% decrease in consumption over the next 10-15 years starting from 2012 is implemented. No EV policy or market influences are assumed aside from a normal increase in EV (based on the purchasing rate of new EVs in 2015) which now leads to approximately 50 vehicles in 2015. The growth rate in the number of overnight tourists stays is determined from the 2005-2016 data to be 0.14% (SREA, 2016), and extrapolated into the future.

Scenario 2: Tourism impact

This scenario examines the possible impact of the hotel based tourism growth on electricity demand. It uses the *Scenario 1* characteristics apart from varying overnight tourist stays growth rates. For tourism growth rates, obtained from the historical data (SREA, 2016), two different cases are studied, namely, a reduction in the growth rate from 0.14% per month to 0.07% per month from 2016 until 2050 and an increase in the growth rate (of 0.14% per month) to 0.28% per month from 2016 until 2050. Furthermore, these two cases are of interest to EDA and the Regional Directorate for Energy of the Açores (Botelho, 2015; Nunes, 2015). The scenario seeks to establish upper and lower bounds of the tourism influence upon the system. Importantly for São Miguel, it is assumed that no new hotel construction is warranted due to the low existing occupancy rate on the island of 32% (Isle-pact, 2012; SREA, 2016), with the growth rate being doubled as a maximum for this scenario otherwise keeping the modelling broadly within the assumptions.

Scenario 3: Energy efficiency measures

This scenario encapsulates *Scenario 1*, apart from variations in the energy efficiency policy. Two case studies are considered: namely, the doubling (to 12%) and tripling (to 18%) of the original policy targets across the policy timeline of 10-15 years. This is a long-term energy efficiency target, which is discontinued after 15 years. It is also assumed that the energy efficiency measures are fully adopted by the consumers (it is assumed that there are no adoption dynamics).

Scenario 4: EV expansion

This scenario examines the possible influence of EV expansion. The baseline case is used as the purchasing rate of EV on the island in late 2015. It is also assumed that light-duty vehicles are the target for EV expansion. The baseline case is compared to three other policy cases: a market-based adoption policy for diffusion of technologies (Bass, 1969), a target of approximately 2000 EVs by 2020 (as suggested by EDA) (Botelho, 2015), and a combination of the 2020 EV and the market-based adoption policies.

Table 5.2 presents the key SD demand model variables allied with the four scenarios described above and their respective data sources.

Variable Name/ Unit	Exogenous/ Endogenous	Base value	Sensitivity ranges	Reference data
GDP per Capita/ Thousands of Euros/Month	Exogenous	Extrapolated from data	None	http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf/
Avg consumption per tourist-night stays/ MW*h/night stays	Exogenous	0.0027	0.0027- 0.0039	http://www.onecaribbean.org/content/files/CHENACT%20-CREF.pdf
tourist stays growth rate/%/Month	Exogenous	0.14	0.07 – 0.28	SREA, 2016
Registered Population/ People	Exogenous	131609 (in the year 2005)	None	http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf/
Energy Efficiency enactment year/ Months	Exogenous	84 (in the year 2011)	None	http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf/
Energy efficiency policy timeline/ Months	Exogenous	180	None	http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf/
Energy efficiency reduction/%	Exogenous	6	6-18	http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf/
Renewables policy portfolio/%	Exogenous	0.45	0.45-0.55	Author's own elaboration
Electric vehicles policy timeline/ Months	Exogenous	52 (from 2016- 2020)	None	(Bothelo, 2015 and Nunes, 2015)
Total Population of Vehicles/ Vehicles	Exogenous	45,000 (in year 2005)	None	Parness, 2007
initial commercial services consumption/ MW*h/Month	Exogenous	9853	None	http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-EI%C3%A9trica.aspx
initial industrial consumption/ MW*h/industries	Exogenous	156	None	http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-EI%C3%A9trica.aspx
initial public services consumption /MW*h/Month	Exogenous	3950	None	http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-EI%C3%A9trica.aspx

Table 5.2 Key initial values and parameter values of the SD demand model

5.4 Results discussions

Endogenous demand dynamics of the sub-model based on the scenarios described in Section 5.3 are detailed within this section. Priority policy areas are considered along with whether long-term system responses may be counter-intuitive as the island pursues exogenous and politically driven low-carbon policies.

5.4.1 Scenario-Specific Demand Dynamics

Tourism Impact

Figure 5.4 displays the influence of changing the growth rate of the number of overnight stays and the corresponding average monthly demand. The bottom half of Figure 5.4 displays the effects on long-term hotel demand, while the upper half shows the resultant effects on the long-term system-wide demand. In both cases, the “business as usual” scenario (black curve in the bottom half of the figure and the red curve in the top half of the figure) lies between the curves corresponding to reduced and the increased overnight stay growth rates. However, the impact is higher within the hotel consumption portion from 2016 and is only evident by a very small change from 2040 onwards within the total system demand. This phenomenon occurs because the hotel sector commands a very small share of the consumption within the island system. Hence with a doubling (or even tripling) of the hotel consumption, there will not be visible effects in the shorter term.

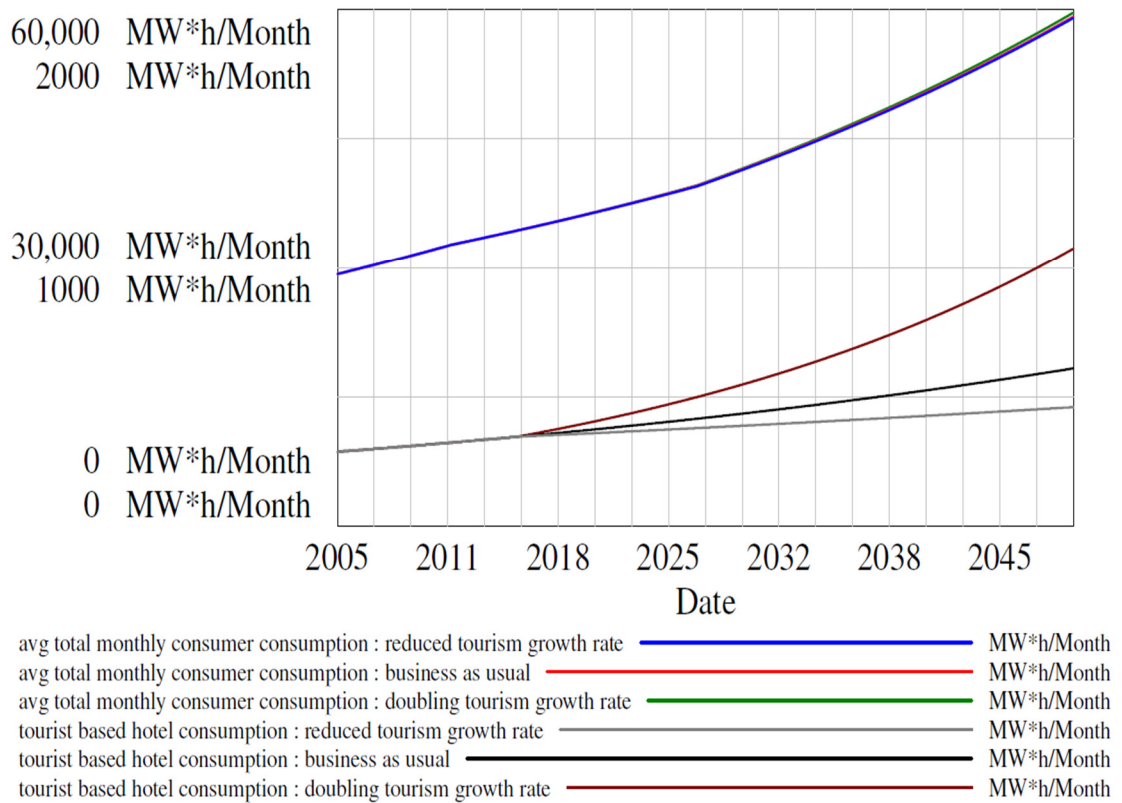


Figure 5.4 Impact of varying tourism on the total monthly demand of the electricity system

A pragmatic conclusion from these results is that tourism on São Miguel has a low long-term impact on electricity demand, and policies that either increase or decrease tourism do not significantly affect system-wide demand. However, it is evident that consumer demand within the hotel sector will be increased by a significant amount in the case of increasing the overnight stays rate and decreased in the case of decreasing the overnight stays rate, compared to the “business as usual” scenario. It is important to stress that the tourism share of the total system consumption is initially very low, which is one reason for the observations. An island system that has a relatively large share of demand based on tourism will show a greater influence of tourism on the long-term demand. This can be attributed to the larger amount of occupancies and the need to have increases in hotel builds in the long-term. In this work, centring on São Miguel, the occupancy threshold for new hotel build is not reached and hence new builds is not handled in any of the scenarios considered.

Energy Efficiency Measures

Figure 5.5 shows the varying impacts of energy efficiency measures on the long-term demand for the whole system. The energy efficiency measures are applied to the aggregated system as a whole and not restricted to specific consumer types. The current energy efficiency policy of 6% demand-reduction from 2012 for 15 years (proposed by EDA and the Regional Directorate of Energy) is reflected by a slight dip in the trend of the load curve (red curve) for the “business as usual” scenario shown in Figure 5.5.

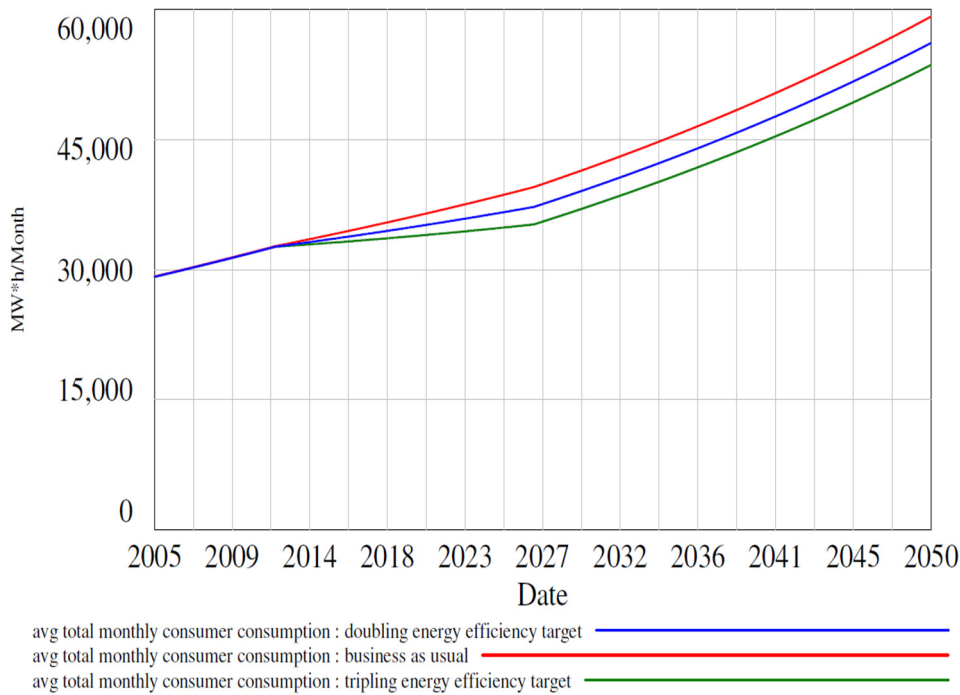


Figure 5.5 Impact of energy efficiency measures on the total monthly demand

The effects on the long-term demand load of doubling and tripling (blue and green curves respectively) the required demand reductions over the same timelines show greater deviations from the initial trend of the load curve, with tripling the reductions having the largest effect.

The results reveal that energy efficiency measures can be applied as a blunt policy tool with high impact. Reductions in consumption in the long-term are guaranteed if efficiency measures are

applied. With greater reductions achieved for the more aggressive shorter term (10 - 15 years) targets. This means energy efficiency policies have a significant impact on the demand dynamics of the electricity system and can be applied as an additional safeguard for long-term energy security.

EV Expansion

The introduction of EVs within island systems such as the Açores has been very slow and without any policy support (Nunes, 2015). This is contrary to mainland Portugal where there are various incentives initiated to encourage their adoption. In late 2015, São Miguel has a fleet of approximately 50 EVs. Given the current low uptake on the island and in the absence of other major changes, the “business as usual” scenario has been modelled revealing that there would be approximately 110 EVs on São Miguel by 2050, based on the 2015 purchasing rate in this scenario.

EV expansion for the electrification of the transportation sector has been posited to be integral to increasing the renewables capacity of the island system (Botelho, 2015). Since the base case has a small number of EVs there is considerable potential for policies to drive their expansion. These include setting explicit target numbers or incentivising the market adoption of EV. The comparisons shown in Figures 5.6 and 5.7 provides insight into the number of EVs resulting from policies other than the “business as usual” case (red curve). Figure 5.6 also shows (right-hand scale) the equivalent amounts of long-term monthly demand that will be added to the electricity network from these different cases of EV expansion. The number of EVs and the associated demand to 2050 shows greatly differing dynamics depending on the chosen policy. The blue line indicates the number of EVs to 2050, following market-based expansion based on adoption diffusion. The hybrid policy (grey curve) of planning for a fixed amount of vehicles by 2020 and then supporting market adoption, yields the greatest impact on EV penetration. It is important to note here that the overall growth of all vehicles in the island leads to approximately 92,000 by 2050. Hence, in the hybrid policy scenario, EVs achieve between 45 to 55% of the total vehicle share within this island system.

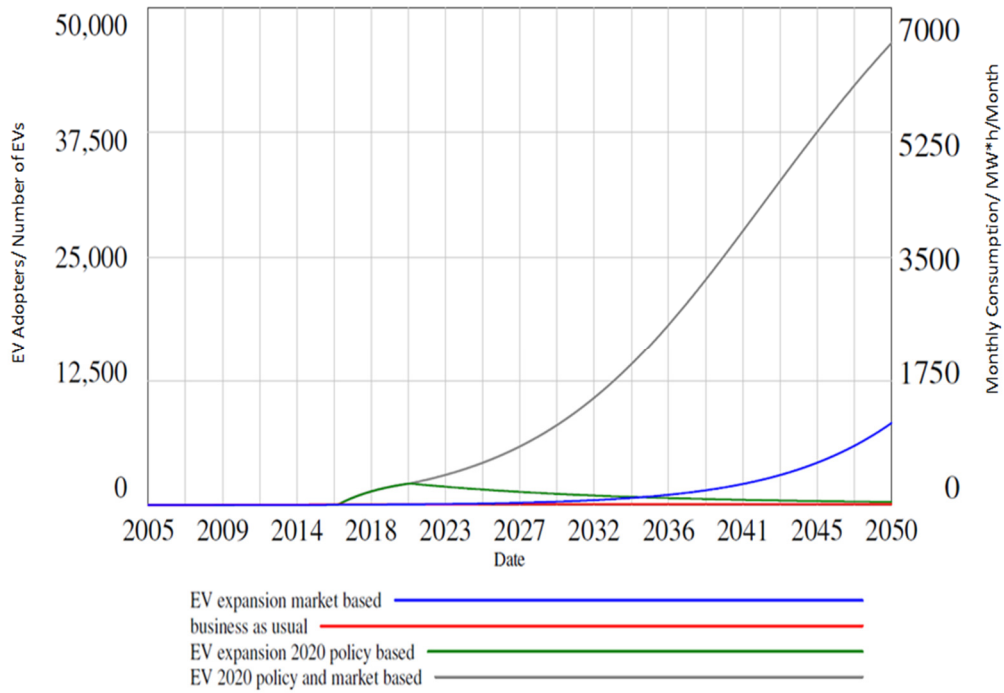


Figure 5.6 Model output for the number of EV adopters and monthly EV consumption under varying cases EV expansion policies

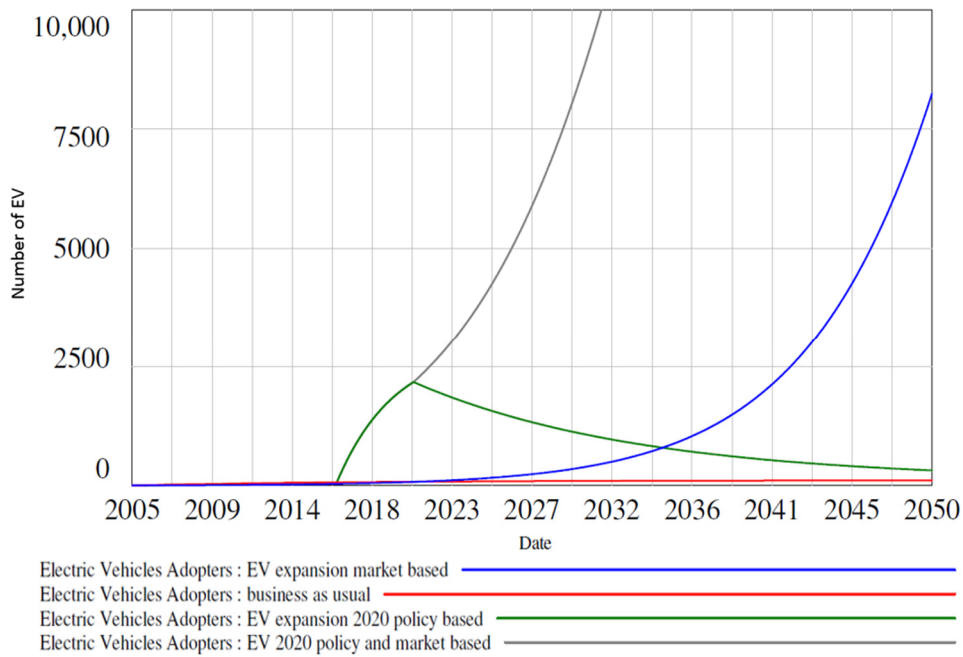


Figure 5.7 Magnified output for the number of EV adopters under varying cases of EV expansion policies (from Fig. 5.6)

Interestingly, the results reveal that a 2020 policy which has no on-going support to encourage the sustained use of EV (green curve) will lead to a gradual decline in EV numbers and EV-based

electricity demand in the longer term. This is confirmed by the hybrid case in which the 2020 policy target is used along with market adoption and which leads to an exponential increase in the number of EVs (not more than 55% of the overall amount of vehicles in the island) and corresponding electricity demand. We suggest here that to achieve this and even higher levels of electrification, the chosen policy can be guided by the key stakeholders, by, for example, replacing company and government vehicles with EV and actively promoting their benefits and encouraging the rest of the island to adopt, a concept embraced by the Regional Directorate of Energy (Nunes, 2015).

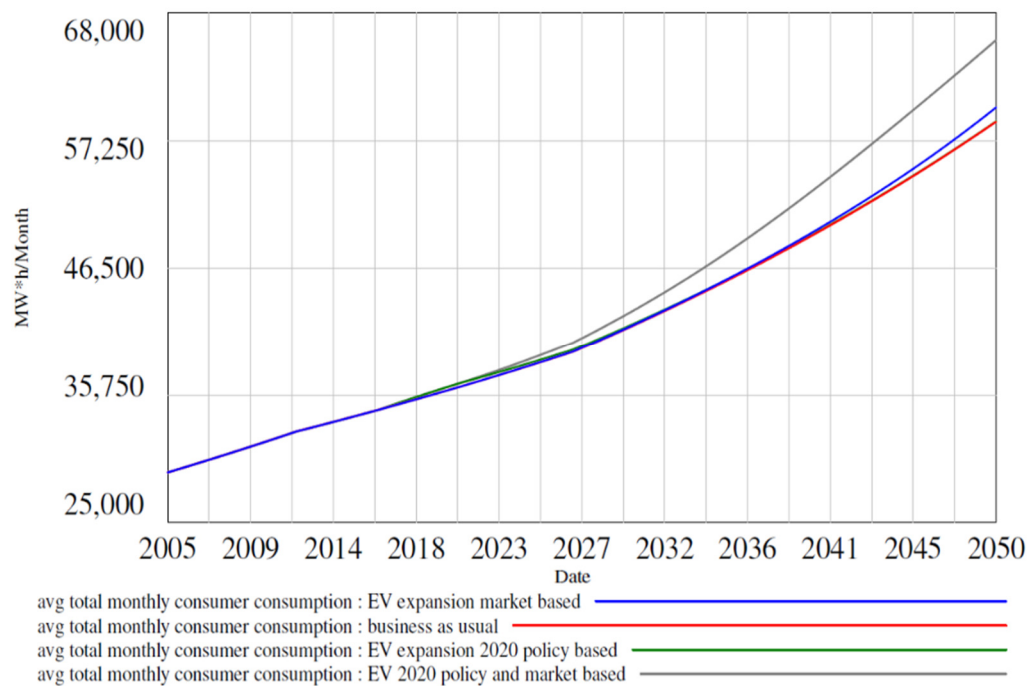


Figure 5.8 Impact of different EV expansion policies on the total monthly demand of the electricity system

Figure 5.8 shows the impact of EV on the whole-system, long-term demand. It reveals that the hybrid policy has the highest impact on long-term demand dynamics and that EV expansion can have either a marginally small or a high impact on the long-term demand dynamics and presents uncertainty challenges for policymakers. As shown in (Bakker and Jacob Trip, 2013; Green, Skerlos and Winebrake, 2014) and discussed above, government intervention can be useful to facilitate/lead EV adoption; however, policies must be carefully applied to avoid compromising

security in meeting this demand. Conversely, the environmental benefits and advent of more renewables capacity, facilitated by high amounts of electrification of the transportation sector encourages EV expansions in the absence of policy targets or incentives (IEA, 2013).

This analysis reveals that EV expansion is potentially more interesting in terms of the long-term impact compared to both tourism growth and energy efficiency measures, though energy efficiency remains the most powerful for guiding the long-term demand dynamics. In addition, supply-side influenced demand such as energy efficiency will have a stricter (narrower) range of impacts on the long-term demand compared to demand-side influenced factors such as EVs or even tourism. The range of possible outlooks for the EVs on the long-term demand can vary from being negligible to being very large.

5.4.2 Long-Term Demand and Supply Confidence Bounds

Figure 5.9 shows the confidence bounds for the long-term demand for the system obtained from a series of 200 MCMC simulations randomly sampling the four scenarios detailed in Section 5.3. Key variables, their sensitivity ranges, and related information sources are used as given in Table 5.2. The results show that the demand can be tightly bounded with a 75% probability given the combinations of different policies for electrification, energy efficiency and tourism, implying that long-term demand dynamics driven by policy can provide a relatively stable outlook for the system. However, careful considerations must be given to the policy choices since the 95% confidence bounds (blue regions) are upwardly skewed over a larger uncertainty range when compared to the mean (red line).

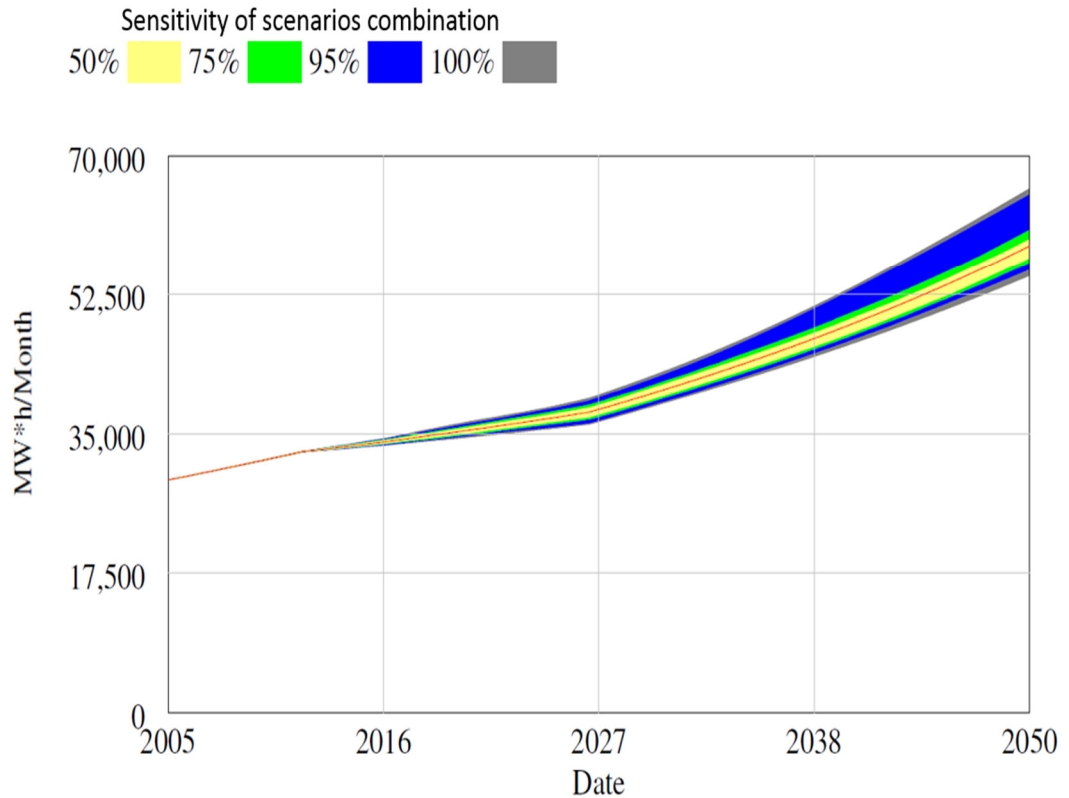


Figure 5.9 Total monthly demand sensitivity of the electricity system for the different policies from 2005 to 2050

Figure 5.10 displays the MCMC simulation confidence bounds for the installed renewable capacity in MW. The greater disparity that is evident in the 75% - 100% confidence bounds is mainly driven by the renewable energy policies. The results reveal that the installed renewables pathway based on a 45% portfolio share to 2020 is accurate, as observed with the narrow confidence bounds. However as the time-period extends, the scenario combinations driving the renewables policy introduces uncertainty. The lower confidence bound is guided by the energy efficiency measures whilst the upper part is bounded by the policies relating to the electrification of the transport sector. This suggests that greater electrification will, in the long-term, lead to more renewable capacity within isolated island systems. This inference will be studied in more detail in Chapter 6.

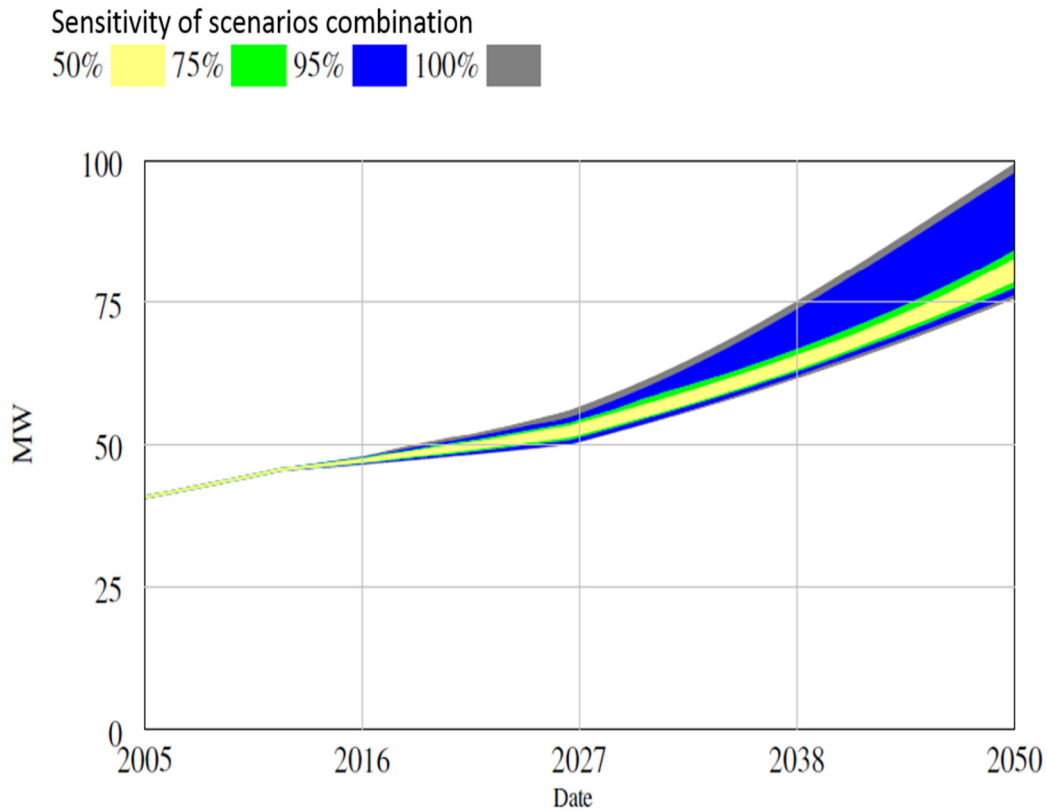


Figure 5.10 Sensitivity of the total installed renewable capacity of the electricity system for the different policies from 2005 to 2050

5.5 Conclusions

This chapter has presented an SD sub-model that satisfies research sub-question 3 of this thesis. The isolated electricity system of São Miguel is used as a case study for modelling the long-term demand dynamics as an endogenous consequence of existing and future low-carbon policies. In addition, this sub-model has analysed a series of policy scenarios which emphasise differing critical factors for the long-term endogenous demand dynamics and identify the most important and interesting to policymakers which fulfil their environmental and energy security objectives.

By applying a series of pragmatic assumptions, the low-carbon policies for electrification of the transportation sector, energy efficiency measures and increased tourism provide an insightful understanding of the endogenous demand dynamics of the island electricity system. Based on the model behaviour for these scenarios, it can be concluded that the long-term demand is significantly influenced by implementing successful energy efficiency measures. This is, however, a brute force

solution for reducing the long-term monthly demand and can be a useful policy for safeguarding the energy security of the system. EV expansion is not as influential, although it can still provide medium-to-large stimuli on the long-term demand dynamics. This is demonstrated by the different demand projections for EV expansion by 2050. Longer-term demand is uncertain with both small and large changes feasible depending upon the way EV are adopted and related policies pursued. If specific policy targets are withdrawn once they have been achieved, long-term demand will converge closer to the “business as usual” path. This shift is small compared to a hybrid policy involving the market effects, which is very large for such adoption of EVs. In such cases, the long-term demand dynamics can diverge from the “business as usual” scenario.

Finally, for islands such as São Miguel policies relating to conventional tourism have a very low impact on the long-term monthly consumption trends, indicating that systems with a very small initial tourism economy need a substantial increase in tourism if this is to impact the long-term electricity demand. The implemented tourism policies in this case study made little impression on the long-term demand, implying that isolated island systems with a low economic share of tourist activities are largely unaffected by energy-related policies which focus solely on tourism. Furthermore, for isolated island systems pursuing low-carbon objectives, it is the policy behaviour of the locals rather than externals (tourists) that will make the key impact on the future electricity system. This can, however, be different in smaller and less developed island systems (IRENA, 2014) than the one studied in this paper, but fundamentally what matters to any island system is knowing that its mechanisms are able to reduce the demand as a safeguard and eliminate the need for additional generating capacity. EV electrification policies are useful in reducing the environmental impacts of high CO₂ emissions; however, they have a lower impact on the long-term demand than successful energy efficiency measures. The model provides new clear insights into the most important and influential policies for the endogenous demand dynamics from the key socio-techno-economic aspects typical to the structure of isolated island electricity systems.

This chapter has provided a novel approach to identifying the most influential and efficient policies by understanding the structure of the system useful for the long-term electricity consumption of isolated island systems. The approach has given guidelines and policy directions for prospective energy solutions as these systems transition to low-carbon electricity production. The demand policy implications are highlighted as important in making informed decisions and being aware of which policies are the priorities where the focus for energy security and environmental issues must be directed. This provides a platform for understanding how low-carbon policies impact the long-term endogenous demand. In addition, the use of this endogenous demand formulation will give a better understanding, as required in Chapter 2, of the low-carbon system than with the use of demand forecasts which are unable to capture causal feedback effects within the system. The next chapter will extend the formulation of the endogenous demand presented above to understand the impact of low-carbon policies on the endogenous capacity mix for renewables integration and their environmental consequences. In that chapter, renewables are disaggregated and the long-term capacity mix is derived from an endogenous consequence of the endogenous demand, low-carbon policies and long-term investment decisions.

Chapter 6. Emerging Low-Carbon System Capacity Mix

In the previous two chapters, 4 and 5, the SD method is used to support the analysis of specific aspects of a transitioning low-carbon island system. From the insights gained in these previous chapters, it is clear that a richer understanding of the overarching research question of this thesis can be achieved once these sub-models are synthesised together. Chapter 6 integrates the sub-model structures developed in chapters 4 and 5 to establish a more comprehensive model of the system. This new model fully captures the necessary endogenous characteristics of the evolving low-carbon isolated island electricity system. The chapter provides a detailed analysis for the integration of the fossil fuel, renewables, and endogenous demand sub-models. Furthermore, prospective long-term investment solutions and policy recommendations are also developed from the scenarios and the analysis contained within this chapter.

6.1 Overview

Satisfying an evolving electricity demand is an imperative of electricity providers, policy makers and governments alike. As shown in Barrett (2006) and Warren (2014) there are numerous strategies proposed to tackle this problem. One of the key proposals from these authors involves increased investment into new generation capacities. However, without care, this might lead to an excess of generation capacity within an island electricity system. Many island systems are already endowed with high levels of reserve legacy fossil-based capacity (Weisser, 2004a), further large-scale investments in either fossil fuel or renewables capacity may not be justified given the amount of latent capacity available (EDA, 2016). Concurrently, some of this excess capacity is required to maintain reliability and to provide a reserve of supply, the capacity margin concept is explored in Section 4.2.3, which need to be increased when electricity demand is increasing (Erdinc, Paterakis

and Catalaõ, 2015). Small isolated island systems typically operate with higher levels of electricity capacity and system redundancy as is seen in more interconnected systems. Hence it is not unusual to see within these systems a wider variety of types of electricity generation sources and the preference for several smaller generation units instead of larger generation assets. As seen before in earlier chapters the electricity provider in São Miguel estimates that spare capacity margins are above 30% so the impetus for new generation capacity is more focused on reducing CO₂ emissions and on achieving fossil fuel import independence (EDA, 2016). This is consistent with an environmentally friendly focus by replacing decommissioned fossil generation and increasing new capacity with renewable sources.

Other possible ways to meet increasing electricity demand include inter-island grid interconnectivity (Eurelectric, 2012), which if available, can provide a means of increased flexibility within an island grid system (Marrero and Ramos-Real, 2010). However, this is infeasible in most cases, such as in the Açores as these islands are geographically too distant for economic interconnections. Other considerations include the prospects of demand-side management and large-scale pumped hydro energy storage (Barrett, 2006; Eurelectric, 2012; Warren, 2014). Demand-side management for island systems in this thesis is considered in the context of the charging of Electric Vehicles (EVs) during periods of low electricity demand (i.e. at night time). The prospect for pumped-hydro storage is also limited due to the geographical constraints of most small island systems such as the case study of this thesis, São Miguel. The energy company in São Miguel has undertaken evaluation studies into the siting of a pumped-hydro project and concluded that no suitable conditions exist for the required dams but that smaller reservoir storage is possible (Botelho, 2015). Energy storage, although on a lesser scale, remains a viable option within this island system. All of these factors influence investments into electricity generation capacity and requires that small island systems are planned and treated somewhat differently from larger continental grids. Issues relating to the generalisation of our findings and methods are discussed in Chapter 7.

In addition to these factors, and as seen in chapter 5, energy efficiency mechanisms, adoption of EVs and tourism increases have impacts on the long-term endogenous electricity demand and hence can drive the capacity investments within the system. In chapter 5, an understanding is given, of the endogenous demand which stems from low-carbon policy targets together with the investment structure of an island system transitioning to low-carbon based generation mix. This understanding provides insights into the future capacity investments needed for the system. It also represents the challenges and opportunities such as how to sustain renewables uptake for the electricity grid and the technologies necessary to increase that uptake level. Hence, the synthesis model examined within this chapter, and derived from the previous sub-models of the thesis, defines the holistic view of the environmental and security (fossil fuel import independence) concerns, and the policies for the electrically isolated system. Furthermore, the synthesis model explores how the long-term affordability (using the overnight basis of the base year (2005) levelised cost of electricity (LCOE) (NREL, 2016) values and not the usual discounted cash flow formulation) rather than externally originated electricity tariffs are an endogenous consequence of capacity investments. The respective LCOE values are used within the learning curve implementation as done in Section 4.3. This formulation is then incorporated to understand a stable/improved generation mix of renewables and other technology portfolios that are effective to meet the environmental and the necessary energy security concerns of fossil fuel import independence of the island system. Details of the comprehensive model are presented in the next section.

6.2 Synthesis

The comprehensive model of this chapter is achieved by integrating the sub-model structures of the fossil, renewables and demand sub-models for the system. The key structures from these sub-models are merged into one model together with the economic attractiveness for capacity investments within the system. This integration reflects the subsystem architecture diagram of Figure 3.6. In addition, the renewable capacity (considered within the renewables/demand sub-models) is disaggregated to reflect the different types of renewable sources, as may be possible

within the isolated island system. This renewable sources disaggregation permits more accurate modelling, as the technological advancement and profitability of the individual renewable sources, can differ significantly. Furthermore, the synthesis model captures the necessary endogenous characteristics of a low-carbon evolving island electricity system. Details of the quantities that are endogenous in this model are provided in Table 6.1. Prospective long-term investment solutions and policy recommendations are also developed from the defined scenarios and analysis examined in the model. Specifically, the challenges facing those making investment decisions are tackled within this work. The model seeks a better understanding concerning a future portfolio of generation mixes and the possible benefit to stakeholders in pursuit of environmental and energy security concerns.

6.2.1 Synthesis – The Mental Model

The synthesis model is centred on the expanded dynamic hypothesis of Figure 3.4 and the resulting mental model feedback loop diagram is shown in Figure 6.1. The diagram accounts for the key policy and investment feedback relationships that exist when the environmental and energy security concerns of isolated small-island electricity systems are taken into account. Also included are population social factors of the island system and relevant technical aspects of the electricity grid. The key existing relationships are shown in the diagram as four loops, two balancing, and two reinforcing, all interacting at the *long-term low-carbon based capacity mix* and the *demand/capacity ratio* variables. The main aspects captured by the model are the pursuit of low-carbon technologies aided by environmentally driven policies, and the interplay arising from the long-term electricity demand and the affordability of electricity generation technologies.

With these interactions, some key endogenous variables emerge from the model. The low-carbon based capacity mix (consisting of the different disaggregated renewable sources), net CO₂ emissions, net electricity demand and expected revenues per MW of installed capacity are some of the most important endogenous effects captured by the model. Key exogenous variables are the capacity utilisation, GDP changes, low-carbon policy targets and population changes. Some key

variables excluded from the model include off-grid electricity capacity, investment business models, and cash flow constraints. As done in previous chapters, the exogenous variables used were verified with EDA and with global data sources (Isle-pact, 2012; European Commission, 2013; Ilic, Xie and Liu, 2013; IRENA, 2014a; EDA, 2016). The following table, Table 6.1, model boundary chart, summarises the scope of the model by listing the key important endogenous and exogenous variables used for the synthesis model, and the ones which were excluded.

Endogenous	Exogenous	Excluded
Net electricity demand	Overnight tourist stays	Grid balancing
Electric vehicle adopters	GDP changes	Off-grid electricity capacity
Demand/capacity ratio	Low-carbon policy targets	Cash flow constraints
Low-carbon based capacity mix: renewables (disaggregated), fossil fuel and storage	Day/night MIN MAX demand profile	Day visitors (cruise ships)
Expected revenues per MW of installed capacity	Capacity utilisation	Investment business models
Net CO ₂ emissions	Average household size	
Grid quality: capacity factor experience	Capacity investment timeline	
Day/night hourly demand imbalance	Electricity tariffs	
	Population changes	

Table 6.1 Model boundary chart for synthesis model

Shown in Figure 6.1, three of the four loops interact at the *long-term low-carbon based capacity mix* variable and the remaining loop interacts with the *demand/capacity ratio* variable. This loop, the *demand-based energy security loop* (red and black loop) captures the demand-side dynamics of the model, including the endogenous effects of a low-carbon policy agenda. This includes the adoption of electric vehicles and energy efficiency mechanisms. In addition, impacts are captured of niche-type activity such as tourism (islands are widely seen as tourist destinations) together with other social and economic influences on the electricity demand of the island system. This loop is

reproduced from the core aspects shown in Figure 5.1 of the endogenous demand sub model of Chapter 5. It details a loop which has a balancing effect on the *demand/capacity ratio* variable. This variable is useful for ensuring that there is sufficient electricity supply to meet the demand. If the *demand/capacity ratio* is high then the *innovative new demand (electric vehicles adoption)* with a delayed effect, is lower than it otherwise would be. This lowering of *innovative new demand (electric vehicles adoption)* is then reinforced on the 'consumer-type' sector consumption which, in turn, reinforces this effect onto the *net electricity demand*. The lower than normal effect is then reinforced from the *net electricity demand* variable onto the *demand/capacity ratio* variable, thereby completing the *demand-based energy security balancing loop*.

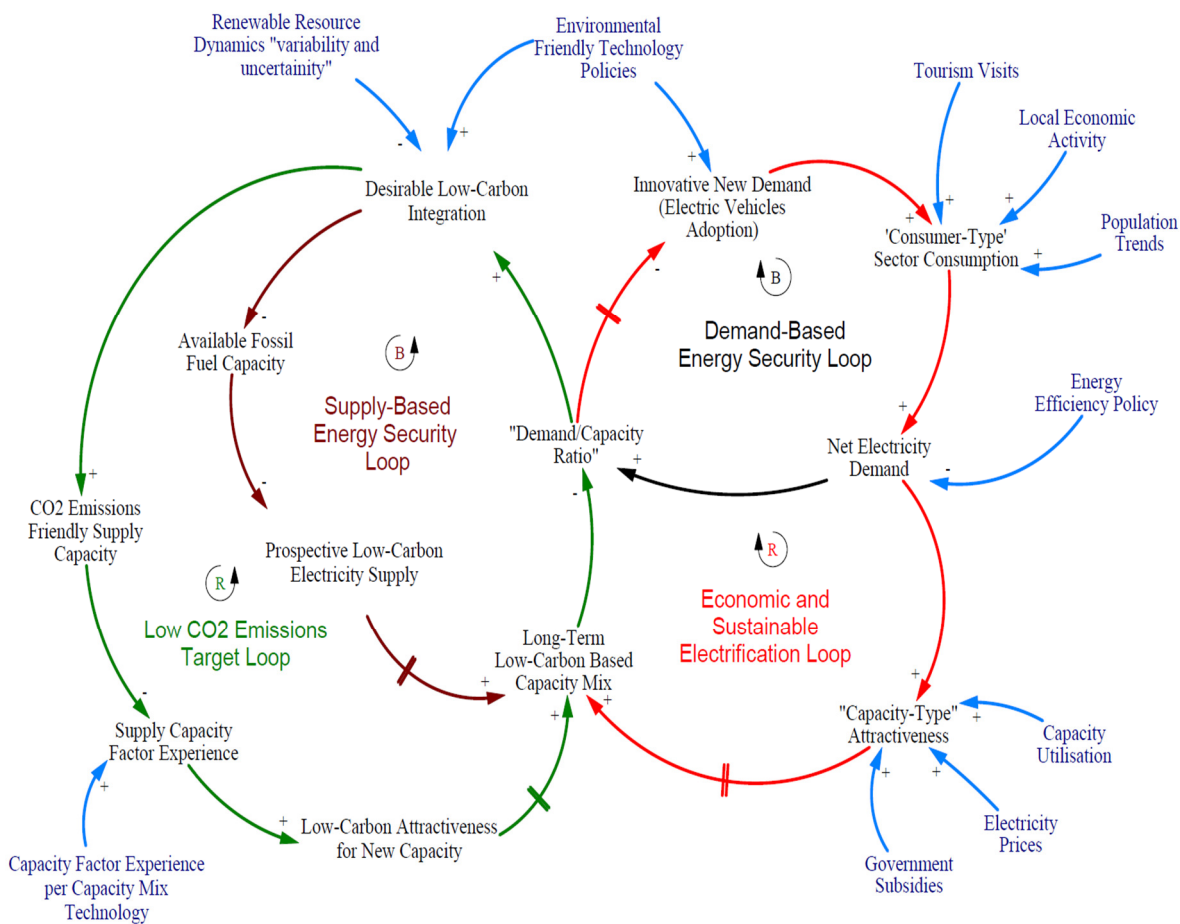


Figure 6.1 Mental model feedback diagram of the island electricity system

The other three loops interacting at the *long-term low-carbon based capacity mix* variable reflect the key supply side dynamics of the system. The outer *low CO₂ emissions target loop* (green loop)

is a reinforcing loop centred on the environmental drive for lower CO₂ emissions. If the *demand/capacity ratio* is high then the *desirable low-carbon integration* variable is higher than what it would otherwise be. Also interacting here are the exogenous effects of the *renewable resource dynamics* and the *environmental friendly technology policies* influences. The *desirable low-carbon integration* variable then reinforces this higher than normal effect on the *CO₂ emissions friendly supply capacity* which then balances the *supply capacity factor experience* (most low-carbon sources reveal low capacity factors⁶) to be lower than it otherwise would be. This decrease in *supply capacity factor experience* is then reinforced onto the *low-carbon attractiveness for new capacity* variable which, in turn, reinforces the decrease onto the *long-term low-carbon based capacity mix* variable. For the completion of the loop, the *long-term low-carbon based capacity mix* variable has a balancing effect on the *demand/capacity ratio*. This variable is now higher than it normally would be and closes the reinforcing *low CO₂ emissions target loop*.

The inner *supply-based energy security loop* (brown and green loop) is also consistent with the environmental drive for lower CO₂ emissions. This loop, however, captures the fossil fuel aspects of this part of the system. As shown above, if the *demand/capacity ratio* is high then the *desirable low-carbon integration* variable is also higher than what it would otherwise be. This increase, however, has a balancing effect on the *available fossil fuel capacity* variable. The resulting lowering effect on this variable has a balancing effect on the *prospective low-carbon electricity supply* variable causing it to increase. This increase, with a delay over time, has a reinforcing effect on the *long-term low-carbon based capacity mix* variable causing it to be higher than it would normally be. As shown above, the completion of this loop involves the *long-term low-carbon based capacity mix* variable having a balancing effect on the *demand/capacity ratio* variable. If the *supply-based energy security loop* were acting on its own, then the *demand/capacity ratio* variable due to the balancing

⁶ Capacity factor experience is defined within this work as the technical availability of the given technology given the reliability and availability factors. These factors are determined from the literature and an average value is utilised for the different types of electricity generating technologies.

effect of the loop would now be lower than it otherwise would be. Both the *low CO₂ emissions target loop* and the *supply-based energy security loop* are clarified by the core policy target aspects shown in Figure 4.5 of chapter 4. Additionally, factors relating to the intermittency of the different disaggregated renewable sources are included within these two loops (unlike the mental model loops of chapter 4).

Also shown in Figure 6.1 is the *economic and sustainable electrification loop* (red and green loop) which captures the key long-term economic aspects of the system on the *long-term low-carbon based capacity mix variable* and, in turn, on the *demand/capacity ratio*. This is a reinforcing loop and assuming a similar starting point as the *demand-based energy security loop*. If the *demand/capacity ratio* is low then the *Innovative new demand (electric vehicles adoption)* with a delay, is higher than it would otherwise be. This higher than normal effect on the *EV electricity demand* is then reinforced onto the '*consumer-type*' *sector consumption* which, in turn, reinforces this effect onto the *net electricity demand*. The *net electricity demand* is now higher than it would otherwise be. This increase has a reinforcing effect on the '*capacity-type*' *attractiveness* causing it to be higher than it otherwise would be. Other exogenous variables key to the long-term economic aspects of the system also interacts with the '*capacity-type*' *attractiveness*. The *capacity utilisation*, *electricity prices*, and *government subsidies* have reinforcing effects on the '*capacity-type*' *attractiveness* variable. The '*capacity-type*' *attractiveness* variable then, with a delay, has a reinforcing effect on the *long-term low-carbon based capacity mix* causing it to be higher than it normally would be. The completion of this loop, similar to the *low CO₂ emissions target loop* and the *supply-based energy security loop* involves the *long-term low-carbon based capacity mix* variable having a balancing effect on the *demand/capacity ratio* variable. Hence, if this loop were acting on its own, the *demand/capacity ratio* variable would be higher than it would otherwise be.

The four loops highlighted, comprise the key components for the synthesis model of this thesis. This model captures the key mental model structure of the environmental and electricity security concerns of an isolated island system as detailed in this work. The mental model is then used to

formulate the important variables needed to develop the formal SD model of this chapter. These formal model formulations are described in the next section.

6.2.2 Synthesis Model Formulation

The model is derived from the mental model feedback loop diagram of Figure 6.1 and implemented as in previous chapters using the Vensim software package. The main mappings of the key stocks and flows and exogenous factors for the synthesis model are shown in Figure 6.3. The most important formulations of these stocks and flows are highlighted within this section. For ease of understanding, the key mental model loops of Figure 6.1 have the same colour coding of the corresponding loop arrows shown in Figure 6.3.

At the top, left-hand side of this diagram is found the *demand-based energy security loop*, which entails the adoption of EVs together with energy efficiency mechanisms to give the ‘*consumer-type*’ *electricity demand*. The ‘*consumer-type*’ *electricity demand* is summed to give a total demand, which is the *net avg electricity demand*. The ‘*consumer-type*’ *electricity demand* is the individual demand from the different electricity consumption sectors. The sectors of consumers are the residential, commercial, industrial, and public services consumers together with the consumption from electric vehicles, as described in chapter 5.

Using the current tri-tariff pricing scheme of São Miguel, the *total of all ‘consumer-type’ electricity sold revenues variable* values are deduced (Ilic, Xie and Liu, 2013; EDA Estimates, 2015). The tariffs used for the various time periods are given from Ilic, Xie and Liu, (2013) and EDA Estimates (2015) and shown in Table 6.3. It is observed within this island system that, on average, over 75% of consumers use the tri-tariff option, whilst fewer than 25% use the fixed tariff option (Bermonte, 2015). Hence, the fixed tariffs (which are normally the median value between the highest and lowest tariffs) are ignored here for the synthesis model implementation. The three main categories of time periods used in the pricing schemes are the peak, shoulder peak and off-peak. In addition, there exists a super-off peak time (Ilic, Xie and Liu, 2013), which is ignored for the implementation

within this model, since the tariffs and hence incentives during this period are similar to the normal off-peak prices. The time periods considered on São Miguel during a daily cycle from both winter and summer seasons are shown in Table 6.2.

Standard time period in winter		Standard time period in summer	
Peak	9:30 a.m. – 11:00 a.m. 5:30 p.m. – 8:00 p.m.	Peak	9:00 a.m. – 11:30 a.m. 7:30 p.m. – 9:00 p.m.
Shoulder peak	8:00 a.m. – 9:30 a.m. 11:00 a.m. – 5:30 p.m. 8:00 p.m. – 10:00 p.m.	Shoulder peak	8:00 a.m. – 9:00 a.m. 11:30 a.m. – 7:30 p.m. 9:00 p.m. – 10:00 p.m.
Normal off-peak	10:00 p.m. – 8:00 a.m.	Normal off-peak	10:00 p.m. – 8:00 a.m.
Super off-peak	1:30 a.m. – 5:30 a.m.	Super off-peak	1:30 a.m. – 5:30 a.m.

Table 6.2 Daily cycle for seasonal tri-tariff time periods

However, since there is weather steadiness for both winter and summer days, the choice of either standard time period should give equally good quality results. The summertime scheduling from Table 6.2 is chosen to be used for the average consumption calculations for the various ‘consumer-type’ sectors. The revised table, Table 6.3, shows the standard time period in summer and the corresponding tariffs for the different consumption sectors. The tariffs are used to calculate the revenues collected from each consumption sector.

Standard time period in summer		Tariffs (euro/MWh)				
Period	Time	Residential	Commercial	Industrial	Public services	Electric vehicles
Peak	9:00 a.m. – 11:30 a.m. 7:30 p.m. – 9:00 p.m.	124.6	124.6	111.7	124.6	124.6
Shoulder peak	8:00 a.m. – 9:00 a.m. 11:30 a.m. – 7:30 p.m. 9:00 p.m. – 10:00 p.m.	96.7	96.7	87	96.7	96.7
Off-peak	10:00 p.m. – 8:00 a.m.	57.1	57.1	52.6	57.1	57.1

Table 6.3 Daily cycle for summer time periods with corresponding tri-tariffs

Based on the time periods shown in Table 6.3, and using details from Bermonte (2015), the corresponding average monthly consumption within each time period for each consumption sector is deduced and expressed as a percentage of total consumption. The main assumptions used are detailed as follows:

A standard operating industrial consumption facility is considered initially for a daily working time of approximately 10 hours starting at 8 am and ending at 6 pm. Hence, it can be assumed that 20% of industrial consumption occurs during peak hours and the remaining 75% occurs during shoulder peak periods. There is also a consideration for having a possible 5% of consumption related to the off-peak hours by load shifting (starting factory operations between 6 am and 7 am on some working days) (Bermonte, 2015).

For commercial services consumption, it is assumed that there exists a working week of approximately 12 hours of operations from 8 am to 8 pm. Hence, it can be assumed that on average there are 3 peak hours per day or 25% of consumption occurs during peak hours, 65% consumption during shoulder peak with a possible 10% from load shifting into the off-peak hours. Public services consumption is similar to commercial services consumption, noting that, in addition, street lighting is accounted for within this consumption sector. It is assumed that for the working week times of 10 hours there are on average 3 peak hours per day or 25% of consumption occurs during peak hours, 60% consumption during shoulder peak with approximately 15% of consumption occurring within the off-peak hours.

The remaining consumption sectors are linked to increased consumption within the home. Residential consumption is considered to have a 16 hours consumption cycle. Assuming a standard household for which persons go to work and/or school for 7-8 hours a day from 8/9 am to 4/5 pm there can be on average 2.5 peak hours per day that individuals are at home. This accounts for 15% of consumption time whilst shoulder peak hours accounts for approximately 35% of consumption with the remaining 50% assumed to occur during off-peak hours due to load shifting.

Electric vehicle consumption is assumed to be tied to the charging of electric vehicles at residential locations. It is also assumed that most of the charging will occur during the off-peak periods at night. Hence, 85% electric vehicles consumption occurs within the off-peak time period and between 10% consumption occurs during the shoulder peak periods and approximately 5% during peak time periods.

The *percentage of monthly 'consumer-type' consumption* occurring within the peak, shoulder peak and off-peak time periods are thus determined for each of the consumer consumption sectors using the following equation: $D_{time\ period}^{sector} = X_{time\ period} * D_{sector}$, where $D_{time\ period}^{sector}$ represents the specific *'consumer-type'* sector consumption for the given time period, in units of MWh/month. $X_{time\ period}$ is the percentage of consumption occurring within this time period and D_{sector} is the average monthly consumption for that specific *'consumer-type'* sector.

It then follows that the *'consumer-type' consumption revenues* generated from the various sectors are calculated using the appropriate tariffs within the different time periods. This is defined using the following equation: $R^{sector} = \sum(P_{time\ period}^{sector} * D_{time\ period}^{sector})$, where R^{sector} represents the revenues generated from consumption within the *'consumer-type'* and $P_{time\ period}^{sector}$ is the corresponding tri-tariff pricing for the time period. The total amount of revenues generated, R^{total} , from electricity sales to all consumers is given as the sum of the individual R^{sector} values. This total is averaged over a two year period (rolling average) to avoid single year anomalies due to one-time events such as generator outages, demand surges or external economic factors. The total amount of revenues generated is used to determine the financial attractiveness of the different installed capacities - referred to in Figure 6.3 as the *'capacity-type'*.

The *'capacity-type'* used in this thesis are fossil fuel (assumed to be entirely heavy fuel oil and diesel), renewable (geothermal, run-of-river, biomass, wind and solar) and energy storage (reservoir-type pumped hydro). The average usage of each of these technologies to meet the electricity demand is key to determine the profitability and hence the financial attractiveness of the

respective generation technology. This average usage/dispatch factor⁷ for the specified generation technology during the peak, shoulder peak and off-peak time periods are defined in general by the merit order⁸ rules of the electricity system.

The following figure, Figure 6.2 shows the typical generation profile (MW) for the São Miguel island system. Since there is fairly steady weather throughout the year as mentioned previously, the load and generation profiles are very similar for both winter and summer days. It can be observed that geothermal and run-of-river hydro are used to their maximum potential both day and night. There is curtailment to the wind at low load times, as can be seen between the hours of 3 am and 10 am. In addition, the necessary frequency balancing fossil generation is seen throughout the entire daily profile with increases in this 'capacity-type' seen during the peak load periods between 6 pm and 10 pm. Biomass and solar are also used but due to their very small quantities, and not being dispatched within the times shown they are not visible in Figure 6.2. The average usage of the different 'capacity-type' to meet the load within the system is assumed to be similar to Figure 6.2 for the purposes of the synthesis model.

Furthermore, for the model and from Figure 6.2, the average usage/dispatch factor for the specific generation technology asset considered is obtained based on its place in the São Miguel "local" merit order. With small isolated island systems, the "local" merit order is more than just a matter of using the lowest marginal generation cost assets first. It is normally based on the appropriate order of dispatch as determined by the utility company to make use of the electricity generation sources available. For example, for system stability reasons there is always some diesel or heavy fuel oil generated power online in such island systems. Specifically for São Miguel, the available

⁷ Dispatch factor is based on the number of hours that this generation technology is employed to meet the total load. It should not be confused with the load factor which is the average load divided by the maximum load in a given time period.

⁸ Merit order is an administrative system management concept applicable to monopolistic electricity systems or those in which a single player is dominant. In such systems the system administrator decides the priority for dispatch of each form of generation. Usually this is based on running technologies with the lowest marginal costs of generation (i.e. fuel costs) first.

base load type renewables of geothermal and run-of-river are fully dispatched firstly along with some of the frequency balancing fossil generation of at least 18-20% (approximately 12MW in 2015) of total demand capacity. Next to be dispatched is usually biomass, then wind, solar and extra fossil as needed. If there is too much supply capacity wind is usually curtailed as a first step (Botelho, 2015; EDA, 2016).

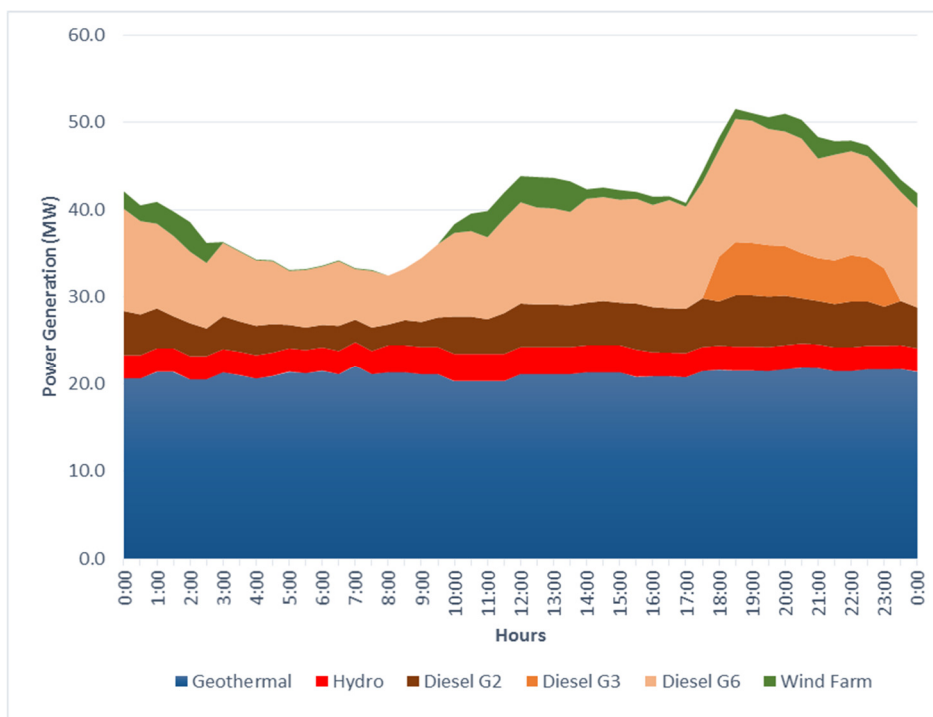


Figure 6.2 Typical São Miguel generation profile for the demand load, in 2015 (EDA)

Indeed, the generation portfolio on the island is also assumed to be influenced by considerations of cost. Due to existing policy pressures, renewable technologies form a major part of current investment plans and the specific renewables technology choices are shaped by not only the usage of these technologies but also the cost considerations of the given technologies (lowest capital cost technologies are preferred). The research work presented here simplifies reality in two key respects: first, the cost calculations do not make use of discounted cash flow. Investors and policy-makers normally place great emphasis on the LCOE (a discounted cash flow concept). In this thesis, adoption of the LCOE of technology specific generation projects within the years 2005-2015 (Silva, 2013) is used (without discounting cash flows over the model simulation) as the overnight

generation technology costs. The second simplification is that in the modelling no installation constraint is imposed on renewables technology choice as a consequence of geography or other physical realities such as spatial planning constraints. The reality is that São Miguel has a set of discrete and island specific opportunities for major renewables expansion, but these specific constraining realities and enabling opportunities are omitted from this SD modelling work which rather focuses on the evolutionary growth of existing technologies as driven by the generation technology ('capacity-type') investment viability and dispatch factor/average usage.

For this model, based on the dispatch of the specified 'capacity-type', the average 'capacity-type' usage hours per month is determined as:

$H_{time\ period}^{capacity\ type} = DF_{time\ period} * H_{time\ period} * D_{month}$, where $H_{time\ period}^{capacity\ type}$ is the 'capacity-type' technology usage for the given time period, in units of hours. $DF_{time\ period}$ ⁹, the dispatch factor is the dispatch of the generation technology expressed as a percentage of time on a daily basis that this technology is used during the specified time period. $H_{time\ period}$ is the daily time period in hours as given in Table 6.3 for the tri-tariff time periods and D_{month} is the number of days per month, defined within this model implementation as 30 days. The average number of hours that the 'capacity-type' can be dispatched per month to meet the demand load is given as follows:

$DH_{monthly}^{capacity\ type} = CF^{capacity\ type} * \sum H_{time\ period}^{capacity\ type}$, where $DH_{monthly}^{capacity\ type}$ is the average number of hours per month that the specified technology can be dispatched. $CF^{capacity\ type}$ is the referenced capacity factor¹⁰ per installed MW of the specific technology as given in the literature (IEA, 2005; Ilic, 2011; EDA, 2016) and is shown in Appendix A2.

For clarity, it is important to note the terminology of some closely related terms when considering the time periods of technology specific generation capacity and their usage. Firstly, it is key to note

⁹ This is expressed as a percentage of total generation dispatched.

¹⁰ The ratio of the net electricity generated, for the time considered, to the energy that could have been generated at continuous full-power operation during the same period (NRC, 2017)

that the capacity factor is not the same as the availability factor of the generation capacity. The availability factor is the total amount of time that the generation asset is able to produce electricity divided by the amount of time in that period (Huron, 2015). This ratio gives a fractional measure of the amount of time that the generation capacity can be used, however, not necessarily at full output power. Realistically, the capacity factor of a specific generation capacity cannot be higher than the availability factor of the same generation capacity. Capacity factor considers the downtime and maintenance of the generation capacity similar to the availability factor but this is now measured against the full potential output of the generation capacity asset. It can also be used for capturing the seasonality effects of intermittent renewables availability in a single metric of usage. Hence, the capacity factor is calculated as follows:

$$CF^{capacity\ type} = \frac{\text{net electricity generated}}{\text{potential total electricity at full power during same time period}} \quad (\text{USNRC, 2017}).$$

With a capacity factor of 0.9 this means that the electricity output from the total generation capacity is, on average, dispatched for 90% of the time period considered.

Dispatching capacity also leads to the terminology of load factor. The load factor is however dependent on the peak load within the system. It is given as a ratio of the average load to the peak load in the electricity system during a specified time period (EIA, 2017). The load factor is more closely aligned with the capacity margins detailed in Section 1.3. It can also be highlighted that the load factors and capacity margins are more relevant as a measure of the reliable availability of an entire electricity system or generation plant to meet the total system load. However, the capacity factor would be more relevant to the specific generation technology as it relates to the theoretical or ‘nameplate’ maximum electricity generation capacity of the specific generation technology.

For the purpose of the model implementation, the capacity factor measure for the capacity usage was chosen due to its suitability for giving a good representation of the possible usage of the different generation technologies from the given standard literature values and the usage hours derived from the model for the installed ‘*capacity-type*’. The time step considered for electricity

generation within the model is monthly and a 100% capacity factor is represented by 1.0. Base load type renewables such as geothermal, which is widely used in the case study island system, can have capacity factors of up to 85% (EDA, 2016).

The profitability of the different ‘capacity-type’ technologies, $CP^{capacity\ type}$, is calculated as a ratio of *expected ‘capacity-type’ revenues per MW of installed capacity* over the *needed breakeven monthly revenues per MW of installed ‘capacity-type’ variables*. A ‘capacity type’ technology is considered to have no profitability unless it secures a proportion of the revenues. The portion of revenues gained from each technology is determined from its usage factor. The ‘capacity-type’ usage factor, $UF^{capacity\ type}$ is calculated as the fractional percentage of time per month that the specific ‘capacity-type’ is dispatched to meet the load. As mentioned above, the evolving dispatch is based on the administered local merit order for São Miguel and is custom built to this model. This is formulated as $\frac{\sum D^{capacity\ type}}{\sum S^{capacity\ type}} = 1$, where $D^{capacity\ type}$ is the demand load in MW that is met by the specific ‘capacity type’ technologies. $S^{capacity\ type}$ is the electricity supply in MW that is generated to satisfy the required $D^{capacity\ type}$ from these technologies. This use of $S^{capacity\ type}$ allows for the generation and/transmission losses and the curtailment of supply within the model.

The *expected ‘capacity-type’ revenues per MW of installed capacity* is modelled as

$$\frac{R^{total} * UF^{capacity\ type}}{IC^{capacity\ type}},$$

where $IC^{capacity\ type}$ is the total installed capacity of the given technology

within the electricity system. It can be seen that $R^{total} * UF^{capacity\ type}$ gives the portion of revenues that is acquired from the usage of the given technology.

The *needed breakeven monthly revenues per MW of installed ‘capacity-type’* is modelled using the ‘capacity type’ LCOE (as an overnight basis value without discounting cash flows) cost, and represented here as $LCOE^{capacity\ type}$.

This is given as follows: $BR^{capacity\ type} = LCOE^{capacity\ type} * DH_{monthly}^{capacity\ type}$, $BR^{capacity\ type}$ is the cost per month per MW of installed capacity required to facilitate breakeven operations for the specific technology. Instead of using the investment cost per capacity installed, the initial $LCOE^{capacity\ type}$ (as the overnight basis cost) from 2005 is used, represented by the ratio of net present value (NPV) of total cost and electricity generation found in the literature (IEA, 2010b; Ilic, Xie and Liu, 2013; Silva, 2013; NREL, 2016) and shown in Appendix A2. For this implementation it is assumed that the initial LCOE of the given ‘capacity-type’ technologies changes, in the long-term, based on new installed capacity only and not on other factors. A suitable learning-by-doing cost reduction progress ratio p is chosen as in Section 4.3.1 and the long-term $LCOE^{capacity\ type}$ is determined by the use of the cost reduction curve implementation similar to that done in Section 4.3.1. The cost reduction learning curves for all renewables and energy storage are implemented. However, the cost reduction learning curves for the LCOE of fossil fuel generation is not implemented for the study described in this chapter. Since, it is not expected that the cost of fossil fuel generation will have significant learning to affect the system.

Subsequently, using the ‘capacity-type’ profitability and the piecewise linear function of profitability as implemented in Black (2005) and shown in Section 4.3.1, the investment attractiveness, and, in turn, the financially desired generation capacity of the various technologies, is determined. For each specific ‘capacity-type’ the variable ‘capacity-type’ profitability is given by the ratio of expected ‘capacity-type’ revenues per MW of installed capacity to the needed breakeven monthly revenues per MW of installed ‘capacity-type’. Each specific ‘capacity-type’ profitability variable is used as an input to the investment attractiveness function. The financially desired capacity is formulated as follows: $FDC^{capacity\ type} = A_R IC^{capacity\ type}$, where A_R is the investment attractiveness piecewise linear function (implemented as a lookup table within the model)¹¹.

¹¹ Shown in detail within Appendix A2

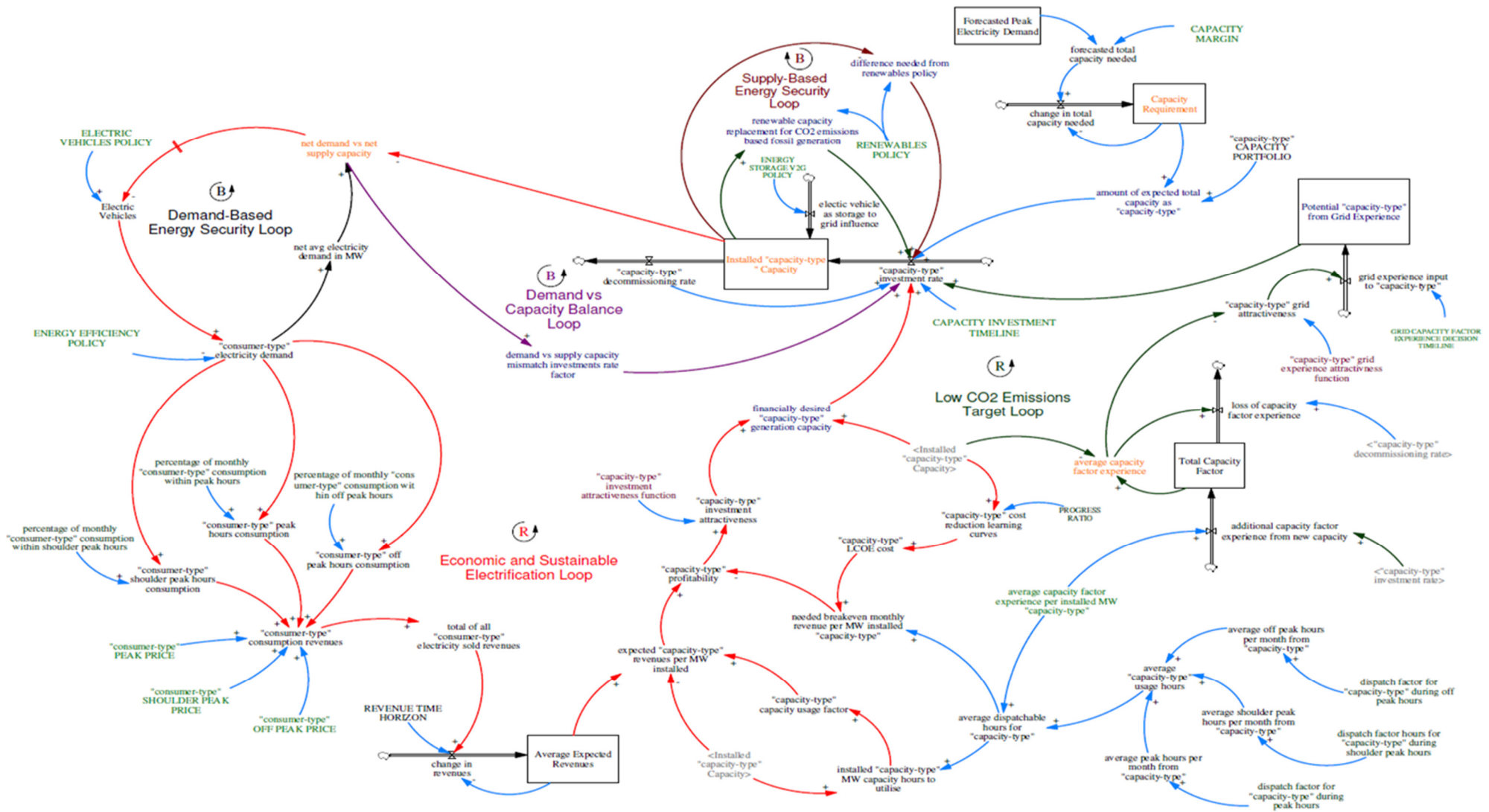


Figure 6.3 Simplified stock and flow diagram for the synthesis model

Within the synthesis model, one aspect of the *low CO₂ emissions target loop* entails the grid quality, which is determined by the input from our coined term called the *capacity factor experience* within this thesis. The *capacity factor experience* is derived from the capacity factor, $CF^{capacity\ type}$ of the various technologies explained previously and given in the literature of all installed generation capacity within the system. This variable is considered as the fractional percentage for the average availability per installed MW of the various generation technologies. A capacity factor experience of 100% implies that the installed capacity is available for the total 720 hours in any given month. To model the *capacity factor experience* variable, the approach in Sterman (2000) pg. 502 for the co-flow structure tracking the attribute of a stock is used. In this case, the attribute of the stock is the *capacity factor experience* and the main stock is the installed electricity generation capacity of the various ‘*capacity-type*’ technologies within the system.

Therefore, in general:

total capacity factor experience =

$$\int \frac{\text{total increase in capacity factor experience} - \text{total decrease in capacity factor experience}}{\Delta t} +$$

*total capacity factor experience*_{t₀}, where *total capacity factor experience*_{t₀} is the initial value for the total capacity factor experience.

The increase in capacity factor experience is:

total increase in capacity factor experience =

$$\sum_i \text{avg capacity factor experience per installed capacity } (i) * \text{capacity investment rate } (i).$$

The decrease in capacity factor experience is:

total decrease in capacity factor experience =

$$\sum_i \text{avg capacity factor experience per installed capacity } (i) * \text{capacity decommissioning rate } (i),$$

where *avg capacity factor experience per installed capacity* = $\frac{\text{total capacity factor experience}}{\text{installed generation capacity}}$

This formulation allows for the capture of the long-term grid quality of supply as determined by the referenced capacity factors and seasonality effects of renewables determined from the capacity installations.

The resulting value of the *capacity factor experience* as calculated from the inputs of the capacity factor, $CF^{capacity\ type}$, attributes to the existing installed ‘capacity-type’ and is then used as an input for the investment decisions to install the specific ‘capacity-type’. This *capacity factor experience* is then used as an investment proxy based on the grid quality of the system¹². The ‘capacity-type’ attractiveness to install the specific capacity from grid quality is formulated as follows: $\frac{d}{dt}GQC^{capacity\ type} = F_{GQ}^{capacity\ type}(capacity\ factor\ experience)$, where $F_{GQ}^{capacity\ type}$ is the grid quality attractiveness logistic function (implemented as a lookup table within the model)¹³.

Another important component of the structure of the synthesis model is the inclusion of the expected capacity portfolio accompanying the various capacity types (fossil fuel, renewables etc.), as in Chapter 5. Within the synthesis model described in this chapter, a formulation is used for ensuring that the investments within the system are able to meet the peak demand requirements of the system.

Other components of importance are the renewable policy targets and renewable replacements for CO₂ intensive fossil fuel generation, as described in Chapter 4. The inclusion of the endogenous usage factor of the fossil generation capacity within these formulations allows for a more accurate endogenous modelling of the long-term CO₂ emissions of the electricity system, unlike what was achieved in Chapter 4.

Additional important dynamic components of the stock and flow structure of the model are the rate of change of installed ‘capacity-type’: $\Delta C^{capacity\ type} / \Delta t = IC_o^{capacity\ type} - IC_D^{capacity\ type}$,

¹² This is not the short-term grid quality but instead the longer-term monthly availability of the grid to supply electricity based on the various types of generation capacity installed. Lots of intermittent renewables will lead to a lower grid quality for the system.

¹³ This is shown in detail in Appendix A2.

where $IC_0^{capacity\ type}$ is the ‘capacity-type’ online rate, $IC_D^{capacity\ type}$ is the decommissioning rate of the ‘capacity-type’ and Δt is the monthly time step.

The investment rate I of the various ‘capacity-type’ technologies is a compound of several model variables. This investment rate underpins the investment drivers within the model. Given that the system is pursuing low carbon renewables, the investment decisions for new capacity is centered on increasing and/or replacing the capacity within the system, preferably with renewables.

The following equation captures the general formulation of this variable:

$$I^{capacity\ type} = \max\left(\frac{FDC^{capacity\ type} - C^{capacity\ type}}{T^{capacity\ type}}, \frac{TC^{demand} - C^{capacity\ type}}{T^{capacity\ type}}, \frac{GQC^{capacity\ type}}{T^{capacity\ type}}, R_{LT}^{renewables}, R_{ET}^{renewables}\right) + IC_D$$

where $FDC^{capacity\ type}$ is the financially desired ‘capacity-type’ capacity; TC^{demand} is the forecasted demand load; $C^{capacity\ type}$ is the installed ‘capacity-type’ capacity; $T^{capacity\ type}$ is the ‘capacity-type’ investment decision timeline; IC_D is the rate of ‘capacity-type’ decommissioning; and R_{LT} and R_{ET} are, respectively, the rates of adjustment to the local renewables and CO₂ emissions targets, as described above and in Section 4.3.1. In addition, $I^{capacity\ type}$ depends upon the *demand/capacity* mismatch within the system. A minimum threshold value of 0.25 is used for allowing investments into the system. IF $\frac{demand}{capacity} > 0.25$, then there are capacity investments within the system ELSE there are no investments. Further details of the formulations used for the implementations within this model can be found in Appendix A2.

Model Validation

As in the previous sub-models, the synthesis model is simulated on a monthly time-step over a 45 years’ time horizon from 2005 until 2050. Rigorous validation steps are taken to ensure the robustness of the model for studying low-carbon energy transitioning within isolated island systems. Section 3.3 gives an overview of the model validation steps necessary to build confidence

in the model. Within this section, the details of the model calibrations and the sensitivity analysis of model validations are given. Full details of the remaining steps are shown in Appendix B1.

The calibration period used for the validation of the synthesis model covers the time period from 2005 to 2015. As a first step, the patterns of behaviour of important system variables are compared with the real system data for these variables. It is expected that the important simulated variables follow the same trends as the real system data. The important variables highlighted for visual inspection here are the “installed fossil generation capacity”, “installed renewables aggregated capacity” and “installed energy storage capacity”. Figure 6.4 shows the simulated base model output data compared with the historical data of the corresponding real system variables. There are no installed energy storage capacity within the system over the calibration period and this is reflected in Figure 6.4.

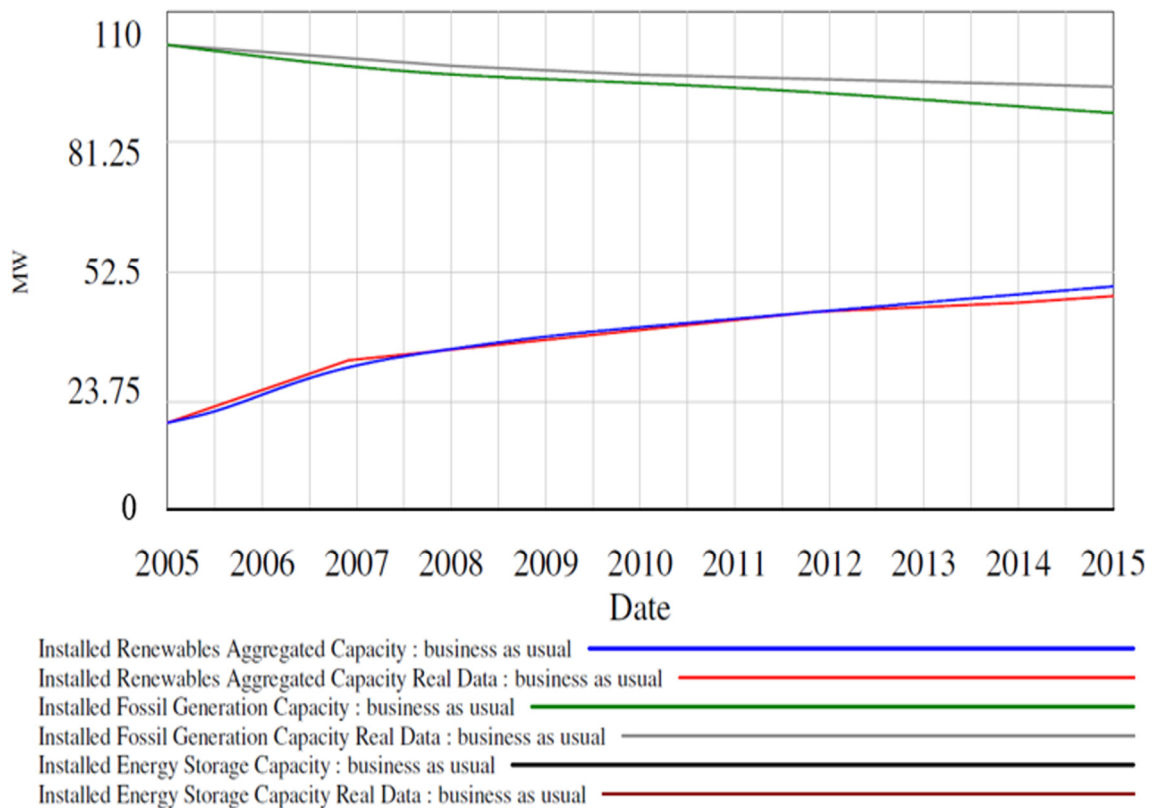


Figure 6.4 Comparison of base model output data and real data for the synthesis model

More comprehensive statistical methods are also used to aid model calibration. As in Section 5.2.2 for the validation of the endogenous demand sub-model, a statistical measure of fit R^2 and Theil inequality statistics Sterman (2000) Chp 21 are used to characterize the sources of error within the analytical comparisons of both data sets. After refinements to the model formulations, and with further simulations of the base case model output, the resulting statistical values of some of the important variables are reported in Table 6.4. These important variables are the installed generation capacity technologies and the average monthly electricity demand, in total, and for the various consumer sectors. Some results from the average monthly total demand variable have been highlighted in Section 5.2.2. This table, however, gives a comparative view to the sectors that make up the total consumer consumption.

Variable	R^2	MAE/M	U^m	U^s	U^c
avg total monthly consumer consumption	28.08%	0.0492	0.10	0.00	0.90
avg commercial services monthly consumption	69.66%	0.0870	0.14	0.02	0.84
avg residential household monthly consumption	24.82%	0.0395	0.06	0.04	0.90
avg industrial business monthly consumption	25.08%	0.0461	0.10	0.00	0.90
avg public services monthly consumption	26.70%	0.0263	0.27	0.54	0.19
Installed Fossil Generation Capacity	46.20%	0.0193	0.65	0.32	0.03
Installed Renewables Aggregated Capacity	99.40%	0.0144	0.23	0.04	0.74

Table 6.4 Model fits of historical data to some important variables

For the statistical values shown in Table 6.4, MAE/M variable is the mean absolute error (MAE) divided by the mean (M) of the data. R^2 is given as one minus the ratio of the sum of the squared error to the total sum of error squares. This measures the point-by-point correspondence of the model output with historical data. Only the installed renewables capacity variable has a very high R^2 value since it is the only variable that showed excellent point-by-point correspondence of the model output with historical data. The statistical measure is used to further confirm the model fit of the historical data and model output. This measure, the Theil inequality statistics also seen in Section 5.2.2 decomposes the total *mean square error* (MSE) between the model run and real data

into three components, U^m , U^s and U^c . These three components arise from the bias (unequal means of simulated and actual data), unequal variances (difference in variance), and unequal covariation (due to point-to-point covariance), and satisfy $U^M + U^S + U^C = 1$. Statistical values are not given for installed energy storage because average historical energy storage capacity is zero. The monthly consumption for the total and most of the various consumption sector variables reproduces the real data behaviour very well with the MSE concentrated in the unequal covariations. This implies that the model variables have the same mean and trends as the historical data, but differ from the historical data point-by-point as in Section 5.2.2 for the *avg total monthly consumer consumption* variable. The installed renewables capacity has excellent point-by-point correspondence of model and historical data which is statistically confirmed further by its MSE concentrated in the “bias” and the “unequal covariation”. The installed fossil capacity reveals a good point-by-point correspondence of the model and historical data and has a level of MSE concentrated in the bias. This implies that the trends are well-represented but there is a slight shifting of the model simulation run from the data. However, this shifting can be ignored since the (MAE/M) mean absolute error is only 2% of the average of the historical fossil generation data. Using the Theil statistics measure of these key variables non-systematic errors are elaborated for the model. In this work, the model emulates the historical data very well within the calibration period. The next section details the scenarios used to evaluate the model. The sensitivity analysis of the key model variables together with the details of the reality checks and the extreme case testing, can be found in Appendix B1.

6.3 Policy Scenarios

The scenarios used to evaluate critically the evolution of the generation mix and the effect on environmental CO₂ emissions are based on the policy scenarios of Section 4.3.2 and Section 5.3. The chosen scenarios, together with the baseline (business as usual) scenario, are derived from the literature (Isle-pact, 2012; European Commission, 2013; Botelho, 2015; Nunes, 2015). A total of four energy-related policy scenarios are considered together with a business-as-usual case. These

four other scenarios are *energy efficiency measures*, *tourism impacts*, *EV expansion* (as detailed in Section 5.3) and *renewables policies* (from Section 4.3.2). These scenarios are posited to be potentially interesting drivers for the future of the evolving electricity system and can give insights into the environmental and energy security concerns of the isolated island system.

At this point it is appropriate to comment on an aspect of terminology used within the thesis. As noted in Section 3.6, the research programme started with a set of scenario planning assessments concerning electricity futures in the Açores. The scenario planning was qualitative and followed the well-established, two-axis four quadrant approach as described in Lindgren and Bandhold (2009). In this chapter however, as with Sections 4.2.3, 4.3.3 and 5.3, the term scenario is used in a rather different sense. Scenario is considered within these sections as an SD long-term analysis (policy or influence based) into the future in which one aspect is given dominance or particularly emphasised in some way. This allows for the scenarios presented in this chapter.

In addition, the synthesis model presented within this chapter brings together a range of considerations previously located in the smaller and more closely bounded models focussed on, for example, the renewable integration futures or endogenous electricity demand futures. The synthesis model therefore has the capability to be constrained or given emphasis in various ways. At the risk of somewhat oversimplifying, for giving dominance to one policy or influence, which can be focussed on or not within the model. By exploring the synthesis model through such scenarios it becomes possible to reveal key aspects of the potential for electricity futures on the island of São Miguel. Such insights can then be held in mind when considering the behaviour of the synthesis model with the combined scenarios, found in Section 6.4.2, of all policies and influences. The different individual scenarios used within this chapter and for the model are now described.

Scenario 1: Business as usual

This scenario extrapolates the current trend of key factors and policies within the island system as detailed here. The scenario uses system data from 2005 to 2015, together with the past and present

policies and the prevailing economic and social conditions. Two important factors are the island population, which is determined by the current birth and death rates, and the GDP per capita; both being extrapolated up to 2050 from the 2005-2015 historical data. The existing policy for energy efficiency target of 6% decrease in consumption across all consumer-type sectors over the following 15 years starting from 2012 is implemented. The renewable policy, which was enacted in mid-2008 to achieve approximately 75% renewable generation by 2020, was adjusted to 45% renewable installation. This adjustment of the policy is made to reflect a business-as-usual with realistic rates of actual installations in 2015 (EDA, 2016). Also, a medium term goal of 30% reduced CO₂ emissions by 2020 is implemented within this scenario. There is also a 12 MW goal for a small reservoir energy storage project to begin in 2018, considered as a policy objective for the system (Botelho, 2015). In addition, and as in Section 5.3, there are no EV policies or pronounced market influences apart from a normal increase in EVs (based on the purchasing rate of about 4 new EVs per year in 2015) which currently results in a total of approximately 50 vehicles in 2015. Further to this, the growth rate in the number of overnight tourist stays is determined from the 2005-2016 historical data to be 0.14% (SREA, 2016), starting with an initial value of 96000 in January 2005 and extrapolated into the future. Using these system aspects as key inputs, the long-term trends and impacts within the system are simulated.

Scenario 2: Tourism impact

This scenario, which is similar to the one examined in Section 5.3, explores the effects of changing tourism on the generation mix and environmental impacts of the electricity system. It uses the Scenario 1 characteristics apart from the growth in the number of overnight tourist stays. For tourism growth rates, given from the historical data (SREA, 2016), two different cases are studied, namely, a one and a half times increase of the growth rate from 0.14% per month to 0.21% per month from 2016 until 2050 and a doubling of the growth rate from 0.14% per month to 0.28% per month from 2016 until 2050. These cases are of interest to EDA and the Regional Directorate for

Energy of the Açores (Botelho, 2015; Nunes, 2015). It is assumed here that no new hotel construction is warranted because of the low average occupancy rate on the island of 32% (Isle-pact, 2012; SREA, 2016), and the growth rate has only been doubled for this scenario (leading to a tripling of the average occupancy rate to 96% which does not warrant new hotel builds).

Scenario 3: Energy efficiency measures

This scenario corresponds to Scenario 1, apart from variations in the energy efficiency policy as described in Section 5.3. Two case studies are considered: namely, the doubling (to 12%) and tripling (to 18%) of the original policy targets across the policy timeline of 15 years. The energy efficiency policy measures are proposed to be discontinued after 15 years (Botelho, 2015; Nunes, 2015). Longer timelines are considered for the sensitivity analysis shown in Appendix B2. It is also assumed that the energy efficiency measures are fully adopted by the consumers (no adoption dynamics is considered for this model). However, the extreme case for non-adoption of the doubling and tripling measures will be reflected in the “business as usual” (Scenario 1) case.

Scenario 4: EV expansion

This scenario examines the possible influence of EV expansion. As with the previous scenarios, it corresponds to Scenario 1 apart from the EV expansion. It is assumed that light-duty vehicles are the target for EV expansion. The baseline case is compared to three other policy cases as in Section 5.3: a market-based adoption policy for diffusion of technologies (Bass, 1969), a target of approximately 2500 EVs by 2020 (Botelho, 2015), and a combination of the 2020 EV and the market-based adoption policies.

Scenario 5: Renewables policies

This scenario features two case studies of renewable policies based on aspects of Scenario 1. The CO₂ emissions policy emphasis and installed renewable capacity targets within the system as described in Section 4.3.2 are the basis for the scenarios. For this scenario, a target of 30% reduction in CO₂ emissions and 45% installed renewable capacity within the system by 2050 is examined. In

addition, a more aggressive 50% reduction in CO₂ emissions with 75% installed renewable capacity within the system by 2030 is also considered.

6.4 Results

The long-term installed capacities of the various generation technologies based on the scenarios detailed in section 6.3 are shown within this section. The environmental impacts as represented by the CO₂ emissions within the system are also presented. The result from the “business as usual” scenario is used for comparisons and shown with the various simulation runs. In addition, a discussion of high and aggressive policies versus low and relaxed policies from all of the scenarios given in Section 6.3 is detailed together with their impacts on capacity investments.

6.4.1 Modelling Analysis

Tourism impact

Figure 6.5 displays the influence of changing the growth rate of the number of overnight stays on the installed fossil generation capacity. For one and a half times and doubling the overnight growth rate, the trajectory of the installed fossil generation is unchanged. There are also negligible differences between these simulation runs. The same observation holds for Figure 6.6, which shows the installed energy storage capacity under the various model runs for overnight tourist stays. It can be safe to say that the “business as usual” scenario installations are the same as the other two simulation runs in terms of fossil generation and energy storage capacity installations. In both Figures 6.5 and 6.6 it seems that the range of tourism futures (within the assumptions given) has very little impact on the provision of fossil fuel generation capacity or energy storage installations. Furthermore, in Figure 6.6 there is a very clear feature of energy storage growth from 2018 followed by a later decline most likely linked to the policy objectives for storage within the system. The reader is urged to keep this in mind as other scenarios are later explored.

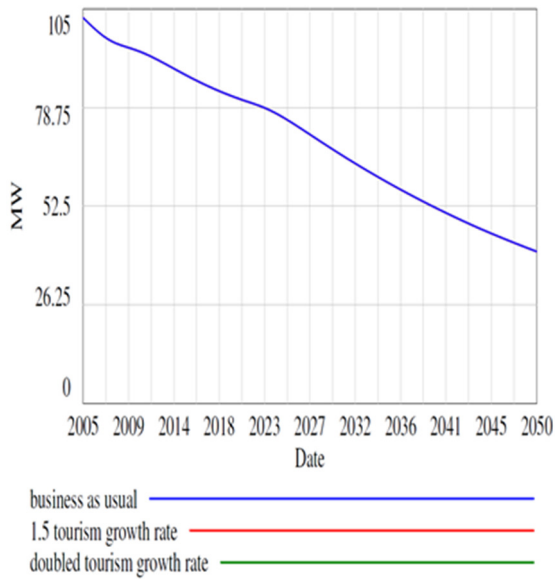


Figure 6.5 Impact of tourism changes on installed fossil generation capacity

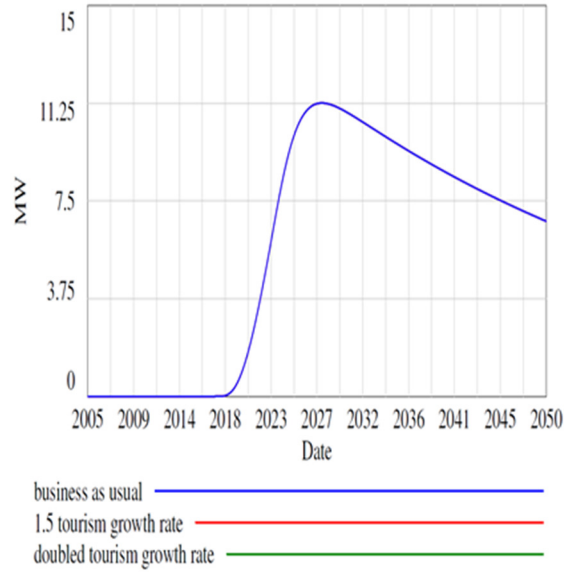


Figure 6.6 Impact of tourism changes on installed energy storage capacity

However, for installed renewables capacity the variations from the “business as usual” scenario of the various cases of overnight tourist stays are a bit more visible, as shown in Figure 6.7. This is evident, with a thickening of the simulation lines from around the year 2030, in which the higher demand simulation runs (one and a half times and doubling of overnight tourist stays) warrants the installation of more renewables capacity to meet this demand. This can be attributed to the local merit order of generation dispatch in São Miguel, where renewables capacity is the preferred choice compared to fossil generation and energy storage, and hence there is a slight matching deviation for installed renewables capacity to meet demand changes.

These results show that tourism will have a low impact on the long-term installed capacities and any impacts, if present, will be concentrated with the generation technology that is favoured for new capacity expansion.

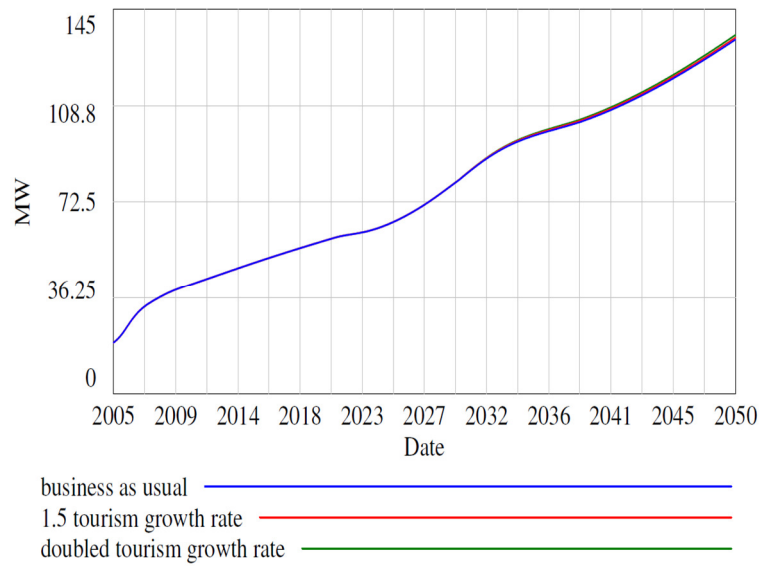


Figure 6.7 Impact of tourism changes on installed aggregated renewable capacity

The corresponding impacts on the accumulated CO₂ emissions and the rate of monthly CO₂ emissions are shown in Figures 6.8 and 6.9 respectively. As expected, the differences in the trajectories of the various scenarios are also negligible. This is due to the fact that the CO₂ emissions are dependent on fossil generation which has shown negligible differences for the various overnight tourist stays simulation runs.

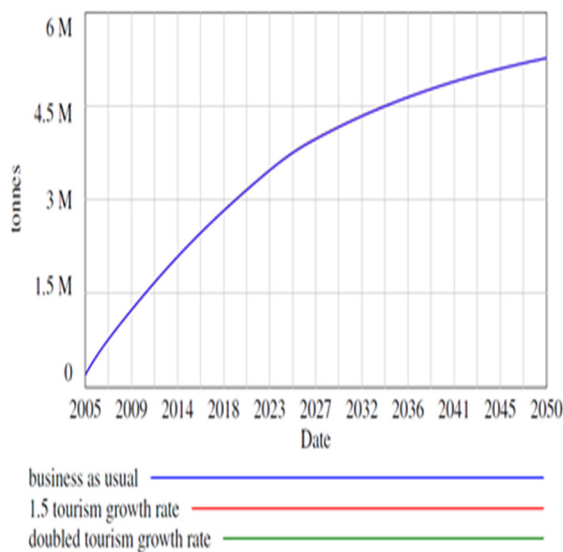


Figure 6.8 Impact of tourism changes on accumulated CO₂ emissions

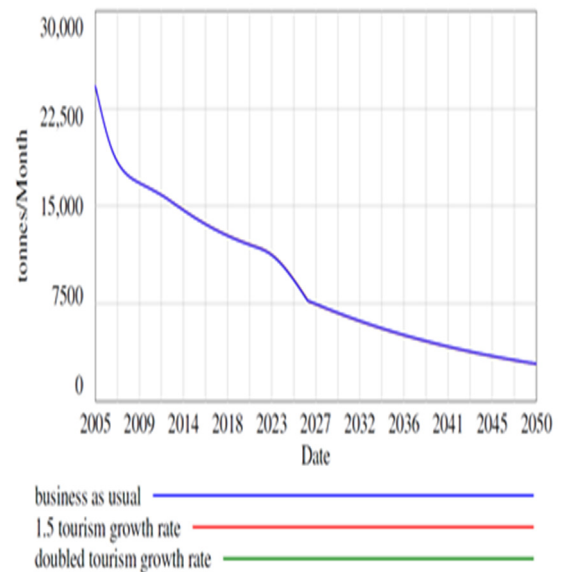


Figure 6.9 Impact of tourism changes on monthly CO₂ emissions

It is observed, as with the “business as usual” scenario, however, that the accumulated CO₂ emissions from the island system are increasing (the accumulated CO₂ emissions stock cannot decrease unless you remove CO₂ from the atmosphere), at a slowing rate, since the amount of fossil generation capacity and monthly CO₂ emissions decreases in general, over time for all three simulation runs.

Energy efficiency measures

Figures 6.10, 6.11, and 6.12 show the impacts of energy efficiency measures on the long-term installed generation capacities of fossil, energy storage, and renewables respectively. The effect of the various simulation runs of doubling and tripling the energy efficiency target (over the 15 years’ timeline) on the installed fossil generation and energy storage is negligible. As in the earlier case of tourism, energy efficiency futures appear to have very little impact on either energy storage or the role played by fossil fuel generation within this island system. The simulation runs in both the fossil generation and energy storage cases appear to be in line with “business as usual” scenario. Additionally, in Figure 6.11 the distinctive energy storage trajectory related to the policy objectives for energy storage and seen earlier in Figure 6.6 is once again replicated within the scenario runs of this section. This phenomena is likely to be expected and the issues related to it will be commented on further later in this chapter in the context of the combined scenarios analysis (i.e. “all policies on”).

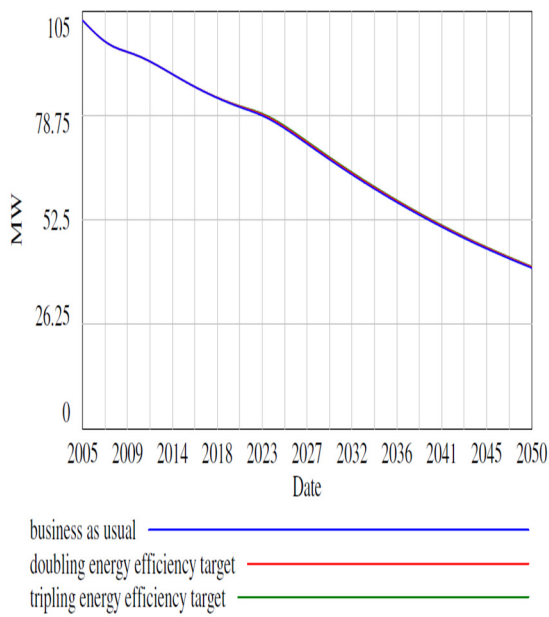


Figure 6.10 Impact of energy efficiency scenarios on installed fossil generation capacity

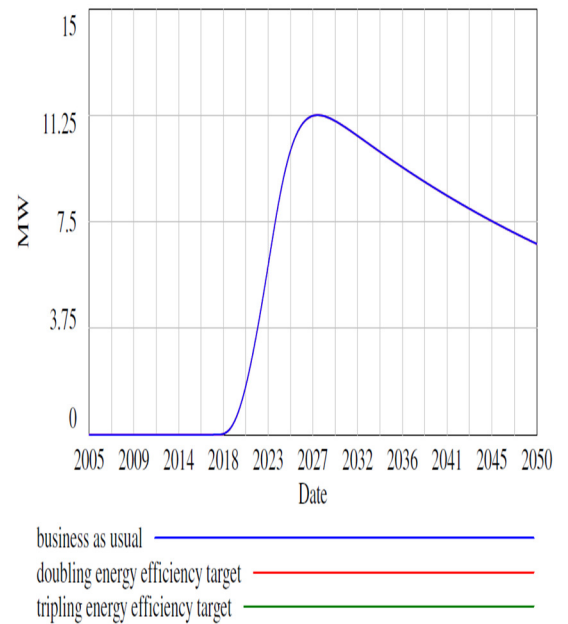


Figure 6.11 Impact of energy efficiency scenarios on installed energy storage capacity

The energy efficiency futures on the installed renewables capacity is much more pronounced as shown in Figure 6.12 than with the energy storage and fossil generation futures discussed above. The installed renewables capacity for the tripling of energy efficiency measure is lower than that of the doubling measure which is lower than the “business as usual” scenario after the 15 years’ timeline for energy efficiency policy. This observation is valid under the assumption that, in the long-term, renewables are the preferred ‘capacity-type’ to be installed within the system. Hence, to satisfy the change in the long-term demand from the varying energy efficiency measures there will be a proportionated change in the installed renewables capacity. The installation changes are not very visible for the earlier part of the simulation until around the year 2023, since the installed capacities during those initial years were sufficient to meet the variations in the demand given from energy efficiency measures. These results reveal that energy efficiency measures will have an impact on the long-term investments and this will be directly applicable to the generation technology that is preferred for capacity installations. In other words, energy efficiency measures

impacts on generation capacity investments are driven by the pre-existing direction of capacity installation policies such as renewables integration.

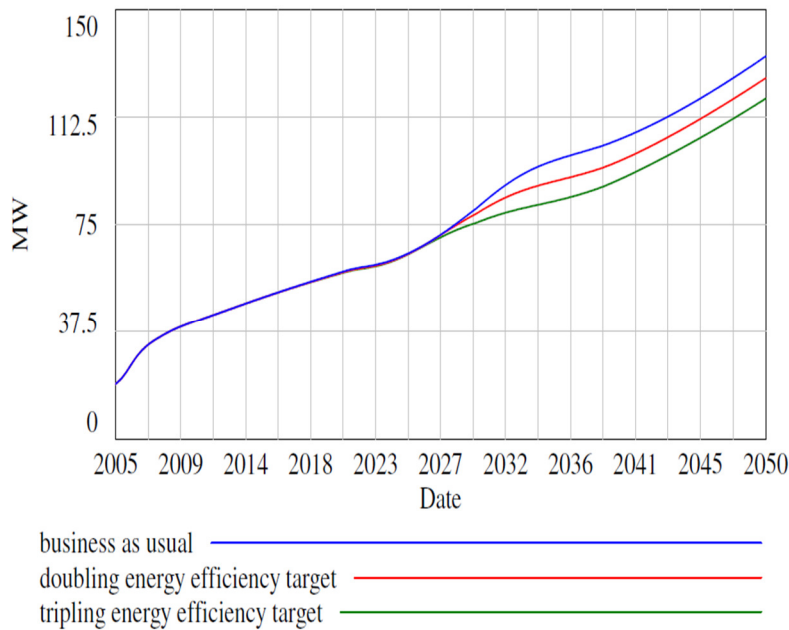


Figure 6.12 Impact of energy efficiency scenarios on installed aggregated renewable capacity

Figures 6.13 and 6.14 shows the corresponding impacts on the long-term accumulated CO₂ emissions and the monthly rate of CO₂ emissions respectively. In both cases, there is a slight dip in the trajectories of the doubling and tripling energy efficiency measures compared to “business as usual”. This dip is most visible during the energy efficiency policy time period 2012 to 2027. The distinctions between the various simulation runs for the monthly CO₂ emissions are more pronounced than with the accumulated CO₂ emissions.

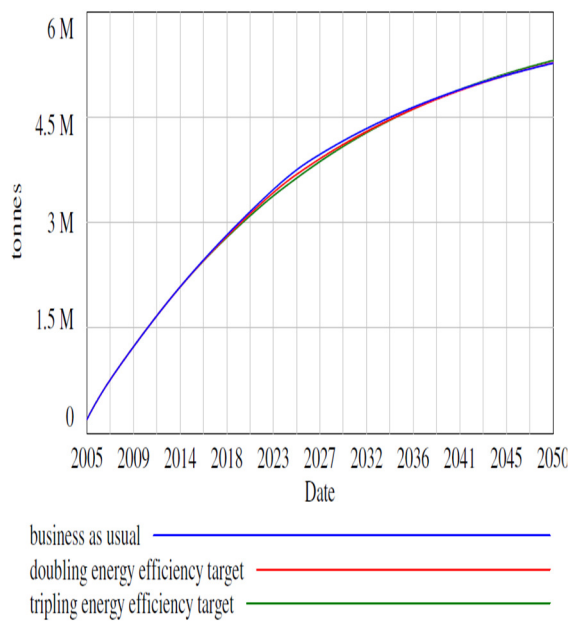


Figure 6.13 Impact of energy efficiency scenarios on accumulated CO₂ emissions

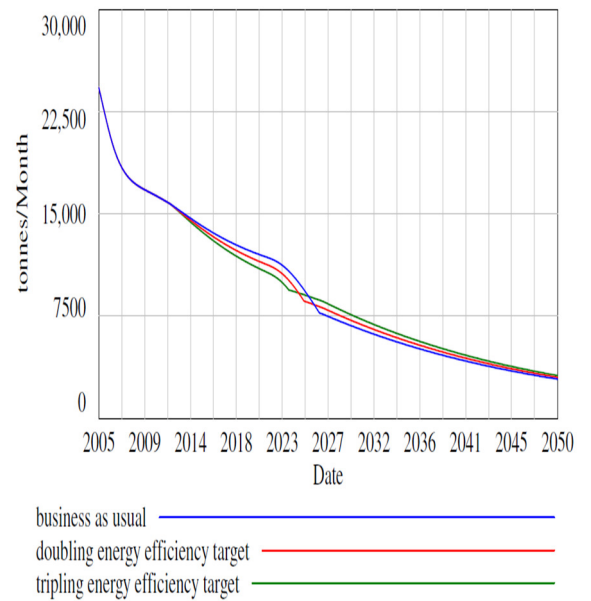


Figure 6.14 Impact of energy efficiency scenarios on monthly CO₂ emissions

The results reveal that with less demand as influenced by higher energy efficiency measures, there will be slightly less monthly CO₂ emissions and accumulated CO₂ emissions within the system. However, after the energy efficiency measures are removed, the system will tend to have increased CO₂ emissions since more fossil generation would now be utilised up to the level of the “business as usual” scenario. This can be attributed to the fact that the demand will again increase after the energy efficiency measures are removed. Hence the fossil generation utilisation levels needed for the frequency balancing of the electricity system is again similar to the levels of the “business as usual” scenario. Note here that the monthly CO₂ emissions are directly related to the actual usage of fossil fuel and not strictly on the installed capacity. Also important here is that the higher demand after the energy efficiency policy measures are removed is satisfied in part by increasing the renewables capacity.

EV expansion

The influences on the installed fossil generation and energy storage capacities of the various EV expansion policies together with “business as usual” are shown in Figures 6.15 and 6.16 respectively. In both cases, and in all scenarios, there are no discernible differences from the “business as usual” scenario in the installed capacities given.

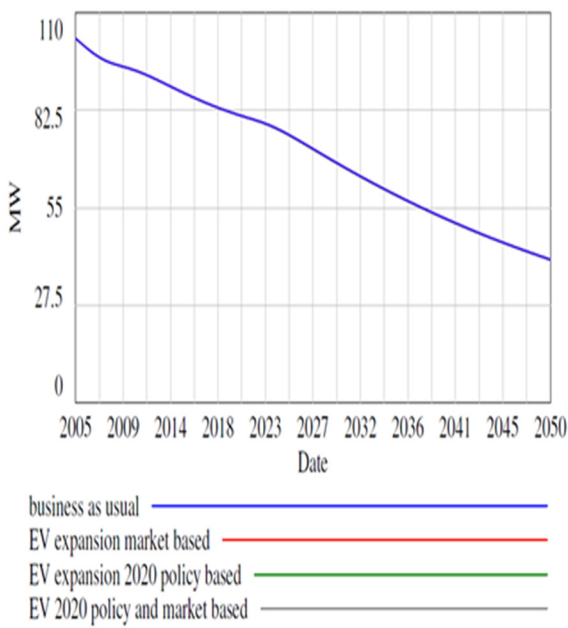


Figure 6.15 Impact of EV expansion policies on installed fossil generation capacity

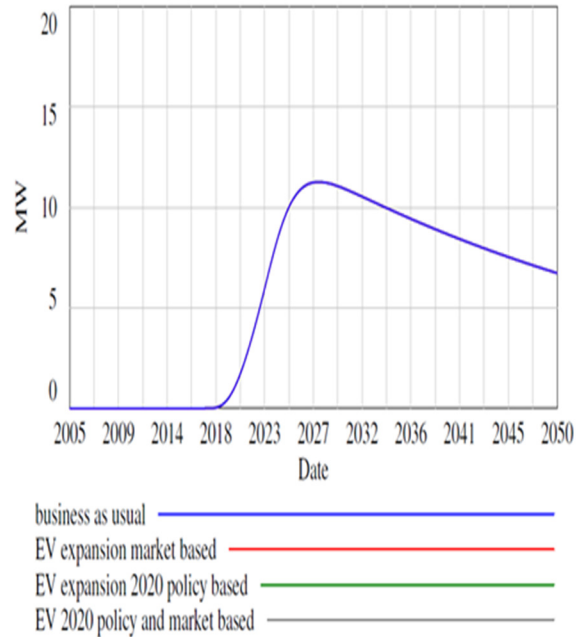


Figure 6.16 Impact of EV expansion policies on installed energy storage capacity

However, as shown in Figure 6.17, there are various visible long-term impacts on the trajectories of the installed renewables capacity for the different EV expansion policies. It can be seen that the combined EV expansion market and 2020 policy (grey line) results in a higher renewables capacity by 2050 than all other scenarios. In addition, for the other scenarios of market-based and only a 2020 EV policy the penetration of renewables has very similar trajectories and hovers around the “business as usual” scenario in the long-term. This result substantiates the assertion of Section 5.4.1, that EV expansion is a key aspect to increasing the renewables capacity of the island system. There is also a slight dip around 2027 - 2032 (highly visible with the combined EV expansion and 2020 policy scenarios) in the amount of installed renewable capacity for the simulation runs with

more EVs (red, green and grey lines). This implies that fewer capacity investments were facilitated up to a point with higher EV penetration (assuming that the EVs have a mainly off-peak charging routine at low load periods as explained in Section 6.2.2 and Chapter 5). This result remains valid where renewables capacity is the preferred generation source for new capacity investments.

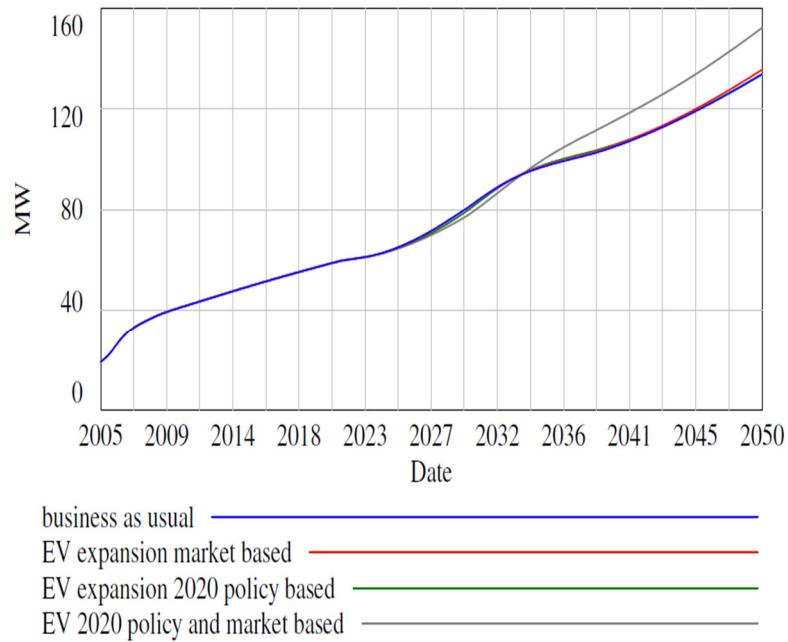


Figure 6.17 Impact of EV expansion policies on installed aggregated renewable capacity

Figures 6.18 and 6.19 show the corresponding impacts of the various EV expansion policies on the long-term accumulated CO₂ emissions and the monthly CO₂ emissions rate respectively. The impacts of the EV expansion policies in both figures are very similar. The combined EV expansion market and 2020 policy proved to have less monthly and accumulated CO₂ emissions by 2050. The other scenarios for the EV expansion policies achieved almost negligible differences in their monthly and accumulated CO₂ emissions by 2050. Also observed is a slightly higher monthly CO₂ emission for the combined EV expansion market and 2020 policy over the period 2020 - 2030. This can imply that slightly more fossil generation was utilised to meet the increase in demand from EVs as the system operators deferred from investment in new low-carbon (renewables) capacity. This

is a short-lived phenomenon over a few years arising from the need to meet higher demand and from delays in new capacity investments.

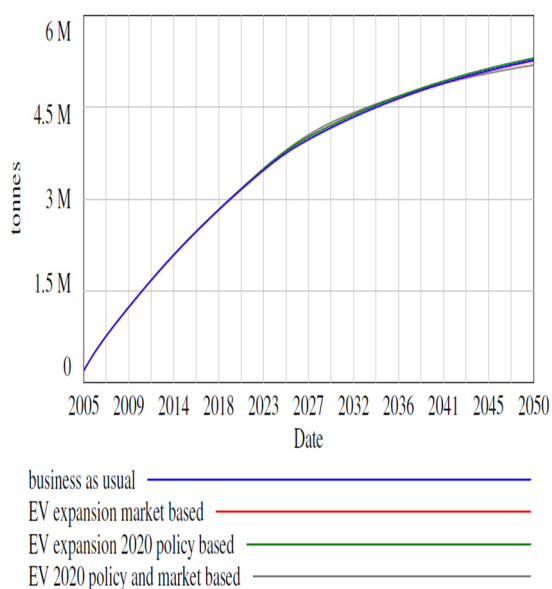


Figure 6.18 Impact of EV expansion policies on accumulated CO₂ emissions

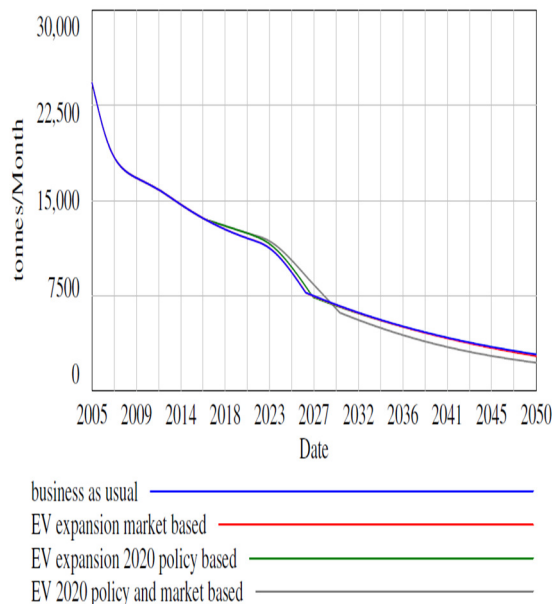


Figure 6.19 Impact of EV expansion policies on monthly CO₂ emissions

Renewables policy

Figure 6.20 shows the effects on the installed fossil generation of changing the renewables policy. For the “business as usual” scenario, the renewables policy seeks to have 45% of the total electricity generation capacity installed in 2005 as renewables by 2020. In addition, this policy implements a 30% reduction of the 2005 CO₂ emissions level. The long-term effect of this policy on the installed fossil generation policy shows a steady decline in installations of this generation source from about 103MW in 2005 to about 35MW in 2050. From these results, it is also seen that the 2030 high renewables policy follows a similar downwards trend but at a higher rate of decline till 2030, at which time it tapers off then settles above the “business as usual” scenario. The 2050 renewables policy implements the renewables capacity and emissions goals of the “business as usual” scenario over the entire timeline (until 2050) of the simulation. The trend shown here is a slight drop in installed capacity, which then gradually increases, and settles at a slightly lower capacity than the

2005 installation value. With such a less aggressive renewables policy implementation the higher amounts of installed fossil generation capacity will stubbornly remain within the system due to the longer timeline of this goal unlike the “business as usual” and 2030 high renewable policy scenarios.

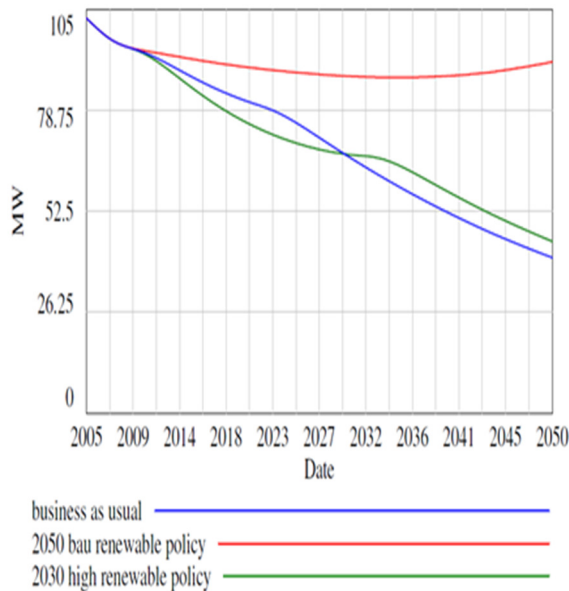


Figure 6.20 Impact of renewable policy on installed fossil generation capacity

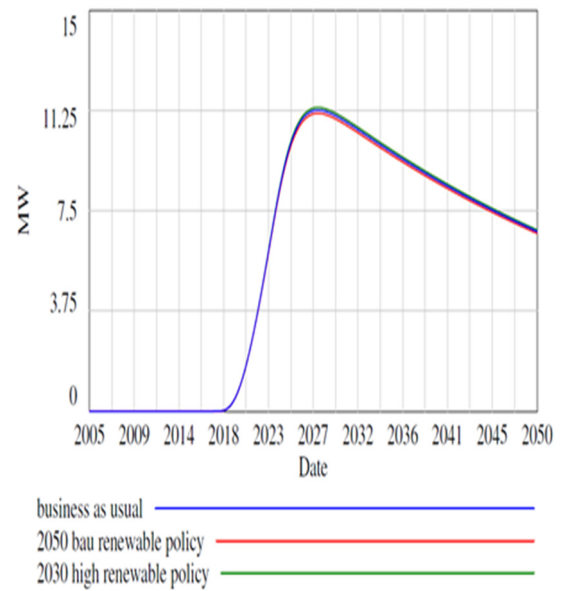


Figure 6.21 Impact of renewable policy on installed energy storage capacity

The impact of the various renewables policies on the installed energy storage capacity is less pronounced as shown in Figure 6.21. Here it is observed that there are small to minimal impacts on the installation of energy storage under these various simulation runs. This can be attributed to the fact that there are separate non-related energy storage policies that guides these installations within the system. However, the minimal impacts revealed from the various scenarios shows that renewables policies have the potential (in the absence of energy storage policies) to impact energy storage capacity in the long term.

Figure 6.22 shows the effects of the various renewables policies on the installed renewables capacity. The “business as usual” and 2030 high renewables policy scenarios shows similar trajectory trends in the quantities of installed renewables within the system by 2050. Within both simulation runs, they are initially s-shaped curves as the desired installations are achieved followed

by further installations to meet the long-term increasing electricity demand. In addition, these s-shaped curves are oscillating after an overshoot SD archetype (Sterman 2000) pg. 121), along the upward trajectory of the installed renewables carrying capacity. Conversely, the 2050 renewables policy simulation gradually increases installed renewables capacity over the timeline of the simulation to about 90MW in 2050. This scenario run had the lowest rate of installations and resulted in the least amount of installed renewables capacity by 2050. This implies that relaxing the renewables policy will have less influence on substantially increasing the quantities of installed renewables capacity.

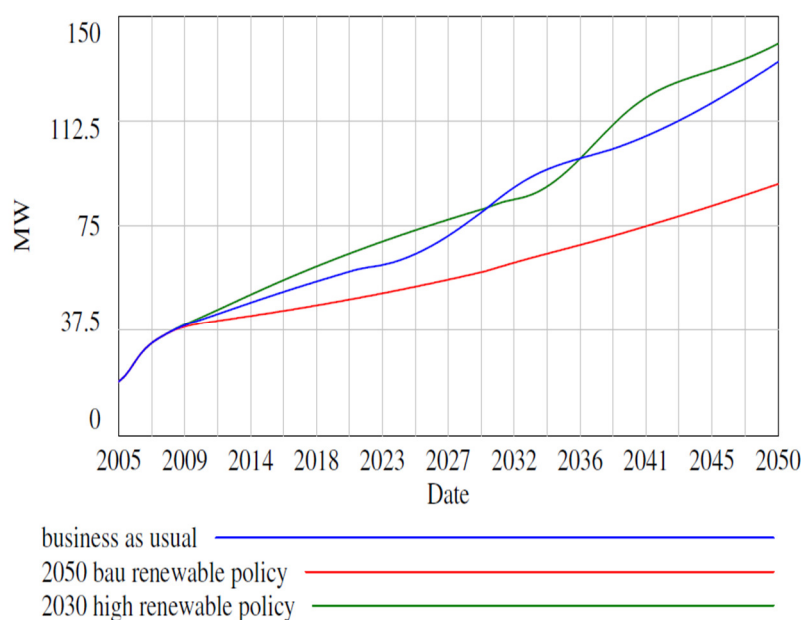


Figure 6.22 Impact of renewables policy scenarios on aggregated installed renewable capacity

Figures 6.23 and 6.24 shows the corresponding impacts of the various renewables policies on the long-term accumulated, and the monthly rate of CO₂ emissions respectively. The “business as usual” and 2030 high renewables policy simulation runs achieved a comparable amount of monthly and accumulated CO₂ emissions by 2050. Although, the 2030 high renewables policy proved to achieve less CO₂ emissions in the shorter term before settling back to the “business as usual” levels of CO₂ emissions. The 2050 renewable policy proved to be a significant source of CO₂ emissions, accumulating about 9 million tonnes by 2050. Also seen is that a high rate of monthly emissions

remains throughout the simulation run. These results reveal that a balance should be found for the appropriate renewables policies. A long-term non-aggressive policy is not to be considered to reduce the environmental concerns of CO₂ emissions. Additionally, slightly aggressive policies such as the “business as usual” can give similar emissions as highly aggressive policies such as the 2030 high renewable policy.

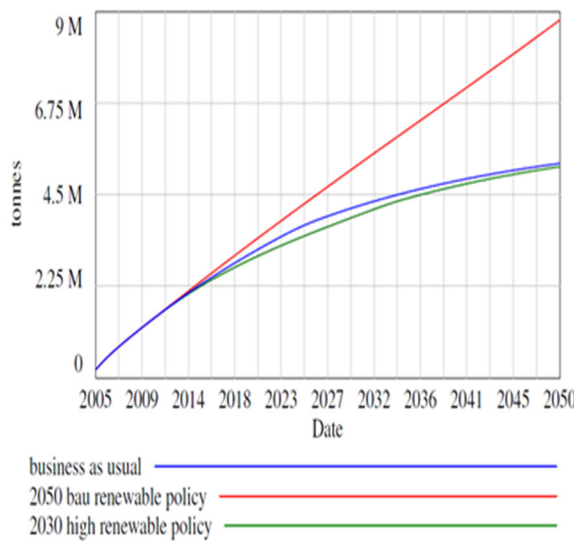


Figure 6.23 Impact of renewable policy scenarios on accumulated CO₂ emissions

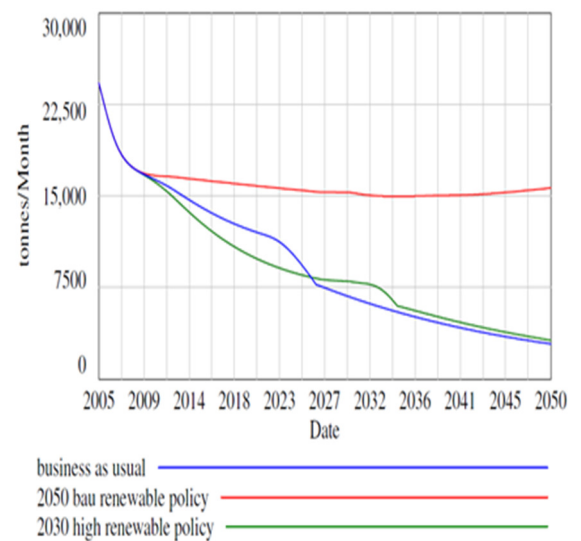


Figure 6.24 Impact of renewable policy scenarios on monthly CO₂ emissions

6.4.2 Combined Scenarios Analysis

The previous section detailed results of individual policies and drivers acting on their own. This section gives a more comprehensive consideration of policies and drivers. A simple approach was taken in which all of the aggressive policies and drivers “all policies high” were simulated at once and compared to all of the less aggressive policies and drivers “relax all policies” being simulated at once. For example, with the aggressive policies and high driver influences the 2030 high renewables policy was combined with the high EV expansion, high energy efficiency measures (18% reduction) and a high tourism growth rate.

Naïvely it would be expected that a combined scenario analysis might reveal profound systemic observations that had previously been missed. In reality, however, what it does is reinforce

observations and conclusions that were already visible within the preceding individual scenario-by-scenario analysis. This reinforcement of the prior observations gives insights into what are the key issues for the future of the system in reality when all real world influences and policies are in place. In addition, this combined scenarios approach can be tested more robustly in a MCMC sensitivity analysis to give model confidence bounds as done in Section 6.5 and within Appendix B2 (to include GDP growth rates sensitivity). Results for the combined scenario analysis were obtained and compared to “business as usual” for the key variables being used for the scenarios of Section 6.4.1. Figure 6.25 shows the effects on the installed fossil generation of the different combined scenario simulation runs. The “relax all policies” simulation run had the most fossil generation capacity in the long-term compared to “business as usual” and to the “all policies high” simulation run which had the least. These results also reflect the results of the high and low renewable policy scenarios from Figure 6.22 implying that fossil generation is highly influenced by the type of renewable policy that stems from the environmental and energy security concerns of the system.

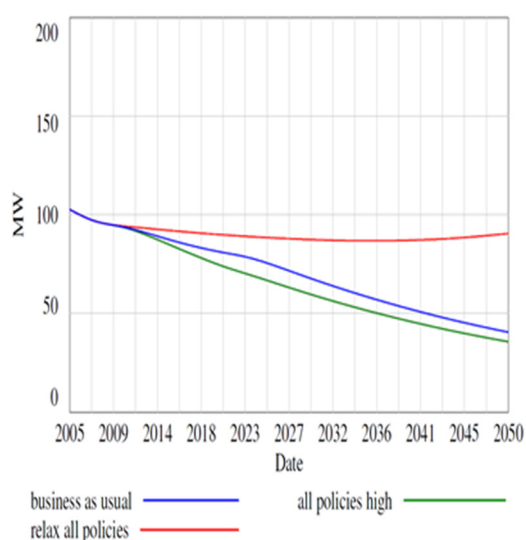


Figure 6.25 Impact of combined scenarios on installed fossil generation capacity

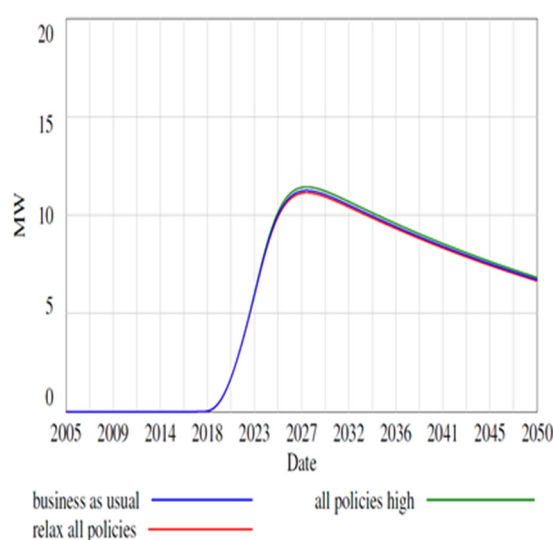


Figure 6.26 Impact of combined scenarios on installed energy storage capacity

Figure 6.25 reveals a range of possible futures for fossil fuel generation but in Figure 6.26 once again it can be seen that a very rigid and distinctive evolution of energy storage occurs. In fact, this reproduces the behaviour seen in all the preceding scenario analyses for the energy storage

variable and hence should be unsurprising. At this point it becomes appropriate to comment fully on the origins of this observed behaviour related to the policy objectives for energy storage within the system. In SD analysis, observations of this type are consistent with the influence of a strong external driver and in this case it is the policy goal for a small reservoir energy storage project on the island to commence in 2018. Hence, energy storage within this model is found not to be endogenously driven by model behaviours. The fact that in all scenarios installed energy storage capacity actually decreases at the end of the policy implies that the policy must be upheld in the long-term in order to sustain energy storage within the system. The result also gives insights that distinct and limited (strict) energy storage policy goals are not affected (if ever, it is minimal) by the other policies existing in the system.

That said, it is important to recognize that this SD analysis does not include the possibility of vehicle to grid electricity storage. It is understood that vehicle to grid could become a major part of electricity storage in the years to come and hence build upon earlier and more traditional policy-led energy storage approaches. But springboard from them, and hence avoid the decline in storage seen in the years after 2025 in Figure 6.26 and elsewhere. Energy storage policies should be more aggressive and possibly aligned with other energy policies such as renewables integration within the system.

Figure 6.27 shows the effects of the combined policies simulation runs on the installed renewables capacity. For these results, “relax all policies” simulation runs achieved the least amount of installed renewables whilst the “all policies high” simulation achieved the highest amount of installed renewables in the long-term. The “all policies high” simulation also achieved a deeper penetration of renewables most likely driven by the renewables policy and aided by the high influx of EVs (almost 25% more than “business as usual” by 2020) within the earlier years of the simulation. These results also reflect the high and low renewable policy scenario results of Figure 6.22. This implies, as with the installed fossil generation capacity, that the installed renewables capacity is

strongly influenced by the existing renewables policy. The oscillations within this simulation run as seen for the renewables policy scenario in the previous section provides some evidence of the influence of renewables policy on the renewables capacity installed. This is evidenced from the s-shaped archetypes (of the balancing effects) of the various (2030 and 2050) goal-seeking targets of the renewables policy. In addition, it can be seen that a high penetration of renewables can still exist even under high energy efficiency measures and EV expansion within the system. Conversely, it can be seen that a lower penetration of renewables capacity can exist with weak energy efficiency measures.

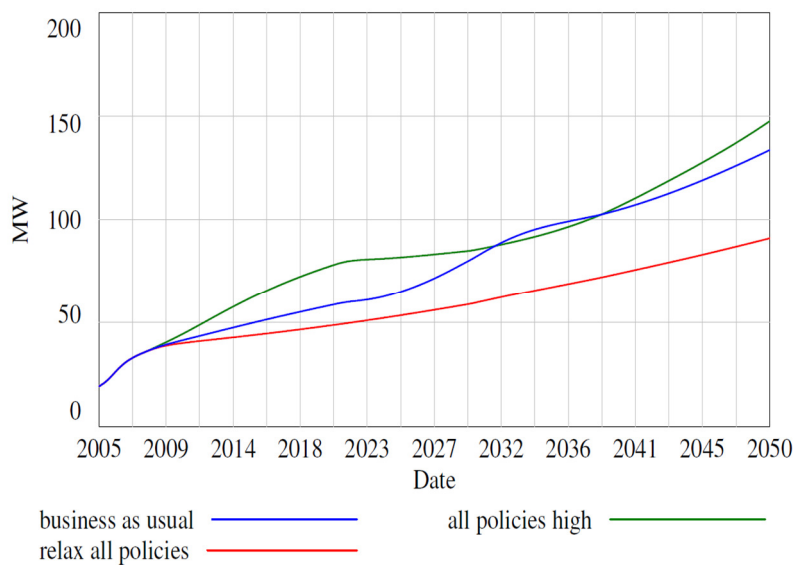


Figure 6.27 Impact of combined scenarios on aggregated installed renewable capacity

Figures 6.28 and 6.29 shows the corresponding impacts of the combined scenarios simulation runs on the long-term accumulated, and the monthly rate of CO₂ emissions respectively. The “business as usual” and “all policies high” simulations achieved a comparable amount of monthly and accumulated CO₂ emissions by 2050. However, the “relax all policies” simulation run was very weak in reducing the monthly amount of CO₂ emissions, which actually began to increase by 2040. In addition, the accumulated levels of CO₂ emissions was the highest (80% to 90% more than the other simulation runs) for the “relax all policies” simulation in 2050. The “all policies high” simulation was able to hinder the continuous long-term increases in CO₂ emissions and have the least amount by

2050. These results indicate that an approach of not being aggressive with energy policies in the island system will hinder the environmental and energy security objectives of the system. However, policies do not have to be overly aggressive since similar environmental objectives can still be achieved with slightly less aggressive policies similar to “business as usual”.

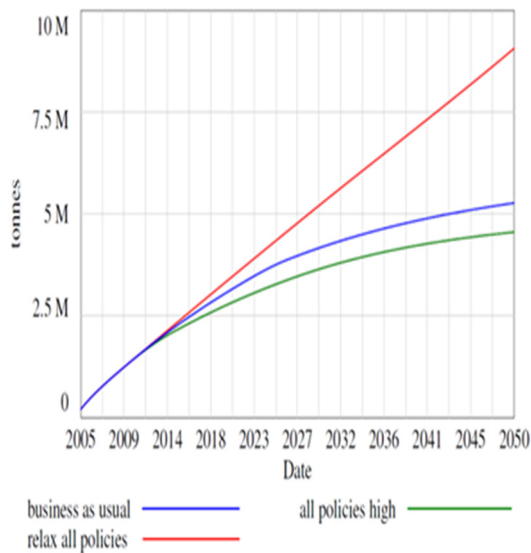


Figure 6.28 Impact of combined scenarios on accumulated CO₂ emissions

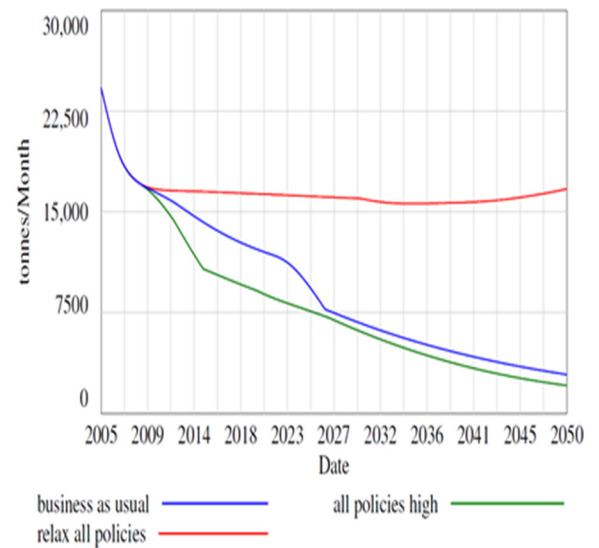


Figure 6.29 Impact of combined scenarios on installed energy storage capacity

The choice and balance of the policies for the environmental and energy security concerns is an imperative for the system and strongly influences pathway and investments for reducing these concerns. The next section gives a simplified view of the influences of the financial driving force that can exist within the island system for capacity investments.

6.4.3 Profitability Impact on Capacity Investments

In the previous sections of the model analysis, the focus is directed to the policies that exist/can exist for meeting environmental and energy security concerns. It was observed that the installed renewables policies are very influential within the system and that the installed capacity can exhibit S-shaped growth with overshoot and oscillations. In this section, the financial attractiveness linked to the profitability of the installed capacities is used to gauge the impacts within the installed capacities of the system. The only difference from the previous analysis scenarios is the use of high

electricity tariffs for the “business as usual” scenario (fixed at double the 2005 tariffs shown in Table 6.3).

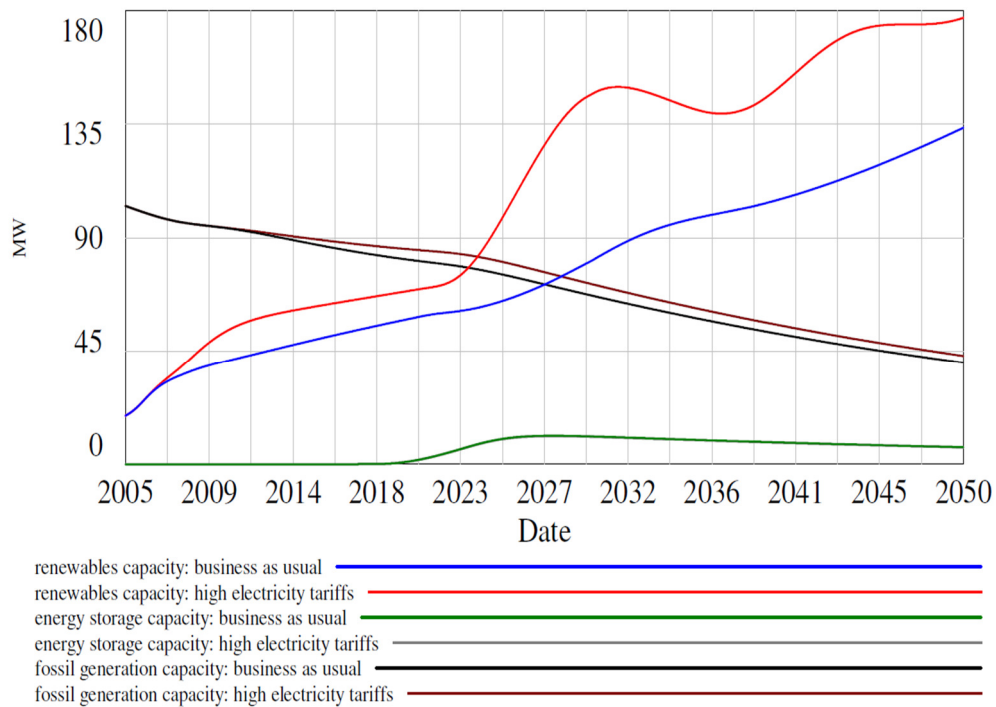


Figure 6.30 Impact of increased profitability on installed capacity

Figure 6.30 displays the sensitivity of the increased profitability on the investments in the different installed capacities. The investments in energy storage showed no changes in capacity investments with the high electricity tariffs. This is again due to the fixed energy storage policy for capacity, as noted in Section 6.2.1 hence no investments are made with excess revenues available. Also shown is the fossil generation investments downwards trajectory which is not changed but there is a greater delay in the removal of installed fossil generation from the system. This can be due to installed fossil generation remaining slightly more financially attractive than in “business as usual” due to the higher financial prosperity of the electricity company from the excess revenues collected with the higher electricity tariffs.

For the installed renewables capacity, the investments within this capacity were increased under high electricity tariffs. A lot more renewables capacity was installed in the long-term, by 2050. A more prominent S-shaped growth with overshoot SD archetype (Sterman, 2000) is also visible. This

red curve have pronounced periods of high renewables growth then a slowdown and this phenomena is repeated for the timeline of the simulation. These occurring oscillations, however, appear to be damped which indicates that there might be some local stability for the trajectory of the installed renewables capacity. A strong indicator that the cycles necessary for the renewables investments is constrained by a negative feedback probably link to the financial upkeep of the new installations. Additionally, this phenomena might be also linked to the environmental and energy security driven renewables policy goals of the system. Taking this into account, it can be said that the financial viability of the electricity company can provide for a greater penetration of low-carbon, however, the low-carbon policies should be focused upon for quicker damping (as shown by the “business as usual” simulation run) of the probable oscillations this might result in impact the system.

The detailed sensitivity analysis of the model to include expected revenues are shown in Appendix B2. However, the next section gives the long-term confidence bounds and sensitivity of the model to the various policy scenarios simulated in both Sections 6.4.1 and 6.4.2.

6.5 Confidence Bounds of Synthesis Modelling Policy Analysis

This section details the results on the confidence bounds of the installed capacities for the disaggregated renewable sources together with the fossil generation and energy storage. In addition, the confidence bounds for the accumulated CO₂ emissions are shown. These results are obtained by applying the standard Vensim multivariate MCMC sensitivity analysis as applied to the policy scenarios discussed in Section 6.3 and for varying, the average consumption for nightly tourist stays. A total of 200 simulations were conducted, with the program randomly selecting values from the sensitivity ranges of the parameters shown in Table 6.5. The switches¹⁴ used for model implementation in the Vensim software for the EV expansion were also activated.

¹⁴ Switches are implementation within the Vensim software for turning on and off policy/specific implementations within the model using a binary (1) on and (0) off concept.

Variable Name/Unit	Base value	Sensitivity ranges
avg consumption per tourist-night stays/ MW*h/night stays	0.0027	0.0020 - 0.0035
tourist stays growth rate/ %/Month	0.14	0.07 - 0.28
energy efficiency reduction/%	6	6 - 18
renewables policy portfolio/%	45	45 - 75
renewables policy timeline/ Months	156 months	156 - 506 (for 13 - 42 years)
CO ₂ emissions target/ fraction	0.3	0.3 – 0.5
Time to meet EU CO ₂ emissions target/ Months	180 months	180 - 540 (for 15 - 45 years)

Table 6.5 Important variables for the policy sensitivity analysis

The results displayed in the following graphs shows the confidence bounds as coloured bands using the percentiles of 50%, 75%, 95% and 100%. For example, a 75% confidence bound (green) indicates that 75% of all sensitivity runs fall within the top and bottom green bands (to include the 50% yellow band), 90% within the blue bands and 100% within the grey bands. The resulting range of possible outcomes for the capacity installations of the different technologies and the accumulated CO₂ emissions of the system under the given ranges of these policies are shown in the following graph, Figure 6.31.

Figure 6.31 displays the range of outcomes in MW for the installed capacities of the disaggregated renewables capacity of the system. The base-load renewables such as geothermal and run-of-river hydro have the largest (possible) installed capacities outcomes. Geothermal is bounded within a higher range than the run-of-river hydro. The other renewables such as biomass, wind and micro/mini generation (solar) are bounded within lower ranges of installed capacities.

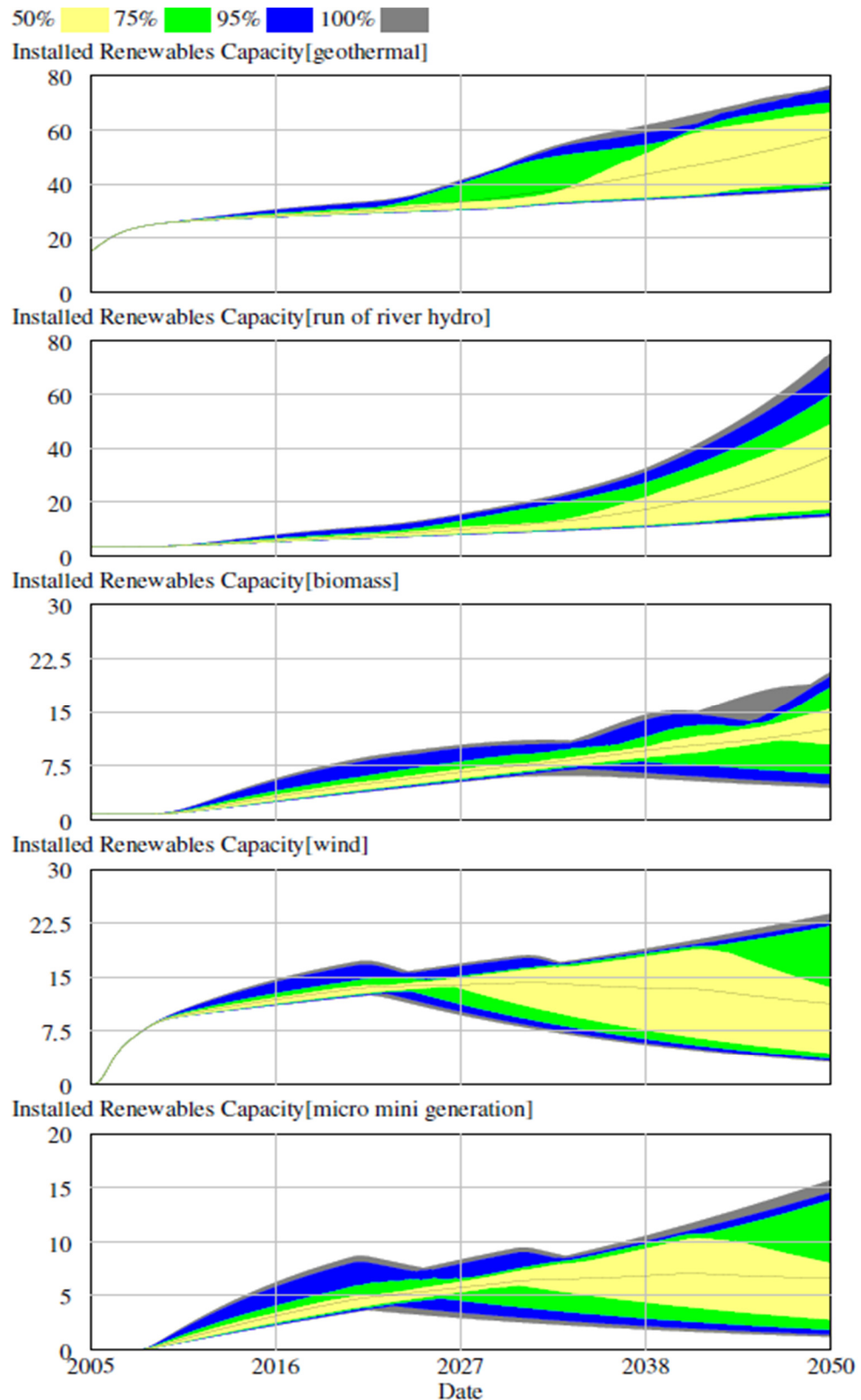


Figure 6.31 Sensitivity of the installed disaggregated renewables capacity

This implies that the base-load renewables will be more prominent in the long-term than the more intermittent renewables (the limits to their installations can be restricted by the availability of the

respective heat and water resources within the island). Although biomass is not an intermittent renewable source it is observed that it struggles to compete with the more familiar (learning-by-doing) and cost-effective base-load renewables in the long term.

Figure 6.32 shows the range of possible outcomes of the aggregated renewables capacity by 2050. This graph is the accumulated reflection (summation) of Figure 6.31 as all of the individual renewable sources are combined to show the confidence bounds of the total amount of possible renewables to 2050 under these scenarios. The figure shows that the confidence bounds are aligned with an increasing trajectory. This observation implies that in the long run under any combinations of the various policies of Section 6.3 there will be increased renewables capacity.

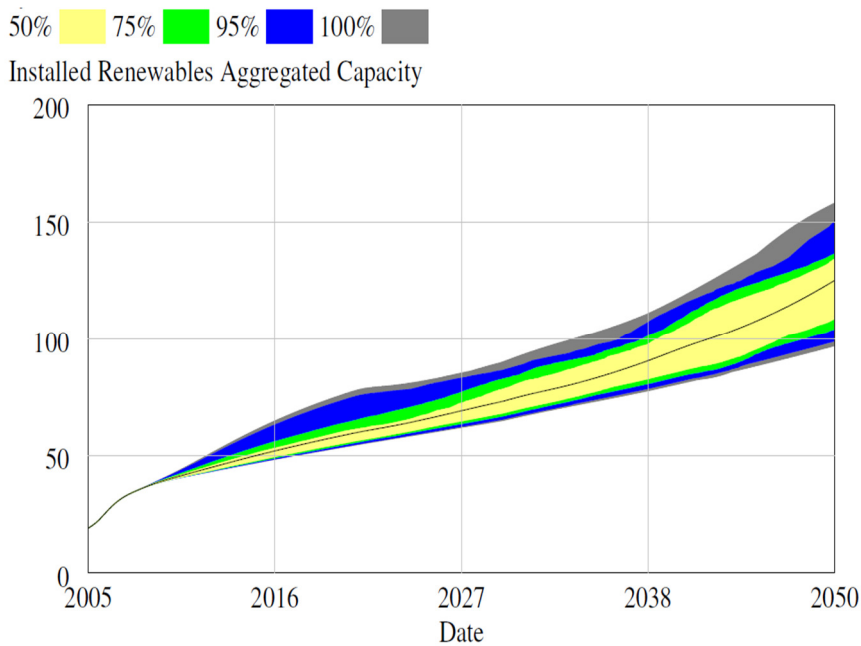


Figure 6.32 Sensitivity of the installed aggregated renewables capacity with various policies

Figure 6.33 displays the range of possible outcomes of the installed energy storage capacity by 2050. From this figure, we can conclude that energy storage will be tightly bounded by 2050 under these various policies. The observations stem from the fact that energy storage within this system is driven by a singular policy, as detailed in Sections 6.3 and 6.4.2. However, variations to this policy to embrace the effects of renewables will lead to larger ranges of outcomes as shown in Appendix B2 for the detailed sensitivity analysis of the model.

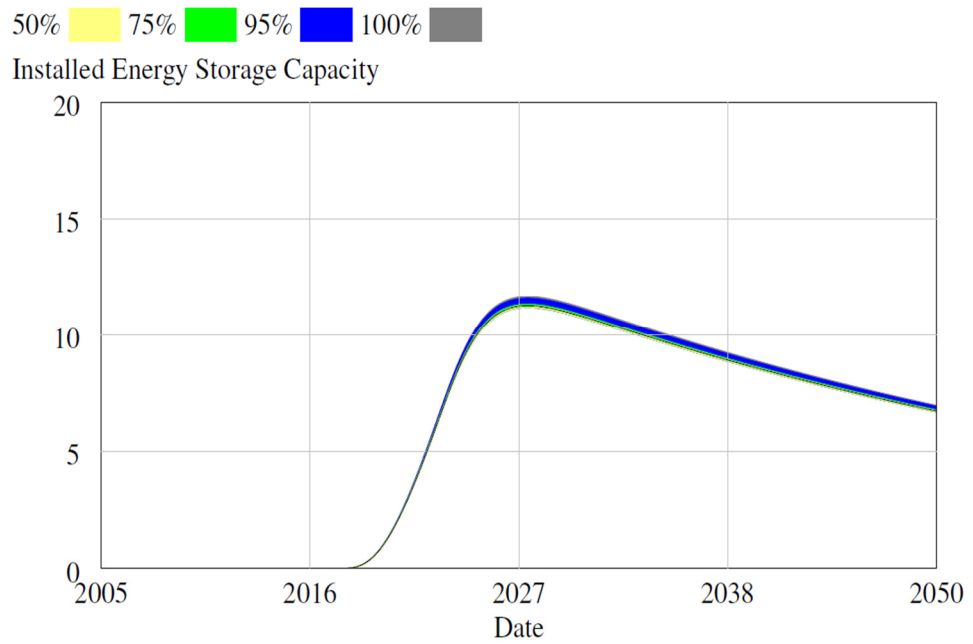


Figure 6.33 Sensitivity of the installed energy storage capacity with various policies

The following figure, Figure 6.34, captures the range of possible outcomes for the installed fossil generation and shows that, in the long term, there will be a decreased amount of capacity installed from fossil generation. This observation implies that in the long-run, any combinations of the

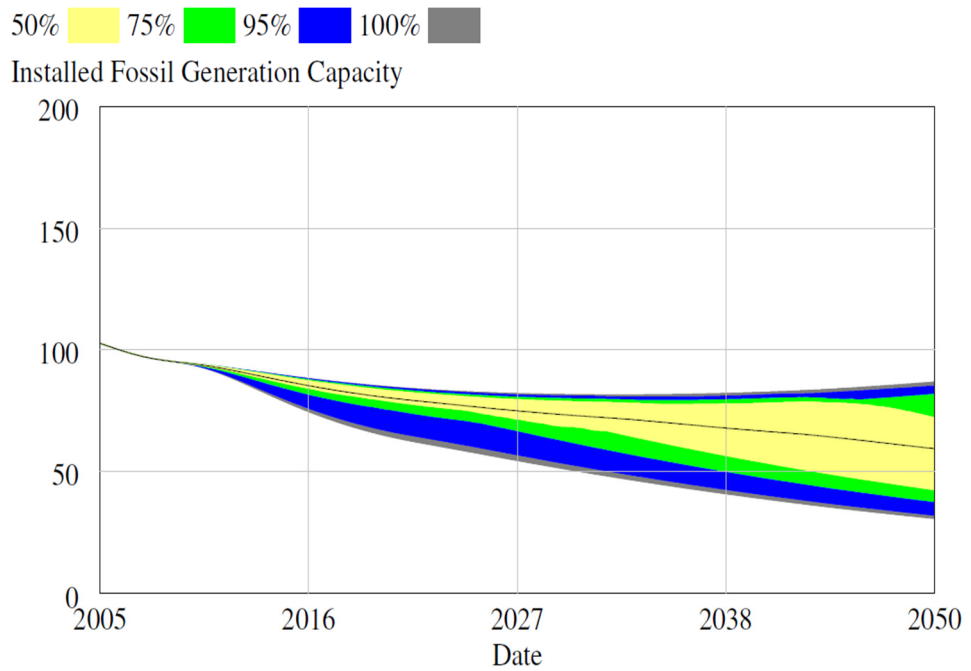


Figure 6.34 Sensitivity of the installed fossil generation capacity with various policies

various policies of Section 6.3 (considering the results from the “relax all policies” and “all policies high” simulation runs of Section 6.4.2) will lead to a decreased amount of fossil generation capacity by 2050. Also observed is the wide range of installed fossil generation by 2050 which implies that the policies applied to the system for larger removal of fossil generation should be closely aligned to the lower part of the range of possible outcomes (driven by the renewables policy) shown in Figure 6.34.

Figure 6.35 gives the range of possible outcomes for the accumulated CO₂ emissions until 2050. This range of possible outcomes is bounded over a very large range and is guided by the large range of possible outcomes of the installed fossil generation within the system.

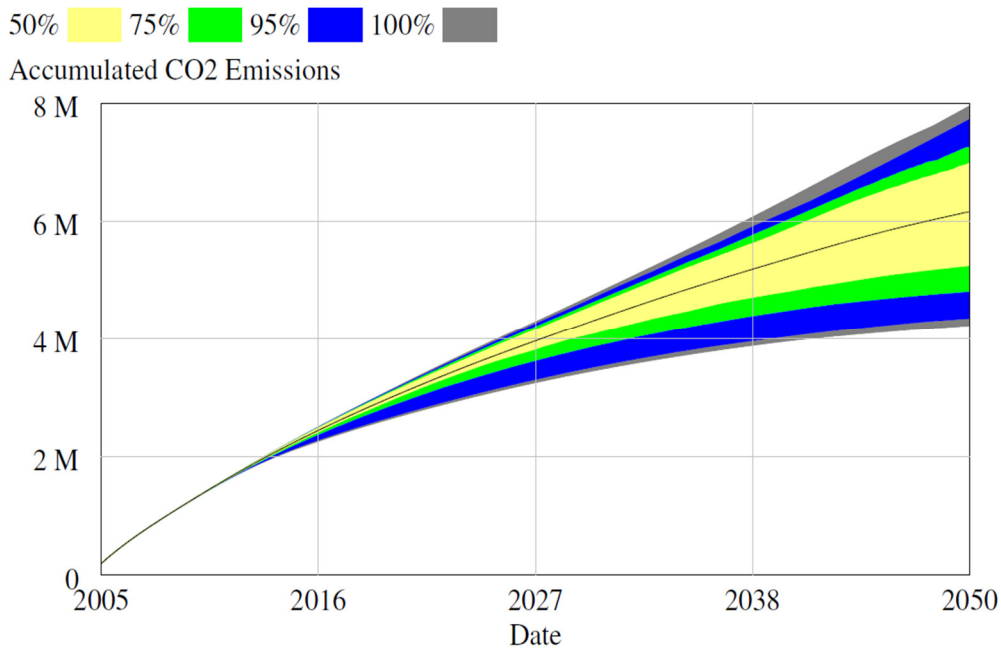


Figure 6.35 Sensitivity of the accumulated CO₂ emissions with various policies

This observation reinforces the fact that the correct policies must be adhered to in order to minimise the environmental effects of CO₂ emissions from the system. Policies that keep the installed fossil generation lower, in the long run, will thereby keep the accumulated CO₂ emissions lower and prove to be the best choices for a low-carbon evolving isolated electricity system.

These confidence bounds for the policy scenarios gives a view of the wide ranging possible outcomes that each of the key variables examined can experience in the long term. The next section details the key investment and environmental implications for the island system as observed from the analysis and results of this and the previous sections.

6.6 Long-term Investments and Environmental Implications

The key stakeholders responsible for the investments and policy of the electricity system are expected to ensure a sustainable electricity supply. In so doing, they are faced with a requirement to lower the CO₂ emissions while providing secure electricity supply. Hence, there is an incentive by policy makers and key stakeholders to explore policies to sustain the renewables uptake and, at the same time, a sustainable capacity mix (insulated from fossil fuel dependency). This pursuit of low-carbon policies within island electricity systems has many benefits but also provides challenges. Further inspection of the modelling and policy analysis used in Sections 6.4 and 6.5 provide a basis to understand the implications of environmental factors and energy security concerns on the long-term capacity investments within these isolated island systems.

It is observed that, in the long term, the capacity mix will be endowed with an increasing amount of renewables capacity and a decreasing amount of fossil generation capacity within the various individual scenarios. Even under the scenarios such as tourism which are not focused on CO₂ emissions, there is still an inherent loss of fossil generation. This is due to the current focus on renewables integration and reinforces the fact that the capacity mix will move from a fossil fuel base to a low-carbon base. It also follows that in the long term; the monthly and total accumulation rate of CO₂ emissions is expected to decrease. Hence, the environmental challenges of tackling global warming and climate change will be less. However, the effects of this reduction on the global scale will be very small compared to a proportional reduction by larger developed nations. Hence, the desire to be a part of the common agenda to reducing the effects of climate change can be the incentive that is sought after by smaller isolated island systems. In addition, removing the energy

security import dependency on fossil fuel will drive a renewables agenda. The long-term outlooks for the isolated island electricity system low-carbon capacity mix and resulting environmental concerns will be driven by policies to reduce CO₂ emissions and fossil fuel import dependency, particularly the existing renewables policies.

Following account, it is important to note that this low-carbon base of installed capacity is preferred. The difficulty lies in sustaining the quantities of renewables within the capacity mix. For all the policy scenarios, it is observed that a high penetration of EVs gives the highest installed renewables capacity by 2050. In addition, EV expansion in its correct quantities can delay capacity investments in the shorter term and then encourages this higher penetration of renewables in the long term. Energy efficiency measures also reduce the need for capacity investments and the quantity of installed renewables capacity by 2050 is lowest in the electricity system with highest energy efficiency measures. It is also observed that with aggressive renewables policy there is a pronounced decrease in the rate of fossil generation. The resulting accumulated CO₂ emissions also show the largest deviations from current trends and hence even less environmental consequences, unlike the least aggressive renewables policies. According to Figure 6.31, it is also observed that, in the long term, base-load type renewables such as geothermal and run of river prove to be more valuable to island systems than non-base load renewables such as wind and solar. In addition, with restrictive energy storage policies, it can be seen that installed energy storage capacity will play less of a role in the long-term capacity mix, with negligible changes from other factors apart from the renewables and EV expansion policy influences.

These observations reveal that policymakers and investors should be aware of the long-term consequences of their actions and ensure that the possibility of the outcomes will be those desired for the island system. It is seen that the capacity investments within the system and the environmental implications are intertwined and depend heavily on the focus of the policies within the system. In addition, the financial viability of the system can lead to higher oscillations within the system capacity (low-carbon) which can lead to unwanted oscillations on its own but is damped

by the policies. Hence, with the right mix of policies, the investor decision making can be improved and the desired low-carbon based capacity mix can be achieved.

6.7 Conclusions

This chapter presents the synthesis model, which is a combination of the previous three sub-models, and thereby research sub-question 4 of this thesis has been achieved. The work integrates the most critical challenges as environmental and energy security concerns converge for the isolated island electricity system. It has been seen that the low-carbon policies of EV electrification and renewables integration are important for sustaining the uptake of renewables within the generation capacity mix. In addition, the fossil generation capacity will be substantially removed from the generation mix in the long-term whilst base-load type renewables (such as geothermal and run of river) will play a bigger role in the future of these systems, unlike more intermittent and variable sources such as wind generation. As a consequence CO₂ emissions and their environmental impact will also be much reduced in the long-term. In general, by giving the new details from this chapter for the policy and endogenous technology-specific (disaggregated renewables, fossil fuel, and energy storage) long-term economic attractiveness these insights were obtained. Also seen is that a focus on financial viability will oscillate (with high uncertainty) the installed capacities of the generation technology that is favoured within the system, hence a mix of policies is useful for these electrically isolated island systems.

Following account, the key dynamics surrounding the uptake of renewables within the isolated island system is presented within this chapter giving prospective solutions for the long-term investment strategies of emerging low-carbon island electricity systems. Demand-based policies such as tourism and energy efficiency will have low impacts or decreased effects on the long-term installed capacities of the system. Any impacts, if present will be concentrated on the generation technology that is favoured for capacity expansion within the system (low-carbon renewables). This

enhances the energy security of the system and contributes to a more environmentally friendly outlook for the system in the long-term.

Electrification with EVs is seen to sustain the uptake of renewables, particularly base load type renewables in the long-term, but it also increases the long-term demand although it can aid in deferring capacity investments in the shorter-term. The increase in renewables is due to the increase in electricity demand created by a larger number of EVs and this demand is met by capacity from renewable sources. The environmental benefits are also great. Also seen is that energy storage will need more aggressive long-term policies in order to be sustained within the generation mix and the concept of vehicle to grid is probably needed for future storage increases.

Additionally, it is seen that, in the long-term, investment in fossil generation is non-existent however it stubbornly remains within the generation mix. This persistence of fossil fuel generation is attributed to the fact that it is needed for the frequency balancing of the electricity system so cannot be completely removed from the system. Innovations in low-carbon frequency-balancing generation sources such as done by Martínez-Lucas *et al.* (2016) and Inoue, Genchi and Kudoh (2017) can play a large role in further decreasing the environmental impacts and in enhancing the energy security of the system. The next chapter will provide the necessary insights gained from this modelling work, give directions for future work, and summarise the main conclusions of this thesis.

Chapter 7. Summary and Conclusions

This final Chapter brings the conclusions from the previous chapters of the thesis together. The fulfilment of the research work set out for the thesis is firstly established and the associated key findings are detailed. The main research contributions are then presented together with the policy and investment implications which highlight the high-level conclusions, novel contribution and the generalisation of the research work. Suggestions to future work are subsequently given followed by a reflective final summary.

7.1 Summary of Key Findings

The vast majority of countries around the world have embraced a path of addressing the future security of their electricity supply in light of the environmental concerns of the existing legacy systems. Extensive efforts are aimed at understanding the expected transition into low-carbon electricity systems of today and the future. It is anticipated that these systems will eventually evolve from smarter low-carbon systems to become the smart grid electricity systems of the distant future. A holistic view of the socio-techno-economic aspects of the existing complex system in light of the low-carbon policies and investments of the system will enrich stakeholders with the necessary insights and provide them with benefits of an evolving electricity system.

The research presented in the previous chapters contributes to the existing literature on transitioning low-carbon electricity systems in the context of energy security and environmental concerns for isolated island systems. It seeks understanding to the question:

What does the convergence of environmental and energy security concerns imply for small isolated electricity systems?

To answer this overarching research question, the following was done:

- The research objectives were explored within the context of four research sub-questions.
- A pragmatic range of low-carbon policies, influences and key aspects such as electric vehicles were emulated to give light into the long-term trends and behaviours of important aspects (such as generation capacity investments) of the system.
- A novel policy and investment analysis framework, akin to an IRP process was developed for the complex causal system dynamics that exists within such systems.

Firstly, in Chapter 4 the thesis explored the capacity investment structure of existing electricity systems, in which a simplified fossil generation only system is assumed. This was done within the context of the sub-question:

1. *How are fossil-fuel-based island systems influenced by electricity demand and capacity margin standards?*

Key findings are summarised:

- Large capacity margins in the island system are a critical, but not a desired, driver for the fossil fuel generation capacity investments.
- The electricity demand forecast is a necessary driver for capacity expansion within the electricity system
- Fossil generation capacity investments are driven by the need for new capacity (electricity demand) and not by financial incentives.
- The security of electricity supply (fossil fuel import independence) for such systems is enhanced by careful inspection of the capacity margin and demand growth rate of the system.

Also found in Chapter 4, is the analysis of the process and influences of renewables integration via low-carbon policies on the existing fossil generation capacity. The effectiveness of these policies for long-term renewables capacity investments was examined. This was achieved by answering sub-question two.

2. *How effective are low-carbon policy targets within a small isolated island electricity system?*

The key findings and answers to this question follows:

- It was observed that local renewables installation targets are very influential for the renewables capacity investments in the system.
- Setting short-term very high targets within an island electricity system is not very productive since meeting these targets early is inefficient or impractical if the targets are just too high.
- There are increased emissions reductions benefits by having more aggressive targets.
- The financial health of the system can possibly be jeopardised due to higher investment costs needed over a short period of time trying to achieve aggressive targets (seen as oscillations in Chapter 6 representative of boom bust cycles).

Chapter 4, in answering the two subquestions above, also supports the idea of Jamasb, Nuttall and Pollitt (2008) that island systems typically suffer from a weaker innovation landscape and have limited opportunities for learning-by-doing cost reductions. In addition, it lends to the idea that setting successful renewables targets should be further investigated for such systems.

Chapter 5 provided the long-term trends of pragmatic influences and low-carbon policies on the endogenous electricity demand of the system. The most influential and efficient low-carbon policies for the long-term endogenous demand were identified within the context of the following sub-question.

3. *How is electricity demand endogenously influenced by low-carbon policies, and what are the long-term implications on isolated islands?*

Key findings are summarised:

- Energy efficiency remains the most powerful for guiding the long-term demand dynamics and for safeguarding the energy security of the system.

- EV expansion is found to be potentially more interesting in terms of the long-term demand impacts compared to both tourism growth and energy efficiency measures.
- EV expansion presents electricity demand uncertainty challenges for policymakers.
- It is shown that isolated island systems with a low economic share of tourist activities are largely unaffected by energy-related policies which focus solely on tourism (within the hotel builds assumptions used in the model).
- Island systems that has a relatively large share of demand based on tourism might show greater influence of tourism changes on the long-term electricity demand.

To answer the final sub-question, the sub-models from Chapters 4 and 5 are brought together and analysed in Chapter 6 for answering the question.

4. *How can energy policy and investor decision-making be improved by system dynamics insights?*

In answering this question this chapter integrated the key endogenous socio-techno-economic transitional factors typical to the structure of low-carbon island electricity systems. The holistic, system dynamics view for the long-term capacity investments and policies within these evolving low-carbon based systems driven by the environmental and energy security concerns are subsequently captured.

The following key findings and answers to the question are highlighted:

- Low-carbon policies of EV electrification and renewables integration policies are important for sustaining the uptake of renewables within the generation capacity mix.
- EV expansion in appropriate quantities can defer capacity investments by 5-10% in the shorter term whilst however increasing the amount of renewables capacity in the longer-term.

-
- High penetration of EVs gives the highest installed renewables capacity by 2050, up to 30% more than the installed capacities of the highest energy efficiency measures (reduces the need for renewables capacity investments) which gives the lowest by 2050.
 - Fossil generation capacity will be substantially removed from the generation mix in the long-term whilst base-load type renewables (such as geothermal and run of river) will take on a bigger role unlike more intermittent and variable sources such as wind generation.
 - It was observed that CO₂ emissions can be much more reduced, by up to 50%, along with its environmental impacts in the long-term for the system.
 - Energy storage policies should be more aggressive and possibly aligned with other energy policies in order to sustain energy storage within the system in the long-term. For the use of restrictive energy storage policies, the installed energy storage capacity will play less of a role in the long-term capacity mix.
 - The financial viability of the electricity system can oscillate (more uncertainty) the installed capacities of the low-carbon generation (generation technology that is favoured within the system) in the long term in the absence of low-carbon policies.
 - A mix of low-carbon policies is useful for isolated island systems since the renewables policies act as a damping mechanism for the renewables capacity investments.
 - It is also inferred that for a deeper penetration of low-carbon renewable sources within the island system, energy storage has a bigger role to play and the frequency balancing of the electricity system needs to be provided by low-carbon sources such as fly-wheels (although not correctly applicable for this island size). Innovations in low-carbon frequency-balancing generation sources (examples as done by Martínez-Lucas *et al.* (2016), Inoue, Genchi and Kudoh (2017) and Muñoz-Benavente *et al.* (2017)) can play a large role in further decreasing the environmental impacts and in enhancing the energy security of the system.
 - SD insights shows that a non-comprehensive approach of policies in the electrically-isolated island system will hinder the environmental and energy security objectives of the system.

In essence, this research presents a proof of concept and each case study system should be examined thoroughly to understand the contextual factors but can be assured that the general approach highlighted in this thesis gives significant insights into the implications of environmental and energy security concerns on isolated island electricity systems.

7.2 Key Contributions

The research work of this thesis has both academic and applied contributions to the field of energy and electricity policy. The high level summary contributions are subsequently given. A detailed comprehensive modelling platform was built that simulates the electricity capacity investments and policy influences within transitioning low-carbon electricity grids. This platform captures the key causal relationships from the implications of the environmental and energy security concerns commonly found in isolated island electricity systems. This includes the endogenous demand dynamics (resulting from the low-carbon policies and key influences) to identify policy barriers and incentives needed for sustainable futures of (smart/er) electricity systems. The simulation model is used to inform electricity policy planning and demonstrates a novel approach to generation capacity investments/expansion.

The work also extends the existing energy and electricity policy literature by employing a systematic SD-based approach for implicit understanding of the convergence of environmental and energy security concerns in isolated island systems. It incorporates the impact of transitioning factors inherent to future low-carbon electricity systems such as EV expansion, energy efficiency measures, energy storage, renewables integration and the inherent LCOE (overnight cost basis and not the usual discounted cash flow) of the different electricity generation technologies. Using these factors to contribute to the policy guidance for improved decision-making with the long-term investment (integrated resource planning) strategies and generation mixes of island electricity systems and for increasing the uptake of renewables - further reducing environmental impacts from the system.

Additionally, this research developed a modular integrated resource planning (IRP)-type electricity capacity investment and policy modelling framework that integrates social, technical and economic aspects of the system and can be used to represent electricity systems in islands around the world. While the approach developed in this thesis was demonstrated on a system inspired by the case of São Miguel, it can be applied to other island systems. An island system that has a low-carbon agenda and is electrically isolated can be represented using the modelling platform developed for this thesis. For extension, to larger and interconnected systems the exogenous electricity tariffs and LCOE representations used within this thesis will have to be reformulated to represent the appropriate electricity markets that exist within these systems as appropriate. This can include the cross-border trading of electricity and provisions for capacity markets.

7.2.1 Policy Implications

The policy implications of this research lie in the areas of informing the policy focus areas and also showing the opportunities that policy makers have to shape the development and future of low-carbon isolated electricity systems. For the policy focus area aspects, this research shares some main insights as follows:

- Policy decisions surrounding capacity margins within isolated island systems are not critical, as is a focus on tourism for the development of the low-carbon system.
- Electricity demand growth is seen to be important for the general system development.
- Low-carbon policies such as EV expansion and energy efficiency measures greatly influences the long-term endogenous demand and generation capacity mix.
- Energy efficiency is highly important and can act as a brute force solution useful for safeguarding the energy security of the electricity system.
- It can be suggested that the policy behaviour of the locals rather than the externals that will have the key impacts on the long-term electricity demand - also of importance to the energy security of the system.

For shaping the development of future low-carbon isolated island electricity systems we see that:

- The issue of renewables targets is of tremendous value for ensuring emissions reductions and to attain feasible levels of low-carbon capacity within the electricity system.
- Policy makers should be aware and guided by the lack of outright benefits associated with an urgency to meet low-carbon targets together with the financial implications of these policy choices. The policy efforts should be to capture the right mix of low-carbon policies, especially the renewables integration policy which can militate against the long-term uncertainty of financially driven capacity investments.
- EV expansion policy in its appropriate levels probably aided by Governmental intervention pays huge dividends for sustaining the uptake of low-carbon generation in the long-term and can defer capacity investments in the shorter-term by approximately 5-10%.
- To facilitate a deeper penetration of renewables in the long-term key stakeholders and policy makers will need to have confidence in the prospects of low-carbon frequency balancing innovations.
- Energy storage policies should be more aggressive and possibly aligned with other energy policies and must be upheld in the long-term in order to sustain energy storage within the system. Policy makers must build upon earlier and more traditional policy-led energy storage approaches and springboard from them.

The implications from this work suggest that island system policy-makers should consider adopting a carefully-paced approach to low-carbon transitioning systems. With the convergence of environmental and energy security concerns the appropriate policies for high EV expansion, gradually paced renewables integration, energy storage and energy efficiency measures together with a desire for low-carbon frequency balancing (innovation) will enhance and improve the investor decision making and the desired sustainable low-carbon based capacity mix can be achieved.

7.3 Directions for Future Research

The policy and investment approach developed for this research work is comprehensive but not without need for improvement. Three areas of further research have been identified. The first extends the analyses presented in Chapter 6 to include areas for innovation such as EV to grid storage and low-carbon frequency balancing. Hypothetical scenarios of EV to grid storage can further improve the long-term investment outlook and see the influence of such policies on the system. Concurrently, an innovation landscape for low-carbon frequency balancing is necessary and should be pursued globally.

A second area for future research involves improvements in the model to include a wider range of social and economic aspects such as low-carbon jobs, endogenous economic (GDP) outlooks, CO₂ emissions taxation, demand side management services and off-grid generation. Additional details for improvements can be found in Section 3.6. In addition, the further refinement and exploration of causes of capacity investment oscillations with a financial origin for boom and bust cycles can be pursued. This can be achieved by improving the LCOE aspect of the model to include better cost analysis such as a pure NPV for operational and other cost representations.

A final area for future work involves consideration for the inputs of other qualitative or social science research that enhances the simulation model generalisation. Considerations to the ethnographic analyses of consumer and generator choices for low-carbon assets in isolated islands and other countries will aid to make the model more generalisable. In addition, the market effects to include market imperfections of interconnected grid systems will need implementation. To provide a transferrable methodology that gives a means to understand fully the low-carbon island electricity system's overall sustainability guidelines for future development and utilisation.

7.4 Reflections and Final Summary

This research work would help stakeholders to better understand the emerging policy and investment strategies, and interactions of the low-carbon deployment and system growth of the

integrated resources, to enable them to make more effective strategies and decisions. The model developed for the case study isolated island system is transferrable to other systems with the same political oversight and contextual settings. However, modification would be needed for islands systems that are fully stand alone to account for inherent issues such as power purchase agreements. Some even larger adjustments would be needed for larger systems that may have market dynamics and/or interconnected grids.

The use of SD to complete this research work was chosen based on its applicability to enhance learning in complex systems. SD is an excellent tool for capturing the long-term temporal understanding of a complex system from the key causal relationships which makes up the structure of these systems. Once key causal relationships are identified, the models are calibrated and then simulated to give a range of possible outcomes of the key trends in the system and not with the intention of prediction nor optimisation of the system. Additionally, SD models can tend to become very complex with many variables. As seen within this work, only the number of variables in the synthesis model were very high, but it was built up from smaller less complex models which were already thoroughly analysed during the research study. In thorough reflection, the benefits of this method far outweighed its weaknesses for the understanding sought within this research work.

The underlying work that consolidates all four research sub-questions was developed in an incremental step-by-step manner. An initial sub-model of a purely legacy (fossil-based) electricity system was developed for understanding the key concepts for capacity investments within the system. A separate sub-model was then developed to analyse the renewable integration within the existing system, then a second sub-model was developed to understand the long-term low-carbon policy influenced endogenous demand. Finally, the two sub-models were brought together as a synthesis model to capture all of the key aspects that influence the long-term investment and sustainability guidelines. This included capturing unintuitive (tourism is not very influential whilst policies not financial stability should drive the system) and surprising opportunities (low-carbon frequency balancing) within these systems. Additionally, it is seen that the capacity investments

within the system and the environmental implications are intertwined and depend heavily on the focus of the policies within the system. These observations reveal that policymakers and investors should be aware of the long-term consequences of their actions and ensure that the possibility of the outcomes will be those desired for the island system. Thereby empowering consumers, distributors and governments, the key stakeholders, with stabilised cost of electricity for households and businesses. In addition, there will be reduced dependence on imported fossil fuels and reduced greenhouse gas emissions.

Appendix A Model Documentation

This appendix gives the documentation of all variables, data inputs and other assumptions for the system dynamics models produced for this thesis in the style recommended by Martinez-Moyano (2012). This documentation contains the description of the different variables and the structure of the model. The interactive hyperlinked (HTML) details of the content of the model documentation contained within Appendix A will be archived on a publicly available website.

General Notes

The models shown are the renewables integration sub-model and the synthesis model. The synthesis model contains the full structure of the demand sub-model together with parts of the renewables integration and fossil fuel sub-models. All models begin simulations in 2005 and run for 45 years up to 2050. There are 10 years of model calibrations from 2005 to 2015 and 35 years of model simulations. The time unit of 1 month is used and the time step is set to 0.0833 in the renewables sub-model and 0.015625 in the synthesis model. There is one view in the renewables integration model and there are six views in the synthesis model, of which two are derived from the demand sub-model. In the models, red fonts indicate variables that are passed from the current view to another, green fonts are constants (also in capitals), blue fonts are policy leverage variables and brown fonts represents other important variables. Other aspects shown within the appendix are the lookup tables of the investment and grid quality attractiveness functions. In addition, the capacity factors of the various generating technologies, electricity tariffs and LCOE values used for the models are clearly displayed within the model documentation. The main sources of data used for the models are (IEA, 2010a; ERSE, 2012, 2014; Isle-pact, 2012; Ilic, Xie and Liu, 2013; Botelho, 2015; Nunes, 2015; EDA, 2016; European Commission, 2016), where additional sources have been used this has been clearly stated in the model description.

A.1 Renewables Integration Model Documentation

Model Description:

Model Information	Number
Total Number of Variables	72
Total Number of State Variables (Level+Smooth+Delay Variables)	14 (19.4%)
Total Number of Stocks (Stocks in Level+Smooth+Delay Variables) †	14 (19.4%)
Total Number of Macros	0
Variables with Source Information	0
Variables with Dimensionless Units	6 (8.3%)
Function Sensitivity Parameters	0
Data Lookup Tables	1
Time Unit	Month
Initial Time	2005
Final Time	2050
Reported Time Interval	TIME STEP
Time Step	0.0833
Model Is Fully Formulated	Yes
VPM File Available	Yes

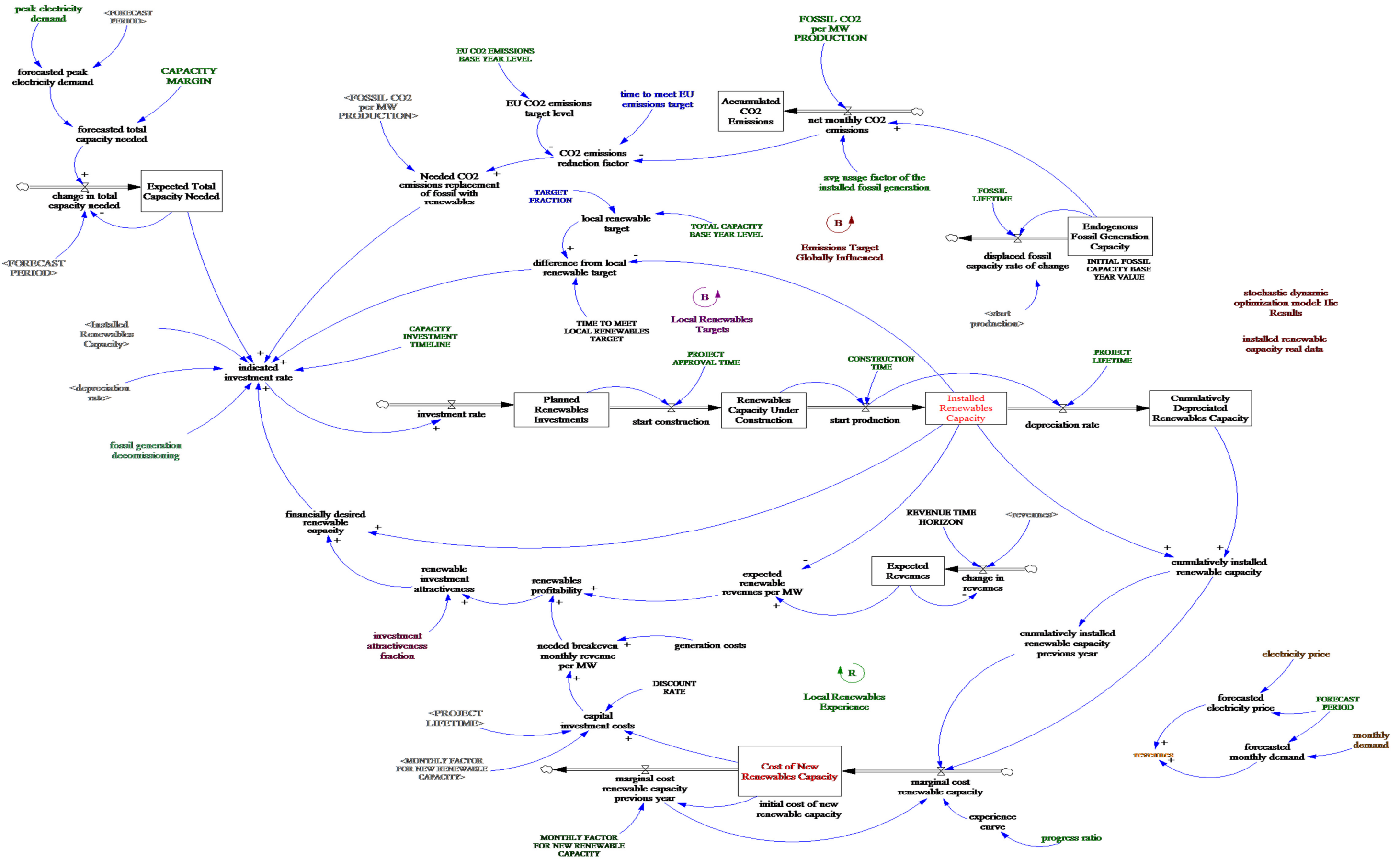
Listing of the various variable types as documented from the model:

Types:	L : Level	SM : Smooth *	DE : Delay * †	LI : Level Initial	I : Initial
	C : Constant	F : Flow	A : Auxiliary	D : Data	
	G : Game (1)	T : Lookup ††			

* (state variables / total stocks)

† Total stocks do not include fixed delay variables.




















†† (lookup variables / lookup tables).




















stochastic dynamic optimization model: Ilic Results
 installed renewable capacity real data








Renewables Integration Sub-Model








Listing of ALL variables contained within the model in Alphabetic order:

Variable Type	Variable Name, Units and Description
#1 L 	Accumulated CO2 Emissions (tonnes) = $\int \text{net monthly CO2 emissions } dt + [0]$ Description: The stock of accumulated CO2 emissions level since 2005. The initial value is taken as 0.
#2 C  	avg usage factor of the installed fossil generation (fraction [0.2,0.75,0.05]) = 0.35 Description: The average usage factor of the installed fossil generation capacity. The value 0.35 has been chosen because, in 2005, the base year, an average of 34.27MW of fossil fuel capacity was used to meet the demand, which is 35% of the installed base of 102.66MW Used by: net monthly CO2 emissions - Total monthly rate/flow of CO2 emissions calculated from the fossil fuel capacity used.
#3 C  	CAPACITY INVESTMENT TIMELINE (Months [6, 24]) = 12 Description: The length of time needed before making a decision about renewable investments. This is the time that precedes the project approval time. This is fixed and is taken to be 12 months. Used by: indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.
#4 C  	CAPACITY MARGIN (fraction [0.15, 0.45]) = 0.3 Description: The capacity margin as defined in the literature is chosen to be 0.3, since it is the desired value for the energy regulators in the island. Used by: forecasted total capacity needed - Forecasted total capacity required, based on the present capacity margin and the forecasted peak demands of the system.
#5 A  	capital investment costs (\$/(MW*Month)) = $(\text{Cost of New Renewables Capacity}/\text{MONTHLY FACTOR FOR NEW RENEWABLE CAPACITY}) * (\text{DISCOUNT RATE}/(1-(1+\text{DISCOUNT RATE})^{-(\text{PROJECT LIFETIME})}))$ Description: The monthly capital investment costs per MW of new renewables capacity. The formula for the (overnight) investment costs is taken from Dyer (2010). Used by: needed breakeven monthly revenue per MW - Monthly revenue required to cover the capital investments and generation costs.
#6 F,A   	change in revenues (\$/Month/Month) = $(\text{revenues}-\text{Expected Revenues})/\text{REVENUE TIME HORIZON}$ Description: This is the rate of change in the revenues generated over the revenue horizon. Used by: Expected Revenues - Stock of rolling average of revenues generated from electricity sales.
#7 F,A   	change in total capacity needed (MW/Month) = $(\text{forecasted total capacity needed}-\text{Expected Total Capacity Needed})/\text{FORECAST PERIOD}$ Description: The rate of change in the total capacity needed for the capacity forecast period. Used by: Expected Total Capacity Needed - This is used for smoothing the total capacity needed over the capacity investment timeline.
#8 A  	CO2 emissions reduction factor (tonnes/Month/Month) = $(\text{EU CO2 emissions target level}-\text{net monthly CO2 emissions})/\text{time to meet EU emissions target}$ Description: The monthly discrepancy between the target CO2 emissions rate and the actual CO2 emissions rate Used by: Needed CO2 emissions replacement of fossil with renewables - The renewables capacity required to close the CO2 emissions gap. The formulation reflects the removal of fossil fuel generation.
#9 C  	CONSTRUCTION TIME (Months [0, 36]) = 12 Description: The assumed time to construct new renewables capacity from the literature. This value is taken to be 12 months, based on wind and solar construction times. Used by: start production - Rate of start of production of renewables capacity, taking into account the delay caused by the construction of renewables capacity.

#10 L 	<p>Cost of New Renewables Capacity (\$/MW) $= \int \text{marginal cost renewable capacity} - \text{marginal cost renewable capacity previous year } dt + [\text{initial cost of new renewable capacity}]$</p> <p>Description: The accumulation of the overnight investment cost per MW of installed renewable capacity. Used by: capital investment costs - The monthly capital investment costs per MW of new renewables capacity. The formula for the (overnight) investment costs is taken from Dyer (2010). marginal cost renewable capacity previous year - Change in marginal overnight cost of renewables over time.</p>
#11 L 	<p>Cumulatively Depreciated Renewables Capacity (MW) $= \int \text{depreciation rate } dt + [0]$</p> <p>Description: Stock of all renewables ever installed over the model simulation period. The initial value is assumed to be 0 in 2005. Used by: cumulatively installed renewable capacity - The cumulated sum of all renewables capacity installed since the start of the simulation.</p>
#12 A 	<p>cumulatively installed renewable capacity (MW) $= \text{Cumulatively Depreciated Renewables Capacity} + \text{Installed Renewables Capacity}$</p> <p>Description: The cumulated sum of all renewables capacity installed since the start of the simulation. Used by: cumulatively installed renewable capacity previous year - Cumulatively installed renewable capacity for the previous year. Implemented with a fixed delay formulation. marginal cost renewable capacity - The marginal cost of installing renewables capacity. Calculated from the learning-curve cost reduction methodology of Pruyt and Kwakkel (2011).</p>
#13 DE	<p>cumulatively installed renewable capacity previous year (MW) $= \text{DELAY FIXED} (\text{cumulatively installed renewable capacity}, 12, \text{cumulatively installed renewable capacity})$</p> <p>Description: Cumulatively installed renewable capacity for the previous year. Implemented with a fixed delay formulation. Used by: marginal cost renewable capacity - The marginal cost of installing renewables capacity. Calculated from the learning-curve cost reduction methodology of Pruyt and Kwakkel (2011).</p>
#14 DE,F 	<p>depreciation rate (MW/Month) $= \text{DELAY N}(\text{start production}, \text{PROJECT LIFETIME}, \text{start production}, 10)$</p> <p>Description: Accounting for the delay between the start of production and the depreciation of the renewables capacity. Implemented as a delay that accounts for the lifetime of the project. Used by: Cumulatively Depreciated Renewables Capacity - Stock of all renewables ever installed over the model simulation period. The initial value is assumed to be 0 in 2005. indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets. Installed Renewables Capacity - Installed renewables capacity based on capacity investments and decommissioning. The initial installed renewables capacity in 2005 is 19.13 MW, taken from Parness (2011).</p>
#15 A 	<p>difference from local renewable target (MW/Month) $= \text{MAX}(0, (\text{local renewable target} - \text{Installed Renewables Capacity}) / \text{TIME TO MEET LOCAL RENEWABLES TARGET})$</p> <p>Description: The difference between the local renewables target and the installed renewables capacity, adjusted by the time available to meet the local renewables target. Note that the model does not allow a negative rate, so there is an inbuilt push towards installing renewables. Used by: indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#16 C 	<p>DISCOUNT RATE (fraction) $= 0.1$</p> <p>Description: The discount rate of the renewables capital investment. Used by: capital investment costs - The monthly capital investment costs per MW of new renewables capacity. The formula for the (overnight) investment costs is taken from Dyer (2010).</p>
#17 F,A  	<p>displaced fossil capacity rate of change (MW/Month) $= \text{MIN}(\text{start production}, \text{Endogenous Fossil Generation Capacity} / \text{FOSSIL LIFETIME})$</p> <p>Description: This is the outflow of the installed fossil capacity being replaced by the installed renewable capacity. This rate is compared to the normal depreciation of fossil capacity over its lifetime for the implementation. Used by:</p>

	Endogenous Fossil Generation Capacity - Stock of existing fossil generation capacity.
#19 L 	<p>Endogenous Fossil Generation Capacity (MW) $= \int -\text{displaced fossil capacity rate of change } dt + [\text{INITIAL FOSSIL CAPACITY BASE YEAR VALUE}]$</p> <p>Description: Stock of existing fossil generation capacity. Used by: displaced fossil capacity rate of change - This is the outflow of the installed fossil capacity being replaced by the installed renewable capacity. This rate is compared to the normal depreciation of fossil capacity over its lifetime for the implementation. net monthly CO2 emissions - Total monthly rate/flow of CO2 emissions calculated from the fossil fuel capacity used.</p>
#20 A 	<p>EU CO2 EMISSIONS BASE YEAR LEVEL (tonnes/Month) $= 195732/12$</p> <p>Description: In the base year 2005 we consider the total amount, 562721 of CO2 emissions for that year with 195732, coming from electricity production. The value used is 195732/12. Used by: EU CO2 emissions target level - Level of the total amount of CO2 emissions reduction needed over the subsequent policy years to be achieved. A default policy of 30% reduction of 2005 emissions levels is used.</p>
#21 A 	<p>EU CO2 emissions target level (tonnes/Month) $= 0.3 * \text{EU CO2 EMISSIONS BASE YEAR LEVEL}$</p> <p>Description: Level of the total amount of CO2 emissions reduction needed over the subsequent policy years to be achieved. A default policy of 30% reduction of 2005 emissions levels is used. Used by: CO2 emissions reduction factor - The monthly discrepancy between the target CO2 emissions rate and the actual CO2 emissions rate</p>
#22 A 	<p>expected renewable revenues per MW (S/(Month*MW)) $= \text{Expected Revenues}/\text{Installed Renewables Capacity}$</p> <p>Description: The expected monthly revenue per MW of installed renewables capacity. Used by: renewables profitability - The ratio of current revenues to revenues required for breakeven.</p>
#23 L 	<p>Expected Revenues (S/Month) $= \int \text{change in revenues } dt + [\text{revenues}]$</p> <p>Description: Stock of rolling average of revenues generated from electricity sales. Used by: change in revenues - This is the rate of change in the revenues generated over the revenue horizon. expected renewable revenues per MW - The expected monthly revenue per MW of installed renewables capacity.</p>
#24 L 	<p>Expected Total Capacity Needed (MW) $= \int \text{change in total capacity needed } dt + [\text{forecasted total capacity needed}]$</p> <p>Description: This is used for smoothing the total capacity needed over the capacity investment timeline. Used by: change in total capacity needed - The rate of change in the total capacity needed for the capacity forecast period. indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#25 A 	<p>experience curve (Qmal) $= -\text{LOG}(\text{progress ratio}, 2)$</p> <p>Description: Logistic learning curve formula as given in Sterman (2000). Used by: marginal cost renewable capacity - The marginal cost of installing renewables capacity. Calculated from the learning-curve cost reduction methodology of Pruyt and Kwakkel (2011).</p>
#27 A 	<p>financially desired renewable capacity (MW) $= \text{Installed Renewables Capacity} * \text{renewable investment attractiveness}$</p> <p>Description: The capacity that is desired based on the learning curve cost reduction and the existing renewable capacity. Used by: indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#28 C 	<p>FORECAST PERIOD (Months) $= 12$</p> <p>Description: Smoothing period used within the model. Used by:</p>

	<p>change in total capacity needed - The rate of change in the total capacity needed for the capacity forecast period.</p> <p>forecasted electricity price - The forecasted electricity price. This is the electricity price smoothed over the FORECAST PERIOD (taken as 12 months).Initial price in January 2005 is 63090 \$/MW.</p> <p>forecasted monthly demand - The forecasted electricity demand. This is the electricity demand smoothed over the FORECAST PERIOD (taken as 12 months).Initial price in January 2005 is 40.79 MW.</p> <p>forecasted peak electricity demand - The forecasted peak electricity demand smoothed over the FORECAST PERIOD (taken as 12 months) starting from a 2005 peak demand of 62.9 MW.</p>
#29 SM 	<p>forecasted electricity price (\$/MW) = SMOOTHI(electricity price, FORECAST PERIOD,63090)</p> <p>Description: The forecasted electricity price. This is the electricity price smoothed over the FORECAST PERIOD (taken as 12 months).Initial price in January 2005 is 63090 \$/MW.</p> <p>Used by: revenues - Monthly revenues, calculated from the forecasted electricity prices and the expected monthly electricity demand.</p>
#30 SM 	<p>forecasted monthly demand (MW/Month) = SMOOTHI(monthly demand, FORECAST PERIOD,40.79)</p> <p>Description: The forecasted electricity demand. This is the electricity demand smoothed over the FORECAST PERIOD (taken as 12 months).Initial price in January 2005 is 40.79 MW.</p> <p>Used by: revenues - Monthly revenues, calculated from the forecasted electricity prices and the expected monthly electricity demand.</p>
#31 SM 	<p>forecasted peak electricity demand (MW) = SMOOTHI(peak electricity demand, FORECAST PERIOD, 62.9)</p> <p>Description: The forecasted peak electricity demand smoothed over the FORECAST PERIOD (taken as 12 months) starting from a 2005 peak demand of 62.9 MW.</p> <p>Used by: forecasted total capacity needed - Forecasted total capacity required, based on the present capacity margin and the forecasted peak demands of the system.</p>
#32 LI,A 	<p>forecasted total capacity needed (MW) = (CAPACITY MARGIN*forecasted peak electricity demand)+forecasted peak electricity demand</p> <p>Description: Forecasted total capacity required, based on the present capacity margin and the forecasted peak demands of the system.</p> <p>Used by: change in total capacity needed - The rate of change in the total capacity needed for the capacity forecast period. Expected Total Capacity Needed - This is used for smoothing the total capacity needed over the capacity investment timeline.</p>
#33 A 	<p>FOSSIL CO2 per MW PRODUCTION (tonnes/(Month*MW)) = 0.8*(24*30)</p> <p>Description: The monthly amount of CO2 produced per MW of fossil capacity used. Calculated from 0.8 tonnes/MWh as given in Silva (2013). Other values (not implemented) are 0.59 tonnes/MWh (from DAPTRA).</p> <p>Used by: Needed CO2 emissions replacement of fossil with renewables - The renewables capacity required to close the CO2 emissions gap. The formulation reflects the removal of fossil fuel generation. net monthly CO2 emissions - Total monthly rate/flow of CO2 emissions calculated from the fossil fuel capacity used.</p>
#34 C 	<p>fossil generation decommissioning (MW/Month) = 0</p> <p>Description: Rate of decommissioning of fossil generation capacity. This variable is set to 0MW/Month as a temporary value since fossil is being directly replaced in the endogenous fossil generation part of model.</p> <p>Used by: indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#35 C 	<p>FOSSIL LIFETIME (Months) = 240</p> <p>Description: Lifetime of typical fossil generation capacity.....420(normal project lifetime) - 180(time online thus far)</p> <p>Used by: displaced fossil capacity rate of change - This is the outflow of the installed fossil capacity being replaced by the installed renewable capacity. This rate is compared to the normal depreciation of fossil capacity over its lifetime for the implementation.</p>

#36 A 	<p>generation costs ($\\$/(\text{MW} \cdot \text{Month})$) [92.5,105,1]) $= 93 \cdot 720$ Description: Average generation costs per MW month in US dollars. The value used is 93 $\\$/\text{MWh}$ (Silva 2013). Used by: needed breakeven monthly revenue per MW - Monthly revenue required to cover the capital investments and generation costs.</p>
#37 A 	<p>indicated investment rate (MW/Month) $= \text{MAX}((\text{Expected Total Capacity Needed} - \text{Installed Renewables Capacity}) / \text{CAPACITY INVESTMENT TIMELINE}, (\text{financially desired renewable capacity} - \text{Installed Renewables Capacity}) / \text{CAPACITY INVESTMENT TIMELINE}) + \text{MAX}(\text{Needed CO2 emissions replacement of fossil with renewables difference from local renewable target}) + \text{fossil generation decommissioning} + \text{depreciation rate}$ Description: Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets. Used by: investment rate - Rate of the investment in renewables capacity. The MAX formulation is used to avoid negative renewables investments.</p>
#38 LI,C 	<p>initial cost of new renewable capacity ($\\$/\text{MW}$) [1.056e+006,1.769e+006]) $= 1.056e+006$ Description: Initial marginal overnight cost of new renewable capacity in 2005. Taken from IEA (2005) which gives the average value for the various renewables to be in the range 1056-1769$\\$/\text{kW}$. Used by: Cost of New Renewables Capacity - The accumulation of the overnight investment cost per MW of installed renewable capacity.</p>
#39 LI,C 	<p>INITIAL FOSSIL CAPACITY BASE YEAR VALUE (MW) $= 102$ Description: Installed fossil capacity in 2005 (EDA, 2008). Used by: Endogenous Fossil Generation Capacity - Stock of existing fossil generation capacity.</p>
#41 D,A 	<p>installed renewable capacity real data (MW) $= \text{GET XLS DATA}('Data.xlsx', 'Sheet1', '1', 'b23')$ Description: Real data of installed renewables capacity from 2005 to 2014.</p>
#42 L 	<p>Installed Renewables Capacity (MW) $= \int \text{start production} - \text{depreciation rate} dt + [19.13]$ Description: Installed renewables capacity based on capacity investments and decommissioning. The initial installed renewables capacity in 2005 is 19.13 MW, taken from Parness (2011). Used by: cumulatively installed renewable capacity - The cumulated sum of all renewables capacity installed since the start of the simulation. difference from local renewable target - The difference between the local renewables target and the installed renewables capacity, adjusted by the time available to meet the local renewables target. Note that the model does not allow a negative rate, so there is an inbuilt push towards installing renewables. expected renewable revenues per MW - The expected monthly revenue per MW of installed renewables capacity. financially desired renewable capacity - The capacity that is desired based on the learning curve cost reduction and the existing renewable capacity. indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#43 L 	<p>investment attractiveness fraction (Dimless) [0,1]) $= [(0,0)-(10,10)], (0,0.1), (0.5,0.6), (0.8,0.9), (1,1), (1.2,1.1), (1.5,1.25), (2,1.5), (5,1.5), (10,1.5)$ Description: Investment attractiveness lookup function (from (Black, 2005)) See fig 7-13. This is used for capacity expansion/investments. Used by: renewable investment attractiveness - The attractiveness of investment in renewables, based on the aggregated renewables technology profitability.</p>

#44 F,A WAB →	<p>investment rate (MW/Month) = MAX(0, indicated investment rate)</p> <p>Description: Rate of the investment in renewables capacity. The MAX formulation is used to avoid negative renewables investments.</p> <p>Used by: Planned Renewables Investments - The planned renewables investments. The 2005 initial value is 9W, taken from (Silva, 2013) which gave 9MW or 22MW of geothermal/wind new capacity planned for 2013.</p>
#45 A WAB	<p>local renewable target (MW) = TARGET FRACTION * TOTAL CAPACITY BASE YEAR LEVEL</p> <p>Description: The local target in MW of renewables capacity. Calculated from the target fraction set and the base-year capacity installed.</p> <p>Used by: difference from local renewable target - The difference between the local renewables target and the installed renewables capacity, adjusted by the time available to meet the local renewables target. Note that the model does not allow a negative rate, so there is an inbuilt push towards installing renewables.</p>
#46 F,A WAB →	<p>marginal cost renewable capacity (\$/MW/Month) = marginal cost renewable capacity previous year * (cumulatively installed renewable capacity / cumulatively installed renewable capacity previous year)^(-experience curve)</p> <p>Description: The marginal cost of installing renewables capacity. Calculated from the learning-curve cost reduction methodology of Pruyt and Kwakkel (2011).</p> <p>Used by: Cost of New Renewables Capacity - The accumulation of the overnight investment cost per MW of installed renewable capacity.</p>
#47 F,A WAB →	<p>marginal cost renewable capacity previous year (\$/MW/Month) = Cost of New Renewables Capacity / MONTHLY FACTOR FOR NEW RENEWABLE CAPACITY</p> <p>Description: Change in marginal overnight cost of renewables over time.</p> <p>Used by: Cost of New Renewables Capacity - The accumulation of the overnight investment cost per MW of installed renewable capacity. marginal cost renewable capacity - The marginal cost of installing renewables capacity. Calculated from the learning-curve cost reduction methodology of Pruyt and Kwakkel (2011).</p>
#48 D,A WAB	<p>monthly demand (MW/Month) = GET XLS DATA('Data.xlsx', 'Sheet1', '1', 'b4')</p> <p>Description: MW/Month data for electricity demand from 2005 to 2014.</p> <p>Used by: forecasted monthly demand - The forecasted electricity demand. This is the electricity demand smoothed over the FORECAST PERIOD (taken as 12 months). Initial price in January 2005 is 40.79 MW.</p>
#49 C WAB	<p>MONTHLY FACTOR FOR NEW RENEWABLE CAPACITY (Months) = 12</p> <p>Description: Gives the equivalent monthly period costing of the new renewable capacity.</p> <p>Used by: capital investment costs - The monthly capital investment costs per MW of new renewables capacity. The formula for the (overnight) investment costs is taken from Dyer (2010). marginal cost renewable capacity previous year - Change in marginal overnight cost of renewables over time.</p>

#50 A VAB	<p>needed breakeven monthly revenue per MW ($\\$/(\text{MW} \cdot \text{Month})$)</p> <p>= capital investment costs + generation costs</p> <p>Description: Monthly revenue required to cover the capital investments and generation costs.</p> <p>Used by:</p> <p>renewables profitability - The ratio of current revenues to revenues required for breakeven.</p>
#51 A VAB	<p>Needed CO2 emissions replacement of fossil with renewables (MW/Month)</p> <p>= $\text{MAX}(0, -(\text{CO2 emissions reduction factor}/\text{FOSSIL CO2 per MW PRODUCTION}))$</p> <p>Description: The renewables capacity required to close the CO2 emissions gap. The formulation reflects the removal of fossil fuel generation.</p> <p>Used by:</p> <p>indicated investment rate - Investment rate in renewables capacity. It is calculated by considering at all of the potential renewables replacements needed directly and indirectly, together with the financially desired capacity and the investments needed to achieve policy and emissions targets.</p>
#52 F.A VAB ⚡	<p>net monthly CO2 emissions ($\text{tonnes}/\text{Month}$)</p> <p>= Endogenous Fossil Generation Capacity * avg usage factor of the installed fossil generation * FOSSIL CO2 per MW PRODUCTION</p> <p>Description: Total monthly rate/flow of CO2 emissions calculated from the fossil fuel capacity used.</p> <p>Used by:</p> <p>Accumulated CO2 Emissions - The stock of accumulated CO2 emissions level since 2005. The initial value is taken as 0.</p> <p>CO2 emissions reduction factor - The monthly discrepancy between the target CO2 emissions rate and the actual CO2 emissions rate</p>
#54 L VAB	<p>Planned Renewables Investments (MW)</p> <p>= $\int \text{investment rate} - \text{start construction } dt + [9]$</p> <p>Description: The planned renewables investments. The 2005 initial value is 9MW, taken from (Silva, 2013) which gave 9MW or 22MW of geothermal/wind new capacity planned for 2013.</p> <p>Used by:</p> <p>start construction - Rate of start of construction of renewables capacity, taking into account the delay between investment decisions and financial approvals for the start of construction.</p>
#55 G ⚡	<p>progress ratio (Dmol)</p> <p>= GAME (0.9)</p> <p>Description: Progress ratio as used in the learning curve formula of Pruyt and Kwakkel (2011). A progress ratio of 90% means that for each doubling of the cumulatively installed capacity leads to a cost reduction of 10%.</p> <p>Used by:</p> <p>experience curve - Logistic learning curve formula as given in Sterman (2000).</p>
#56 C VAB	<p>PROJECT APPROVAL TIME (Months)</p> <p>= 3</p> <p>Description: Project approval time. A value of 3 months is used in the model.</p> <p>Used by:</p> <p>start construction - Rate of start of construction of renewables capacity, taking into account the delay between investment decisions and financial approvals for the start of construction.</p>
#57 C VAB	<p>PROJECT LIFETIME (Months)</p> <p>= 360</p> <p>Description: Lifetime of renewables project. The default value is taken to be 30 years.</p> <p>Used by:</p> <p>capital investment costs - The monthly capital investment costs per MW of new renewables capacity. The formula for the (overnight) investment costs is taken from Dyer (2010).</p> <p>depreciation rate - Accounting for the delay between the start of production and the depreciation of the renewables capacity. Implemented as a delay that accounts for the lifetime of the project.</p>
#58 A VAB	<p>renewable investment attractiveness (Dmol)</p> <p>= investment attractiveness fraction * renewables profitability</p> <p>Description: The attractiveness of investment in renewables, based on the aggregated renewables technology profitability.</p> <p>Used by:</p> <p>financially desired renewable capacity - The capacity that is desired based on the learning curve cost reduction and the existing renewable capacity.</p>
#59 L VAB	<p>Renewables Capacity Under Construction (MW)</p> <p>= $\int \text{start construction} - \text{start production } dt + [10.5]$</p> <p>Description: The renewables capacity under construction. The initial value in 2005 is assumed to be 10.5MW. Assuming about 10.5MW remains to be constructed.</p> <p>Used by:</p> <p>start production - Rate of start of production of renewables capacity, taking into account the delay caused by the construction of renewables capacity.</p>

#60 A VAB	<p>renewables profitability (Q_{mul})</p> <p>= expected renewable revenues per MW/needed breakeven monthly revenue per MW</p> <p>Description: <i>The ratio of current revenues to revenues required for breakeven.</i></p> <p>Used by:</p> <p>renewable investment attractiveness - The attractiveness of investment in renewables, based on the aggregated renewables technology profitability.</p>
#61 C VAB	<p>REVENUE TIME HORIZON (Months)</p> <p>= 24</p> <p>Description: <i>Time horizon to perceive revenues (to avoid single year anomalies due to price).</i></p> <p>Used by:</p> <p>change in revenues - This is the rate of change in the revenues generated over the revenue horizon.</p>
#62 LI,A VAB	<p>revenues (\$/Month)</p> <p>= forecasted electricity price*forecasted monthly demand</p> <p>Description: <i>Monthly revenues, calculated from the forecasted electricity prices and the expected monthly electricity demand.</i></p> <p>Used by:</p> <p>change in revenues - This is the rate of change in the revenues generated over the revenue horizon.</p> <p>Expected Revenues - Stock of rolling average of revenues generated from electricity sales.</p>
#64 F,A VAB →	<p>start construction (MW/Month)</p> <p>= Planned Renewables Investments/PROJECT APPROVAL TIME</p> <p>Description: <i>Rate of start of construction of renewables capacity, taking into account the delay between investment decisions and financial approvals for the start of construction.</i></p> <p>Used by:</p> <p>Planned Renewables Investments - The planned renewables investments. The 2005 initial value is 9W, taken from (Silva, 2013) which gave 9MW or 22MW of geothermal/wind new capacity planned for 2013.</p> <p>Renewables Capacity Under Construction - The renewables capacity under construction. The initial value in 2005 is assumed to be 10.5MW. Assuming about 10.5MW remains to be constructed.</p>
#65 F,A VAB →	<p>start production (MW/Month)</p> <p>= Renewables Capacity Under Construction/CONSTRUCTION TIME</p> <p>Description: <i>Rate of start of production of renewables capacity, taking into account the delay caused by the construction of renewables capacity.</i></p> <p>Used by:</p> <p>depreciation rate - Accounting for the delay between the start of production and the depreciation of the renewables capacity. Implemented as a delay that accounts for the lifetime of the project.</p> <p>displaced fossil capacity rate of change - This is the outflow of the installed fossil capacity being replaced by the installed renewable capacity. This rate is compared to the normal depreciation of fossil capacity over its lifetime for the implementation.</p> <p>Installed Renewables Capacity - Installed renewables capacity based on capacity investments and decommissioning. The initial installed renewables capacity in 2005 is 19.13 MW, taken from Parness (2011).</p> <p>Renewables Capacity Under Construction - The renewables capacity under construction. The initial value in 2005 is assumed to be 10.5MW. Assuming about 10.5MW remains to be constructed.</p>
#67 C VAB	<p>TARGET FRACTION (fraction)</p> <p>= 0.5</p> <p>Description: <i>The renewable policy fraction with a default value of 0.5. This is the target fraction of installed renewables capacity over the total installed capacity.</i></p> <p>Used by:</p> <p>local renewable target - The local target in MW of renewables capacity. Calculated from the target fraction set and the base-year capacity installed.</p>
#69 C VAB	<p>TIME STEP (Month [0,?])</p> <p>= 0.0833</p> <p>Description: <i>The time step for the simulation.</i></p> <p>Used by:</p> <p>SAVEPER - The frequency with which output is stored.</p>
#70 C VAB	<p>time to meet EU emissions target (Months [120,540])</p> <p>= 300</p> <p>Description: <i>Time period over which the EU CO2 emissions target should be achieved. The default timeline for policy implementation is 300 months. Set increments of 120 months or 10 year CO2 policies.</i></p> <p>Used by:</p> <p>CO2 emissions reduction factor - The monthly discrepancy between the target CO2 emissions rate and the actual CO2 emissions rate</p>

#71 C VAB	<p>TIME TO MEET LOCAL RENEWABLES TARGET (Months [120,540]) = 300</p> <p>Description: <i>The policy dates that the renewables target should be achieved by. Default of 10 year policy starting in 2010 (60 months into simulation)</i></p> <p>Used by: difference from local renewable target - The difference between the local renewables target and the installed renewables capacity, adjusted by the time available to meet the local renewables target. Note that the model does not allow a negative rate, so there is an inbuilt push towards installing renewables.</p>
#72 C VAB	<p>TOTAL CAPACITY BASE YEAR LEVEL (MW) = 133</p> <p>Description: <i>Total installed capacity in the base year 2005, taken as 133MW from EDA, (2008).</i></p> <p>Used by: local renewable target - The local target in MW of renewables capacity. Calculated from the target fraction set and the base-year capacity installed.</p>
Data Variables	Name and Description
#18 D,A VAB	<p>electricity price:INTERPOLATE: (\$/MW) = GET XLS DATA('Data.xlsx', 'Sheet1', '1', 'b11')</p> <p>Description: <i>Data for electricity prices 2005 to 2014</i></p>
#53 D,A VAB	<p>peak electricity demand:INTERPOLATE: (MW) = GET XLS DATA('Data.xlsx', 'Sheet1', '1', 'b7')</p> <p>Description: <i>Data for the peak demand in the base year, 2005.</i></p>
#66 D,A VAB	<p>"stochastic dynamic optimization model: Ilic Results" (MW) = GET XLS DATA('Data.xlsx', 'Sheet1', '1', 'b26')</p> <p>Description: <i>Ilic et al. (2013) Chp 20 pg.546 - Stochastic optimisation results for renewables integration in the case study, Sao Miguel.</i></p>

A.2 Synthesis Model Documentation

Model Description:

Model Information	Number
Total Number of Variables	409
Total Number of State Variables (Level+Smooth+Delay Variables)	38 (9.3%)
Total Number of Stocks (Stocks in Level+Smooth+Delay Variables) †	84 (20.5%)
Total Number of Macros	0
Variables with Source Information	0
Variables with Dimensionless Units	35 (8.6%)
Function Sensitivity Parameters	0
Data Lookup Tables	5
Time Unit	Month
Initial Time	0
Final Time	540
Reported Time Interval	TIME STEP
Time Step	0.015625
Model Is Fully Formulated	Yes
VPM File Available	Yes

Listing of the various variable types as documented from the model:

L : Level	SM : Smooth *	DE : Delay * †	LI : Level Initial	I : Initial
C : Constant	F : Flow	A : Auxiliary	D : Data	
G : Game (1)	T : Lookup ††			

* (state variables / total stocks)

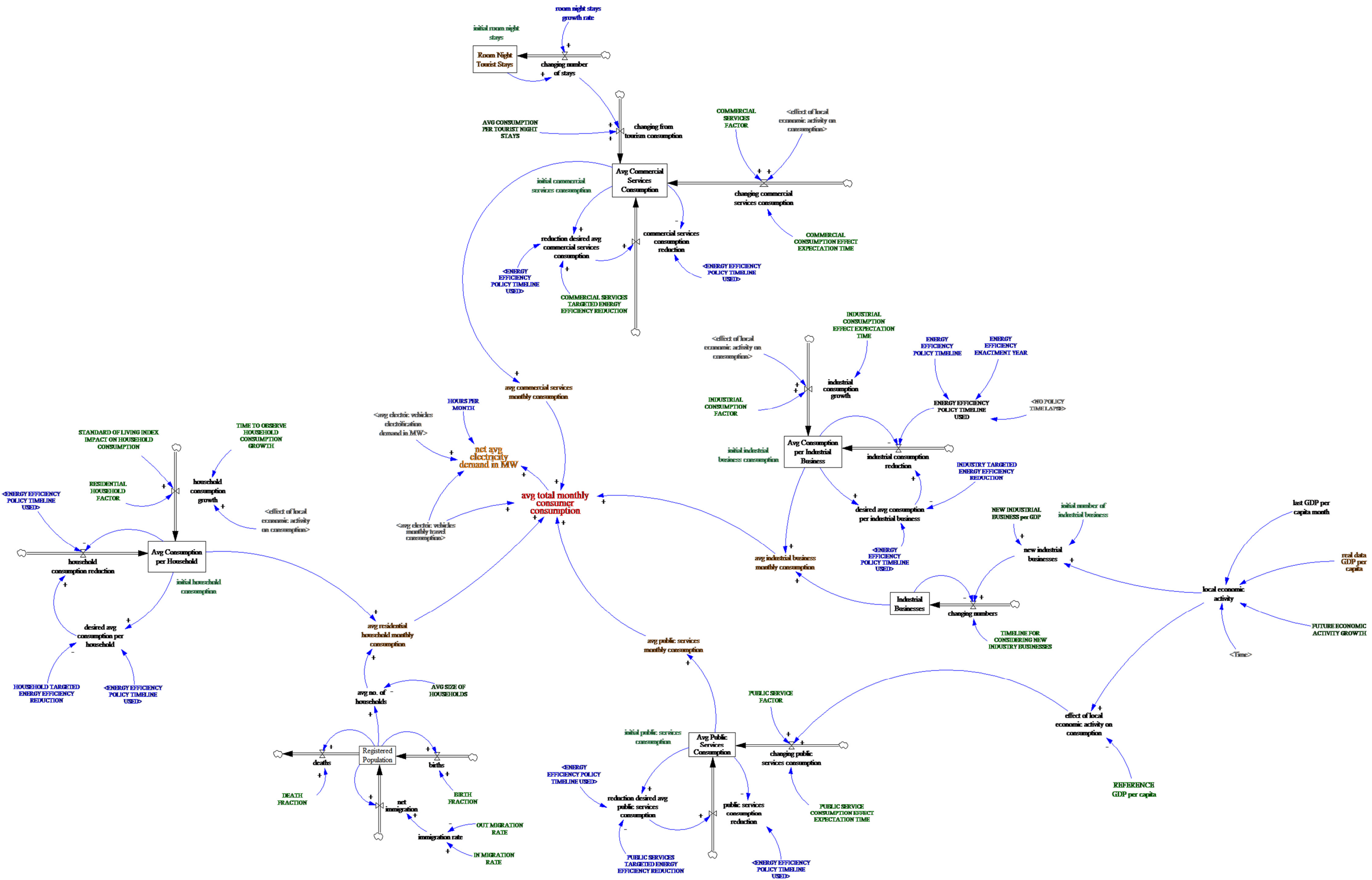
† Total stocks do not include fixed delay variables.

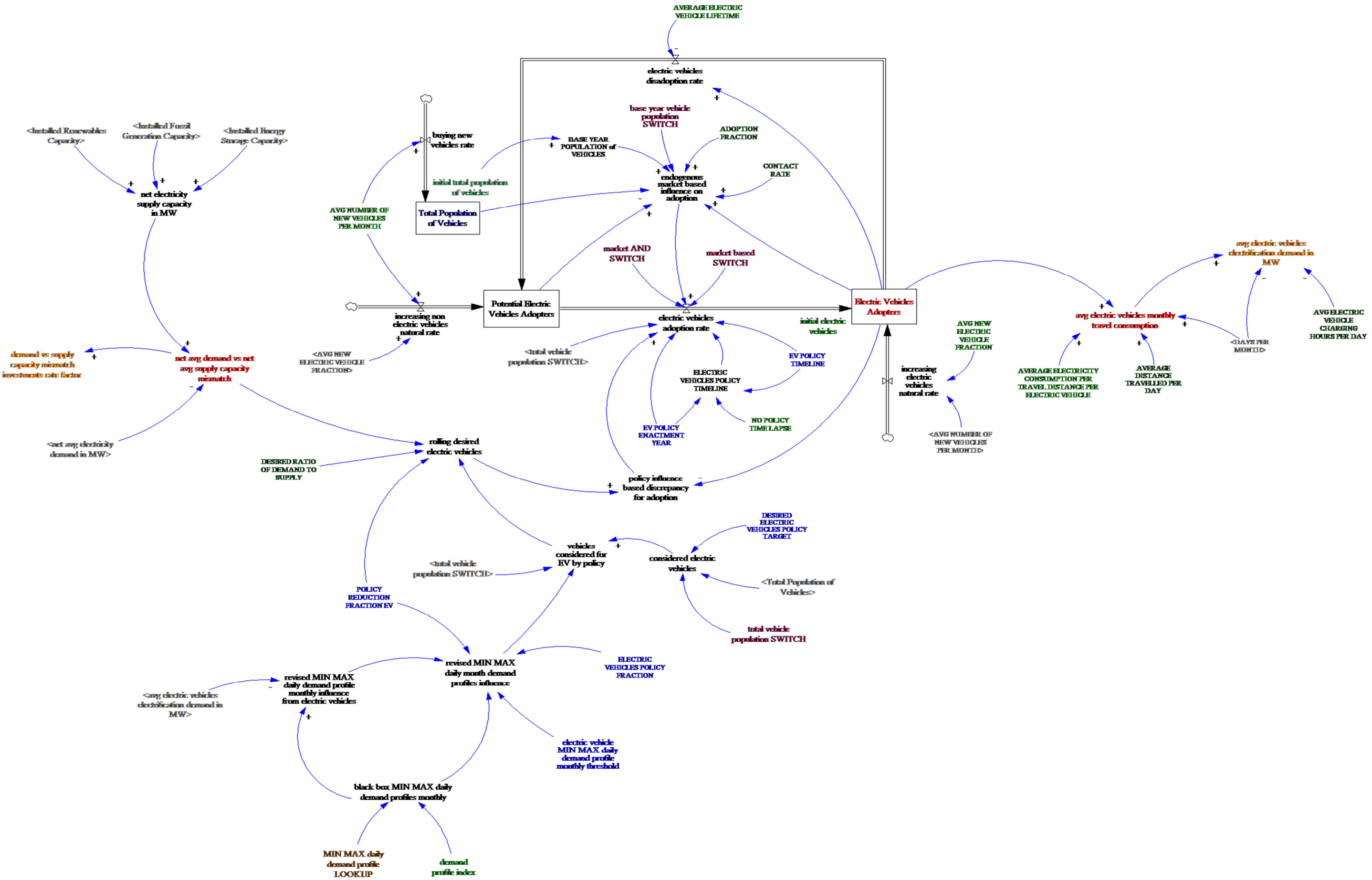
†† (lookup variables / lookup tables).

Different views present in the model:

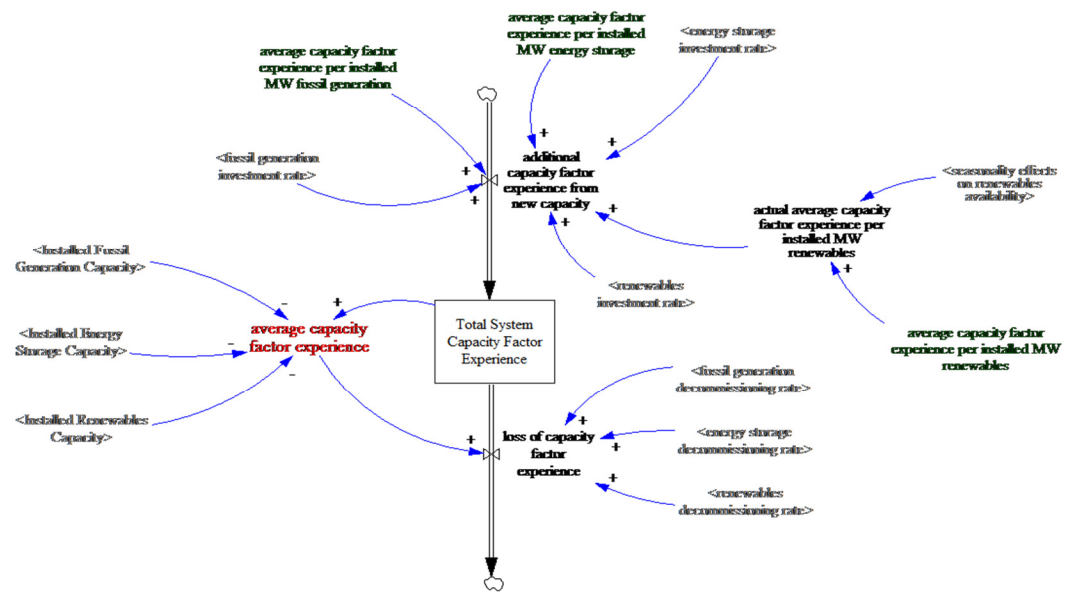
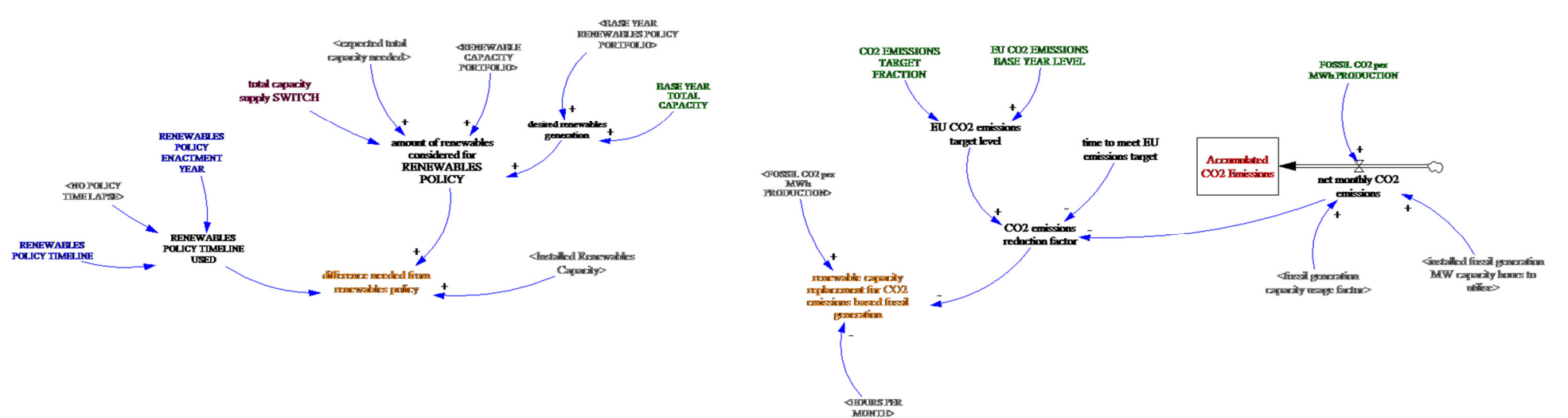
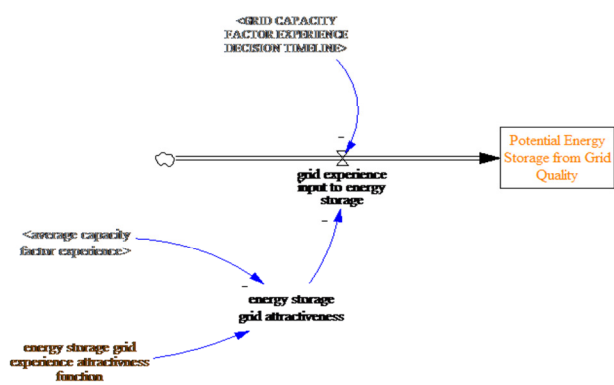
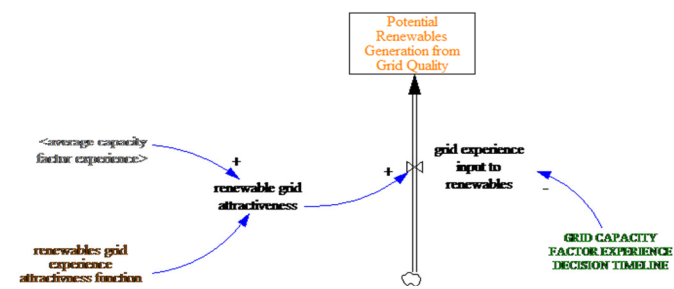
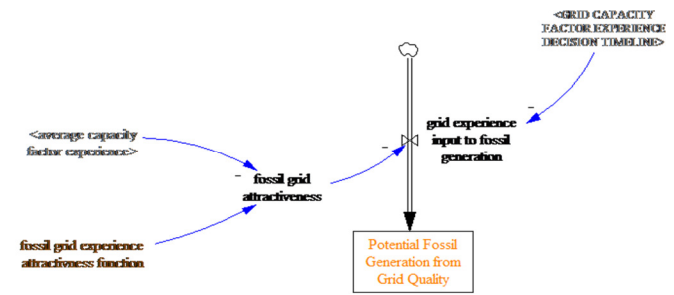
Net Electricity Demand (92 variables)	Mismatch and Demand Imbalance Black Box (74 variables)	Policy, CO2 Emissions, Capacity Factor and Grid Quality (83 variables)	Financial and Economic Aspects (192 variables)	Installed Supply Capacity and Learning Curve (117 variables)
Seasonality Effects Expected Capacity and Real Data (46 variables)				

Net Electricity Demand View

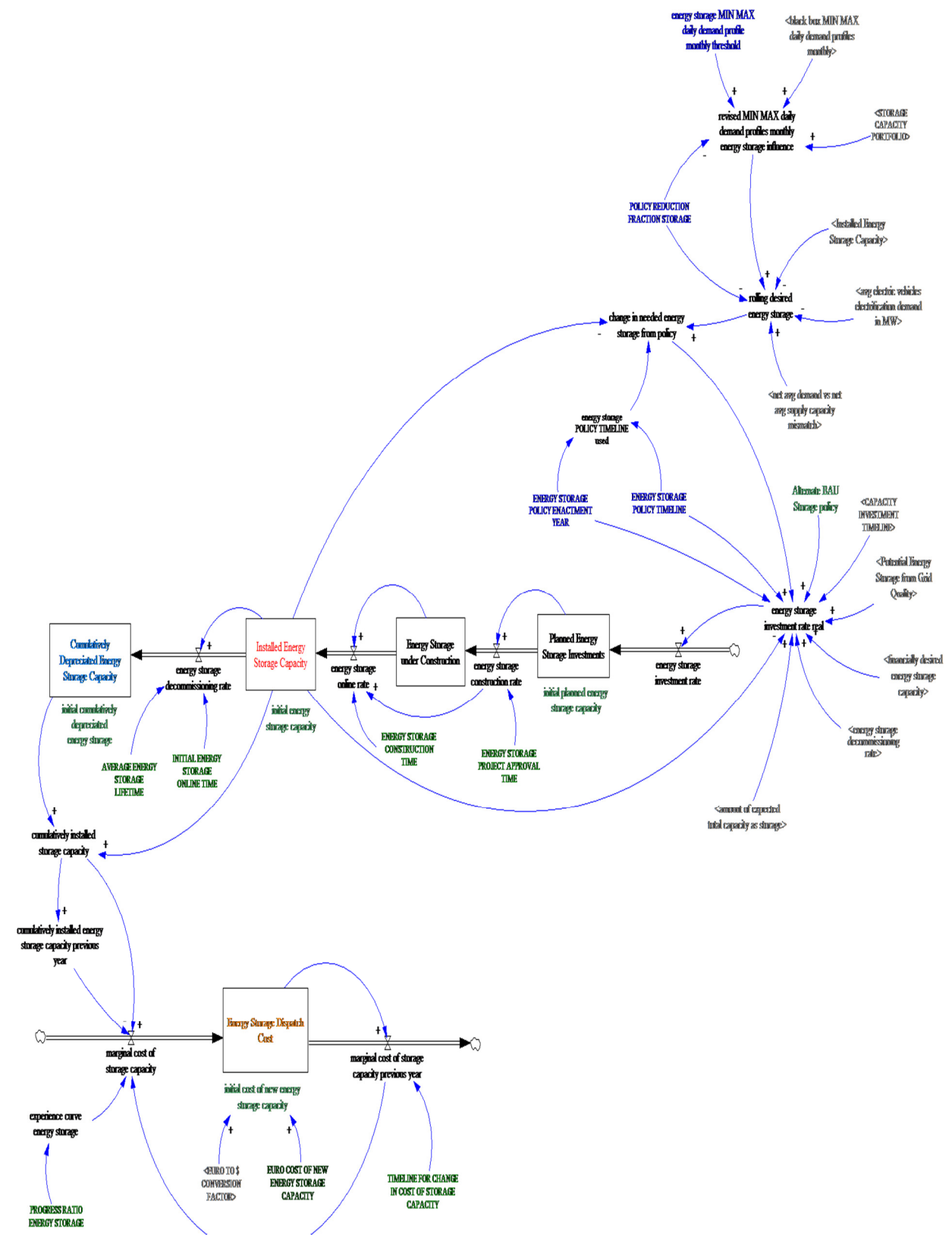
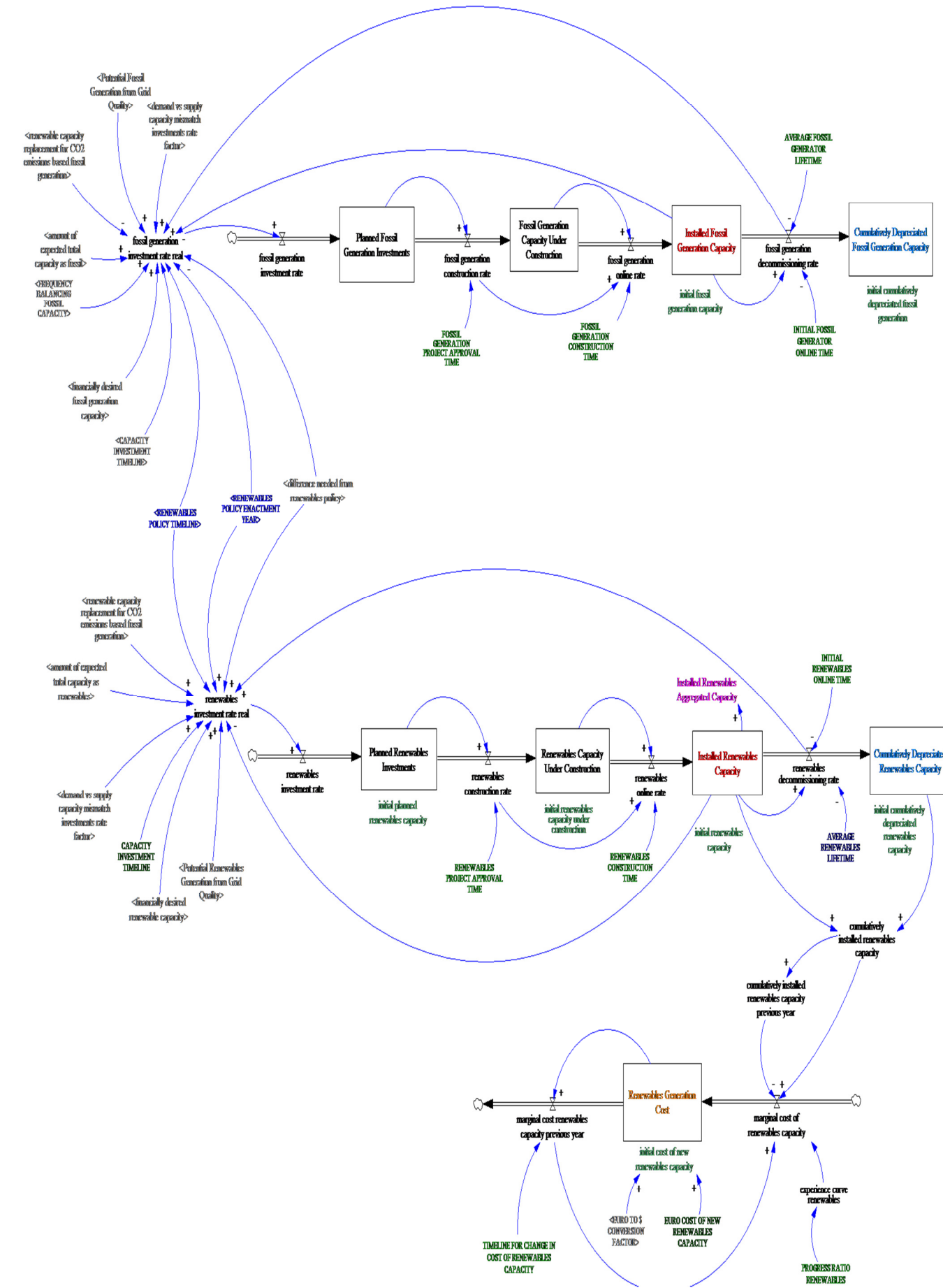




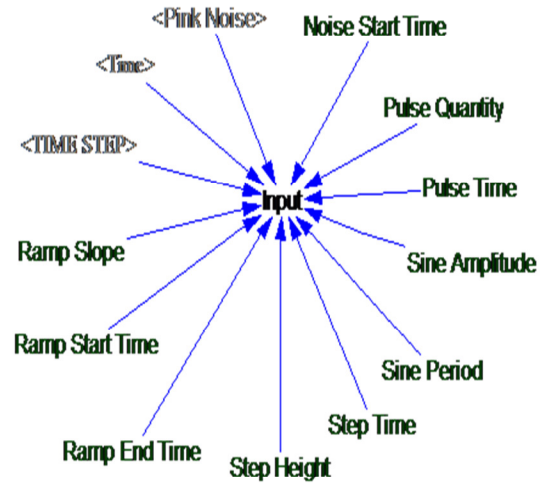
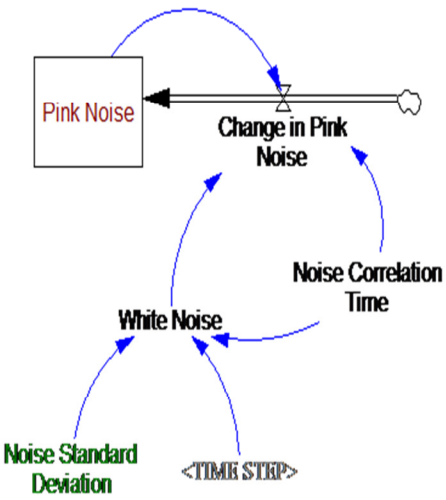
Mismatch and Demand Imbalance Black Box View



Policy, CO2 Emissions, Capacity Factor and Grid Quality View



Installed Supply Capacity and Learning Curve View



seasonality effects on renewables: availability

real data commercial consumption

real data industrial consumption

real data residential consumption

real data public services consumption

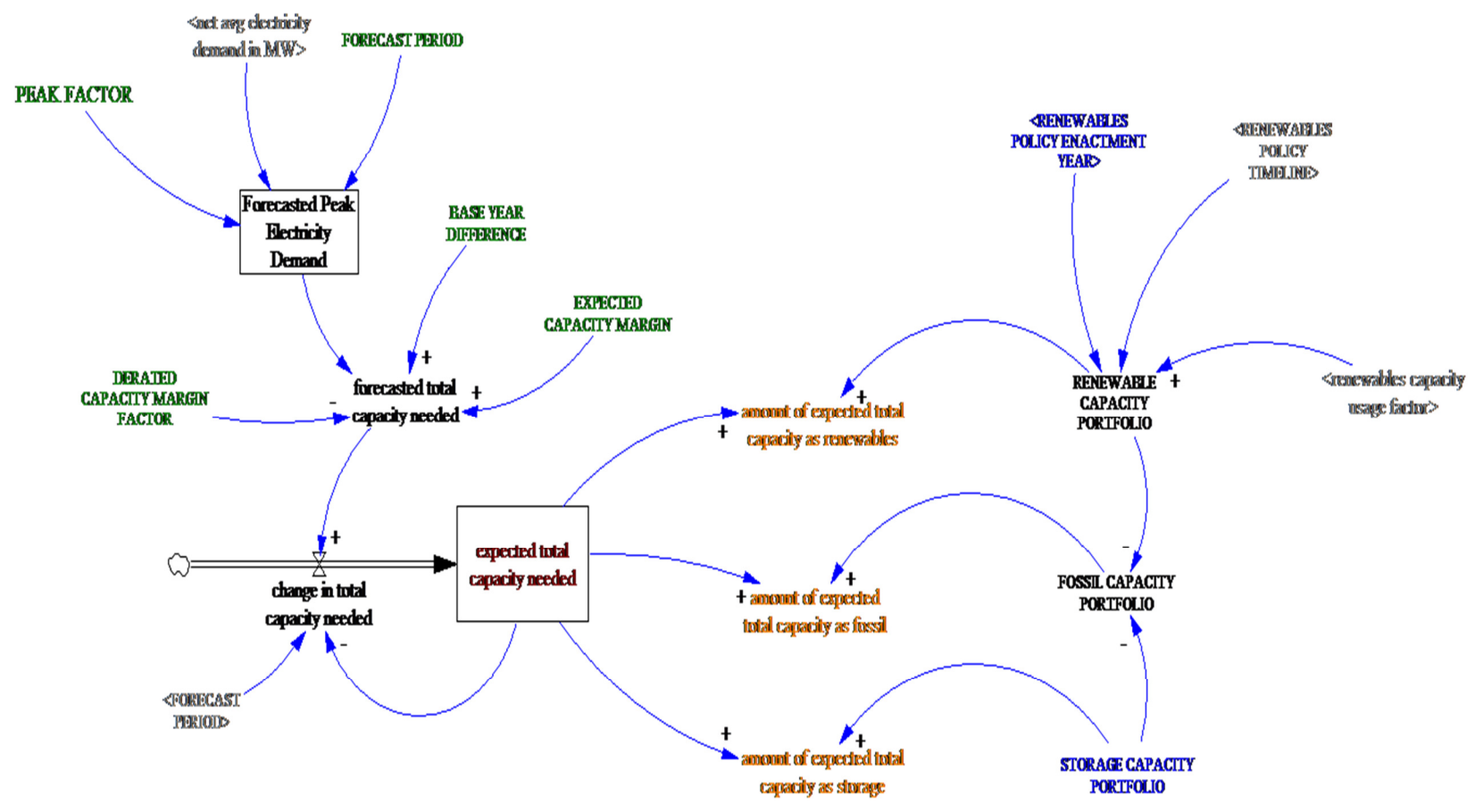
real data total monthly consumption

installed fossil capacity real data

installed renewable capacity real data









installed storage capacity real data

real data registered population










Seasonality Effects Expected Capacity and Real Data View

Listing of ALL variables contained within the model in Alphabetic order:

Variable Type	<u>Variable Name</u> , Units and Description
#1 L 	<p>Accumulated CO2 Emissions (tonnes) $= \int \text{net monthly CO2 emissions } dt + [195732]$ Description: The stock of accumulated CO2 emissions level. The initial value is based on the amount of CO2 emissions assumed in 2004 of 195732. The initial value can also be used as zero. Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p>
#2 LI,A 	<p>actual average capacity factor experience per installed MW renewables (fraction) actual average capacity factor experience per installed MW renewables [type] = average capacity factor experience per installed MW renewables[type]*seasonality effects on renewables availability[type] Description: Gives the capacity factor experience based on the monthly seasonality influences. The yearly effects of the renewables on the amount of capacity factor experience.....Accounts for the maintenance and downtime of the technology 100% capacity factor is 1.0. A monthly measure of 0.9 means 90% of the month of capacity factor experience is achieved. Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute average dispatchable hours for renewables - The amount of hours within a month that the specific renewable technology is dispatched base on capacity factor and merit order usage Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#3 F,A   	<p>additional capacity factor experience from new capacity (MW/Month) $= (\text{average capacity factor experience per installed MW fossil generation} * \text{fossil generation investment rate} + (\text{average capacity factor experience per installed MW energy storage} * \text{energy storage investment rate}) + (\sum(\text{actual average capacity factor experience per installed MW renewables}[\text{type}!] * \text{renewables investment rate}[\text{type}!])))$ Description: Increase in the capacity factor experience attribute Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#4 C 	<p>ADOPTION FRACTION (Dmnl [0,0.05,5e-005]) = 0.002 Description: The fraction of times a contact between an active adopter and a potential adopter results in adoption. Based on the data of the present EV adoption we can safely assume 2 in every 1000 persons will adopt. Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small.</p>
#5 A 	<p>aggregated renewables dispatchable MW capacity hours (MW*h/Month) $= \sum(\text{installed renewables MW capacity hours to utilise}[\text{type}!])$ Description: used to normalise the usage of the renewables technologies Present in 1 view: Financial and Economic Aspects Used by: renewables capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</p>
#6 C 	<p>Alternate BAU Storage policy (MW [15, 30, 0.1]) = 12 Description: The amount of energy storage capacity investments planned to start project in 2018 and used as an alternate storage policy. Present in 1 view:</p>

	<p>Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>
#7 A WAB	<p>amount of expected total capacity as fossil (MW) = expected total capacity needed*FOSSIL CAPACITY PORTFOLIO</p> <p>Description: Given the investment portfolio we should have this amount of fossil in the generation mix to meet forecasted demand levels..</p> <p>Present in 2 views: Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed.</p>
#8 A WAB	<p>amount of expected total capacity as renewables (MW) amount of expected total capacity as renewables [type] = expected total capacity needed*RENEWABLE CAPACITY PORTFOLIO[type]</p> <p>Description: Given the investment portfolio we should invest in this amount of the specific renewable technology in the generation mix to meet forecasted demand levels.</p> <p>Present in 2 views: Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
#9 A WAB	<p>amount of expected total capacity as storage (MW) = expected total capacity needed*STORAGE CAPACITY PORTFOLIO</p> <p>Description: Given the investment portfolio we should have this amount of storage in the generation mix to meet forecasted demand levels.</p> <p>Present in 2 views: Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>
#10 A WAB	<p>amount of renewables considered for RENEWABLES POLICY (MW) = IF THEN ELSE(total capacity supply SWITCH = 1, $\sum(\text{RENEWABLE CAPACITY PORTFOLIO}[\text{type!}])$*expected total capacity needed, desired renewables generation)</p> <p>Description: This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted.</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: difference needed from renewables policy - Monthly amount of capacity needed to achieve policy goals by the policy timeline.</p>
#11 A WAB	<p>average capacity factor experience (Dmnl) = $\frac{\text{Total System Capacity Factor Experience}}{(\text{Installed Energy Storage Capacity} + \text{Installed Fossil Generation Capacity} + (\sum(\text{Installed Renewables Capacity}[\text{type!}])))}$</p> <p>Description: Capacity factor attribute as determined from the different installed capacity stocks.</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: energy storage grid attractiveness - Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of energy storage that should be considered. fossil grid attractiveness - Attractiveness of the fossil generation technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered. loss of capacity factor experience - Decrease in the capacity factor attribute renewable grid attractiveness - Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered.</p>

<p>#12 LI,C VAB</p>	<p>average capacity factor experience per installed MW energy storage (fraction [0,1,0.05]) = 0.9 Description: <i>This is the referenced capacity factor: Accounts for the maintenance and downtime of the technology 100% capacity factor which is 1.0 A monthly measure 0.9 means 90% of the month of capacity factor experience. IEA 2005</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute average dispatchable hours for energy storage - The amount of hours within a month that energy storage is dispatched base on capacity factor and merit order usage Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
<p>#13 LI,C VAB</p>	<p>average capacity factor experience per installed MW fossil generation (fraction [0,1,0.05]) = 0.85 Description: <i>This is the referenced capacity factor: 100% capacity factor which is 1.0 A monthly measure 0.9 means 90% of the month of capacity factor experience....Accounts for the maintenance and downtime of the technology. IEA 2005</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute average dispatchable hours for fossil generation - The amount of hours within a month that fossil generation is dispatched base on capacity factor and merit order usage Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
<p>#14 C VAB</p>	<p>average capacity factor experience per installed MW renewables (fraction) average capacity factor experience per installed MW renewables [type] = 0.8,0.9,0.6,0.2,0.18 Description: <i>720h is equivalent to 100% capacity factor which is 1.0 This is a monthly measure. Geothermal has between 0.6 and 0.95 capacity factor: openei.org data: wind is between 15-40%, biomass 75-90%, solar 15-35%, Run of river Hydro biomass 75-90%, solar 15-40%, Run of river Hydro 80-95% This accounts for the maintenance and downtime of the technology</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: actual average capacity factor experience per installed MW renewables - Gives the capacity factor experience based on the monthly seasonality influences. The yearly effects of the renewables on the amount of capacity factor experience.....Accounts for the maintenance and downtime of the technology 100% capacity factor is 1.0. A monthly measure of 0.9 means 90% of the month of capacity factor experience is achieved.</p>
<p>#15 A VAB</p>	<p>average dispatchable hours for energy storage (h/Month) = average capacity factor experience per installed MW energy storage*average energy storage usage hours Description: <i>The amount of hours within a month that energy storage is dispatched base on capacity factor and merit order usage</i> Present in 1 view: Financial and Economic Aspects Used by: installed energy storage MW capacity hours to utilise - For the monthly demand.....active energy used hours from energy storage needed breakeven monthly revenue per MW installed energy storage - Revenues needed due to installed energy storage capacities and usage of the capacity</p>
<p>#16 A VAB</p>	<p>average dispatchable hours for fossil generation (h/Month) = average capacity factor experience per installed MW fossil generation*average fossil generation usage hours Description: <i>The amount of hours within a month that fossil generation is dispatched base on capacity factor and merit order usage</i> Present in 1 view: Financial and Economic Aspects Used by: installed fossil generation MW capacity hours to utilise - For the monthly demand.....active energy used hours from fossil generation needed breakeven monthly revenue per MW installed fossil generation - Revenues needed due to installed fossil generation capacities and usage of the capacity</p>







#17 A 	average dispatchable hours for renewables (h/Month) average dispatchable hours for renewables [type] = actual average capacity factor experience per installed MW renewables[type]*average renewables usage hours[type] Description: <i>The amount of hours within a month that the specific renewable technology is dispatched base on capacity factor and merit order usage</i> Present in 1 view: Financial and Economic Aspects Used by: installed renewables MW capacity hours to utilise - For the monthly demand.....active energy used hours from the different renewables technologies needed breakeven monthly revenue per MW installed renewables - Revenues needed due to the installed renewable technologies capacity and usage of this capacity
#18 C 	AVERAGE DISTANCE TRAVELLED PER DAY (KM/day [26, 36,2]) = 26 Description: <i>The average distanced travelled by an electric vehicle every month. Mean travel distance of 26Km per day = 780Km per month.....36Km per day = 1040Km per Month. Parness (2011)</i> Present in 2 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: avg electric vehicles monthly travel consumption - The monthly MWh that is demanded by an average EV under normal operation 0.00494MWh/vehicle considering average consumption per Km and the average distance travelled per month
#19 A 	AVERAGE ELECTRIC VEHICLE LIFETIME (Months [120,180]) = =156 Description: <i>Considering the average lifetime of an electric vehicle, it is assumed to be 10-15 years</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: electric vehicles disadoption rate - The discard rate is assumed to be first-order, with an average lifetime as given.
#20 A 	AVERAGE ELECTRICITY CONSUMPTION PER TRAVEL DISTANCE PER ELECTRIC VEHICLE (MW*h/KM/vehicles [0.000172,0.000202,5e-005]) = =0.00019 Description: <i>Ranges between (27 kW-h/100 mi or 17.2 kW-h/100 km) to (31 kW-h/100 mi or 20.2 kW-h/100 km)</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: avg electric vehicles monthly travel consumption - The monthly MWh that is demanded by an average EV under normal operation 0.00494MWh/vehicle considering average consumption per Km and the average distance travelled per month
#21 C 	AVERAGE ENERGY STORAGE LIFETIME (Months [360,600,120]) = 480 Description: <i>Assumed from global data that hydro lifetime is almost infinite.....Hence we use the value larger than the total simulation period of 30 to 50 year (600)</i> http://www.eia.gov/forecasts/aeo/assumptions/pdf/0554(2014).pdf EDA views small reservoir as a 40 years (480 months) investment project Present in 1 view: Installed Supply Capacity and Learning Curve Used by: energy storage decommissioning rate - Accounting for the depreciation of energy storage
#22 A 	average energy storage usage hours (h/Month) = average off peak hours per month from energy storage + average peak hours per month from energy storage + average shoulder peak hours per month from energy storage Description: <i>Sum of hours per month that energy storage is dispatched to meet the demand load</i> Present in 1 view: Financial and Economic Aspects Used by: average dispatchable hours for energy storage - The amount of hours within a month that energy storage is dispatched base on capacity factor and merit order usage
#23 A 	average fossil generation usage hours (h/Month) = average off peak hours per month from fossil generation + average peak hours per month from fossil generation + average shoulder peak hours per month from fossil generation Description: <i>Sum of hours per month that fossil generation is dispatched to meet the demand load</i> Present in 1 view:

	<p>Financial and Economic Aspects</p> <p>Used by: average dispatchable hours for fossil generation - The amount of hours within a month that fossil generation is dispatched base on capacity factor and merit order usage</p>
#24 C VAB	<p>AVERAGE FOSSIL GENERATOR LIFETIME (Months [360,480]) = 480</p> <p>Description: Global data suggest 35 years (420 months) as the nominal time. In São Miguel they suggest an extra 5 years from these generating units up to 480 months (Default value)</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: fossil generation decommissioning rate - Accounting for the depreciation of the fossil generation capacity.</p>
#25 A VAB	<p>average off peak hours per month from energy storage (h/Month [6,10,4]) = STANDARD OFF PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for energy storage during off peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average energy storage usage hours - Sum of hours per month that energy storage is dispatched to meet the demand load</p>
#26 A VAB	<p>average off peak hours per month from fossil generation (h/Month [?,?,4]) = STANDARD OFF PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for fossil generation during off peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average fossil generation usage hours - Sum of hours per month that fossil generation is dispatched to meet the demand load</p>
#27 A VAB	<p>average off peak hours per month from renewables (h/Month) average off peak hours per month from renewables [type] = STANDARD OFF PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for renewables during off peak hours[type]</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average renewables usage hours - Sum of hours per month that renewables is dispatched to meet the demand load</p>
#28 A VAB	<p>average peak hours per month from energy storage (h/Month [1.5,4,0.5]) = STANDARD PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for energy storage during peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average energy storage usage hours - Sum of hours per month that energy storage is dispatched to meet the demand load</p>
#29 A VAB	<p>average peak hours per month from fossil generation (h/Month [1.5,4,0.5]) = STANDARD PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for fossil generation during peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average fossil generation usage hours - Sum of hours per month that fossil generation is dispatched to meet the demand load</p>
#30 A VAB	<p>average peak hours per month from renewables (h/Month [1.5,4,0.5]) average peak hours per month from renewables [type] = STANDARD PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for renewables during peak hours[type]</p> <p>Description: <i>Data source for derivation: Ilic et al (2013) pg 145 table 4.12</i></p> <p>Present in 1 view:</p> <ul style="list-style-type: none"> • Financial and Economic Aspects <p>Used by:</p>











	<ul style="list-style-type: none"> average renewables usage hours - Sum of hours per month that renewables is dispatched to meet the demand load
#31 C VAB	<p>average renewable lifetime (Months [240,360]) = 300</p> <p>Description: Assuming a project lifetime of 20 to 30 years (240 months) for a wind turbine project, geothermal and solarhttp://www.eia.gov/forecasts/aeo/assumptions/pdf/0554(2014).pdf pg 30</p> <p>Not Present In Any View</p>
#32 C VAB	<p>AVERAGE RENEWABLES LIFETIME (Months [120,540,1]) AVERAGE RENEWABLES LIFETIME [type] = 420,540,540,240,300</p> <p>Description: Project lifetime of 20 years (240 months) for a wind turbine project 35 years (420 months) for a Geothermal and 25 years (300 months) for Solar 540 months for run of river and biomass</p> <p>Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve</p> <p>Used by: renewables decommissioning rate - Accounting for the depreciation of the renewable capacity</p>
#33 A VAB	<p>average renewables usage hours (h/Month) average renewables usage hours [type] = average off peak hours per month from renewables[type]+average peak hours per month from renewables[type]+average shoulder peak hours per month from renewables[type]</p> <p>Description: Sum of hours per month that renewables is dispatched to meet the demand load</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average dispatchable hours for renewables - The amount of hours within a month that the specific renewable technology is dispatched base on capacity factor and merit order usage</p>
#34 A VAB	<p>average shoulder peak hours per month from energy storage (h/Month) = STANDARD SHOULDER PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for energy storage during shoulder peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average energy storage usage hours - Sum of hours per month that energy storage is dispatched to meet the demand load</p>
#35 A VAB	<p>average shoulder peak hours per month from fossil generation (h/Month) = STANDARD SHOULDER PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor hours for fossil generation during shoulder peak hours</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average fossil generation usage hours - Sum of hours per month that fossil generation is dispatched to meet the demand load</p>
#36 A VAB	<p>average shoulder peak hours per month from renewables (h/Month) average shoulder peak hours per month from renewables [type] = STANDARD SHOULDER PEAK HOURS PER DAY*DAYS PER MONTH*dispatch factor for renewables during shoulder peak hours[type]</p> <p>Description: Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average renewables usage hours - Sum of hours per month that renewables is dispatched to meet the demand load</p>
#37 L VAB	<p>Avg Commercial Services Consumption (MW*h/Month) = changing commercial services consumption+commercial services consumption reduction+changing from tourism consumption dt + [initial commercial services consumption]</p> <p>Description: Stock of commercial services consumption</p> <p>Present in 2 views: Net Electricity Demand Financial and Economic Aspects</p> <p>Used by: avg commercial services monthly consumption - This is the average commercial services consumption (based on the stochastic variation if (on))</p>

	<p>commercial services consumption reduction - Monthly change in commercial services consumption reduction, a negative value, as a flow into the average commercial services consumption</p> <p>reduction desired avg commercial services consumption - Desired average commercial services consumption based on the energy efficiency targets (policy)</p>
#38 A VAB	<p>avg commercial services monthly consumption (MW*h/Month) = Avg Commercial Services Consumption</p> <p>Description: <i>This is the average commercial services consumption (based on the stochastic variation if (on))</i></p> <p>Present in 2 views: Net Electricity Demand Financial and Economic Aspects</p> <p>Used by: avg total monthly consumer consumption - Aggregated monthly consumption of the various consumer sectors commercial services off peak hours consumption - Derived consumption during off peak hours commercial services peak hours consumption - Derived consumption during peak hours commercial services shoulder peak hours consumption - Derived consumption during shoulder peak hours</p>
#39 L VAB	<p>Avg Consumption per Household (MW*h/(Month*households)) = \inthousehold consumption growth+household consumption reduction dt + [initial household consumption]</p> <p>Description: <i>Stock of average consumption per household</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: avg residential household monthly consumption - This is the monthly consumption from the number of households and the average consumption per household (based on the stochastic variation if (on)) desired avg consumption per household - Desired average consumption per household based on the energy efficiency targets (policy) household consumption reduction - Monthly change in household consumption reduction, a negative value, as a flow into the average household consumption</p>
#40 L VAB	<p>Avg Consumption per Industrial Business (MW*h/industries) = \intindustrial consumption growth+industrial consumption reduction dt + [initial industrial business consumption]</p> <p>Description: <i>Stock of industrial business consumption</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: avg industrial business monthly consumption - This is the average industrial business consumption (based on the stochastic variation if (on)) desired avg consumption per industrial business - Desired average consumption per industrial business based on the energy efficiency targets (policy) industrial consumption reduction - Monthly change in industrial business consumption reduction, a negative value, as a flow into the average industrial business consumption</p>
#41 C VAB	<p>AVG CONSUMPTION PER TOURIST NIGHT STAYS (MW*h/night stays [0.002,0.0039,0.0001]) = 0.0027</p> <p>Description: <i>Global data from http://www.onecaribbean.org/content/files/CHENACT%20-CREF.pdf pg60.0027 as the default value</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: changing from tourism consumption - Due to the consumption from tourism overnight hotel stays</p>
#42 C VAB	<p>AVG ELECTRIC VEHICLE CHARGING HOURS PER DAY (h/day [0,24,1]) = 10</p> <p>Description: <i>Average number of hours per day for the EV operation which reflects the electrification demand that will be needed from the EV assuming the key charging times are between 10pm and 7am every night.</i></p> <p>Present in 3 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve</p> <p>Used by: avg electric vehicles electrification demand in MW - Based on the times of EV operation we can determine a more accurate average MW of electric vehicle consumption on a monthly time factor.</p>
#43 C VAB	<p>AVG ELECTRIC VEHICLE COMMUTING HOURS PER DAY (h/day [0, 24]) = 2</p> <p>Description: <i>average number of hours per day for the storage operation when EV is not charging or being driven. Assuming the key charging times are between 10pm and 5am every night and a further 2-3 hrs for commuting.....we have approximately 0.5 of a day per vehicle used for storage to the grid.....24</i></p>

	<p>hours in a day</p> <p>Present in 1 view:</p> <p>Installed Supply Capacity and Learning Curve</p>
#44 A VAB	<p>avg electric vehicles electrification demand in MW (MW)</p> <p>= avg electric vehicles monthly travel consumption/(AVG ELECTRIC VEHICLE CHARGING HOURS PER DAY* DAYS PER MONTH)</p> <p>Description: Based on the times of EV operation we can determine a more accurate average MW of electric vehicle consumption on a monthly time factor.</p> <p>Present in 3 views:</p> <p>Net Electricity Demand</p> <p>Mismatch and Demand Imbalance Black Box</p> <p>Installed Supply Capacity and Learning Curve</p> <p>Used by:</p> <p>net avg electricity demand in MW - 720 hours per (30 days Vensim) month used to change from MWh to MW.....electric vehicles MW consumption is calculated from the assumed operational hours of the EVs</p> <p>revised MIN MAX daily demand profile monthly influence from electric vehicles - Based on the adopted electric vehicles this is the monthly average reduction in the gap that can be achieved (increases in the demand base)</p> <p>rolling desired energy storage - Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.</p>
#45 A VAB	<p>avg electric vehicles monthly travel consumption (MW*h/Month)</p> <p>= (Electric Vehicles Adopters*AVERAGE ELECTRICITY CONSUMPTION PER TRAVEL DISTANCE PER ELECTRIC VEHICLE*AVERAGE DISTANCE TRAVELLED PER DAY*DAYS PER MONTH)</p> <p>Description: The monthly MWh that is demanded by an average EV under normal operation 0.00494MWh/vehicle considering average consumption per Km and the average distance travelled per month</p> <p>Present in 4 views:</p> <p>Net Electricity Demand</p> <p>Mismatch and Demand Imbalance Black Box</p> <p>Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Financial and Economic Aspects</p> <p>Used by:</p> <p>avg electric vehicles electrification demand in MW - Based on the times of EV operation we can determine a more accurate average MW of electric vehicle consumption on a monthly time factor.</p> <p>avg total monthly consumer consumption - Aggregated monthly consumption of the various consumer sectors</p> <p>electric vehicles off peak hours consumption - Derived consumption during off peak hours</p> <p>electric vehicles peak hours consumption - Derived consumption during peak hours</p> <p>electric vehicles shoulder peak hours consumption - Derived consumption during shoulder peak hours</p> <p>net avg electricity demand in MW - 720 hours per (30 days Vensim) month used to change from MWh to MW.....electric vehicles MW consumption is calculated from the assumed operational hours of the EVs</p>
#46 A VAB	<p>avg industrial business monthly consumption (MW*h/Month)</p> <p>= Avg Consumption per Industrial Business*Industrial Businesses</p> <p>Description: This is the average industrial business consumption (based on the stochastic variation if (on))</p> <p>Present in 2 views:</p> <p>Net Electricity Demand</p> <p>Financial and Economic Aspects</p> <p>Used by:</p> <p>avg total monthly consumer consumption - Aggregated monthly consumption of the various consumer sectors</p> <p>industrial off peak hours consumption - Derived consumption during off peak hours</p> <p>industrial peak hours consumption - Derived consumption during peak hours</p> <p>industrial shoulder peak hours consumption - Derived consumption during shoulder peak hours</p>
#47 A VAB	<p>AVG NEW ELECTRIC VEHICLE FRACTION (fraction [0.001, 0.009])</p> <p>= 0.01</p> <p>Description: Percentage of new vehicles bought every month being an electric vehicle without any policy or marketing influence..... Own elaboration using Parness (2011)</p> <p>Present in 1 view:</p> <p>Mismatch and Demand Imbalance Black Box</p> <p>Used by:</p> <p>increasing electric vehicles natural rate - Natural number of new electric vehicles bought every month without any policy or market influences</p> <p>increasing non electric vehicles natural rate - Number of new non-electric vehicles that are bought every month</p>
#48 A VAB	<p>"avg no. of households" (households)</p> <p>= Registered Population/AVG SIZE OF HOUSEHOLDS</p> <p>Description: Based on the registered population and the average size of households</p> <p>Present in 1 view:</p> <p>Net Electricity Demand</p> <p>Used by:</p>

	<p>avg residential household monthly consumption - This is the monthly consumption from the number of households and the average consumption per household (based on the stochastic variation if (on))</p>
<p>#49 A </p>	<p>AVG NUMBER OF NEW VEHICLES PER MONTH (vehicles/Month [80,110]) = 85</p> <p>Description: 1000 to 1200 per year = 83 to 100 per month http://estatistica.azores.gov.pt/upl/%7B032836b6-856d-44d7-b0ea-22cfb223d373%7D.htm and https://mitei.mit.edu/system/files/Environmental-Cost-Impacts-Vehicle-Electrification-Azores-Parness.pdf</p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: buying new vehicles rate - Inflow based on new vehicles buying rate increasing electric vehicles natural rate - Natural number of new electric vehicles bought every month without any policy or market influences increasing non electric vehicles natural rate - Number of new non-electric vehicles that are bought every month</p>
<p>#50 L </p>	<p>Avg Public Services Consumption (MW*h/Month) = \int changing public services consumption + public services consumption reduction dt + initial public services consumption</p> <p>Description: Stock of average public services consumption</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: avg public services monthly consumption - This is the average monthly public services consumption (based on the stochastic variation if (on)) public services consumption reduction - Monthly change in public services consumption reduction, a negative value, as a flow into the average public services consumption reduction desired avg public services consumption - Desired average public services consumption based on the energy efficiency targets (policy)</p>
<p>#51 A </p>	<p>avg public services monthly consumption (MW*h/Month) = Avg Public Services Consumption</p> <p>Description: This is the average monthly public services consumption (based on the stochastic variation if (on))</p> <p>Present in 2 views: Net Electricity Demand Financial and Economic Aspects</p> <p>Used by: avg total monthly consumer consumption - Aggregated monthly consumption of the various consumer sectors public services off peak hours consumption - Derived consumption during off peak hours public services peak hours consumption - Derived consumption during peak hours public services shoulder peak hours consumption - Derived consumption during shoulder peak hours</p>
<p>#52 A </p>	<p>avg residential household monthly consumption (MW*h/Month) = Avg Consumption per Household * "avg no. of households"</p> <p>Description: This is the monthly consumption from the number of households and the average consumption per household (based on the stochastic variation if (on))</p> <p>Present in 2 views: Net Electricity Demand Financial and Economic Aspects</p> <p>Used by: avg total monthly consumer consumption - Aggregated monthly consumption of the various consumer sectors residential off peak hours consumption - Derived consumption during off peak hours residential peak hours consumption - Derived consumption during peak hours residential shoulder peak hours consumption - Derived consumption during shoulder eak hours</p>
<p>#53 C </p>	<p>AVG SIZE OF HOUSEHOLDS (people/households [2.5,3.45]) = 3.45</p> <p>Description: http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf page 622.5 gives a better reflection to the total number of EDA electricity customers</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: "avg no. of households" - Based on the registered population and the average size of households</p>
<p>#54 A </p>	<p>avg total monthly consumer consumption (MW*h/Month) = avg commercial services monthly consumption + avg public services monthly consumption + avg industrial business monthly consumption + avg residential household monthly consumption + avg electric vehicles monthly travel consumption</p> <p>Description: Aggregated monthly consumption of the various consumer sectors</p> <p>Present in 1 view: Net Electricity Demand</p>

	<p>Used by: net avg electricity demand in MW - 720 hours per (30 days Vensim) month used to change from MWh to MW.....electric vehicles MW consumption is calculated from the assumed operational hours of the EVs</p>
#55 C VAB	<p>avg usage factor of the installed fossil generation (fraction [0.2,0.75,0.05]) = 0.45 Description: <i>In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p>
#56 A VAB	<p>BASE YEAR DIFFERENCE (MW [10,40,10]) = =30 Description: <i>Difference from trough to peak demand of the system in 2005</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: forecasted total capacity needed - Based on the present capacity margin and the forecasted peak demands of the system BAU case together with the derated capacity margins.</p>
#57 A VAB	<p>BASE YEAR POPULATION of VEHICLES (vehicles) = initial total population of vehicles Description: <i>Number of vehicles in the island in 2005</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small.</p>
#58 C VAB	<p>BASE YEAR RENEWABLES POLICY PORTFOLIO (fraction [0,1,0.05]) = 0.45 Description: <i>represents the fraction of the base year renewables that should be achieved</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Seasonality Effects Expected Capacity and Real Da Used by: desired renewables generation - Absolute amount of renewables desired based on base year, 2005 values</p>
#59 A VAB	<p>BASE YEAR TOTAL CAPACITY (MW) = =133 Description: <i>The total amount of capacity from all generation technologies that was installed in the base year 2005. This is 133MW</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: desired renewables generation - Absolute amount of renewables desired based on base year, 2005 values</p>
#60 C VAB	<p>base year vehicle population SWITCH (Dmnl [0,1]) = 0 Description: <i>on (1) and off (0). Used for total vehicle base year population simulations</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small.</p>
#61 A VAB	<p>BIRTH FRACTION (fraction/Month) = =0.001042 Description: Birth rate in 2005 per 1000 people. Divide by 12 for a monthly rate (12.5/1000)/12 http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf pg59 http://azores.gov.pt/Portal/en/entidades/pgra/noticias/Azores+lead+birth+rate+in+Portugal.htm (11.7/1000) birth rate Present in 1 view: Net Electricity Demand Used by: births - Inflow of births to the population</p>







<p>#62 F,A   </p>	<p>births (people/Month) = Registered Population*BIRTH FRACTION Description: Inflow of births to the population Present in 1 view: Net Electricity Demand Used by: Registered Population - The monthly amount of people counted as the population of São Miguel. Aging population details:plan_action_strategique_eu2020_acores_en.pdf page 60131609 in 2001 and 137830 in 2011.....2005 approximates to 134720Initial value from ERNA_andre_leonardo_kiti document137856 population number in 2011 Azores censusdata2011</p>
<p>#63 A </p>	<p>black box MIN MAX daily demand profiles monthly (MW) = MIN MAX daily demand profile LOOKUP(demand profile index) Description: Choosing the normalized profile based on the randomly given index of the data values Present in 2 views: Mismatch and Demand Imbalance Black Box Installed Supply Capacity and Learning Curve Used by: revised MIN MAX daily demand profile monthly influence from electric vehicles - Based on the adopted electric vehicles this is the monthly average reduction in the gap that can be achieved (increases in the demand base) revised MIN MAX daily demand profiles monthly energy storage influence - If the MIN MAX difference remains high then we should continue with the energy storage policy, if not then we can reduce the energy storage policy to 1%This assumes that the larger the gap then more excess storage supply is needed in the daytime proportional to the avoided curtailed amount in the night time. revised MIN MAX daily month demand profiles influence - If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a fraction of the current EV policy fraction</p>
<p>#64 F,A  </p>	<p>buying new vehicles rate (vehicles/Month) = AVG NUMBER OF NEW VEHICLES PER MONTH Description: Inflow based on new vehicles buying rate Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: Total Population of Vehicles - Stock of total vehicle population in the island system.</p>
<p>#65 C </p>	<p>CAPACITY INVESTMENT TIMELINE (Months [12, 30, 3]) = 18 Description: Time to make investment decisions for new capacity additions. This is a fixed timeline when all investment decisions are considered Present in 1 view: Installed Supply Capacity and Learning Curve Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline. fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
<p>#66 A </p>	<p>change in needed energy storage from policy (MW/Month) = (rolling desired energy storage-Installed Energy Storage Capacity)/energy storage POLICY TIMELINE used Description: Discrepancy needed to meet the energy policy goals. Present in 1 view: Installed Supply Capacity and Learning Curve Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>
<p>#67 F,A  </p>	<p>Change in Pink Noise (1/Months) Change in Pink Noise [type] = (White Noise[type] - Pink Noise[type])/Noise Correlation Time[type] Description: Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input. Used sparingly in this thesis work Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p>

	<p>Used by: Pink Noise - Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user. Adopted from Sterman (2000)</p>
#68 F,A  	<p>change in revenues (\$/Month/Month) = (total electricity sold revenues-Expected Revenues)/REVENUE TIME HORIZON Description: <i>Change in he revenue generated over the revenue horizon</i> Present in 1 view: Financial and Economic Aspects Used by: Expected Revenues - Stock of rolling average of revenues generated</p>
#69 F,A  	<p>change in total capacity needed (MW/Month) = (forecasted total capacity needed-expected total capacity needed)/FORECAST PERIOD Description: <i>Inflow of total capacity needed</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: expected total capacity needed - Smoothing the total capacity needed based on the capacity investment timeline.</p>
#70 F,A  	<p>changing commercial services consumption (MW*h/Month/Month) = (COMMERCIAL SERVICES FACTOR*effect of local economic activity on consumption)/COMMERCIAL CONSUMPTION EFFECT EXPECTATION TIME Description: <i>Commercial services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month</i> Present in 1 view: Net Electricity Demand Used by: Avg Commercial Services Consumption - Stock of commercial services consumption</p>
#71 F,A  	<p>changing from tourism consumption (MW*h/(Month*Month)) = changing number of stays*AVG CONSUMPTION PER TOURIST NIGHT STAYS Description: <i>Due to the consumption from tourism overnight hotel stays</i> Present in 1 view: Net Electricity Demand Used by: Avg Commercial Services Consumption - Stock of commercial services consumption</p>
#72 F,A  	<p>changing number of stays (night stays/(Month*Month)) = Room Night Tourist Stays*room night stays growth rate Description: <i>Monthly change in number of room night stays from tourism</i> Present in 1 view: Net Electricity Demand Used by: changing from tourism consumption - Due to the consumption from tourism overnight hotel stays Room Night Tourist Stays - Stock of room night tourist stays</p>
#73 F,A  	<p>changing numbers (industries/Month/Month) = (new industrial businesses-Industrial Businesses)/TIMELINE FOR CONSIDERING NEW INDUSTRY BUSINESSES Description: <i>Number of monthly changing industries per month</i> Present in 1 view: Net Electricity Demand Used by: Industrial Businesses - Stock of industrial businesses</p>
#74 F,A  	<p>changing public services consumption (MW*h/Month/Month) = (PUBLIC SERVICE FACTOR*effect of local economic activity on consumption)/PUBLIC SERVICE CONSUMPTION EFFECT EXPECTATION TIME Description: <i>Public services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month</i> Present in 1 view: Net Electricity Demand Used by: Avg Public Services Consumption - Stock of average public services consumption</p>
#75 C 	<p>CHARGING EV OFF PEAK PRICE (euro/(h*MW)) = 57.1 Description: <i>Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs. 144-145 price data and EDA (2015) estimates</i> Present in 1 view: Financial and Economic Aspects</p>

	<p>Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>
#76 C VAB	<p>CHARGING EV PEAK PRICE (euro/(h*MW)) = 124.6 Description: Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>
#77 C VAB	<p>CHARGING EV SHOULDER PEAK PRICE (euro/(h*MW)) = 96.7 Description: Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>
#78 A VAB	<p>CO2 emissions reduction factor (tonnes/Month/Month) = (EU CO2 emissions target level-net monthly CO2 emissions)/time to meet EU emissions target Description: The monthly discrepancy resulting from the amount of CO2 emissions and the targeted CO2 emissions reduction Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: renewable capacity replacement for CO2 emissions based fossil generation - The renewable potential from the gap of CO2 emissions. The amount of MW of renewable capacity needed to close the emissions gap.</p>
#79 C VAB	<p>CO2 EMISSIONS TARGET FRACTION (fraction) = 0.3 Description: The percentage of CO2 emissions reduction of the base year (2005) value Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: EU CO2 emissions target level - Target year level of the total amount of CO2 emissions reduction needed over the subsequent years to achieve this value as a fraction of the base year value Given on a monthly assumption basis..... default of 30% reduction of 2005 emissions levels</p>
#80 A VAB	<p>COMMERCIAL CONSUMPTION EFFECT EXPECTATION TIME (Months) = =1 Description: Consumption effect expectation time observed on a monthly basis Present in 1 view: Net Electricity Demand Used by: changing commercial services consumption - Commercial services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month</p>
#81 F,A VAB →	<p>commercial services consumption reduction (MW*h/(Month*Month)) = ZIDZ((reduction desired avg commercial services consumption-Avg Commercial Services Consumption),ENERGY EFFICIENCY POLICY TIMELINE USED) Description: Monthly change in commercial services consumption reduction, a negative value, as a flow into the average commercial services consumption Present in 1 view: Net Electricity Demand Used by: Avg Commercial Services Consumption - Stock of commercial services consumption</p>
#82 A VAB	<p>commercial services consumption revenues (\$/Month) = EURO TO \$ CONVERSION FACTOR*(commercial services off peak hours consumption*COMMERCIAL SERVICES OFF PEAK PRICE+commercial services shoulder peak hours consumption*COMMERCIAL SERVICES SHOULDER PEAK PRICE+commercial services peak hours consumption*COMMERCIAL SERVICES PEAK PRICE) Description: Revenues generated from commercial services consumption Present in 1 view: Financial and Economic Aspects Used by: total electricity sold revenues - Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model</p>

#83 C VAB	<p>COMMERCIAL SERVICES FACTOR (MW*h/Month) = 23.2</p> <p>Description: <i>Elasticity measure for commercial services consumption. For a value of 0.5, a 1% increase in GDP will boost the consumption by 0.5%</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: changing commercial services consumption - Commercial services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month</p>
#84 A VAB	<p>commercial services off peak hours consumption (h*MW/Month) = avg commercial services monthly consumption * percentage of monthly commercial services consumption within off peak hours</p> <p>Description: <i>Derived consumption during off peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#85 C VAB	<p>COMMERCIAL SERVICES OFF PEAK PRICE (euro/(h*MW)) = 57.1</p> <p>Description: <i>Use of Illic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#86 A VAB	<p>commercial services peak hours consumption (h*MW/Month) = avg commercial services monthly consumption * percentage of monthly commercial consumption within peak hours</p> <p>Description: <i>Derived consumption during peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#87 C VAB	<p>COMMERCIAL SERVICES PEAK PRICE (euro/(h*MW)) = 124.6</p> <p>Description: <i>Use of Illic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#88 A VAB	<p>commercial services shoulder peak hours consumption (h*MW/Month) = avg commercial services monthly consumption * percentage of monthly commercial services consumption within shoulder peak hours</p> <p>Description: <i>Derived consumption during shoulder peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#89 C VAB	<p>COMMERCIAL SERVICES SHOULDER PEAK PRICE (euro/(h*MW)) = 96.7</p> <p>Description: <i>Use of Illic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption</p>
#90 C VAB	<p>COMMERCIAL SERVICES TARGETED ENERGY EFFICIENCY REDUCTION (fraction [0, 1, 0.01]) = 0.94</p> <p>Description: <i>Percentage of commercial services electricity demand that is desired to be reduced. 6% reduction is equivalent to 94% of the current value</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: reduction desired avg commercial services consumption - Desired average commercial services consumption based on the energy efficiency targets (policy)</p>








#91 A 	<p>considered electric vehicles (vehicles) = IF THEN ELSE(total vehicle population SWITCH = 1, Total Population of Vehicles, DESIRED ELECTRIC VEHICLES POLICY TARGET)</p> <p>Description: <i>Choosing the policy method of the total amount of vehicles versus an absolute number of electric vehicles</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: vehicles considered for EV by policy - This is the absolute number of electric vehicles desired by policy makers at the specified time. The specified time is the time when the policy is enacted.....2015 is the default value....this is 10 years or 120 months into the simulation.</p>
#92 C 	<p>CONTACT RATE (1/Months [2, 15]) = 10</p> <p>Description: <i>The rate at which active adopters come into contact with potential adopters.</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small.</p>
#93 L 	<p>Cumulatively Depreciated Energy Storage Capacity (MW) = \int energy storage decommissioning rate dt + [initial cumulatively depreciated energy storage]</p> <p>Description: <i>Stock of all energy storage over the total simulation timeline.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: cumulatively installed storage capacity - Sum of the total ever installed storage capacity</p>
#94 L 	<p>Cumulatively Depreciated Fossil Generation Capacity (MW) = \int fossil generation decommissioning rate dt + [initial cumulatively depreciated fossil generation]</p> <p>Description: <i>Stock of all fossil generation over the total simulation timeline.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p>
#95 L 	<p>Cumulatively Depreciated Renewables Capacity (MW) Cumulatively Depreciated Renewables Capacity [type] = \int renewables decommissioning rate[type] dt + [initial cumulatively depreciated renewables capacity [type]]</p> <p>Description: <i>Stock of all renewables generation over the total simulation timeline.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: cumulatively installed renewables capacity - Sum of the total ever installed renewable capacity of the specific renewable technologies</p>
#96 DE	<p>cumulatively installed energy storage capacity previous year (MW) = DELAY FIXED (cumulatively installed storage capacity, 12, cumulatively installed storage capacity)</p> <p>Description: <i>Cumulatively installed storage capacity for previous month: for use in learning curve formula</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: marginal cost of storage capacity - Learning curve cost reduction implementation.</p>
#97 A 	<p>cumulatively installed renewables capacity (MW) cumulatively installed renewables capacity [type] = Cumulatively Depreciated Renewables Capacity[type]+Installed Renewables Capacity[type]</p> <p>Description: <i>Sum of the total ever installed renewable capacity of the specific renewable technologies</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: cumulatively installed renewables capacity previous year - Cumulatively installed renewable capacity for previous year: for use in learning curve formula marginal cost of renewables capacity - Learning curve cost reduction implementation.</p>
#98 DE	<p>cumulatively installed renewables capacity previous year (MW) cumulatively installed renewables capacity previous year [type] = DELAY FIXED (cumulatively installed renewables capacity[type], 12, cumulatively installed renewables capacity[type])</p> <p>Description: <i>Cumulatively installed renewable capacity for previous year: for use in learning curve formula</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p>

	<p>Used by: marginal cost of renewables capacity - Learning curve cost reduction implementation.</p>
#99 A 	<p>cumulatively installed storage capacity (MW) = Cumulatively Depreciated Energy Storage Capacity+Installed Energy Storage Capacity Description: <i>Sum of the total ever installed storage capacity</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: cumulatively installed energy storage capacity previous year - Cumulatively installed storage capacity for previous month: for use in learning curve formula marginal cost of storage capacity - Learning curve cost reduction implementation.</p>
#100 A 	<p>DAYS PER MONTH (days/Month) = =30 Description: <i>Number of days in a month from the Vensim modelling software</i> Present in 3 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: average off peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average off peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average off peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average shoulder peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average shoulder peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average shoulder peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 avg electric vehicles electrification demand in MW - Based on the times of EV operation we can determine a more accurate average MW of electric vehicle consumption on a monthly time factor. avg electric vehicles monthly travel consumption - The monthly MWh that is demanded by an average EV under normal operation 0.00494MWh/vehicle considering average consumption per Km and the average distance travelled per month</p>
#101 A 	<p>DEATH FRACTION (fraction/Month) = =0.00081 Description: <i>Death rate in 2005 per 1000 people. Divide by 12 for a monthly rate (9.7/1000)/12</i> http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf http://azores.gov.pt/Portal/en/entidades/pgra/noticias/Azores+lead+birth+rate+in+Portugal.htm (9.7/1000) Present in 1 view: Net Electricity Demand Used by: deaths - Outflow of deaths from the population</p>
#102 F,A  	<p>deaths (people/Month) = Registered Population*DEATH FRACTION Description: <i>Outflow of deaths from the population</i> Present in 1 view: Net Electricity Demand Used by: Registered Population - The monthly amount of people counted as the population of São Miguel. Aging population details: plan_action_strategique_eu2020_acores_en.pdf page 60131609 in 2001 and 137830 in 2011.....2005 approximates to 134720 Initial value from ERNA_andre_leonardo_kiti document137856 population number in 2011 Azores censusdata2011</p>
#103 A 	<p>demand profile index (Dmnl) = RANDOM UNIFORM(1, 1095+1 , 0) Description: <i>INTEGER(RANDOM UNIFORM(1, 1095+1 , 0))RANDOM UNIFORM(2013, 2016.03+0.002767, 0)</i> Present in 1 view:</p>

	<p>Mismatch and Demand Imbalance Black Box Used by: black box MIN MAX daily demand profiles monthly - Choosing the normalized profile based on the randomly given index of the dat values</p>
#104 A VAB	<p>demand vs supply capacity mismatch investments rate factor (Dmnl) = net avg demand vs net avg supply capacity mismatch Description: Gauge for ensuring that there is capacity investments but not too much or too little to prevent over investments and blackouts Present in 2 views: Mismatch and Demand Imbalance Black Box Installed Supply Capacity and Learning Curve Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
#105 C VAB	<p>DERATED CAPACITY MARGIN FACTOR (fraction [0.83,0.86,0.01]) = 0.83 Description: The capacity ratings of the thermal generator by a factor which reflects the statistically expected level of reliable availability from that plant type during a given season (monthly in our case).....This accounts for the downtime of the generation technologies etc. http://www.eia.gov/forecasts/aeo/assumptions/pdf/0554(2014).pdf gives 14% to 17% pg 100 Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: forecasted total capacity needed - Based on the present capacity margin and the forecasted peak demands of the system BAU case together with the de-rated capacity margins.</p>
#106 A VAB	<p>desired avg consumption per household (MW*h/Month/households) = IF THEN ELSE(ENERGY EFFICIENCY POLICY TIMELINE USED>0, Avg Consumption per Household*HOUSEHOLD TARGETED ENERGY EFFICIENCY REDUCTION, Avg Consumption per Household) Description: Desired average consumption per household based on the energy efficiency targets (policy) Present in 1 view: Net Electricity Demand Used by: household consumption reduction - Monthly change in household consumption reduction, a negative value, as a flow into the average household consumption</p>
#107 A VAB	<p>desired avg consumption per industrial business (MW*h/industries) = IF THEN ELSE(ENERGY EFFICIENCY POLICY TIMELINE USED>0, Avg Consumption per Industrial Business*INDUSTRY TARGETED ENERGY EFFICIENCY REDUCTION , Avg Consumption per Industrial Business) Description: Desired average consumption per industrial business based on the energy efficiency targets (policy) Present in 1 view: Net Electricity Demand Used by: industrial consumption reduction - Monthly change in industrial business consumption reduction, a negative value, as a flow into the average industrial business consumption</p>
#108 C VAB	<p>DESIRED ELECTRIC VEHICLES POLICY TARGET (vehicles [3000,41000,1000]) = 4800 Description: Absolute number of electric vehicles desired.....base year of 2010 has 51000 vehicles.....6% = 2500 and 80% = 41000 Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: considered electric vehicles - Choosing the policy method of the total amount of vehicles versus an absolute number of electric vehicles</p>
#109 C VAB	<p>DESIRED RATIO OF DEMAND TO SUPPLY (fraction [0.3,1,0.05]) = 0.8 Description: Acceptable ratio of (avg demand/supply capacity) Present in 1 view: Mismatch and Demand Imbalance Black Box Used by:</p>







	rolling desired electric vehicles - Based on the year of the policy and the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the electric vehicle policy if there is more demand than supply
#110 A VAB	desired renewables generation (MW) = BASE YEAR RENEWABLES POLICY PORTFOLIO * BASE YEAR TOTAL CAPACITY Description: Absolute amount of renewables desired based on base year, 2005 values Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: amount of renewables considered for RENEWABLES POLICY - This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted.
#111 A VAB	difference needed from renewables policy (MW/Month) = ZIDZ(amount of renewables considered for RENEWABLES POLICY - \sum (Installed Renewables Capacity[type!])), RENEWABLES POLICY TIMELINE USED) Description: Monthly amount of capacity needed to achieve policy goals by the policy timeline. Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts
#112 C VAB	dispatch factor for energy storage during off peak hours (fraction [0,1,0.05]) = 0 Description: EDA merit order dispatch: Percentage of time on a daily basis that energy storage is used during off peak hours. Less than 1 implies that the technology is curtailed.....0 up to 2023 and then 0.05 in the reservoir storage investment year 2023 Present in 1 view: Financial and Economic Aspects Used by: average off peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#113 C VAB	dispatch factor for energy storage during peak hours (fraction [0,1,0.05]) = 0 Description: EDA merit order dispatch: Percentage of time on a daily basis that energy storage is used during off peak hours. Less than 1 implies that the technology is curtailed.....0 up to 2023 and then 0.5 in the reservoir storage investment year 2023 Present in 1 view: Financial and Economic Aspects Used by: average peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#114 C VAB	dispatch factor for energy storage during shoulder peak hours (fraction [0,1,0.05]) = 0 Description: EDA merit order dispatch: Percentage of time on a daily basis that energy storage is used during off peak hours. Less than 1 implies that the technology is curtailed.....0 up to 2023 and then 0.3 in the reservoir storage investment year 2023 Present in 1 view: Financial and Economic Aspects Used by: average shoulder peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#115 C VAB	dispatch factor for fossil generation during off peak hours (fraction [0,1,0.01]) = 1 Description: EDA merit order dispatch: Fraction of time on a daily basis that fossil generation is used during off peak hours. Less than 1 implies that the technology is curtailed.....usually the 18.2 MW generator is left on for frequency balancing (18.2/102.8) at all time Present in 1 view: Financial and Economic Aspects Used by:



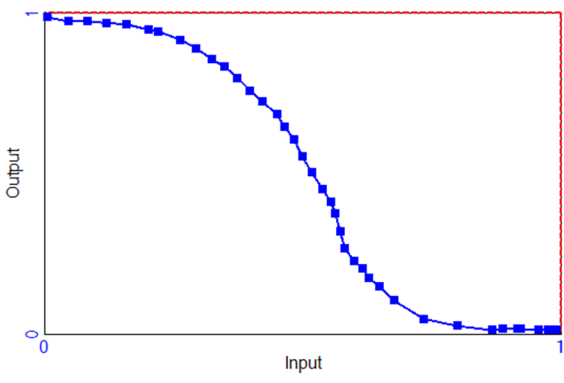




	average off peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#116 C VAB	dispatch factor for fossil generation during peak hours (fraction [0,1,0.05]) = 1 Description: EDA merit order dispatch: Percentage of time on a daily basis that fossil generation is used during peak hours. Less than 1 implies that the technology is curtailed.....usually about 3 or 4 of the generators is left on during this time period one/two 7.5MW and one/two 18.2 MW ((18.2+7.5)/102.8) at all time Present in 1 view: Financial and Economic Aspects Used by: average peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#117 C VAB	dispatch factor for renewables during off peak hours (fraction [0,1,0.05]) dispatch factor for renewables during off peak hours [type] = 1,1,0.5,0.2,0.05 Description: EDA merit order dispatch: Percentage of time on a daily basis that renewables is used during off peak hours. Less than 1 implies that the technology is curtailed.....1 for Geothermal, 1 for run of river, 0.2 for Wind, 0.5 for biomass and 0.02 for micro generation Present in 1 view: Financial and Economic Aspects Used by: average off peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#118 C VAB	dispatch factor for renewables during peak hours (fraction [0,1,0.05]) dispatch factor for renewables during peak hours [type] = 1,1,1,1,0.5 Description: EDA merit order dispatch: Percentage of time on a daily basis that renewables is used during peak hours. Less than 1 implies that the technology is curtailed.....1 for Geothermal, 1 for run of river, 1 for biomass, 1 for Wind,0.5 micro generation Present in 1 view: Financial and Economic Aspects Used by: average peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#119 C VAB	dispatch factor for renewables during shoulder peak hours (fraction [0,1,0.05]) dispatch factor for renewables during shoulder peak hours [type] = 1,1,1,0.5,0.2 Description: EDA merit order dispatch: Percentage of time on a daily basis that renewables is used during shoulder peak hours. Less than 1 implies that the technology is curtailed.....1 for Geothermal, 1 for biomass,1 for run of river,0.5 for Wind, 0.2 micro generation Present in 1 view: Financial and Economic Aspects Used by: average shoulder peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#120 C VAB	dispatch factor hours for fossil generation during shoulder peak hours (fraction [0,1,0.05]) = 1 Description: EDA merit order dispatch: Percentage of time on a daily basis that renewables is used during shoulder peak hours. Less than 1 implies that the technology is curtailed.....usually about 2 of the generators is left on during this time period one 7.5MW and one 18.2 MW ((18.2+7.5)/102.8) at all time Present in 1 view: Financial and Economic Aspects Used by: average shoulder peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12
#121 A VAB	effect of local economic activity on consumption (Dmnl) = local economic activity/REFERENCE GDP per capita Description: Normalised GDP per capita to 2005 reference year Present in 1 view: Net Electricity Demand Used by: changing commercial services consumption - Commercial services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month changing public services consumption - Public services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month household consumption growth - Household consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per household per month industrial consumption growth - Industrial business consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per industrial business

#122 C 	electric vehicle MIN MAX daily demand profile monthly threshold (MW [5,15,1]) = 12 Description: <i>The tolerated difference between peaks and troughs of daily demand</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: revised MIN MAX daily month demand profiles influence - If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a fraction of the current EV policy fraction
#123 A 	electric vehicle to grid storage fraction (vehicles/Month) = electric vehicles adoption rate * EV to GRID as STORAGE FRACTION Description: <i>avg number of adopted electric vehicles that will provide storage on a monthly basis</i> Present in 1 view: Installed Supply Capacity and Learning Curve
#124 L,LI  	Electric Vehicles Adopters (vehicles) = electric vehicles adoption rate + increasing electric vehicles natural rate - electric vehicles disadoption rate dt + [initial electric vehicles] Description: <i>Stock of EVs. Initial value in 2005;we assume that this is about 50 EV in 2015 and 0 in 2005</i> Present in 3 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: avg electric vehicles monthly travel consumption - The monthly MWh that is demanded by an average EV under normal operation 0.00494MWh/vehicle considering average consumption per Km and the average distance travelled per month electric vehicles disadoption rate - The discard rate is assumed to be first-order, with an average lifetime as given. endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small. policy influence based discrepancy for adoption - The monthly amount of adoption needed to achieve the desired electric vehicle policy within the given timeline Potential Electric Vehicles Adopters - The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and re-enter the market.
#125 F,A  	electric vehicles adoption rate (vehicles/Month) = IF THEN ELSE(total vehicle population SWITCH = 1, IF THEN ELSE(market based SWITCH =1, endogenous market based influence on adoption ,IF THEN ELSE(market AND SWITCH = 1:AND: GET TIME VALUE(0,0,0)> EV POLICY ENACTMENT YEAR + EV POLICY TIMELINE), endogenous market based influence on adoption + (ZIDZ(policy influence based discrepancy for adoption,ELECTRIC VEHICLES POLICY TIMELINE))), ZIDZ(policy influence based discrepancy for adoption,ELECTRIC VEHICLES POLICY TIMELINE))), IF THEN ELSE(market based SWITCH = 1, endogenous market based influence on adoption ,IF THEN ELSE(market AND SWITCH = 1 :AND: GET TIME VALUE(0,0,0)> EV POLICY ENACTMENT YEAR + EV POLICY TIMELINE), endogenous market based influence on adoption + (ZIDZ(policy influence based discrepancy for adoption,ELECTRIC VEHICLES POLICY TIMELINE))), ZIDZ(policy influence based discrepancy for adoption,ELECTRIC VEHICLES POLICY TIMELINE)))) Description: <i>The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.</i> Present in 2 views: Mismatch and Demand Imbalance Black Box Installed Supply Capacity and Learning Curve Used by: electric vehicle to grid storage fraction - avg number of adopted electric vehicles that will provide storage on a monthly basis Electric Vehicles Adopters - Stock of EVs. Initial value in 2005;we assume that this is about 50 EV in 2015 and 0 in 2005 Potential Electric Vehicles Adopters - The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and re-enter the market.
#126 A 	electric vehicles consumption revenues (\$/Month) = EURO TO \$ CONVERSION FACTOR *(electric vehicles off peak hours consumption * CHARGING EV OFF PEAK PRICE + electric vehicles shoulder peak hours consumption * CHARGING EV SHOULDER PEAK PRICE + electric vehicles peak hours consumption * CHARGING EV PEAK PRICE)

	<p>Description: <i>Revenues generated from electric vehicles consumption</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: total electricity sold revenues - Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model</p>
#127 F,A VAB →	<p>electric vehicles disadoption rate (vehicles/Month) = Electric Vehicles Adopters/AVERAGE ELECTRIC VEHICLE LIFETIME</p> <p>Description: <i>The discard rate is assumed to be first-order, with an average lifetime as given.</i></p> <p>Present in 2 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: Electric Vehicles Adopters - Stock of EVs. Initial value in 2005;we assume that this is about 50 EV in 2015 and 0 in 2005 Potential Electric Vehicles Adopters - The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and reenter the market.</p>
#128 A VAB	<p>electric vehicles off peak hours consumption (h*MW/Month) = avg electric vehicles monthly travel consumption*percentage of electric vehicles consumption within off peak hours</p> <p>Description: <i>Derived consumption during off peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>
#129 A VAB	<p>electric vehicles peak hours consumption (h*MW/Month) = avg electric vehicles monthly travel consumption*percentage of electric vehicles consumption within peak hours</p> <p>Description: <i>Derived consumption during peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>
#130 C VAB	<p>ELECTRIC VEHICLES POLICY FRACTION (fraction [0.01,0.5,0.05]) = 0.06</p> <p>Description: <i>Desired percentage of electric vehicles</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: revised MIN MAX daily month demand profiles influence - If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a fraction of the current EV policy fraction</p>
#131 A VAB	<p>ELECTRIC VEHICLES POLICY TIMELINE (Months [12,420,60]) = IF THEN ELSE(GET TIME VALUE(0,0,0)>EV POLICY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)<EV POLICY ENACTMENT YEAR+EV POLICY TIMELINE, EV POLICY TIMELINE ,NO POLICY TIME LAPSE)</p> <p>Description: <i>The policy dates that the electric vehicles target should be achieved. Based on the different types of policies implemented with the "no policy" implementation</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.</p>
#132 A VAB	<p>electric vehicles shoulder peak hours consumption (h*MW/Month) = avg electric vehicles monthly travel consumption*percentage of electric vehicles consumption within shoulder peak hours</p> <p>Description: <i>Derived consumption during shoulder peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles consumption revenues - Revenues generated from electric vehicles consumption</p>

<p>#133 A VAB</p>	<p>endogenous market based influence on adoption (vehicles/Month) = IF THEN ELSE(base year vehicle population SWITCH=1, (CONTACT RATE*ADOPTION FRACTION*Potential Electric Vehicles Adopters*Electric Vehicles Adopters)/BASE YEAR POPULATION of VEHICLES,(CONTACT RATE*ADOPTION FRACTION*Potential Electric Vehicles Adopters*Electric Vehicles Adopters)/Total Population of Vehicles) Description: Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small. Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.</p>
<p>#134 C VAB</p>	<p>ENERGY EFFICIENCY ENACTMENT YEAR (Months [60,540,12]) = 84 Description: Represents the year during the simulation time in months from 2005 when the policy is enacted 84 represents the year 2012 used as the default model value. Present in 1 view: Net Electricity Demand Used by: ENERGY EFFICIENCY POLICY TIMELINE USED - The policy dates that the energy efficiency target should be achieved. Default of 10 year policy starting in 2010 (60 months into simulation). Use of an infinity value.....zero gives a floating point error 500years = 6000 months</p>
<p>#135 C VAB</p>	<p>ENERGY EFFICIENCY POLICY TIMELINE (Months [120, 540, 60]) = 180 Description: The policy dates that the energy efficiency target should be achieved. This is given in months as the lifetime of the target period starting in 2012 as default. 180 represents a 15 year energy efficiency target policy timeline. This is the default policy date that the energy efficiency target should be achieved. Present in 1 view: Net Electricity Demand Used by: ENERGY EFFICIENCY POLICY TIMELINE USED - The policy dates that the energy efficiency target should be achieved. Default of 10 year policy starting in 2010 (60 months into simulation). Use of an infinity value.....zero gives a floating point error 500years = 6000 months</p>
<p>#136 A VAB</p>	<p>ENERGY EFFICIENCY POLICY TIMELINE USED (Month) = IF THEN ELSE(GET TIME VALUE(0,0,0)>ENERGY EFFICIENCY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)<ENERGY EFFICIENCY ENACTMENT YEAR+ ENERGY EFFICIENCY POLICY TIMELINE, ENERGY EFFICIENCY POLICY TIMELINE ,NO POLICY TIME LAPSE) Description: The policy dates that the energy efficiency target should be achieved. Default of 10 year policy starting in 2010 (60 months into simulation). Use of an infinity value.....zero gives a floating point error 500years = 6000 months Present in 1 view: Net Electricity Demand Used by: commercial services consumption reduction - Monthly change in commercial services consumption reduction, a negative value, as a flow into the average commercial services consumption desired avg consumption per household - Desired average consumption per household based on the energy efficiency targets (policy) desired avg consumption per industrial business - Desired average consumption per industrial business based on the energy efficiency targets (policy) household consumption reduction - Monthly change in household consumption reduction, a negative value, as a flow into the average household consumption industrial consumption reduction - Monthly change in industrial business consumption reduction, a negative value, as a flow into the average industrial business consumption public services consumption reduction - Monthly change in public services consumption reduction, a negative value, as a flow into the average public services consumption reduction desired avg commercial services consumption - Desired average commercial services consumption based on the energy efficiency targets (policy) reduction desired avg public services consumption - Desired average public services consumption based on the energy efficiency targets (policy)</p>
<p>#137 A VAB</p>	<p>energy storage capacity usage factor (Dmnl) = IF THEN ELSE((HOURS PER MONTH*(net avg electricity generation in MW-FREQUENCY BALANCING FOSSIL CAPACITY))-Σ(installed renewables MW capacity hours to utilise[type!]))>=installed energy storage MW capacity hours to utilise, installed energy storage MW capacity hours to utilise/(HOURS PER MONTH*net avg electricity</p>








	<p>generation in MW),IF THEN ELSE(((HOURS PER MONTH*FREQUENCY BALANCING FOSSIL CAPACITY)/(HOURS PER MONTH*net avg electricity generation in MW)+SUM(renewables capacity usage factor[type!])<1, 1-(((HOURS PER MONTH*FREQUENCY BALANCING FOSSIL CAPACITY)/(HOURS PER MONTH*net avg electricity generation in MW)+SUM(renewables capacity usage factor[type!]))), 0))</p> <p>Description: Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: expected energy storage revenues per MW installed - Based on the expected installed capacity usage and expected revenues. Use of ZIDZ to avoid division errors fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW total capacity usage factor - Used for normalisation checking of the usage factor</p>
#138 F,A  	<p>energy storage construction rate (MW/Month) = Planned Energy Storage Investments/ENERGY STORAGE PROJECT APPROVAL TIME</p> <p>Description: Accounting for the delay between investment decision project write ups and financial approvals for the start of construction.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage online rate - Accounting for the delay from construction to commissioning of the energy storage. Energy Storage under Construction - The stock of energy storage under construction. Planned Energy Storage Investments - The stock of planned energy storage capacity investments.</p>
#139 C 	<p>ENERGY STORAGE CONSTRUCTION TIME (Months [6, 60, 2]) = 36</p> <p>Description: 30 months for pumped hydro and 6 months for battery plant. Use of small reservoir as default: 36 months</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage online rate - Accounting for the delay from construction to commissioning of the energy storage.</p>
#140 F,A  	<p>energy storage decommissioning rate (MW/Month) = IF THEN ELSE(GET TIME VALUE(0,0,0)<(AVERAGE ENERGY STORAGE LIFETIME-INITIAL ENERGY STORAGE ONLINE TIME),Installed Energy Storage Capacity/(AVERAGE ENERGY STORAGE LIFETIME-INITIAL ENERGY STORAGE ONLINE TIME),Installed Energy Storage Capacity/AVERAGE ENERGY STORAGE LIFETIME)</p> <p>Description: Accounting for the depreciation of energy storage</p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve</p> <p>Used by: Cumulatively Depreciated Energy Storage Capacity - Stock of all energy storage over the total simulation timeline. energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline. Installed Energy Storage Capacity - Stock of installed energy storage based on capacity investments and decommissioning loss of capacity factor experience - Decrease in the capacity factor attribute</p>
#141 L 	<p>Energy Storage Dispatch Cost (\$/(MW*h)) = \intmarginal cost of storage capacity-marginal cost of storage capacity previous year dt + initial cost of new energy storage capacity</p> <p>Description: Stock of the energy storage LCOE cost in dollars</p> <p>Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve</p> <p>Used by: marginal cost of storage capacity previous year - Change in marginal cost of renewables technologies over time</p>

	needed breakeven monthly revenue per MW installed energy storage - Revenues needed due to installed energy storage capacities and usage of the capacity
#142 A 	energy storage grid attractiveness (MW) = energy storage grid experience attractiveness function (average capacity factor experience) Description: <i>Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of energy storage that should be considered.</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: grid experience input to energy storage - Inflow of potential capacity from grid quality
#143 T 	energy storage grid experience attractiveness function (MW) = [(0,0)-(1,1)],(0.00611621,0.986842),(0.0458716,0.973684),(0.0825688,0.973684),(0.119266,0.969298),(0.159021,0.964912),(0.201835,0.947368),(0.220183,0.942982),(0.262997,0.916667),(0.293578,0.890351),(0.324159,0.855263),(0.348624,0.833333),(0.373089,0.798246),(0.397554,0.758772),(0.422018,0.723684),(0.449541,0.684211),(0.464832,0.644737),(0.48318,0.605263),(0.498471,0.552632),(0.51682,0.504386),(0.538226,0.451754),(0.553517,0.412281),(0.562691,0.377193),(0.571865,0.320175),(0.58104,0.267544),(0.599388,0.22807),(0.614679,0.20614),(0.626911,0.175439),(0.648318,0.149123),(0.675841,0.105263),(0.733945,0.0482456),(0.798165,0.0263158),(0.865443,0.0131579),(0.88685,0.0175439),(0.914373,0.0175439),(0.920489,0.0175439),(0.957187,0.0131579),(0.975535,0.0131579),(0.990826,0.0131579) Description: <i>Grid quality attractiveness lookup function for energy storage (Authors own elaboration)</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: energy storage grid attractiveness - Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of energy storage that should be considered.
	
#144 A 	energy storage investment attractiveness (Dmnl) = investment attractiveness function (energy storage profitability) Description: <i>Based on energy storage technology profitability</i> Present in 1 view: Financial and Economic Aspects Used by: financially desired energy storage capacity - The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the energy storage capacity
#145 F,A  	energy storage investment rate (MW/Month) = MAX(0, energy storage investment rate real) Description: <i>MAX formulation used to avoid negative energy storage investments</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute Planned Energy Storage Investments - The stock of planned energy storage capacity investments.
#146 A 	energy storage investment rate real (MW/Month) = IF THEN ELSE(GET TIME VALUE(0,0,0)<= ENERGY STORAGE POLICY ENACTMENT YEAR ,MAX(0,(financially desired energy storage capacity - Installed Energy Storage Capacity)/ CAPACITY INVESTMENT TIMELINE)+ energy storage decommissioning rate ,IF THEN ELSE(GET TIME VALUE(0,0,0)> ENERGY STORAGE POLICY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)< ENERGY STORAGE POLICY ENACTMENT YEAR + ENERGY STORAGE POLICY TIMELINE ,MAX(Alternate BAU Storage policy / ENERGY STORAGE POLICY TIMELINE , change in needed energy storage from policy) + energy storage decommissioning rate + (Potential Energy Storage from Grid Quality / CAPACITY INVESTMENT TIMELINE),MIN(MAX(0,(financially desired energy storage capacity + Potential







	<p>$\frac{\text{Energy Storage from Grid Quality-Installed Energy Storage Capacity}}{\text{CAPACITY INVESTMENT TIMELINE}} + \text{MIN}(0, \text{energy storage decommissioning rate}), \text{MAX}(0, (\text{amount of expected total capacity as storage} + \frac{\text{Potential Energy Storage from Grid Quality-Installed Energy Storage Capacity}}{\text{CAPACITY INVESTMENT TIMELINE}} + \text{MAX}(0, \text{energy storage decommissioning rate})))$</p> <p>Description: During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage investment rate - MAX formulation used to avoid negative energy storage investments</p>
#147 C VAB	<p>energy storage MIN MAX daily demand profile monthly threshold (MW [5,15,1]) = 10</p> <p>Description: The tolerated difference between peaks and troughs of daily demand.....use of 10MW as the default value</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: revised MIN MAX daily demand profiles monthly energy storage influence - If the MIN MAX difference remains high then we should continue with the energy storage policy, if not then we can reduce the energy storage policy to 1%This assumes that the larger the gap then more excess storage supply is needed in the daytime proportional to the avoided curtailed amount in the night time.</p>
#148 DE,F VAB	<p>energy storage online rate (MW/Month) = DELAY3I(energy storage construction rate, ENERGY STORAGE CONSTRUCTION TIME, Energy Storage under Construction/ENERGY STORAGE CONSTRUCTION TIME)</p> <p>Description: Accounting for the delay from construction to commissioning of the energy storage.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Energy Storage under Construction - The stock of energy storage under construction. Installed Energy Storage Capacity - Stock of installed energy storage based on capacity investments and decommissioning</p>
#149 C VAB	<p>ENERGY STORAGE POLICY ENACTMENT YEAR (Months [156,540,12]) = 150</p> <p>Description: Represents the year during the simulation time in months from 2005 when the policy is enacted180 represents the year 2020.....150 represents the year end 2017/2018.....540 represents no policy enacted</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline. energy storage POLICY TIMELINE used - Timeline for the energy storage policy based on the shorter time step (daily profile) of the model effects to be considered. The policy dates that the energy storage target should be achieved. Default of 5 year policy starting in 2015(120 months into simulation)Use of an infinity value.....zero gives a floating point error 500years = 6000 months</p>
#150 C VAB	<p>ENERGY STORAGE POLICY TIMELINE (Months [120, 540, 60]) = 60</p> <p>Description: The policy dates that the energy storage policy target should be achieved by. This is given in months as the lifetime of the target period.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline. energy storage POLICY TIMELINE used - Timeline for the energy storage policy based on the shorter time step (daily profile) of the model effects to be considered. The policy dates that the energy storage target should be achieved. Default of 5 year policy starting in 2015(120 months into simulation)Use of an infinity value.....zero gives a floating point error 500years = 6000 months</p>
#151 A VAB	<p>energy storage POLICY TIMELINE used (Months [12,420,60]) = IF THEN ELSE(GET TIME VALUE(0,0,0)>ENERGY STORAGE POLICY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)<ENERGY STORAGE POLICY ENACTMENT YEAR + ENERGY STORAGE POLICY TIMELINE, ENERGY STORAGE POLICY TIMELINE,6000)</p> <p>Description: Timeline for the energy storage policy based on the shorter time step (daily profile) of the model</p>

	<p>effects to be considered. The policy dates that the energy storage target should be achieved. Default of 5 year policy starting in 2015(120 months into simulation)Use of infinity value.....zero gives a floating point error 500years = 6000 months</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: change in needed energy storage from policy - Discrepancy needed to meet the energy policy goals.</p>
#152 A VAB	<p>energy storage profitability (Dmnl) = ZIDZ(expected energy storage revenues per MW installed, needed breakeven monthly revenue per MW installed energy storage)</p> <p>Description: Ratio of revenues over needed LCOE baseline revenues.</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: energy storage investment attractiveness - Based on energy storage technology profitability</p>
#153 C VAB	<p>ENERGY STORAGE PROJECT APPROVAL TIME (Months [1,12,1]) = 3</p> <p>Description: Accounting for the delay time between investment decision project write ups and financial approvals for start of construction....Use of 3 months as the default for energy storage projects.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of construction.</p>
#154 L VAB	<p>Energy Storage under Construction (MW) = energy storage construction rate-energy storage online rate dt + [0]</p> <p>Description: The stock of energy storage under construction.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage online rate - Accounting for the delay from construction to commissioning of the energy storage.</p>
#155 C VAB	<p>EU CO2 EMISSIONS BASE YEAR LEVEL (tonnes/Month) = 16311</p> <p>Description: Base year of 2005. Give the total amount of CO2 emissions over the year. Total in 2005 is 562721 with 195732 coming from electricity production (Pina, (2011)). The monthly value can be averaged to be 195732/(12 months) per year.....</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: EU CO2 emissions target level - Target year level of the total amount of CO2 emissions reduction needed over the subsequent years to achieve this value as a fraction of the base year value Given on a monthly assumption basis..... default of 30% reduction of 2005 emissions levels</p>
#156 A VAB	<p>EU CO2 emissions target level (tonnes/Month) = CO2 EMISSIONS TARGET FRACTION*EU CO2 EMISSIONS BASE YEAR LEVEL</p> <p>Description: Target year level of the total amount of CO2 emissions reduction needed over the subsequent years to achieve this value as a fraction of the base year value Given on a monthly assumption basis..... default of 30% reduction of 2005 emissions levels</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: CO2 emissions reduction factor - The monthly discrepancy resulting from the amount of CO2 emissions and the targeted CO2 emissions reduction</p>
#157 C VAB	<p>EURO COST OF NEW ENERGY STORAGE CAPACITY (euro/(MW*h) [70,110,1]) = 75</p> <p>Description: Initial marginal cost of new renewable capacity for initial year, 2005.....IEA (2005) and Sliva (2013) for these LCOE costs; Hydro 75 euro/MWh</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: initial cost of new energy storage capacity - Initial marginal cost of new energy storage for base year converted to dollars</p>
#158 C VAB	<p>EURO COST OF NEW RENEWABLES CAPACITY (euro/(MW*h) [70,107,0.5]) EURO COST OF NEW RENEWABLES CAPACITY [type] = 84,75,107,74,230</p> <p>Description: Initial marginal cost of new renewable capacity for initial year, 2005.....IEA (2005) and Sliva (2013) for these LCOE costs Wind 74 euro/MWh; Hydro 75 euro/MWh; Geothermal 84 euro/MWh.....from Silva</p>







	<p>(2013) but Ilic et al (2013) pgs 134,136 and 542 also has 19.8 euro/MWh pg. 136; Biomass 107 euro/MWh; Solar from IEA (2005) is around 230 euro/MWh</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: initial cost of new renewables capacity - Initial marginal cost of new renewable capacity for base year converted to dollars</p>
#159 C VAB	<p>EURO FOSSIL GENERATION COST (euro/(MW*h) [150,211]) = 168</p> <p>Description: LCOE cost per MWh in euros the base year, 2005.....initial cost of new renewable capacity: Use of IEA (2005) and Sliva (2013) for LCOE costs</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: fossil generation cost - LCOE cost per MWh in dollars in the base year, 2005.....initial cost of new renewable capacity: Use of IEA (2005) and Sliva (2013) for LCOE costs</p>
#160 C VAB	<p>EURO TO \$ CONVERSION FACTOR (\$/euro [1.08,1.5,0.01]) = 1.23</p> <p>Description: http://www.x-rates.com/historical/?from=USD&amount=1&date=2016-01-01 Default value of 1.25 based on the average over the last 10 years = 1.23</p> <p>Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve</p> <p>Used by: commercial services consumption revenues - Revenues generated from commercial services consumption electric vehicles consumption revenues - Revenues generated from electric vehicles consumption fossil generation cost - LCOE cost per MWh in dollars in the base year, 2005.....initial cost of new renewable capacity: Use of IEA (2005) and Sliva (2013) for LCOE costs industrial consumption revenues - Revenues generated from industrial consumption initial cost of new energy storage capacity - Initial marginal cost of new energy storage for base year converted to dollars initial cost of new renewables capacity - Initial marginal cost of new renewable capacity for base year converted to dollars public services consumption revenues - Revenues generated from public services consumption residential consumption revenues - Revenues generated from residential consumption</p>
#161 C VAB	<p>EV POLICY ENACTMENT YEAR (Months [60,540,12]) = 540</p> <p>Description: Represents the year during the simulation time in months from 2005 when the policy is enacted 120 represents the year 2015.....540 represents no EV policy, the default value.</p> <p>Present in 2 views: Mismatch and Demand Imbalance Black Box Installed Supply Capacity and Learning Curve</p> <p>Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy. ELECTRIC VEHICLES POLICY TIMELINE - The policy dates that the electric vehicles target should be achieved. Based on the different types of policies implemented with the "no policy" implementation</p>
#162 C VAB	<p>EV POLICY TIMELINE (Months [36, 420, 12]) = 52</p> <p>Description: The policy dates that the electric vehicles target should be achieved. Set increments of months for the electric vehicles target policies. Use of STEP function to signal recent electric vehicles policy. Default of 5 year policy starting in 2015(120 months into simulation) for 60 months</p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy. ELECTRIC VEHICLES POLICY TIMELINE - The policy dates that the electric vehicles target should be achieved. Based on the different types of policies implemented with the "no policy" implementation</p>

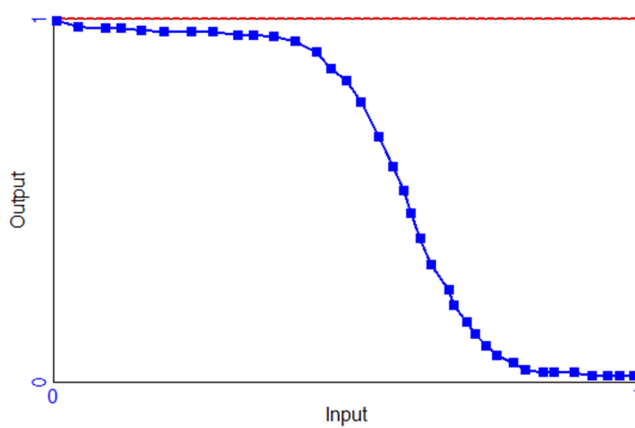
#163 C 	EV to GRID as STORAGE FRACTION (fraction [0.1,1,0.05]) = 0.75 Description: average fraction of all newly adopted electric vehicles that can be considered as storage for the grid Present in 1 view: Installed Supply Capacity and Learning Curve Used by: electric vehicle to grid storage fraction - avg number of adopted electric vehicles that will provide storage on a monthly basis
#164 C 	EXPECTED CAPACITY MARGIN (fraction [0.15,0.65]) = 0.32 Description: the current capacity margin of the system in São Miguel Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: forecasted total capacity needed - Based on the present capacity margin and the forecasted peak demands of the system BAU case together with the de-rated capacity margins.
#165 A 	expected energy storage revenues per MW installed (\$/(Month*MW)) = ZIDZ((energy storage capacity usage factor * Expected Revenues) , Installed Energy Storage Capacity) Description: Based on the expected installed capacity usage and expected revenues. Use of ZIDZ to avoid division errors Present in 1 view: Financial and Economic Aspects Used by: energy storage profitability - Ratio of revenues over needed LCOE baseline revenues.
#166 A 	expected fossil generation revenues per MW installed (\$/(Month*MW)) = (fossil generation capacity usage factor * Expected Revenues)/ Installed Fossil Generation Capacity Description: Based on the expected installed fossil generation capacity usage and expected revenues Present in 1 view: Financial and Economic Aspects Used by: fossil generation profitability - Ratio of revenues over needed LCOE baseline revenues.
#167 A 	expected renewables revenues per MW installed (\$/(Month*MW)) expected renewables revenues per MW installed [type] = ZIDZ((renewables capacity usage factor [type]* Expected Revenues), Installed Renewables Capacity [type]) Description: Based on the expected installed renewable technologies capacity usage and expected revenues Present in 1 view: Financial and Economic Aspects Used by: renewables profitability - Ratio of revenues over needed LCOE baseline revenues.
#168 L 	Expected Revenues (\$/Month) = \int change in revenues dt + [total electricity sold revenues] Description: Stock of rolling average of revenues generated Present in 1 view: Financial and Economic Aspects Used by: change in revenues - Change in the revenues generated over the revenue horizon expected energy storage revenues per MW installed - Based on the expected installed capacity usage and expected revenues. Use of ZIDZ to avoid division errors expected fossil generation revenues per MW installed - Based on the expected installed fossil generation capacity usage and expected revenues expected renewables revenues per MW installed - Based on the expected installed renewable technologies capacity usage and expected revenues
#169 L 	expected total capacity needed (MW) = \int change in total capacity needed dt + [forecasted total capacity needed] Description: Smoothing the total capacity needed based on the capacity investment timeline. Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Seasonality Effects Expected Capacity and Real Da Used by: amount of expected total capacity as fossil - Given the investment portfolio we should have this amount of fossil in the generation mix to meet forecasted demand levels.. amount of expected total capacity as renewables - Given the investment portfolio we should invest in this amount of the specific renewable technology in the generation mix to meet forecasted demand levels.











	<p>amount of expected total capacity as storage - Given the investment portfolio we should have this amount of storage in the generation mix to meet forecasted demand levels.</p> <p>amount of renewables considered for RENEWABLES POLICY - This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted.</p> <p>change in total capacity needed - Inflow of total capacity needed</p>
#170 A VAB	<p>experience curve energy storage (Dmnl) = -LOG(PROGRESS RATIO ENERGY STORAGE, 2) Description: Logistic learning curve formula. Present in 1 view: Installed Supply Capacity and Learning Curve Used by: marginal cost of storage capacity - Learning curve cost reduction implementation.</p>
#171 A VAB	<p>experience curve renewables (Dmnl) = -LOG(PROGRESS RATIO RENEWABLES, 2) Description: Logistic learning curve formula. Present in 1 view: Installed Supply Capacity and Learning Curve Used by: marginal cost of renewables capacity - Learning curve cost reduction implementation.</p>
#172 C VAB	<p>FINAL TIME (Month) = 540 Description: The final time for the simulation. Not Present In Any View</p>
#173 A VAB	<p>financially desired energy storage capacity (MW) = Installed Energy Storage Capacity*energy storage investment attractiveness Description: The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the energy storage capacity Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>
#174 A VAB	<p>financially desired fossil generation capacity (MW) = Installed Fossil Generation Capacity*fossil generation investment attractiveness Description: The capacity that is desired based on the financial benefits of the fossil generation capacity Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed.</p>
#175 A VAB	<p>financially desired renewable capacity (MW) financially desired renewable capacity [type] = Installed Renewables Capacity[type]*renewable investment attractiveness[type] Description: The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the renewables capacity Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
#176 C VAB	<p>FORECAST PERIOD (Months [6,24,6]) = 12 Description: Time taken to perceive the peak electricity demand.....smoothing period Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: change in total capacity needed - Inflow of total capacity needed Forecasted Peak Electricity Demand - Forecasting the peak electricity demand.</p>

#177 SM 	Forecasted Peak Electricity Demand (MW) = SMOOTH(PEAK FACTOR * net avg electricity demand in MW , FORECAST PERIOD) Description: <i>Forecasting the peak electricity demand.</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: forecasted total capacity needed - Based on the present capacity margin and the forecasted peak demands of the system BAU case together with the de-rated capacity margins.
#178 LI,A 	forecasted total capacity needed (MW) = BASE YEAR DIFFERENCE + (((EXPECTED CAPACITY MARGIN * Forecasted Peak Electricity Demand)+ Forecasted Peak Electricity Demand)/ DERATED CAPACITY MARGIN FACTOR) Description: <i>Based on the present capacity margin and the forecasted peak demands of the system BAU case together with the de-rated capacity margins.</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: change in total capacity needed - Inflow of total capacity needed expected total capacity needed - Smoothing the total capacity needed based on the capacity investment timeline.
#179 A 	FOSSIL CAPACITY PORTFOLIO (fraction [0, 1]) = IF THEN ELSE(\sum (RENEWABLE CAPACITY PORTFOLIO [type!])+ STORAGE CAPACITY PORTFOLIO <1, 1-(\sum (RENEWABLE CAPACITY PORTFOLIO [type!])+ STORAGE CAPACITY PORTFOLIO), 0) Description: <i>The investment percentage that is targeted to fossil fuel generation</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: amount of expected total capacity as fossil - Given the investment portfolio we should have this amount of fossil in the generation mix to meet forecasted demand levels..
#180 C 	FOSSIL CO2 per MWh PRODUCTION (tonnes/(MW*h) [0.55,0.9,0.01]) = 0.59 Description: <i>Conversion of the 0.59 tonnes/MWh to tonnes/MW per month basis. DAPTRA quotes this value as being (527Kg/MWh) 0.59 tonnes/MWh. Silva (2013) quotes 0.8tonnes/MWh</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: net monthly CO2 emissions - The total monthly CO2 emissions given the amount of fossil generation that is used within the system renewable capacity replacement for CO2 emissions based fossil generation - The renewable potential from the gap of CO2 emissions. The amount of MW of renewable capacity needed to close the emissions gap.
#181 L 	Fossil Generation Capacity Under Construction (MW) = \int fossil generation construction rate - fossil generation online rate dt + [0] Description: <i>The stock of fossil generation capacity under construction. The initial value is zero in 2005.</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: fossil generation online rate - Accounting for the delay from construction of the fossil generation capacity
#182 A 	fossil generation capacity usage factor (Dmnl) = IF THEN ELSE((HOURS PER MONTH *(net avg electricity generation in MW-FREQUENCY BALANCING FOSSIL CAPACITY)- \sum (installed renewables MW capacity hours to utilise [type!])- installed energy storage MW capacity hours to utilise > \sum (installed renewables MW capacity hours to utilise [type!]), 1-SUM(renewables capacity usage factor [type!]), 1-(SUM(renewables capacity usage factor [type!])+ energy storage capacity usage factor)) Description: <i>Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW</i> Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: expected fossil generation revenues per MW installed - Based on the expected installed fossil generation capacity usage and expected revenues net monthly CO2 emissions - The total monthly CO2 emissions given the amount of fossil generation that is used within the system total capacity usage factor - Used for normalisation checking of the usage factor

<p>#183 F,A VAB →</p>	<p>fossil generation construction rate (MW/Month) = Planned Fossil Generation Investments/FOSSIL GENERATION PROJECT APPROVAL TIME Description: Accounting for the delay between investment decision project write ups and financial approvals for the start of capacity construction Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Fossil Generation Capacity Under Construction - The stock of fossil generation capacity under construction. The initial value is zero in 2005. fossil generation online rate - Accounting for the delay from construction of the fossil generation capacity Planned Fossil Generation Investments - The stock of planned fossil generation capacity investmentsthere are no fossil generation capacity investment plans in 2005</p>
<p>#184 C VAB</p>	<p>FOSSIL GENERATION CONSTRUCTION TIME (Months [24, 60, 6]) = 36 Description: Fossil generation construction time ranges between 2-5 years. Use of 3 years (36 months) as default value. http://bv.com/docs/reports-studies/nrel-cost-report.pdf Present in 1 view: Installed Supply Capacity and Learning Curve Used by: fossil generation online rate - Accounting for the delay from construction of the fossil generation capacity</p>
<p>#185 A VAB</p>	<p>fossil generation cost (\$/(MW*h) [185,260]) = EURO FOSSIL GENERATION COST*EURO TO \$ CONVERSION FACTOR Description: LCOE cost per MWh in dollars in the base year, 2005.....initial cost of new renewable capacity: Use of IEA (2005) and Sliva (2013) for LCOE costs Present in 1 view: Financial and Economic Aspects Used by: needed breakeven monthly revenue per MW installed fossil generation - Revenues needed due to installed fossil generation capacities and usage of the capacity</p>
<p>#186 F,A VAB →</p>	<p>fossil generation decommissioning rate (MW/Month) = IF THEN ELSE(GET TIME VALUE(0,0,0)<(AVERAGE FOSSIL GENERATOR LIFETIME-INITIAL FOSSIL GENERATOR ONLINE TIME),Installed Fossil Generation Capacity/(AVERAGE FOSSIL GENERATOR LIFETIME-INITIAL FOSSIL GENERATOR ONLINE TIME),Installed Fossil Generation Capacity/AVERAGE FOSSIL GENERATOR LIFETIME) Description: Accounting for the depreciation of the fossil generation capacity. Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: Cumulatively Depreciated Fossil Generation Capacity - Stock of all fossil generation over the total simulation timeline. fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. Installed Fossil Generation Capacity - Stock of installed fossil generation technology based on capacity investments and decommissioning loss of capacity factor experience - Decrease in the capacity factor attribute</p>
<p>#187 A VAB</p>	<p>fossil generation investment attractiveness (Dmnl) = investment attractiveness function(fossil generation profitability) Description: Based on fossil generation technology profitability Present in 1 view: Financial and Economic Aspects Used by: financially desired fossil generation capacity - The capacity that is desired based on the financial benefits of the fossil generation capacity</p>
<p>#188 F,A VAB →</p>	<p>fossil generation investment rate (MW/Month) = MAX(0,fossil generation investment rate real) Description: MAX formulation used to avoid negative fossil generation investments Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute Planned Fossil Generation Investments - The stock of planned fossil generation capacity investmentsthere are no fossil generation capacity investment plans in 2005</p>

<p>#189 A </p>	<p>fossil generation investment rate real (MW/Month) = IF THEN ELSE(GET TIME VALUE(0,0,0)<=RENEWABLES POLICY ENACTMENT YEAR :AND: demand vs supply capacity mismatch investments rate factor>0.25,fossil generation decommissioning rate,IF THEN ELSE(GET TIME VALUE(0,0,0)>RENEWABLES POLICY ENACTMENT YEAR:AND: GET TIME VALUE(0,0,0)<RENEWABLES POLICY ENACTMENT YEAR + RENEWABLES POLICY TIMELINE:AND: demand vs supply capacity mismatch investments rate factor>0.25,fossil generation decommissioning rate-MAX(difference needed from renewables policy,renewable capacity replacement for CO2 emissions based fossil generation) + Potential Fossil Generation from Grid Quality/CAPACITY INVESTMENT TIMELINE,IF THEN ELSE(Installed Fossil Generation Capacity>FREQUENCY BALANCING FOSSIL CAPACITY,MIN(MAX(0,(financially desired fossil generation capacity-Installed Fossil Generation Capacity)/CAPACITY INVESTMENT TIMELINE+fossil generation decommissioning rate-renewable capacity replacement for CO2 emissions based fossil generation+Potential Fossil Generation from Grid Quality/CAPACITY INVESTMENT TIMELINE),(amount of expected total capacity as fossil-Installed Fossil Generation Capacity)/CAPACITY INVESTMENT TIMELINE+fossil generation decommissioning rate-renewable capacity replacement for CO2 emissions based fossil generation+Potential Fossil Generation from Grid Quality/CAPACITY INVESTMENT TIMELINE),MAX(0,fossil generation decommissioning rate+Potential Fossil Generation from Grid Quality/CAPACITY INVESTMENT TIMELINE))))))</p> <p>Description: Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: fossil generation investment rate - MAX formulation used to avoid negative fossil generation investments</p>
<p>#190 DE,F </p>	<p>fossil generation online rate (MW/Month) = DELAY3I(fossil generation construction rate, FOSSIL GENERATION CONSTRUCTION TIME, Fossil Generation Capacity Under Construction/FOSSIL GENERATION CONSTRUCTION TIME)</p> <p>Description: Accounting for the delay from construction of the fossil generation capacity</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Fossil Generation Capacity Under Construction - The stock of fossil generation capacity under construction. The initial value is zero in 2005. Installed Fossil Generation Capacity - Stock of installed fossil generation technology based on capacity investments and decommissioning</p>
<p>#191 A </p>	<p>fossil generation profitability (Dmnl) = IF THEN ELSE(expected fossil generation revenues per MW installed=0 :OR: needed breakeven monthly revenue per MW installed fossil generation=0, 0, expected fossil generation revenues per MW installed/needed breakeven monthly revenue per MW installed fossil generation)</p> <p>Description: Ratio of revenues over needed LCOE baseline revenues.</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: fossil generation investment attractiveness - Based on fossil generation technology profitability</p>
<p>#192 C </p>	<p>FOSSIL GENERATION PROJECT APPROVAL TIME (Months [1,12,1]) = 6</p> <p>Description: 6 months is the default time for fossil generation projects</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: fossil generation construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of capacity construction</p>
<p>#193 A </p>	<p>fossil grid attractiveness (MW) = fossil grid experience attractiveness function(average capacity factor experience)</p> <p>Description: Attractiveness of the fossil generation technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered.</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: grid experience input to fossil generation - Inflow of potential capacity from grid quality</p>
<p>#194 T </p>	<p>fossil grid experience attractiveness function (MW) = [(0,0)- (1,1)],(0.00611621,0.995614),(0.0428135,0.97807),(0.088685,0.973684),(0.116208,0.973684),(0.149847,0.969298),(0.189602,0.964912),(0.235474,0.964912),(0.272171,0.964912),(0.314985,0.95614),(0.342508,0.95614),(0.376147,0.951754),(0.412844,0.938596),(0.449541,0.907895),(0.474006,0.864035),(0.501529,0.828947),(0.525994,0.77193),(0.556575,0.675439),(0.58104,0.592105),(0.599388,0.526316),(0.611621,0.464912),(0.626911,0.394737),(0.64526,0.324561),(0.675841,0.254386),(0.685015,0.210526),(0.706422,0.166667),(0.721713,0.131579),</p>









	<p>(0.740061,0.100877),(0.75841,0.0745614),(0.785933,0.0526316),(0.807339,0.0350877),(0.83792,0.0263158),(0.856269,0.0263158),(0.889908,0.0263158),(0.920489,0.0175439),(0.948012,0.0175439),(0.969419,0.0175439),(0.993884,0.0175439)</p> <p>Description: <i>Grid quality attractiveness lookup function for fossil generation (Authors own elaboration)</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: fossil grid attractiveness - Attractiveness of the fossil generation technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered.</p> 
<p>#195 C VAB</p>	<p>FREQUENCY BALANCING FOSSIL CAPACITY (MW [6, 20, 2]) = 18</p> <p>Description: <i>The minimal possible (technically) amount of fossil generation capacity needed for frequency balancing. Bothelo (2015)</i></p> <p>Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve</p> <p>Used by: energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. renewables capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</p>
<p>#196 C VAB</p>	<p>FUTURE ECONOMIC ACTIVITY GROWTH (fraction/Month [0.00119,0.001191]) = 0.0011905</p> <p>Description: <i>GDP changed from 0.78 to 0.88 per month in 7 years (7*12) months = 840.0011905 per month is the forecasted default growth rate</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: local economic activity - Use of real data where available and a forecast for future trends</p>
<p>#197 C VAB</p>	<p>GRID CAPACITY FACTOR EXPERIENCE DECISION TIMELINE (Months [6,36,6]) = 24</p> <p>Description: <i>Observation timeline of the technology for considering new capacity based on the capacity experience</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p>

	<p>Used by: grid experience input to energy storage - Inflow of potential capacity from grid quality grid experience input to fossil generation - Inflow of potential capacity from grid quality grid experience input to renewables - Inflow of potential capacity from grid quality</p>
#198 F,A  	<p>grid experience input to energy storage (MW/Month) = energy storage grid attractiveness/GRID CAPACITY FACTOR EXPERIENCE DECISION TIMELINE Description: <i>Inflow of potential capacity from grid quality</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: Potential Energy Storage from Grid Quality - Stock of potential capacity from grid quality</p>
#199 F,A  	<p>grid experience input to fossil generation (MW/Month) = fossil grid attractiveness/GRID CAPACITY FACTOR EXPERIENCE DECISION TIMELINE Description: <i>Inflow of potential capacity from grid quality</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: Potential Fossil Generation from Grid Quality - Stock of potential capacity from grid quality</p>
#200 F,A  	<p>grid experience input to renewables (MW/Month) = renewable grid attractiveness/GRID CAPACITY FACTOR EXPERIENCE DECISION TIMELINE Description: <i>Inflow of potential capacity from grid quality</i> Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: Potential Renewables Generation from Grid Quality - Stock of potential capacity from grid quality</p>
#201 A 	<p>HOURS PER DAY (h/day) = =24 Description: <i>Fixed constant of the number of hours in a day</i> Present in 1 view: Installed Supply Capacity and Learning Curve</p>
#202 A 	<p>HOURS PER MONTH (h/Month) = =720 Description: <i>Number of hours in a 30 day month</i> Present in 4 views: Net Electricity Demand Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Used by: energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW net avg electricity demand in MW - 720 hours per (30 days Vensim) month used to change from MWh to MW.....electric vehicles MW consumption is calculated from the assumed operational hours of the EVs renewable capacity replacement for CO2 emissions based fossil generation - The renewable potential from the gap of CO2 emissions. The amount of MW of renewable capacity needed to close the emissions gap. renewables capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</p>
#203 F,A  	<p>household consumption growth (MW*h/(Month*households*Month)) = (STANDARD OF LIVING INDEX IMPACT ON HOUSEHOLD CONSUMPTION*effect of local economic activity on consumption*RESIDENTIAL HOUSEHOLD FACTOR)/TIME TO OBSERVE HOUSEHOLD CONSUMPTION GROWTH Description: <i>Household consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per household per month</i> Present in 1 view: Net Electricity Demand Used by:</p>








	Avg Consumption per Household - Stock of average consumption per household
#204 F,A VAB →	<p>household consumption reduction ($MW \cdot h / (Month \cdot Month \cdot households)$) $= ZIDZ((desired\ avg\ consumption\ per\ household - Avg\ Consumption\ per\ Household), ENERGY\ EFFICIENCY\ POLICY\ TIMELINE\ USED)$</p> <p>Description: Monthly change in household consumption reduction, a negative value, as a flow into the average household consumption</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: Avg Consumption per Household - Stock of average consumption per household</p>
#205 C VAB	<p>HOUSEHOLD TARGETED ENERGY EFFICIENCY REDUCTION (fraction [0, 1, 0.02]) $= 0.94$</p> <p>Description: Percentage of current household electricity demand that is desired to be reduced. 6% reduction is equivalent to 94% of the current value</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: desired avg consumption per household - Desired average consumption per household based on the energy efficiency targets (policy)</p>
#206 A VAB	<p>immigration rate (fraction/Month) $= IN\ MIGRATION\ RATE - OUT\ MIGRATION\ RATE$</p> <p>Description: Based on migrations into and out of the island</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: net immigration - Net change in registered population based on the immigration rate.....+ve indicates increase in population whilst -ve indicates a decrease in the population</p>
#207 A VAB	<p>IN MIGRATION RATE (fraction/Month) $= -0.0017$</p> <p>Description: http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: immigration rate - Based on migrations into and out of the island</p>
#208 F,A VAB →	<p>increasing electric vehicles natural rate (vehicles/Month) $= AVG\ NUMBER\ OF\ NEW\ VEHICLES\ PER\ MONTH * AVG\ NEW\ ELECTRIC\ VEHICLE\ FRACTION$</p> <p>Description: Natural number of new electric vehicles bought every month without any policy or market influences</p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: Electric Vehicles Adopters - Stock of EVs. Initial value in 2005; we assume that this is about 50 EV in 2015 and 0 in 2005</p>
#209 F,A VAB →	<p>increasing non electric vehicles natural rate (vehicles/Month) $= AVG\ NUMBER\ OF\ NEW\ VEHICLES\ PER\ MONTH * (1 - AVG\ NEW\ ELECTRIC\ VEHICLE\ FRACTION)$</p> <p>Description: Number of new non-electric vehicles that are bought every month</p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: Potential Electric Vehicles Adopters - The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and re-enter the market.</p>
#210 L VAB	<p>Industrial Businesses (industries/Month) $= \int changing\ numbers\ dt + [initial\ number\ of\ industrial\ business]$</p> <p>Description: Stock of industrial businesses</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: avg industrial business monthly consumption - This is the average industrial business consumption (based on the stochastic variation if (on)) changing numbers - Number of monthly changing industries per month</p>






#211 A VAB	INDUSTRIAL CONSUMPTION EFFECT EXPECTATION TIME (Months) = =1 Description: Consumption effect expectation time observed on a monthly basis Present in 1 view: Net Electricity Demand Used by: industrial consumption growth - Industrial business consumption growth calculation as it relates to the economic activity of the island.MWh growth per month per industrial business
#212 C VAB	INDUSTRIAL CONSUMPTION FACTOR (MW*h/industries [0,0.5]) = 0.2009 Description: Elasticity measure for industrial business consumption. For a value of 0.5, a 1% increase in GDP will boost the consumption by 0.5% Present in 1 view: Net Electricity Demand Used by: industrial consumption growth - Industrial business consumption growth calculation as it relates to the economic activity of the island.MWh growth per month per industrial business
#213 F,A VAB →	industrial consumption growth (MW*h/(Months*industries)) = (effect of local economic activity on consumption*INDUSTRIAL CONSUMPTION FACTOR)/INDUSTRIAL CONSUMPTION EFFECT EXPECTATION TIME Description: Industrial business consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per industrial business Present in 1 view: Net Electricity Demand Used by: Avg Consumption per Industrial Business - Stock of industrial business consumption
#214 F,A VAB →	industrial consumption reduction (MW*h/(industries*Months)) = ZIDZ(((desired avg consumption per industrial business-Avg Consumption per Industrial Business),ENERGY EFFICIENCY POLICY TIMELINE USED) Description: Monthly change in industrial business consumption reduction, a negative value, as a flow into the average industrial business consumption Present in 1 view: Net Electricity Demand Used by: Avg Consumption per Industrial Business - Stock of industrial business consumption
#215 A VAB	industrial consumption revenues (\$/Month) = EURO TO \$ CONVERSION FACTOR*(industrial off peak hours consumption*INDUSTRIAL OFF PEAK PRICE+industrial shoulder peak hours consumption*INDUSTRIAL SHOULDER PEAK PRICE+industrial peak hours consumption*INDUSTRIAL PEAK PRICE) Description: Revenues generated from industrial consumption Present in 1 view: Financial and Economic Aspects Used by: total electricity sold revenues - Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model
#216 A VAB	industrial off peak hours consumption (h*MW/Month) = avg industrial business monthly consumption*percentage of monthly industrial consumption within off peak hours Description: Derived consumption during off peak hours Present in 1 view: Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#217 C VAB	INDUSTRIAL OFF PEAK PRICE (euro/(h*MW)) = 52.6 Description: Use of Illic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#218 A VAB	industrial peak hours consumption (h*MW/Month) = avg industrial business monthly consumption*percentage of monthly industrial consumption within peak hours Description: Derived consumption during peak hours Present in 1 view:

	Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#219 C VAB	INDUSTRIAL PEAK PRICE (euro/(h*MW)) = 111.7 Description: Use of Ilic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#220 A VAB	industrial shoulder peak hours consumption (h*MW/Month) = avg industrial business monthly consumption *percentage of monthly industrial consumption within shoulder peak hours Description: Derived consumption during shoulder peak hours Present in 1 view: Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#221 C VAB	INDUSTRIAL SHOULDER PEAK PRICE (euro/(h*MW)) = 87 Description: Use of Ilic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: industrial consumption revenues - Revenues generated from industrial consumption
#222 C VAB	INDUSTRY TARGETED ENERGY EFFICIENCY REDUCTION (fraction [0, 1, 0.02]) = 0.94 Description: Percentage fraction of current electricity demand that is desired to be reduced. 6% reduction is equivalent to 94% of the current value Present in 1 view: Net Electricity Demand Used by: desired avg consumption per industrial business - Desired average consumption per industrial business based on the energy efficiency targets (policy)
#223 LI,C VAB	initial commercial services consumption (MW*h/Month [9840,10700,5]) = 9853 Description: initial value of the average commercial services consumption in 2005Base year consumption is 11029MWh including the tourism assumed consumption.9853MWh is used without tourism Present in 1 view: Net Electricity Demand Used by: Avg Commercial Services Consumption - Stock of commercial services consumption
#224 LI,A VAB	initial cost of new energy storage capacity (\$/(MW*h) [80,120,1]) = EURO COST OF NEW ENERGY STORAGE CAPACITY * EURO TO \$ CONVERSION FACTOR Description: Initial marginal cost of new energy storage for base year converted to dollars Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Energy Storage Dispatch Cost - Stock of the energy storage LCOE cost in dollars
#225 LI,A VAB	initial cost of new renewables capacity (\$/(MW*h) [80,140,0.5]) initial cost of new renewables capacity [type] = EURO COST OF NEW RENEWABLES CAPACITY [type]* EURO TO \$ CONVERSION FACTOR Description: Initial marginal cost of new renewable capacity for base year converted to dollars Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Renewables Generation Cost - Stock of the renewable generation LCOE cost in dollars
#226 LI,C VAB	initial cumulatively depreciated energy storage (MW) = 0.001 Description: Initial value of cumulatively depreciated energy storage in 2005. Use of 0.001 to avoid floating point error Present in 1 view: Installed Supply Capacity and Learning Curve Used by:



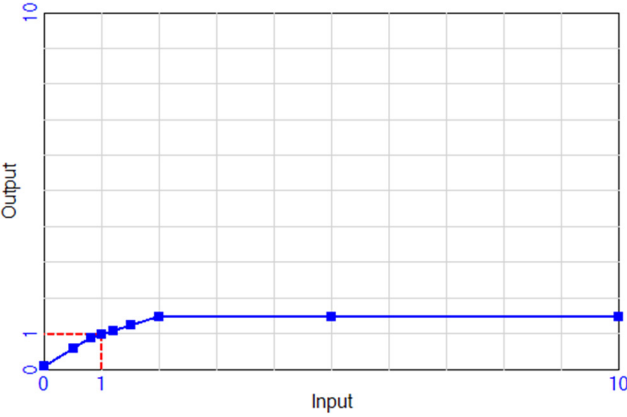




	Cumulatively Depreciated Energy Storage Capacity - Stock of all energy storage over the total simulation timeline.
#227 LI,A 	initial cumulatively depreciated fossil generation (MW) = (11/30)*102.56 Description: <i>Initial value of cumulatively depreciated fossil generation in 2005 based on the fossil generation timeline.</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Cumulatively Depreciated Fossil Generation Capacity - Stock of all fossil generation over the total simulation timeline.
#228 LI,C 	initial cumulatively depreciated renewables capacity (MW) initial cumulatively depreciated renewables capacity [type] = 14.8,3.53,0,0,0 Description: <i>We assumed only geothermal and run of river renewables in 2005</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Cumulatively Depreciated Renewables Capacity - Stock of all renewables generation over the total simulation timeline.
#229 LI,C 	initial electric vehicles (vehicles) = 0 Description: <i>Initial electric vehicles in 2005 is zero.</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: Electric Vehicles Adopters - Stock of EVs. Initial value in 2005;we assume that this is about 50 EV in 2015 and 0 in 2005
#230 LI,C 	initial energy storage capacity (MW [15,30,0.1]) = 0 Description: <i>The initial amount of energy storage capacity already installed in 2005 is zero.....Parness (2011) and EDA (2008)</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Installed Energy Storage Capacity - Stock of installed energy storage based on capacity investments and decommissioning
#231 C 	INITIAL ENERGY STORAGE ONLINE TIME (Months [60, 180, 1]) = 0 Description: <i>This gives the time that the installed technology was already online for in 2005. We assume from the data given that there is no energy storage. EDA (2008)</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: energy storage decommissioning rate - Accounting for the depreciation of energy storage
#232 LI,C 	initial fossil generation capacity (MW [100,120,0.1]) = 102.66 Description: <i>The initial amount of fossil capacity installed in 2005.....Parness (2013)</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Installed Fossil Generation Capacity - Stock of installed fossil generation technology based on capacity investments and decommissioning
#233 C 	INITIAL FOSSIL GENERATOR ONLINE TIME (Months [12, 180, 1]) = 12 Description: <i>We assume from the data given that most of the thermal generators are between 3-15 years (36-180 months) old. Less than 15% of installation are over 3 years old at time 0 (Jan 2005).</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: fossil generation decommissioning rate - Accounting for the depreciation of the fossil generation capacity.
#234 LI,C 	initial household consumption (MW*h/(Month*households) [0.2,0.5,0.01]) = 0.26 Description: <i>Data as given from Azores NESIS book for a 2006 household.....(3.462/12) = 0.2885 Divide by 12 to make this monthly for the whole Azores..... use of 0.26 for São Miguel19153MWh.....134720/3.45</i>













	<p>=39049.....gives 0.4905 per month</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: Avg Consumption per Household - Stock of average consumption per household</p>
#235 LI,C VAB	<p>initial industrial business consumption (MW*h/industries [155,160,0.5]) = 156</p> <p>Description: Using the average number of industries as 35 we get 5480/35 = 156.57MWh (Azores NESIS book)</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: Avg Consumption per Industrial Business - Stock of industrial business consumption</p>
#236 LI,C VAB	<p>initial number of industrial business (industries/Month) = 35</p> <p>Description: initial number of industries in 2005</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: Industrial Businesses - Stock of industrial businesses new industrial businesses - The percentage change of industry base due to the local economic growth</p>
#237 LI,C VAB	<p>initial planned energy storage capacity (MW [15,30,0.1]) = 0</p> <p>Description: The initial amount of energy storage capacity already installed in 2005 is zero.....Parness (2011), Bothelo (2015) and Nunes (2015) provided grounds that a 12MW hydro reservoir storage investment is to be planned to start the project in 2018.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Planned Energy Storage Investments - The stock of planned energy storage capacity investments.</p>
#238 LI,C VAB	<p>initial planned renewables capacity (MW [15,30,0.1]) initial planned renewables capacity [type] = 0,0,0,7,0</p> <p>Description: 9MW wind planned to come online in 2012/2013.....Considering planning time and construction we assume that this is planned in 2011.....Use of 7 MW for wind. All other technologies are zero . However, Geothermal 5MW to be planned in 2017 and a 5MW biomass waste power plant to be planned at the end of 2018 - This was detailed from Bothelo (2015)</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Planned Renewables Investments - Stock of planned renewables capacity for the various technologies. The planned renewable capacity investments from the base year, 2005 onwards.</p>
#239 LI,C VAB	<p>initial public services consumption (MW*h/Month [3950,4060,10]) = 3950</p> <p>Description: initial value of the average public services consumption in 2005Base year consumption is 3950MWh</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: Avg Public Services Consumption - Stock of average public services consumption</p>
#240 LI,C VAB	<p>initial renewables capacity (MW) initial renewables capacity [type] = 14.8,3.53,0.8,0.01,0.0001</p> <p>Description: The initial amount of renewables capacity already installed in 2005.....Parness (2013) gives 19.13MW total renewables. The capacity for the different technologies are: 14.8MW Geothermal Hydro run of river 3.53, 0.8MW biomass, (we use 0.01 MW for wind in 2005 since there is 9MW wind in 2012. 0.0001MW is used for micro generation since 2MW is present in 2015.)The latter two values were done for ensuring no runtime errors within the model</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Installed Renewables Capacity - Stock of installed renewables technologies based on capacity investments and decommissioning</p>
#241 LI,C VAB	<p>initial renewables capacity under construction (MW) initial renewables capacity under construction [type] = 13,0,0,0,0</p> <p>Description: 13MW geothermal was under construction during this time to come online in 2 years. All other technologies do not have any current construction in 2005</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p>

	<p>Used by: Renewables Capacity Under Construction - The stock of renewable capacity under construction.</p>
#242 C 	<p>INITIAL RENEWABLES ONLINE TIME (Months [60, 180, 1]) INITIAL RENEWABLES ONLINE TIME [type] = 120,136,60,0,0 Description: This gives the time that the installed technology was already online in the base year, 2005. We assume from the data given that the only renewables already installed was geothermal and run of river and it is about 11 years (132 months) old and 12 years old (136 months) respectively Parness (2013) Present in 1 view: Installed Supply Capacity and Learning Curve Used by: renewables decommissioning rate - Accounting for the depreciation of the renewable capacity</p>
#243 LI,C 	<p>initial room night stays (night stays/Month) = 96000 Description: 2005 room night stay as base year value use of room nights data from <i>plan_action_strategique_eu2020_acores_en.pdf</i> page 33115000 excluding "other" as given from the data.....Divided by 12 for monthly value....Equals 96000 per month http://estatistica.azores.gov.pt/upl/%7Bcc31256a-c638-463a-9ce2-c148d17e8e31%7D.pdf gives 120,000 in 2016 Present in 1 view: Net Electricity Demand Used by: Room Night Tourist Stays - Stock of room night tourist stays</p>
#244 C 	<p>INITIAL TIME (Month) = 0 Description: The initial time for the simulation. Not Present In Any View Used by: Time - Internally defined simulation time.</p>
#245 LI,C 	<p>initial total population of vehicles (vehicles) = 45000 Description: Initial total population of all vehicles on the island in 2005 was 45,000 in 2005 and 49,000 in 2008 Parness (2011) http://estatistica.azores.gov.pt/upl/%7B032836b6-856d-44d7-b0ea-22cfb223d373%7D.htm Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: BASE YEAR POPULATION of VEHICLES - Number of vehicles in the island in 2005 Total Population of Vehicles - Stock of total vehicle population in the island system.</p>
#246 A 	<p>Input (Dimensionless) Input [type] = 1+STEP(Step Height[type],Step Time[type])+(Pulse Quantity[type]/TIME STEP)*PULSE(Pulse Time[type],TIME STEP)+RAMP(Ramp Slope[type],Ramp Start Time[type],Ramp End Time[type])+Sine Amplitude[type]*SIN(2*3.14159*Time/Sine Period[type])+STEP(1,Noise Start Time[type])*Pink Noise[type] Description: Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000) Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: seasonality effects on renewables availability - Seasonality is affected by this exogenous input, which can be set by the user to a step, pulse, ramp, sine wave, or noise functions. Used sparingly for this thesis</p>
#247 L,LI  	<p>Installed Energy Storage Capacity (MW) = energy storage online rate-energy storage decommissioning rate dt + [initial energy storage capacity] Description: Stock of installed energy storage based on capacity investments and decommissioning Present in 4 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: average capacity factor experience - Capacity factor attribute as determined from the different main capacity stocks change in needed energy storage from policy - Discrepancy needed to meet the energy policy goals. cumulatively installed storage capacity - Sum of the total ever installed storage capacity energy storage decommissioning rate - Accounting for the depreciation of energy storage energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>

	<p>expected energy storage revenues per MW installed - Based on the expected installed capacity usage and expected revenues. Use of ZIDZ to avoid division errors</p> <p>financially desired energy storage capacity - The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the energy storage capacity</p> <p>installed energy storage MW capacity hours to utilise - For the monthly demand.....active energy used hours from energy storage</p> <p>net electricity supply capacity in MW - Net electricity supply considering the losses that can occur within the generation and transmission of the system. (if on (1) stochastic variations (Not used for thesis) in supply can be simulated</p> <p>rolling desired energy storage - Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.</p> <p>Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#248 A 	<p>installed energy storage MW capacity hours to utilise (MW*h/Month) = Installed Energy Storage Capacity*average dispatchable hours for energy storage Description: For the monthly demand.....active energy used hours from energy storage Present in 1 view: Financial and Economic Aspects Used by: energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW total MW capacity hours to utilise - Sum of all generating technologies available hours to meet demand load - based on installed capacities</p>
#249 D,A 	<p>installed fossil capacity real data :LOOK FORWARD: (MW) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b25') Description: Dan Cross (2008) Parness (2011) and EDA Not Present In Any View</p>
#250 L,LI  	<p>Installed Fossil Generation Capacity (MW) = fossil generation online rate-fossil generation decommissioning rate dt + [initial fossil generation capacity] Description: Stock of installed fossil generation technology based on capacity investments and decommissioning Present in 4 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: average capacity factor experience - Capacity factor attribute as determined from the different main capacity stocks expected fossil generation revenues per MW installed - Based on the expected installed fossil generation capacity usage and expected revenues financially desired fossil generation capacity - The capacity that is desired based on the financial benefits of the fossil generation capacity fossil generation decommissioning rate - Accounting for the depreciation of the fossil generation capacity. fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. installed fossil generation MW capacity hours to utilise - For the monthly demand.....active energy used hours from fossil generation net electricity supply capacity in MW - Net electricity supply considering the losses that can occur within the generation and transmission of the system. (if on (1) stochastic variations (Not used for thesis) in supply can be simulated Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#251 A 	<p>installed fossil generation MW capacity hours to utilise (h*MW/Month) = Installed Fossil Generation Capacity*average dispatchable hours for fossil generation Description: For the monthly demand.....active energy used hours from fossil generation Present in 2 views:</p>

	<p>Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects</p> <p>Used by: net monthly CO2 emissions - The total monthly CO2 emissions given the amount of fossil generation that is used within the system total MW capacity hours to utilise - Sum of all generating technologies available hours to meet demand load - based on installed capacities</p>
#252 D,A VAB	<p>installed renewable capacity real data:LOOK FORWARD: (MW) = GET XLS DATA('datamonth.xlsx','Sheet1', '1', 'b23') Description: <i>Dan Cross (2008) Parness (2011) and EDA</i> Not Present In Any View</p>
#253 A VAB	<p>Installed Renewables Aggregated Capacity (MW) = $\sum(\text{Installed Renewables Capacity}[\text{type!}])$ Description: <i>Sum of all the different renewable technologies considered in the model, namely; Geothermal, run of river, wind, biomass, micro/solar generation.</i> Present in 1 view: Installed Supply Capacity and Learning Curve</p>
#254 L,LI VAB VAB	<p>Installed Renewables Capacity (MW) Installed Renewables Capacity [type] = $\int \text{renewables online rate}[\text{type}] - \text{renewables decommissioning rate}[\text{type}] dt + [\text{initial renewables capacity}[\text{type}]$ Description: <i>Stock of installed renewables technologies based on capacity investments and decommissioning</i> Present in 4 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Installed Supply Capacity and Learning Curve Used by: average capacity factor experience - Capacity factor attribute as determined from the different main capacity stocks cumulatively installed renewables capacity - Sum of the total ever installed renewable capacity of the specific renewable technologies difference needed from renewables policy - Monthly amount of capacity needed to achieve policy goals by the policy timeline. expected renewables revenues per MW installed - Based on the expected installed renewable technologies capacity usage and expected revenues financially desired renewable capacity - The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the renewables capacity Installed Renewables Aggregated Capacity - Sum of all the different renewable technologies considered in the model, namely; Geothermal, run of river, wind, biomass, micro/solar generation. installed renewables MW capacity hours to utilise - For the monthly demand.....active energy used hours from the different renewables technologies net electricity supply capacity in MW - Net electricity supply considering the losses that can occur within the generation and transmission of the system. (if on (1) stochastic variations (Not used for thesis) in supply can be simulated renewables decommissioning rate - Accounting for the depreciation of the renewable capacity renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#255 A VAB	<p>installed renewables MW capacity hours to utilise (h*MW/Month) installed renewables MW capacity hours to utilise [type] = $\text{Installed Renewables Capacity}[\text{type}] * \text{average dispatchable hours for renewables}[\text{type}]$ Description: <i>For the monthly demand.....active energy used hours from the different renewables technologies</i> Present in 1 view: Financial and Economic Aspects Used by: aggregated renewables dispatchable MW capacity hours - used to normalise the usage of the renewables technologies energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra</p>

	<p>fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW</p> <p>renewables capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</p> <p>total MW capacity hours to utilise - Sum of all generating technologies available hours to meet demand load - based on installed capacities</p>
#256 D,A 	<p>installed storage capacity real data:LOOK FORWARD: (MW) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1' , 'b24')</p> <p>Description: <i>Dan Cross (2008) Parness (2011) and EDA</i></p> <p>Not Present In Any View</p>
#257 T 	<p>investment attractiveness function (Dmnl [0,1]) = [(0,0)-(10,10)],(0,0.1),(0.5,0.6),(0.8,0.9),(1,1),(1.2,1.1),(1.5,1.25),(2,1.5),(5,1.5),(10,1.5)</p> <p>Description: <i>The attractiveness of profitability that can be used for capacity expansion/investments.....Investment attractiveness lookup function (from Black, 2005) fig 7-13</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: energy storage investment attractiveness - Based on energy storage technology profitability fossil generation investment attractiveness - Based on fossil generation technology profitability renewable investment attractiveness - Based on the renewable technologies profitability</p> 
#258 I 	<p>last GDP per capita month (Month) = INITIAL(GET DATA LAST TIME(real data GDP per capita))</p> <p>Description: <i>Used for GDP per capita forecast function after last available GDP per capita data point</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: local economic activity - Use of real data where available and a forecast for future trends</p>
#259 A 	<p>local economic activity (Thousands of Euros/Month) = real data GDP per capita*EXP(FUTURE ECONOMIC ACTIVITY GROWTH*MAX(0,Time-last GDP per capita month))</p> <p>Description: <i>Use of real data where available and a forecast for future trends</i></p> <p>Present in 3 views: Net Electricity Demand Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects</p> <p>Used by: effect of local economic activity on consumption - Normalised GDP per capita to 2005 reference year new industrial businesses - The percentage change of industry base due to the local economic growth</p>
#260 F,A  	<p>loss of capacity factor experience (MW/Month) = average capacity factor experience*(fossil generation decommissioning rate+energy storage decommissioning rate+Σ(renewables decommissioning rate[type!]))</p> <p>Description: <i>Decrease in the capacity factor attribute</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p>

	<p>Used by: Total System Capacity Factor Experience - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute</p>
#261 F,A  	<p>marginal cost of renewables capacity (\$/(MW*h)/Month) marginal cost of renewables capacity [type] = marginal cost renewables capacity previous year[type] * (cumulatively installed renewables capacity[type]/cumulatively installed renewables capacity previous year[type])^(-experience curve renewables) Description: <i>Learning curve cost reduction implementation.</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Renewables Generation Cost - Stock of the renewable generation LCOE cost in dollars</p>
#262 F,A  	<p>marginal cost of storage capacity (\$/(MW*h)/Month) = marginal cost of storage capacity previous year * (cumulatively installed storage capacity / cumulatively installed energy storage capacity previous year)^(-experience curve energy storage) Description: <i>Learning curve cost reduction implementation.</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Energy Storage Dispatch Cost - Stock of the energy storage LCOE cost in dollars</p>
#263 F,A  	<p>marginal cost of storage capacity previous year (\$/(MW*h)/Month) = Energy Storage Dispatch Cost/TIMELINE FOR CHANGE IN COST OF STORAGE CAPACITY Description: <i>Change in marginal cost of renewables technologies over time</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Energy Storage Dispatch Cost - Stock of the energy storage LCOE cost in dollars marginal cost of storage capacity - Learning curve cost reduction implementation.</p>
#264 F,A  	<p>marginal cost renewables capacity previous year (\$/(MW*h)/Month) marginal cost renewables capacity previous year [type] = Renewables Generation Cost[type]/TIMELINE FOR CHANGE IN COST OF RENEWABLES CAPACITY Description: <i>Change in marginal cost of renewables technologies over time</i> Present in 1 view: Installed Supply Capacity and Learning Curve Used by: marginal cost of renewables capacity - Learning curve cost reduction implementation. Renewables Generation Cost - Stock of the renewable generation LCOE cost in dollars</p>
#265 C 	<p>market AND SWITCH (Dmnl [0,1,1]) = 0 Description: <i>on (1) and off (0). Used for the Bass diffusion market and policy simulations.</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.</p>
#266 C 	<p>market based SWITCH (Dmnl [0,1,1]) = 0 Description: <i>on (1) and off (0). Used for the Bass difusion simulations.</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.</p>
#267 T,D,A  	<p>MIN MAX daily demand profile LOOKUP (MW) = GET XLS LOOKUPS('black box data.xlsx', 'Sheet 1', 'a','c3') Description: <i>Accessing the excel values to be used for the lookup relationship. Data of the 2013 to 2015 (Bothelo, 2015) hourly consumption is queried.</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by:</p>







	black box MIN MAX daily demand profiles monthly - Choosing the normalized profile based on the randomly given index of the dat values
#268 A VAB	needed breakeven monthly revenue per MW installed energy storage (\$/(MW*Month)) = Energy Storage Dispatch Cost * average dispatchable hours for energy storage Description: Revenues needed due to installed energy storage capacities and usage of the capacity Present in 1 view: Financial and Economic Aspects Used by: energy storage profitability - Ratio of revenues over needed LCOE baseline revenues.
#269 A VAB	needed breakeven monthly revenue per MW installed fossil generation (\$/(MW*Month)) = fossil generation cost * average dispatchable hours for fossil generation Description: Revenues needed due to installed fossil generation capacities and usage of the capacity Present in 1 view: Financial and Economic Aspects Used by: fossil generation profitability - Ratio of revenues over needed LCOE baseline revenues.
#270 A VAB	needed breakeven monthly revenue per MW installed renewables (\$/(MW*Month)) needed breakeven monthly revenue per MW installed renewables [type] = Renewables Generation Cost[type] * average dispatchable hours for renewables[type] Description: Revenues needed due to the installed renewable technologies capacity and usage of this capacity Present in 1 view: Financial and Economic Aspects Used by: renewables profitability - Ratio of revenues over needed LCOE baseline revenues.
#271 A VAB	net avg demand vs net avg supply capacity mismatch (Dmnl) = net avg electricity demand in MW / net electricity supply capacity in MW Description: Net electricity demand in MW/net electricity supply in MW > 1 indicates a blackout when demand is greater than supply. Present in 2 views: Mismatch and Demand Imbalance Black Box Installed Supply Capacity and Learning Curve Used by: demand vs supply capacity mismatch investments rate factor - Gauge for ensuring that there is capacity investments but not too much or too little to prevent over investments and blackouts rolling desired electric vehicles - Based on the year of the policy and the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the electric vehicle policy if there is more demand than supply rolling desired energy storage - Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.
#272 A VAB	net avg electricity demand in MW (MW) = (avg total monthly consumer consumption - avg electric vehicles monthly travel consumption)/ HOURS PER MONTH + avg electric vehicles electrification demand in MW Description: 720 hours per (30 days Vensim) month used to change from MWh to MW.....electric vehicles MW consumption is calculated from the assumed operational hours of the EVs Present in 4 views: Net Electricity Demand Mismatch and Demand Imbalance Black Box Financial and Economic Aspects Seasonality Effects Expected Capacity and Real Da Used by: Forecasted Peak Electricity Demand - Forecasting the peak electricity demand. net avg demand vs net avg supply capacity mismatch - Net electricity demand in MW/net electricity supply in MW > 1 indicates a blackout when demand is greater than supply. net avg electricity generation in MW - This takes into account any losses in the system.....calculated as a percentage of the average demand usage
#273 A VAB	net avg electricity generation in MW (MW) = net avg electricity demand in MW +(SUPPLY AND TRANSMISSION LOSSES FRACTION * net avg electricity demand in MW) Description: This takes into account any losses in the system.....calculated as a percentage of the average demand usage Present in 1 view: Financial and Economic Aspects Used by: energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra


	<p>fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed</p> <p>fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW</p> <p>renewables capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</p>
#274 A VAB	<p>net electricity supply capacity in MW (MW)</p> <p>= (Installed Fossil Generation Capacity+\sum(Installed Renewables Capacity[type!])+Installed Energy Storage Capacity)</p> <p>Description: Net electricity supply considering the losses that can occur within the generation and transmission of the system. (if on (1) stochastic variations (Not used for thesis) in supply can be simulated)</p> <p>Present in 3 views:</p> <p>Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects</p> <p>Used by:</p> <p>net avg demand vs net avg supply capacity mismatch - Net electricity demand in MW/net electricity supply in MW > 1 indicates a blackout when demand is greater than supply.</p>
#275 F,A VAB VAB VAB	<p>net immigration (people/Month)</p> <p>= Registered Population*immigration rate</p> <p>Description: Net change in registered population based on the immigration rate.....+ve indicates increase in population whilst -ve indicates a decrease in the population</p> <p>Present in 1 view:</p> <p>Net Electricity Demand</p> <p>Used by:</p> <p>Registered Population - The monthly amount of people counted as the population of São Miguel. Aging population details:plan_action_strategique_eu2020_acores_en.pdf page 60131609 in 2001 and 137830 in 2011.....2005 approximates to 134720Initial value from ERNA_andre_leonardo_kiti document137856 population number in 2011 Azores censusdata2011</p>
#276 F,A VAB VAB	<p>net monthly CO2 emissions (tonnes/Month)</p> <p>= installed fossil generation MW capacity hours to utilise*fossil generation capacity usage factor*FOSSIL CO2 per MWh PRODUCTION</p> <p>Description: The total monthly CO2 emissions given the amount of fossil generation that is used within the system</p> <p>Present in 1 view:</p> <p>Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by:</p> <p>Accumulated CO2 Emissions - The stock of accumulated CO2 emissions level. The initial value is based on the amount of CO2 emissions assumed in 2005. 195732</p> <p>CO2 emissions reduction factor - The monthly discrepancy resulting from the amount of CO2 emissions and the targeted CO2 emissions reduction</p>
#277 C VAB	<p>NEW INDUSTRIAL BUSINESS per GDP (industries/Thousands of Euros [0,1])</p> <p>= 1</p> <p>Description: assuming 1 new industry per 1 million euros or 1 thousand euros of GDP per capita.....This gives 0.001.....we assume 0.1 to consider foreign investments</p> <p>Present in 1 view:</p> <p>Net Electricity Demand</p> <p>Used by:</p> <p>new industrial businesses - The percentage change of industry base due to the local economic growth</p>
#278 A VAB	<p>new industrial businesses (industries/Month)</p> <p>= initial number of industrial business + (local economic activity*NEW INDUSTRIAL BUSINESS per GDP)</p> <p>Description: The percentage change of industry base due to the local economic growth</p> <p>Present in 1 view:</p> <p>Net Electricity Demand</p> <p>Used by:</p> <p>changing numbers - Number of monthly changing industries per month</p>
#279 C VAB	<p>NO POLICY PORTFOLIO (fraction [0, 0.05])</p> <p>= 0.25</p> <p>Description: Fraction of renewables needed when the renewables policy is not enacted. Equivalent to the base</p>

	<p>year values of 2005 percentage of renewables production</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p>
#280 C VAB	<p>NO POLICY TIME LAPSE (Months [6000, 24000, 120]) = 0</p> <p>Description: Assuming no policy this is the infinite time over which the model simulates.</p> <p>Present in 3 views: Net Electricity Demand Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: ELECTRIC VEHICLES POLICY TIMELINE - The policy dates that the electric vehicles target should be achieved. Based on the different types of policies implemented with the "no policy" implementation ENERGY EFFICIENCY POLICY TIMELINE USED - The policy dates that the energy efficiency target should be achieved. Default of 10 year policy starting in 2010 (60 months into simulation). Use of an infinity value.....zero gives a floating point error 500years = 6000 months RENEWABLES POLICY TIMELINE USED - Use of an infinity value.....zero gives a floating point error 500years = 6000 months</p>
#281 C VAB	<p>Noise Correlation Time (Months) Noise Correlation Time [type] = 2</p> <p>Description: The correlation time constant for Pink Noise.</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Change in Pink Noise - Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input. Used sparingly in this thesis work White Noise - White noise input to the pink noise process implemented for renewables seasonality effects (used sparingly in this thesis).</p>
#282 C VAB	<p>Noise Standard Deviation (Dimensionless) Noise Standard Deviation [type] = 0</p> <p>Description: The standard deviation of the pink noise process.</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: White Noise - White noise input to the pink noise process implemented for renewables seasonality effects (used sparingly in this thesis).</p>
#283 C VAB	<p>Noise Start Time (Months) Noise Start Time [type] = 3</p> <p>Description: Start time for the random input.</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#284 A VAB	<p>OUT MIGRATION RATE (fraction/Month) = =0.00125</p> <p>Description: http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: immigration rate - Based on migrations into and out of the island</p>
#285 C VAB	<p>PEAK FACTOR (fraction [1.1,1.6,0.05]) = 1.55</p> <p>Description: Using averages from the data (http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx) the peak is consistently about 50% larger than the average demand in MW</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Forecasted Peak Electricity Demand - Forecasting the peak electricity demand.</p>
#286 C VAB	<p>percentage of electric vehicles consumption within off peak hours (fraction [0,1,0.01]) = 0.85</p> <p>Description: The electric vehicles consumption can be tied to the residential but we separate it to allow a better</p>

	<p>resolution for off peak charging means.... 5% for peak, 10% for shoulder peak and 85-90% in the off peak period</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles off peak hours consumption - Derived consumption during off peak hours</p>
#287 C VAB	<p>percentage of electric vehicles consumption within peak hours (fraction [0,0.5,0.01]) = 0.05</p> <p>Description: The electric vehicles consumption can be tied to the residential but we separate it to allow a better resolution for off peak charging means.... 5% for peak, 10% for shoulder peak and 85-90% in the off peak period</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles peak hours consumption - Derived consumption during peak hours</p>
#288 C VAB	<p>percentage of electric vehicles consumption within shoulder peak hours (fraction [0,1,0.01]) = 0.1</p> <p>Description: The electric vehicles consumption can be tied to the residential but we separate it to allow a better resolution for off peak charging means.... 5% for peak, 10% for shoulder peak and 85-90% in the off peak period</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: electric vehicles shoulder peak hours consumption - Derived consumption during shoulder peak hours</p>
#289 C VAB	<p>percentage of monthly commercial consumption within peak hours (fraction [0,1,0.01]) = 0.25</p> <p>Description: For the work week times of 12 hours there are on average 3 peak hours per day hence 25% during peak hours,65% during shoulder peak with the possible 10% from load shifting in the off-peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services peak hours consumption - Derived consumption during peak hours</p>
#290 C VAB	<p>percentage of monthly commercial services consumption within off peak hours (fraction [0,1,0.01]) = 0.1</p> <p>Description: For the work week times of 12 hours there are on average 3 peak hours per day hence 25% during peak hours,65% during shoulder peak with the possible 10% from load shifting in the off-peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services off peak hours consumption - Derived consumption during off peak hours</p>
#291 C VAB	<p>percentage of monthly commercial services consumption within shoulder peak hours (fraction [0,1,0.01]) = 0.65</p> <p>Description: For the work week times of 12 hours there are on average 3 peak hours per day hence 25% during peak hours,65% during shoulder peak with the possible 10% from load shifting in the off-peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: commercial services shoulder peak hours consumption - Derived consumption during shoulder peak hours</p>
#292 C VAB	<p>percentage of monthly industrial consumption within off peak hours (fraction [0,1,0.01]) = 0.05</p> <p>Description: For the work week times of 10 hours there are on average 2 peak hours per day hence 20% during peak hours and the other 75-80% during shoulder peak with the possible 5% from load shifting in the off-peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: industrial off peak hours consumption - Derived consumption during off peak hours</p>
#293 C VAB	<p>percentage of monthly industrial consumption within peak hours (fraction [0,1,0.01]) = 0.2</p> <p>Description: For the work week times of 10 hours there are on average 2 peak hours per day hence 20% during peak hours and the other 75-80% during shoulder peak with the possible 5% from load shifting in the off-peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: industrial peak hours consumption - Derived consumption during peak hours</p>

#294 C VAB	percentage of monthly industrial consumption within shoulder peak hours (fraction [0,1,0.01]) = 0.75 Description: For the work week times of 10 hours there are on average 2 peak hours per day hence 20% during peak hours and the other 75-80% during shoulder peak with the possible 5% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: industrial shoulder peak hours consumption - Derived consumption during shoulder peak hours
#295 C VAB	percentage of monthly public services consumption within off peak hours (fraction [0,1,0.01]) = 0.15 Description: Similar to commercial services once you consider the street lighting etc. For the work week times of 10 hours there are on average 3-4 peak hours per day hence 25% during peak hours,60% during shoulder peak with the possible 15% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: public services off peak hours consumption - Derived consumption during off peak hours
#296 C VAB	percentage of monthly public services consumption within peak hours (fraction [0,0.3,0.01]) = 0.25 Description: Similar to commercial services once you consider the street lighting etc. For the work week times of 10 hours there are on average 3-4 peak hours per day hence 25% during peak hours,60% during shoulder peak with the possible 15% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: public services peak hours consumption - Derived consumption during peak hours
#297 C VAB	percentage of monthly public services consumption within shoulder peak hours (fraction [0,1,0.01]) = 0.6 Description: Similar to commercial services once you consider the street lighting etc. For the work week times of 10 hours there are on average 3-4 peak hours per day hence 25% during peak hours,60% during shoulder peak with the possible 15% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: public services shoulder peak hours consumption - Derived consumption during shoulder peak hours
#298 C VAB	percentage of residential consumption within off peak hours (fraction [0,1,0.01]) = 0.2 Description: For the work week times of 7-8 hours there are on average 2-3 peak hours per day but that is the largest time for consumption hence 40% during peak hours,40% during shoulder peak with the possible 20% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: residential off peak hours consumption - Derived consumption during off peak hours
#299 C VAB	percentage of residential consumption within peak hours (fraction [0,0.5,0.01]) = 0.4 Description: For the work week times of 7-8 hours there are on average 2-3 peak hours per day but that is the largest time for consumption hence 40% during peak hours,40% during shoulder peak with the possible 20% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: residential peak hours consumption - Derived consumption during peak hours
#300 C VAB	percentage of residential consumption within shoulder peak hours (fraction [0,1,0.01]) = 0.4 Description: For the work week times of 7-8 hours there are on average 2-3 peak hours per day but that is the largest time for consumption hence 40% during peak hours,40% during shoulder peak with the possible 20% from load shifting in the off-peak hours Present in 1 view: Financial and Economic Aspects Used by: residential shoulder peak hours consumption - Derived consumption during shoulder peak hours









#301 L 	Pink Noise (Dimensionless) Pink Noise [type] = ∫Change in Pink Noise[type] dt + [0] Description: Pink Noise is first-order autocorrelated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user. Adopted from Sterman (2000) Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: Change in Pink Noise - Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input. Used sparingly in this thesis work Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)
#302 L 	Planned Energy Storage Investments (MW) = ∫energy storage investment rate-energy storage construction rate dt + [initial planned energy storage capacity] Description: The stock of planned energy storage capacity investments. Present in 1 view: Installed Supply Capacity and Learning Curve Used by: energy storage construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of construction.
#303 L 	Planned Fossil Generation Investments (MW) = ∫fossil generation investment rate-fossil generation construction rate dt + [0] Description: The stock of planned fossil generation capacity investmentsthere are no fossil generation capacity investment plans in 2005 Present in 1 view: Installed Supply Capacity and Learning Curve Used by: fossil generation construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of capacity construction
#304 L 	Planned Renewables Investments (MW) Planned Renewables Investments [type] = ∫renewables investment rate[type]-renewables construction rate[type] dt + [initial planned renewables capacity[type]] Description: Stock of planned renewables capacity for the various technologies. The planned renewable capacity investments from the base year, 2005 onwards. Present in 1 view: Installed Supply Capacity and Learning Curve Used by: renewables construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of construction
#305 A 	policy influence based discrepancy for adoption (vehicles) = (rolling desired electric vehicles-Electric Vehicles Adopters) Description: The monthly amount of adoption needed to achieve the desired electric vehicle policy within the given timeline Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy.
#306 C 	POLICY REDUCTION FRACTION EV (fraction [0,0.5,0.05]) = 0.25 Description: Fractional amount of the present policy fraction that can be used when not enforcing the full policy.....default of 25% Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: revised MIN MAX daily month demand profiles influence - If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a faction of the current EV policy fraction rolling desired electric vehicles - Based on the year of the policy and the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the electric vehicle policy if there is more demand than supply

<p>#307 C </p>	<p>POLICY REDUCTION FRACTION STORAGE (fraction [0,0.5,0.05]) = 0.25 Description: Fractional amount of the present policy fraction that can be used when not enforcing the full policy.....default of 25% Present in 1 view: Installed Supply Capacity and Learning Curve Used by: revised MIN MAX daily demand profiles monthly energy storage influence - If the MIN MAX difference remains high then we should continue with the energy storage policy, if not then we can reduce the energy storage policy to 1%This assumes that the larger the gap then more excess storage supply is needed in the daytime proportional to the avoided curtailed amount in the night time. rolling desired energy storage - Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.</p>
<p>#308 L </p>	<p>Potential Electric Vehicles Adopters (vehicles) = $\int \text{electric vehicles disadoption rate} + \text{increasing non electric vehicles natural rate} - \text{electric vehicles adoption rate} dt + [\text{Total Population of Vehicles} - \text{Electric Vehicles Adopters}]$ Description: The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and re-enter the market. Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small.</p>
<p>#309 L </p>	<p>Potential Energy Storage from Grid Quality (MW) = $\int \text{grid experience input to energy storage} dt + [0]$ Description: Stock of potential capacity from grid quality Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: energy storage investment rate real - During the energy policy timeline, energy storage capacity is considered. Financially desired energy storage is installed based on the usage of energy storage before, during and after energy policy timeline.</p>
<p>#310 L </p>	<p>Potential Fossil Generation from Grid Quality (MW) = $\int \text{grid experience input to fossil generation} dt + [0]$ Description: Stock of potential capacity from grid quality Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed.</p>
<p>#311 L </p>	<p>Potential Renewables Generation from Grid Quality (MW) = $\int \text{grid experience input to renewables} dt + [0]$ Description: Stock of potential capacity from grid quality Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Used by: renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
<p>#312 A </p>	<p>PROGRESS RATIO ENERGY STORAGE (Dmnl [0.5,1]) = 0.9 Description: A progress ratio of 90% means that for each doubling of the cumulatively installed capacity leads to a cost reduction of 10% Present in 1 view: Installed Supply Capacity and Learning Curve Used by: experience curve energy storage - Logistic learning curve formula.</p>









#313 A VAB	PROGRESS RATIO RENEWABLES (Dmnl) = =0.9 Description: A progress ratio of 90% means that for each doubling of the cumulatively installed capacity leads to a cost reduction of 10% Present in 1 view: Installed Supply Capacity and Learning Curve Used by: experience curve renewables - Logistic learning curve formula.
#314 A VAB	PUBLIC SERVICE CONSUMPTION EFFECT EXPECTATION TIME (Months) = =1 Description: Consumption effect expectation time observed on a monthly basis Present in 1 view: Net Electricity Demand Used by: changing public services consumption - Public services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month
#315 C VAB	PUBLIC SERVICE FACTOR (MW*h/Month) = 0.01 Description: Elasticity measure for public services consumption. For a value of 0.5, a 1% increase in GDP will boost the consumption by 0.5% Present in 1 view: Net Electricity Demand Used by: changing public services consumption - Public services consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per month
#316 F,A VAB VAB →	public services consumption reduction (MW*h/(Month*Month)) = ZIDZ((reduction desired avg public services consumption - Avg Public Services Consumption), ENERGY EFFICIENCY POLICY TIMELINE USED) Description: Monthly change in public services consumption reduction, a negative value, as a flow into the average public services consumption Present in 1 view: Net Electricity Demand Used by: Avg Public Services Consumption - Stock of average public services consumption
#317 A VAB	public services consumption revenues (\$/Month) = EURO TO \$ CONVERSION FACTOR *(public services off peak hours consumption * PUBLIC SERVICES OFF PEAK PRICE + public services shoulder peak hours consumption * PUBLIC SERVICES SHOULDER PEAK PRICE + public services peak hours consumption * PUBLIC SERVICES PEAK PRICE) Description: Revenues generated from public services consumption Present in 1 view: Financial and Economic Aspects Used by: total electricity sold revenues - Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model
#318 A VAB	public services off peak hours consumption (h*MW/Month) = avg public services monthly consumption * percentage of monthly public services consumption within off peak hours Description: Derived consumption during off peak hours Present in 1 view: Financial and Economic Aspects Used by: public services consumption revenues - Revenues generated from public services consumption
#319 C VAB	PUBLIC SERVICES OFF PEAK PRICE (euro/(h*MW)) = 57.1 Description: Use of Illic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: public services consumption revenues - Revenues generated from public services consumption
#320 A VAB	public services peak hours consumption (h*MW/Month) = avg public services monthly consumption * percentage of monthly public services consumption within peak hours Description: Derived consumption during peak hours Present in 1 view: Financial and Economic Aspects


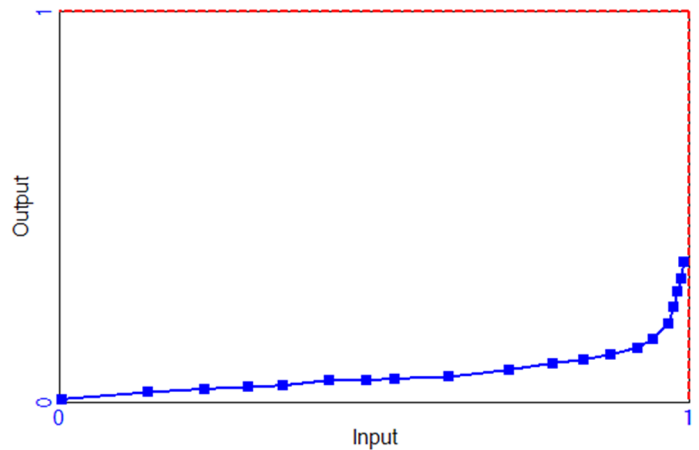





	<p>Used by: public services consumption revenues - Revenues generated from public services consumption</p>
#321 C VAB	<p>PUBLIC SERVICES PEAK PRICE (euro/(h*MW)) = 124.6 Description: Use of Ilic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: public services consumption revenues - Revenues generated from public services consumption</p>
#322 A VAB	<p>public services shoulder peak hours consumption (h*MW/Month) = avg public services monthly consumption * percentage of monthly public services consumption within shoulder peak hours Description: Derived consumption during shoulder peak hours Present in 1 view: Financial and Economic Aspects Used by: public services consumption revenues - Revenues generated from public services consumption</p>
#323 C VAB	<p>PUBLIC SERVICES SHOULDER PEAK PRICE (euro/(h*MW)) = 96.7 Description: Use of Ilic et al.(2011) pgs. 144-145 price data and EDA (2015) estimates Present in 1 view: Financial and Economic Aspects Used by: public services consumption revenues - Revenues generated from public services consumption</p>
#324 C VAB	<p>PUBLIC SERVICES TARGETED ENERGY EFFICIENCY REDUCTION (fraction [0, 1, 0.02]) = 0.94 Description: Percentage of current public services electricity demand that is desired to be reduced. 6% reduction is equivalent to 94% of the current electricity demand value Present in 1 view: Net Electricity Demand Used by: reduction desired avg public services consumption - Desired average public services consumption based on the energy efficiency targets (policy)</p>
#325 C VAB	<p>Pulse Quantity (Dimensionless*Months) Pulse Quantity [type] = 0 Description: The quantity to be injected as a fraction of the base value of Input. For example, to pulse in a quantity equal to 50% of the current value of input, set to .50. Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#326 C VAB	<p>Pulse Time (Months) Pulse Time [type] = 5 Description: Time at which the pulse in Input occurs. Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#327 C VAB	<p>Ramp End Time (Months) Ramp End Time [type] = 1e+009 Description: End time for the ramp input. Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#328 C VAB	<p>Ramp Slope (1/Months) Ramp Slope [type] = 0 Description: Slope of the ramp input, as a fraction of the base value (per month). Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by:</p>






	Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)
#329 C 	Ramp Start Time (Months) Ramp Start Time [type] = 3 Description: Start time for the ramp input. Present in 1 view: Seasonality Effects Expected Capacity and Real Da Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)
#330 D,A 	real data avg yearly commercial consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b69') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#331 D,A 	real data avg yearly industrial consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b71') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#332 D,A 	real data avg yearly public services consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b72') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#333 D,A 	real data avg yearly residential consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b70') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#334 D,A 	real data commercial consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b35') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#335 D,A 	real data GDP per capita:INTERPOLATE: (Thousands of Euros/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b28') Description: 15.5 GDP per Capita in 2010Use of GDP per capita data for Azores * 70% for São Miguel.....divide by 12 to convert to monthly GDP per capita Data sources: http://ec.europa.eu/regional_policy/archive/activity/outermost/doc/plan_action_strategique_eu2020_acores_en.pdf or http://estatistica.azores.gov.pt/upl/%7B119e7ec6-2716-4ab8-94ef-1a52b55b6263%7D.pdf Not Present In Any View
#336 D,A 	real data industrial consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b38') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#337 D,A 	real data public services consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b41') Description: 2005 to 2015 data from EDA: http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#338 D,A 	real data registered population (people) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1', 'b30') Description: http://estatistica.azores.gov.pt/default.aspx?lang_id=2 Present in 1 view: Seasonality Effects Expected Capacity and Real Da

#339 D,A 	real data residential consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1' , 'b36') Description: 2005 to 2015 data from EDA:http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#340 D,A 	real data total monthly consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1' , 'b42') Description: 2005 to 2015 data from EDA:http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#341 D,A 	real data total yearly avg consumption:LOOK FORWARD: (MW*h/Month) = GET XLS DATA('datamonth.xlsx','Sheet1' , '1' , 'b73') Description: 2005 to 2015 data from EDA:http://www.eda.pt/Mediateca/Publicacoes/Producao/Paginas/Produ%C3%A7%C3%A3o-de-Energia-El%C3%A9trica.aspx Not Present In Any View
#342 A 	reduction desired avg commercial services consumption (MW*h/Month) = IF THEN ELSE(ENERGY EFFICIENCY POLICY TIMELINE USED >0, Avg Commercial Services Consumption * COMMERCIAL SERVICES TARGETED ENERGY EFFICIENCY REDUCTION , Avg Commercial Services Consumption) Description: <i>Desired average commercial services consumption based on the energy efficiency targets (policy)</i> Present in 1 view: Net Electricity Demand Used by: commercial services consumption reduction - Monthly change in commercial services consumption reduction, a negative value, as a flow into the average commercial services consumption
#343 A 	reduction desired avg public services consumption (MW*h/Month) = IF THEN ELSE(ENERGY EFFICIENCY POLICY TIMELINE USED >0, Avg Public Services Consumption * PUBLIC SERVICES TARGETED ENERGY EFFICIENCY REDUCTION , Avg Public Services Consumption) Description: <i>Desired average public services consumption based on the energy efficiency targets (policy)</i> Present in 1 view: Net Electricity Demand Used by: public services consumption reduction - Monthly change in public services consumption reduction, a negative value, as a flow into the average public services consumption
#344 C 	REFERENCE GDP per capita (Thousands of Euros/Month) = 0.78 Description: <i>Value of GDP per capita in reference year 2005</i> Present in 1 view: Net Electricity Demand Used by: effect of local economic activity on consumption - Normalised GDP per capita to 2005 reference year
#345 L 	Registered Population (people) = births + net immigration - deaths dt + [131609] Description: <i>The monthly amount of people counted as the population of São Miguel. Aging population details:plan_action_strategique_eu2020_acores_en.pdf page 60131609 in 2001 and 137830 in 2011.....2005 approximates to 134720Initial value from ERNA_andre_leonardo_kiti document137856 population number in 2011 Azores censusdata2011</i> Present in 1 view: Net Electricity Demand Used by: "avg no. of households" - Based on the registered population and the average size of households births - Inflow of births to the population deaths - Outflow of deaths from the population net immigration - Net change in registered population based on the immigration rate.....+ve indicates increase in population whilst -ve indicates a decrease in the population
#346 A 	RENEWABLE CAPACITY PORTFOLIO (fraction [0,1,0.05]) RENEWABLE CAPACITY PORTFOLIO [type] = IF THEN ELSE(GET TIME VALUE(0,0,0)<= RENEWABLES POLICY ENACTMENT YEAR , renewables capacity usage factor [type],IF THEN ELSE(GET TIME VALUE(0,0,0)> RENEWABLES POLICY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)< RENEWABLES POLICY ENACTMENT YEAR + RENEWABLES POLICY TIMELINE , renewables capacity usage factor [type], renewables capacity usage factor [type]))

	<p>Description: <i>The investment percentage that is targeted to renewables technology investments</i></p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: amount of expected total capacity as renewables - Given the investment portfolio we should invest in this amount of the specific renewable technology in the generation mix to meet forecasted demand levels. amount of renewables considered for RENEWABLES POLICY - This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted. FOSSIL CAPACITY PORTFOLIO - The investment percentage that is targeted to fossil fuel generation</p>
#347 A VAB	<p>renewable capacity replacement for CO2 emissions based fossil generation (MW/Month) = MAX(0,-(CO2 emissions reduction factor/FOSSIL CO2 per MWh PRODUCTION)/HOURS PER MONTH)</p> <p>Description: <i>The renewable potential from the gap of CO2 emissions. The amount of MW of renewable capacity needed to close the emissions gap.</i></p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve</p> <p>Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
#348 A VAB	<p>renewable grid attractiveness (MW) = renewables grid experience attractiveness function(average capacity factor experience)</p> <p>Description: <i>Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered.</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: grid experience input to renewables - Inflow of potential capacity from grid quality</p>
#349 A VAB	<p>renewable investment attractiveness (Dmnl) renewable investment attractiveness [type] = investment attractiveness function(renewables profitability[type])</p> <p>Description: <i>Based on the renewable technologies profitability</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: financially desired renewable capacity - The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the renewables capacity</p>
#350 L VAB	<p>Renewables Capacity Under Construction (MW) Renewables Capacity Under Construction [type] = \intrenewables construction rate[type]-renewables online rate[type] dt + [initial renewables capacity under construction[type]]</p> <p>Description: <i>The stock of renewable capacity under construction.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: renewables online rate - Accounting for the delay for construction of renewable capacity</p>
#351 A VAB	<p>renewables capacity usage factor (Dmnl) renewables capacity usage factor [type] = IF THEN ELSE((HOURS PER MONTH*(net avg electricity generation in MW-FREQUENCY BALANCING FOSSIL CAPACITY))>=\sum(installed renewables MW capacity hours to utilise [type!]), installed renewables MW capacity hours to utilise[type]/(HOURS PER MONTH*net avg electricity generation in MW),(installed renewables MW capacity hours to utilise[type]/aggregated renewables dispatchable MW capacity hours)*(HOURS PER MONTH*(net avg electricity generation in MW-FREQUENCY BALANCING FOSSIL CAPACITY)))/(HOURS PER MONTH*net avg electricity generation in MW))</p> <p>Description: <i>Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)</i></p> <p>Present in 3 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Seasonality Effects Expected Capacity and Real Da</p> <p>Used by:</p>









	<p>energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed</p> <p>expected renewables revenues per MW installed - Based on the expected installed renewable technologies capacity usage and expected revenues</p> <p>fossil generation capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW</p> <p>RENEWABLE CAPACITY PORTFOLIO - The investment percentage that is targeted to renewables technology investments</p> <p>total capacity usage factor - Used for normalisation checking of the usage factor</p>
#352 F,A   	<p>renewables construction rate (MW/Month) renewables construction rate [type] = Planned Renewables Investments[type]/RENEWABLES PROJECT APPROVAL TIME[type]</p> <p>Description: Accounting for the delay between investment decision project write ups and financial approvals for the start of construction</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: Planned Renewables Investments - Stock of planned renewables capacity for the various technologies. The planned renewable capacity investments from the base year, 2005 onwards. Renewables Capacity Under Construction - The stock of renewable capacity under construction. renewables online rate - Accounting for the delay for construction of renewable capacity</p>
#353 C 	<p>RENEWABLES CONSTRUCTION TIME (Months [0,42]) RENEWABLES CONSTRUCTION TIME [type] = 30,36,24,12,6</p> <p>Description: Onshore wind is 12 months. Solar is 3 (residential) and 12-24 for solar farms.....use of 6 months. Geothermal is 30 months. Run of river is 36 months and Biomass is 24 months. http://bv.com/docs/reports-studies/nrel-cost-report.pdf</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: renewables online rate - Accounting for the delay for construction of renewable capacity</p>
#354 F,A   	<p>renewables decommissioning rate (MW/Month) renewables decommissioning rate [type] = IF THEN ELSE(GET TIME VALUE(0,0,0)<AVERAGE RENEWABLES LIFETIME[type]-INITIAL RENEWABLES ONLINE TIME[type]),Installed Renewables Capacity[type]/AVERAGE RENEWABLES LIFETIME[type]-INITIAL RENEWABLES ONLINE TIME[type]),Installed Renewables Capacity[type]/AVERAGE RENEWABLES LIFETIME[type])</p> <p>Description: Accounting for the depreciation of the renewable capacity</p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve</p> <p>Used by: Cumulatively Depreciated Renewables Capacity - Stock of all renewables generation over the total simulation timeline. Installed Renewables Capacity - Stock of installed renewables technologies based on capacity investments and decommissioning loss of capacity factor experience - Decrease in the capacity factor attribute renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</p>
#355 L 	<p>Renewables Generation Cost (\$/(MW*h)) Renewables Generation Cost [type] = marginal cost of renewables capacity[type]-marginal cost renewables capacity previous year[type] dt + initial cost of new renewables capacity[type]</p> <p>Description: Stock of the renewable generation LCOE cost in dollars</p> <p>Present in 2 views: Financial and Economic Aspects Installed Supply Capacity and Learning Curve</p> <p>Used by: marginal cost renewables capacity previous year - Change in marginal cost of renewables technologies over time</p>

	<p>needed breakeven monthly revenue per MW installed renewables - Revenues needed due to the installed renewable technologies capacity and usage of this capacity</p>
<p>#356 T </p>	<p>renewables grid experience attractiveness function (MW) = [(0,0)-(1,1),(0.0030581,0.00877193),(0.140673,0.0263158),(0.229358,0.0350877),(0.299694,0.0394737),(0.35474,0.0438596),(0.428135,0.0570175),(0.486239,0.0570175),(0.53211,0.0614035),(0.617737,0.0657895),(0.712538,0.0833333),(0.782875,0.100877),(0.831804,0.109649),(0.874618,0.122807),(0.917431,0.140351),(0.941896,0.162281),(0.966361,0.201754),(0.975535,0.245614),(0.981651,0.285088),(0.987768,0.315789),(0.990826,0.359649)]</p> <p>Description: <i>Grid quality attractiveness lookup function for renewable technologies (Authors own elaboration)</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: renewable grid attractiveness - Attractiveness of the renewables technology based on the average grid capacity factor experiences. This represents the unit MW of renewables that should be considered.</p> 
<p>#357 F,A   </p>	<p>renewables investment rate (MW/Month) renewables investment rate [type] = MAX (0,renewables investment rate real[type])</p> <p>Description: <i>MAX formulation used to avoid negative renewables investments</i></p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve</p> <p>Used by: additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute Planned Renewables Investments - Stock of planned renewables capacity for the various technologies. The planned renewable capacity investments from the base year, 2005 onwards.</p>
<p>#358 A  </p>	<p>renewables investment rate real (MW/Month) renewables investment rate real [type] = IF THEN ELSE(GET TIME VALUE(0,0,0)<=RENEWABLES POLICY ENACTMENT YEAR :AND: demand vs supply capacity mismatch investments rate factor>0.25,MAX(0,((financially desired renewable capacity[type]-Installed Renewables Capacity[type])/CAPACITY INVESTMENT TIMELINE))+renewables decommissioning rate[type],IF THEN ELSE(GET TIME VALUE(0,0,0)>RENEWABLES POLICY ENACTMENT YEAR:AND: GET TIME VALUE(0,0,0)<RENEWABLES POLICY ENACTMENT YEAR + RENEWABLES POLICY TIMELINE :AND: demand vs supply capacity mismatch investments rate factor>0.25,MAX(renewable capacity replacement for CO2 emissions based fossil generation/ELMCOUNT(type),difference needed from renewables policy/ELMCOUNT(type)) + renewables decommissioning rate[type] + (Potential Renewables Generation from Grid Quality/ELMCOUNT(type))/CAPACITY INVESTMENT TIMELINE,MIN(MAX(0,(amount of expected total capacity as renewables[type]-Installed Renewables Capacity[type])/CAPACITY INVESTMENT TIMELINE+renewables decommissioning rate[type]),(financially desired renewable capacity[type]+(Potential Renewables Generation from Grid Quality/ELMCOUNT(type)-Installed Renewables Capacity[type])/CAPACITY INVESTMENT TIMELINE+renewables decommissioning rate[type])))</p> <p>Description: <i>Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: renewables investment rate - MAX formulation used to avoid negative renewables investments</p>

#359 DE,F 	renewables online rate (MW/Month) renewables online rate [type] = DELAY3(renewables construction rate[type] , RENEWABLES CONSTRUCTION TIME[type] , Renewables Capacity Under Construction[type]/RENEWABLES CONSTRUCTION TIME[type]) Description: Accounting for the delay for construction of renewable capacity Present in 1 view: Installed Supply Capacity and Learning Curve Used by: Installed Renewables Capacity - Stock of installed renewables technologies based on capacity investments and decommissioning Renewables Capacity Under Construction - The stock of renewable capacity under construction.
#360 C 	RENEWABLES POLICY ENACTMENT YEAR (Months [12, 540, 12]) = 32 Description: Represents the year during the simulation time in months from 2005 when the policy is enacted,32 months, the default value represents the year 2007. Present in 3 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. RENEWABLE CAPACITY PORTFOLIO - The investment percentage that is targeted to renewables technology investments renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts RENEWABLES POLICY TIMELINE USED - Use of an infinity value.....zero gives a floating point error 500years = 6000 months
#361 C 	RENEWABLES POLICY TIMELINE (Months [120, 540, 60]) = 156 Description: The policy dates that the renewables target should be achieved by. Default of 10 year policy starting in 2010 (60 months into simulation) Present in 4 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da Used by: fossil generation investment rate real - Decommissioned fossil is not brought back online before renewables policy, during and after the policy period but the grid quality aspects are considered.....if there is lower grid quality then more fossil generation can be installed. RENEWABLE CAPACITY PORTFOLIO - The investment percentage that is targeted to renewables technology investments renewables investment rate real - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts RENEWABLES POLICY TIMELINE USED - Use of an infinity value.....zero gives a floating point error 500years = 6000 months
#362 A 	RENEWABLES POLICY TIMELINE USED (Months [12,420,60]) = IF THEN ELSE(GET TIME VALUE(0,0,0)> RENEWABLES POLICY ENACTMENT YEAR :AND: GET TIME VALUE(0,0,0)< RENEWABLES POLICY ENACTMENT YEAR + RENEWABLES POLICY TIMELINE , RENEWABLES POLICY TIMELINE , NO POLICY TIME LAPSE) Description: Use of an infinity value.....zero gives a floating point error 500years = 6000 months Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q Used by: difference needed from renewables policy - Monthly amount of capacity needed to achieve policy goals by the policy timeline.
#363 A 	renewables profitability (Dmnl) renewables profitability [type] = IF THEN ELSE(expected renewables revenues per MW installed[type] =0 :OR: needed breakeven monthly revenue per MW installed renewables[type] =0, 0, expected renewables revenues per MW installed[type] / needed breakeven monthly revenue per MW installed renewables[type])

	<p>Description: Ratio of revenues over needed LCOE baseline revenues.</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: renewable investment attractiveness - Based on the renewable technologies profitability</p>
#364 C VAB	<p>RENEWABLES PROJECT APPROVAL TIME (Months [1,12,1]) RENEWABLES PROJECT APPROVAL TIME [type] = 6,6,6,6,3</p> <p>Description: Accounting for the delay time between investment decision project write ups and financial approvals for start of construction....Use of 6 months as the default for all renewables projects except micro generation with 3 months.</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: renewables construction rate - Accounting for the delay between investment decision project write ups and financial approvals for the start of construction</p>
#365 C VAB	<p>RENEWABLES TIME FOR ONLINE (Months [18,30,6]) = 24</p> <p>Description: Total time from investment decision to commissioning of the technology for generation.....Renewables is 2-3 years on average</p> <p>Not Present In Any View</p>
#366 A VAB	<p>residential consumption revenues (\$/Month) = EURO TO \$ CONVERSION FACTOR*(residential off peak hours consumption*RESIDENTIAL OFF PEAK PRICE+residential shoulder peak hours consumption*RESIDENTIAL SHOULDER PEAK PRICE+residential peak hours consumption*RESIDENTIAL PEAK PRICE)</p> <p>Description: Revenues generated from residential consumption</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: total electricity sold revenues - Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model</p>
#367 C VAB	<p>RESIDENTIAL HOUSEHOLD FACTOR (MW*h/(Month*households)) = 0.009</p> <p>Description: Elasticity measure for household consumption. For a value of 0.5, a 1% increase in GDP will boost the consumption by 0.5%</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: household consumption growth - Household consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per household per month</p>
#368 A VAB	<p>residential off peak hours consumption (h*MW/Month) = avg residential household monthly consumption*percentage of residential consumption within off peak hours</p> <p>Description: Derived consumption during off peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#369 C VAB	<p>RESIDENTIAL OFF PEAK PRICE (euro/(h*MW)) = 57.1</p> <p>Description: Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs. 144-145 price data and EDA (2015) estimates</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#370 A VAB	<p>residential peak hours consumption (h*MW/Month) = avg residential household monthly consumption*percentage of residential consumption within peak hours</p> <p>Description: Derived consumption during peak hours</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#371 C VAB	<p>RESIDENTIAL PEAK PRICE (euro/(h*MW)) = 124.6</p> <p>Description: Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs.</p>

	<p>144-145 price data and EDA (2015) estimates</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#372 A VAB	<p>residential shoulder peak hours consumption (h*MW/Month) = avg residential household monthly consumption*percentage of residential consumption within shoulder peak hours</p> <p>Description: <i>Derived consumption during shoulder peak hours</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#373 C VAB	<p>RESIDENTIAL SHOULDER PEAK PRICE (euro/(h*MW)) = 96.7</p> <p>Description: <i>Same as commercial and public services except for the simple tariff: Use of Ilic et al. (2011) pgs. 144-145 price data and EDA (2015) estimates</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: residential consumption revenues - Revenues generated from residential consumption</p>
#374 C VAB	<p>REVENUE TIME HORIZON (Months) = 24</p> <p>Description: <i>Time to perceive revenues to avoid single year anomalies due to prices etc.</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: change in revenues - Change in the revenues generated over the revenue horizon</p>
#375 A VAB	<p>revised MIN MAX daily demand profile monthly influence from electric vehicles (MW) = black box MIN MAX daily demand profiles monthly-avg electric vehicles electrification demand in MW</p> <p>Description: <i>Based on the adopted electric vehicles this is the monthly average reduction in the gap that can be achieved (increases in the demand base)</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: revised MIN MAX daily month demand profiles influence - If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a fraction of the current EV policy fraction</p>
#376 A VAB	<p>revised MIN MAX daily demand profiles monthly energy storage influence (fraction) = IF THEN ELSE(black box MIN MAX daily demand profiles monthly>0 :AND: black box MIN MAX daily demand profiles monthly>energy storage MIN MAX daily demand profile monthly threshold, STORAGE CAPACITY PORTFOLIO, POLICY REDUCTION FRACTION STORAGE*STORAGE CAPACITY PORTFOLIO)</p> <p>Description: <i>If the MIN MAX difference remains high then we should continue with the energy storage policy, if not then we can reduce the energy storage policy to 1%This assumes that the larger the gap then more excess storage supply is needed in the daytime proportional to the avoided curtailed amount in the night time.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: rolling desired energy storage - Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.</p>
#377 A VAB	<p>revised MIN MAX daily month demand profiles influence (fraction) = IF THEN ELSE(revised MIN MAX daily demand profile monthly influence from electric vehicles>electric vehicle MIN MAX daily demand profile monthly threshold:AND: black box MIN MAX daily demand profiles monthly>0, ELECTRIC VEHICLES POLICY FRACTION, POLICY REDUCTION FRACTION EV*ELECTRIC VEHICLES POLICY FRACTION)</p> <p>Description: <i>If the MIN MAX difference remains high then we should continue with the electric vehicle policy, if not then we can reduce the electric vehicle policy to a fraction of the current EV policy fraction</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: vehicles considered for EV by policy - This is the absolute number of electric vehicles desired by policy makers at the specified time. The specified time is the time when the policy is enacted.....2015 is the default value....this is 10 years or 120 months into the simulation.</p>

#378 A 	<p>rolling desired electric vehicles (vehicles) = IF THEN ELSE(net avg demand vs net avg supply capacity mismatch<DESIRED RATIO OF DEMAND TO SUPPLY,vehicles considered for EV by policy, POLICY REDUCTION FRACTION EV*vehicles considered for EV by policy)</p> <p>Description: <i>Based on the year of the policy and the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the electric vehicle policy if there is more demand than supply</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: policy influence based discrepancy for adoption - The monthly amount of adoption needed to achieve the desired electric vehicle policy within the given timeline</p>
#379 A 	<p>rolling desired energy storage (MW) = IF THEN ELSE(net avg demand vs net avg supply capacity mismatch<0.5 :AND: Installed Energy Storage Capacity<avg electric vehicles electrification demand in MW, Installed Energy Storage Capacity*revised MIN MAX daily demand profiles monthly energy storage influence , POLICY REDUCTION FRACTION STORAGE*Installed Energy Storage Capacity)</p> <p>Description: <i>Based on the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the energy storage policy if there is more demand than supply.</i></p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: change in needed energy storage from policy - Discrepancy needed to meet the energy policy goals.</p>
#380 C 	<p>room night stays growth rate (fraction/Month [8.3e-005,0.01667]) = 0.0014</p> <p>Description: <i>Default value represents 10% per annum growth from 2005 up to 2016. Equivalent to 0.00139 per month (divided by 12)</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: changing number of stays - Monthly change in number of room night stays from tourism</p>
#381 L 	<p>Room Night Tourist Stays (night stays/Month) = [changing number of stays dt + [initial room night stays]</p> <p>Description: <i>Stock of room night tourist stays</i></p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: changing number of stays - Monthly change in number of room night stays from tourism</p>
#382 A 	<p>SAVEPER (Month [0,?]) = TIME STEP</p> <p>Description: <i>The frequency with which output is stored.</i></p> <p>Not Present In Any View</p>
#383 A 	<p>seasonality effects on renewables availability (Dmnl) seasonality effects on renewables availability [type] = Input[type]</p> <p>Description: <i>Seasonality is affected by this exogenous input, which can be set by the user to a step, pulse, ramp, sine wave, or noise functions. Used sparingly for this thesis</i></p> <p>Present in 2 views: Policy, CO2 Emissions, Capacity Factor and Grid Q Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: actual average capacity factor experience per installed MW renewables - Gives the capacity factor experience based on the monthly seasonality influences. The yearly effects of the renewables on the amount of capacity factor experience.....Accounts for the maintenance and downtime of the technology100% capacity factor is 1.0. A monthly measure of 0.9 means 90% of the month of capacity factor experience is achieved.</p>
#384 C 	<p>Sine Amplitude (Dimensionless) Sine Amplitude [type] = 0</p> <p>Description: <i>Amplitude of sine wave in seasonality (fraction of mean).</i></p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#385 C 	<p>Sine Period (Months) Sine Period [type] = 50</p> <p>Description: <i>Period of sine wave in seasonality effects.</i></p> <p>Present in 1 view:</p>

	<p>Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#386 A VAB	<p>STANDARD OF LIVING INDEX IMPACT ON HOUSEHOLD CONSUMPTION (fraction [0, 0.5, 0.001]) = 0.015</p> <p>Description: 0.03% increment per year from world bank data. Divided by 12 to convert to a monthly value.....0.01 default value. This will reflect the possible consumption growth of the individual households based on their individual outputs - works out to 41euro cents per month equivalent change</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: household consumption growth - Household consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per household per month</p>
#387 C VAB	<p>STANDARD OFF PEAK HOURS PER DAY (h/day [6,10,4]) = 10</p> <p>Description: EDA stipulated number of off peak hours in a day....it also includes the super off peak hours 1:30am-5:30am Ilic et al. (2013) pg 145</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average off peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average off peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average off peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p>
#388 C VAB	<p>STANDARD PEAK HOURS PER DAY (h/day [1.5,6,0.5]) = 4</p> <p>Description: EDA stipulated number of peak hours in a day....Ilic et al. (2013) pg 145</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p>
#389 C VAB	<p>STANDARD SHOULDER PEAK HOURS PER DAY (h/day [8,12,2]) = 10</p> <p>Description: EDA stipulated number of shoulder peak hours in a day....Ilic et al. (2013) pg 145</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: average shoulder peak hours per month from energy storage - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average shoulder peak hours per month from fossil generation - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average shoulder peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12</p>
#390 C VAB	<p>Step Height (Dimensionless) Step Height [type] = 0</p> <p>Description: Height of step input to seasonality, as fraction of initial value.</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#391 C VAB	<p>Step Time (Months) Step Time [type] = 5</p> <p>Description: Time for the step input.</p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by:</p>

	<p>Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)</p>
#392 C VAB	<p>STORAGE CAPACITY PORTFOLIO (fraction [0,1,0.05]) = 0.05</p> <p>Description: <i>The investment percentage that is targeted to energy storage</i></p> <p>Present in 2 views: Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: amount of expected total capacity as storage - Given the investment portfolio we should have this amount of storage in the generation mix to meet forecasted demand levels. FOSSIL CAPACITY PORTFOLIO - The investment percentage that is targeted to fossil fuel generation revised MIN MAX daily demand profiles monthly energy storage influence - If the MIN MAX difference remains high then we should continue with the energy storage policy, if not then we can reduce the energy storage policy to 1% This assumes that the larger the gap then more excess storage supply is needed in the daytime proportional to the avoided curtailed amount in the night time.</p>
#393 C VAB	<p>SUPPLY AND TRANSMISSION LOSSES FRACTION (fraction [0.005,0.2,0.005]) = 0.1</p> <p>Description: <i>The generation and transmission losses that can occur within the grid system....this is expressed as a percentage of the demand</i></p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: net avg electricity generation in MW - This takes into account any losses in the system.....calculated as a percentage of the average demand usage</p>
#394 C VAB	<p>TIME STEP (Month [0,?]) = 0.015625</p> <p>Description: <i>The time step for the simulation.</i></p> <p>Present in 1 view: Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: Input - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000) SAVEPER - The frequency with which output is stored. White Noise - White noise input to the pink noise process implemented for renewables seasonality effects (used sparingly in this thesis).</p>
#395 C VAB	<p>time to meet EU emissions target (Months [120,540]) = 180</p> <p>Description: The set date that the reduction in CO2 emissions should be achieved. This is given in months as the lifetime of the reduction period starting in 2005. 15 (2020) to 45 (2050) years. Set increments of 120 months or 10 year CO2 policies.</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: CO2 emissions reduction factor - The monthly discrepancy resulting from the amount of CO2 emissions and the targeted CO2 emissions reduction</p>
#396 A VAB	<p>TIME TO OBSERVE HOUSEHOLD CONSUMPTION GROWTH (Months [?,?,6]) = =1</p> <p>Description: The number of months for observing household consumption growth</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: household consumption growth - Household consumption growth calculation as it relates to the economic activity of the island. MWh growth per month per household per month</p>
#397 A VAB	<p>TIMELINE FOR CHANGE IN COST OF RENEWABLES CAPACITY (Months [1,12,11]) = =12</p> <p>Description: Gives the timeline for perceiving the yearly cost of the new renewables capacity</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: marginal cost renewables capacity previous year - Change in marginal cost of renewables technologies over time</p>
#398 A VAB	<p>TIMELINE FOR CHANGE IN COST OF STORAGE CAPACITY (Months [1,12,11]) = =12</p>

	<p>Description: Gives the timeline for perceiving the yearly cost of the new energy storage capacity</p> <p>Present in 1 view: Installed Supply Capacity and Learning Curve</p> <p>Used by: marginal cost of storage capacity previous year - Change in marginal cost of renewables technologies over time</p>
#399 A 	<p>TIMELINE FOR CONSIDERING NEW INDUSTRY BUSINESSES (Months [12,36]) = =24</p> <p>Description: Every two years for the investment into new industries to come online</p> <p>Present in 1 view: Net Electricity Demand</p> <p>Used by: changing numbers - Number of monthly changing industries per month</p>
#400 C 	<p>total capacity supply SWITCH (Dmnl [0,1,1]) = 0</p> <p>Description: on (1) and off (0)</p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: amount of renewables considered for RENEWABLES POLICY - This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted.</p>
#401 A 	<p>total capacity usage factor (Dmnl) = fossil generation capacity usage factor+\sum(renewables capacity usage factor[type!])+energy storage capacity usage factor</p> <p>Description: Used for normalisation checking of the usage factor</p> <p>Present in 1 view: Financial and Economic Aspects</p>
#402 LI,A 	<p>total electricity sold revenues (\$/Month) = industrial consumption revenues+commercial services consumption revenues+public services consumption revenues+residential consumption revenues+electric vehicles consumption revenues</p> <p>Description: Gives the revenues collected on a monthly basis due to the electricity sold and based on the tariff structures....The only way of generating income within the model</p> <p>Present in 1 view: Financial and Economic Aspects</p> <p>Used by: change in revenues - Change in the revenues generated over the revenue horizon Expected Revenues - Stock of rolling average of revenues generated</p>
#403 A 	<p>total MW capacity hours to utilise (h*MW/Month) = installed energy storage MW capacity hours to utilise+installed fossil generation MW capacity hours to utilise+\sum(installed renewables MW capacity hours to utilise[type!])</p> <p>Description: Sum of all generating technologies available hours to meet demand load - based on installed capacities</p> <p>Present in 1 view: Financial and Economic Aspects</p>
#404 L,LI  	<p>Total Population of Vehicles (vehicles) = \intbuying new vehicles rate dt + [initial total population of vehicles]</p> <p>Description: Stock of total vehicle population in the island system.</p> <p>Present in 2 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: considered electric vehicles - Choosing the policy method of the total amount of vehicles versus an absolute number of electric vehicles endogenous market based influence on adoption - Adoption by word of mouth is driven by the contact rate between potential adopters and active adopters and the fraction of times these interactions will result in adoption. The word of mouth effect is small if the number of active adopters relative to the total population size is small. Potential Electric Vehicles Adopters - The initial number of potential adopters is determined by the total population size and the current number of active adopters. It is reduced by adoption and increased when adopters discard their old unit and re-enter the market.</p>
#405 L 	<p>Total System Capacity Factor Experience ((MW*Month)/Month) = \intadditional capacity factor experience from new capacity-loss of capacity factor experience dt + [Installed Fossil Generation Capacity*average capacity factor experience per installed MW fossil generation+Installed Energy Storage Capacity*average capacity factor experience per installed MW energy storage+\sum(Installed Renewables Capacity[type!]*actual average capacity factor experience per installed MW renewables[type!])]</p> <p>Description: Initial value will be determined from 2005 average based on the total amount of the co-flow</p>

	<p><i>attribute</i></p> <p>Present in 1 view: Policy, CO2 Emissions, Capacity Factor and Grid Q</p> <p>Used by: average capacity factor experience - Capacity factor attribute as determined from the different main capacity stocks</p>
#406 C VAB	<p>total vehicle population SWITCH (Dmnl [0,1,1]) = 0</p> <p>Description: <i>on (1) and off (0). Used for total vehicle population simulations.</i></p> <p>Present in 1 view: Mismatch and Demand Imbalance Black Box</p> <p>Used by: considered electric vehicles - Choosing the policy method of the total amount of vehicles versus an absolute number of electric vehicles electric vehicles adoption rate - The rate at which a potential adopter becomes an active adopter. When the total population switch is on we consider both the total population and the market based adoption from this. Otherwise if the market only based switch is on then we consider only adoption from the market contacts else we consider the absolute value as desired from the policy. vehicles considered for EV by policy - This is the absolute number of electric vehicles desired by policy makers at the specified time. The specified time is the time when the policy is enacted.....2015 is the default value....this is 10 years or 120 months into the simulation.</p>
#407 Sub [sub]	<p>type : geothermal, run of river hydro, biomass, wind, micro mini generation</p> <p>Present in 5 views: Mismatch and Demand Imbalance Black Box Policy, CO2 Emissions, Capacity Factor and Grid Q Financial and Economic Aspects Installed Supply Capacity and Learning Curve Seasonality Effects Expected Capacity and Real Da</p> <p>Used by: actual average capacity factor experience per installed MW renewables - Gives the capacity factor experience based on the monthly seasonality influences. The yearly effects of the renewables on the amount of capacity factor experience.....Accounts for the maintenance and downtime of the technology 100% capacity factor is 1.0. A monthly measure of 0.9 means 90% of the month of capacity factor experience is achieved. additional capacity factor experience from new capacity - Increase in the capacity factor experience attribute aggregated renewables dispatchable MW capacity hours - used to normalise the usage of the renewables technologies amount of expected total capacity as renewables - Given the investment portfolio we should invest in this amount of the specific renewable technology in the generation mix to meet forecasted demand levels. amount of renewables considered for RENEWABLES POLICY - This is the amount of renewables desired by policy makers at the specified time. The specified time is the time when the policy is enacted. average capacity factor experience - Capacity factor attribute as determined from the different main capacity stocks average dispatchable hours for renewables - The amount of hours within a month that the specific renewable technology is dispatched base on capacity factor and merit order usage average off peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 average renewables usage hours - Sum of hours per month that renewables is dispatched to meet the demand load average shoulder peak hours per month from renewables - Data source for derivation: Ilic et al (2013) pg 145 table 4.12 Change in Pink Noise - Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input. Used sparingly in this thesis work Cumulatively Depreciated Renewables Capacity - Stock of all renewables generation over the total simulation timeline. cumulatively installed renewables capacity - Sum of the total ever installed renewable capacity of the specific renewable technologies cumulatively installed renewables capacity previous year - Cumulatively installed renewable capacity for previous year: for use in learning curve formula difference needed from renewables policy - Monthly amount of capacity needed to achieve policy goals by the policy timeline. energy storage capacity usage factor - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing Energy storage will be used once installed</p>

[expected renewables revenues per MW installed](#) - Based on the expected installed renewable technologies capacity usage and expected revenues

[financially desired renewable capacity](#) - The installed capacity that is desired based on the cost reduction learning curves and financial profitability of the renewables capacity

[FOSSIL CAPACITY PORTFOLIO](#) - The investment percentage that is targeted to fossil fuel generation

[fossil generation capacity usage factor](#) - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing.....additional fossil is used if there is not enough renewables and storage. In the base year 34.27MW of fossil was used to meet the demand which is (34.27/102.66), 35% of the installed base of 102.66MW

[initial cost of new renewables capacity](#) - Initial marginal cost of new renewable capacity for base year converted to dollars

[Input](#) - Input is a dimensionless variable which provides a variety of test input patterns, including a step, pulse, sine wave, and random noise. Adopted from Sterman (2000)

[Installed Renewables Aggregated Capacity](#) - Sum of all the different renewable technologies considered in the model, namely; Geothermal, run of river, wind, biomass, micro/solar generation.

[Installed Renewables Capacity](#) - Stock of installed renewables technologies based on capacity investments and decommissioning

[installed renewables MW capacity hours to utilise](#) - For the monthly demand.....active energy used hours from the different renewable technologies

[loss of capacity factor experience](#) - Decrease in the capacity factor attribute

[marginal cost of renewables capacity](#) - Learning curve cost reduction implementation.

[marginal cost renewables capacity previous year](#) - Change in marginal cost of renewables technologies over time

[needed breakeven monthly revenue per MW installed renewables](#) - Revenues needed due to the installed renewable technologies capacity and usage of this capacity

[net electricity supply capacity in MW](#) - Net electricity supply considering the losses that can occur within the generation and transmission of the system. (if on (1) stochastic variations (Not used for thesis) in supply can be simulated

[Pink Noise](#) - Pink Noise is first-order auto-correlated noise. Pink noise provides a realistic noise input to models in which the next random shock depends in part on the previous shocks. The user can specify the correlation time. The mean is 0 and the standard deviation is specified by the user. Adopted from Sterman (2000)

[Planned Renewables Investments](#) - Stock of planned renewables capacity for the various technologies. The planned renewable capacity investments from the base year, 2005 onwards.

[RENEWABLE CAPACITY PORTFOLIO](#) - The investment percentage that is targeted to renewables technology investments

[renewable investment attractiveness](#) - Based on the renewable technologies profitability

[Renewables Capacity Under Construction](#) - The stock of renewable capacity under construction.

[renewables capacity usage factor](#) - Based on the merit order of the utility company.....geothermal, run of river dispatched firstly along with the frequency balancing fossil generation, then biomass, then wind and extra fossil as needed.....if too much supply capacity then the wind is curtailed.....at least 18-20% fossil is kept online for frequency balancing (8-16MW)

[renewables construction rate](#) - Accounting for the delay between investment decision project write ups and financial approvals for the start of construction

[renewables decommissioning rate](#) - Accounting for the depreciation of the renewable capacity

[Renewables Generation Cost](#) - Stock of the renewable generation LCOE cost in dollars

[renewables investment rate](#) - MAX formulation used to avoid negative renewables investments

[renewables investment rate real](#) - Looking at all of the potential amount of renewable replacements needed directly and indirectly.....we derive the amount of investments that can occur as in real systems. Investments is shared across the different renewables technologies based on their usage. ELMCOUNT(type) is used to handle the technologies represented as subscripts

[renewables online rate](#) - Accounting for the delay for construction of renewable capacity

[renewables profitability](#) - Ratio of revenues over needed LCOE baseline revenues.

[seasonality effects on renewables availability](#) - Seasonality is affected by this exogenous input, which can be set by the user to a step, pulse, ramp, sine wave, or noise functions. Used sparingly for this thesis

[total capacity usage factor](#) - Used for normalisation checking of the usage factor

[total MW capacity hours to utilise](#) - Sum of all generating technologies available hours to meet demand load - based on installed capacities

[Total System Capacity Factor Experience](#) - Initial value will be determined from 2005 average based on the total amount of the co-flow attribute

[White Noise](#) - White noise input to the pink noise process implemented for renewables seasonality effects (used sparingly in this thesis).

<p>#408 A VAB</p>	<p>vehicles considered for EV by policy (vehicles [100,2500]) = IF THEN ELSE(total vehicle population SWITCH = 1 , revised MIN MAX daily month demand profiles influence*considered electric vehicles, considered electric vehicles) Description: <i>This is the absolute number of electric vehicles desired by policy makers at the specified time. The specified time is the time when the policy is enacted.....2015 is the default value....this is 10 years or 120 months into the simulation.</i> Present in 1 view: Mismatch and Demand Imbalance Black Box Used by: rolling desired electric vehicles - Based on the year of the policy and the MIN MAX influence policy fraction used.....Looking at our long term installed capacity we will not enforce the electric vehicle policy if there is more demand than supply</p>
<p>#409 A VAB</p>	<p>White Noise (Dimensionless) White Noise [type] = Noise Standard Deviation[type]*((24*Noise Correlation Time[type])/TIME STEP)^0.5*(RANDOM 0 1 - 0.5)) Description: <i>White noise input to the pink noise process implemented for renewables seasonality effects (used sparingly in this thesis).</i> Present in 1 view: Seasonality Effects Expected Capacity and Real Data Used by: Change in Pink Noise - Change in the pink noise value; Pink noise is a first order exponential smoothing delay of the white noise input. Used sparingly in this thesis work</p>

Appendix B Further Validations of Synthesis Model

This appendix gives details of some further validations of the synthesis model performed in the development of the model.

B.1 Reality Checks and Extreme Case Testing

Making use of the modelling software, the reality check functionality can be employed for model testing/validation. In this work the use of test inputs for the conditional part of the constraint equation is used to test the model. When the condition is true and the consequence is not true, then Vensim reports a reality check error. In general the structure is:

name :THE CONDITION: condition :IMPLIES: consequence

The main constraint tests used were:

- (a) no expected revenues : THE CONDITION: expected revenues = 0 :IMPLIES:
investments reduces to zero **- TEST PASSED**
- (b) no fossil generation capacity : THE CONDITION: fossil generation capacity = 0
:IMPLIES: monthly CO₂ emissions = 0 **- TEST PASSED**
- (c) no net avg electricity demand : THE CONDITION: net avg electricity demand = 0
:IMPLIES: net avg demand vs net avg supply capacity mismatch = 0
- TEST PASSED

In addition a few extreme case testing were completed. These tests were used to gauge the wide ranging sensitivity of the model to extreme (hypothetical) situations. Three such tests conducted were:

- (a) Increasing the *revenues expected* to 20 times the simulated value in 2020, it was observed that there were large increases in the *capacity investments of fossil generation and renewables*.
- (b) Very large *GDP per capita* gave very high *net monthly electricity demand*.
- (c) Large amounts of *fossil generation capacity* gave very large *accumulated CO₂ emissions*.

B.2 General Sensitivity Analysis

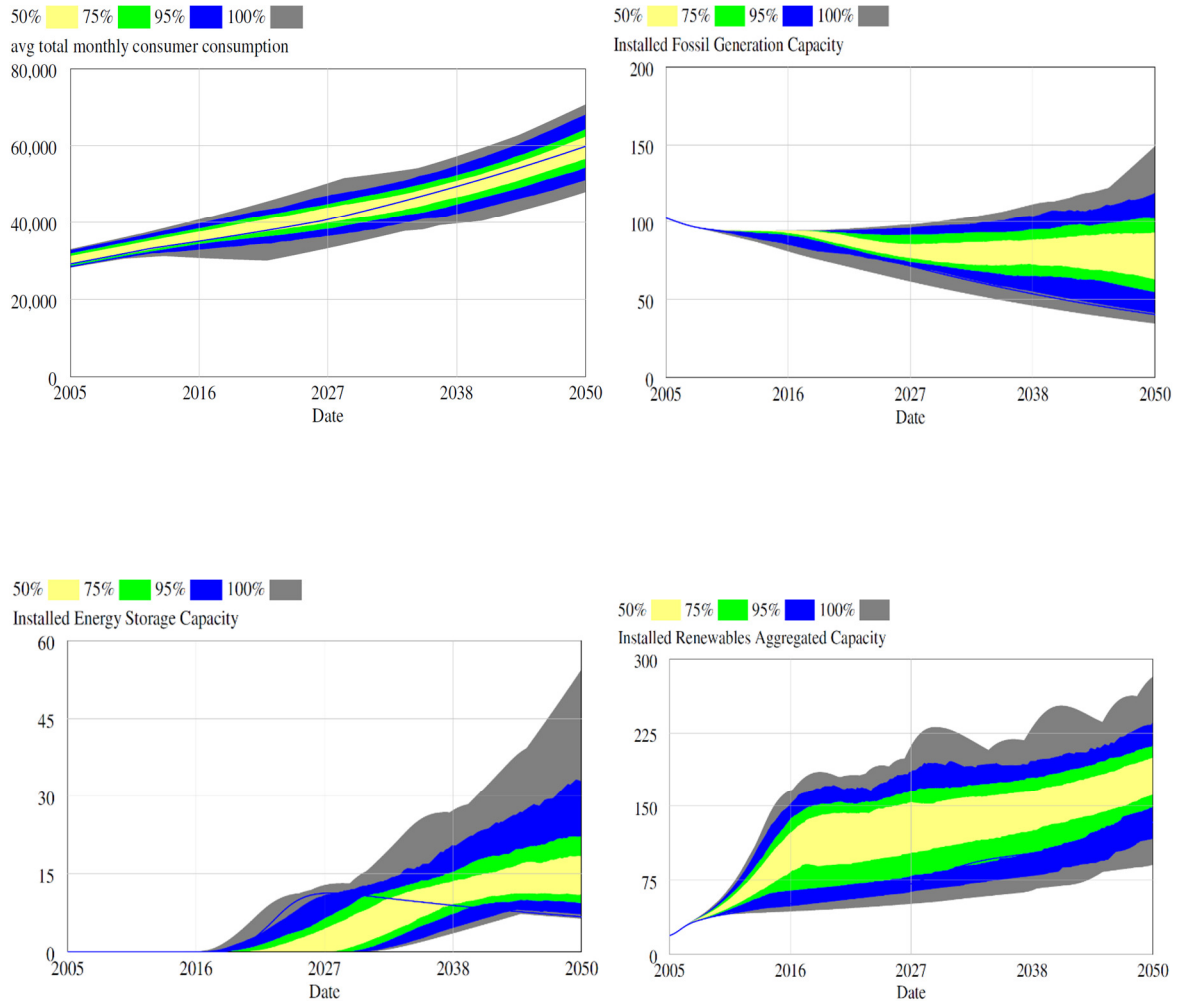
The sensitivity analysis performed here is used for supporting the validity of the model when calibrated to other system characteristics that are similar but not the same as the island of São Miguel.

Variable Name/Unit	Base value	Sensitivity ranges
Economic activity/fraction GDP per month	0.0011905	0.0005000 – 0.0019000
avg consumption per tourist-night stays/ MW*h/night stays	0.0027	0.0015 - 0.0039
tourist stays growth rate/ %/Month	0.14	0.05 - 0.47
avg size of households/ People/household	3.45 (in 2005)	3.1 – 3.8
energy efficiency enactment year/ Months	84 months (the year 2012)	12 - 300 (from the years 2006 - 2030)
energy efficiency policy timeline/ Months	180 months	120 - 360 (for 10 - 30 years)
energy efficiency reduction/ %	6	0 - 30
renewables policy portfolio/ %	45	30 - 75
renewables policy enactment year/ Months	32 months (the year 2007)	12 - 300 (from the years 2006 - 2030)
renewables policy timeline/ Months	156 months	120 - 506 (for 10 - 42 years)
CO ₂ emissions target/ fraction	0.3	0.10 – 0.75
Time to meet EU CO ₂ emissions target/ Months	180 months	120 - 540 (for 10 - 45 years)
energy storage policy enactment year/ Months	150 months (the year 2018)	120 - 300 (from the years 2015 - 2030)
energy storage policy timeline/ Months	60 months	60 - 380 (for 5 - 32 years)
desired electric vehicles policy target / vehicles	2500	1500 - 6000
consumer-type time-period electricity prices/ \$/MW*h	Various base values	-20% to +20% of base value
capacity-type time-period dispatch factor/ fraction	Various base values	-30% to +30% of base value

Table showing the variables used for the sensitivity analysis and the ranges explored

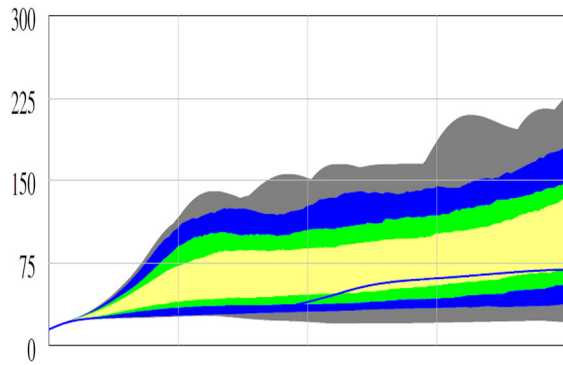
These variables/model constants were chosen as input since they are key policy and influential values within the model. The variables in red are the ones that are not sensitivity tested in Chapter 6. For the sensitivity analysis, the standard Vensim multivariate MCMC is conducted for 500 simulations from

2005 up to 2050. The confidence bounds using the percentiles 50%, 75%, 95% and 100% are shown as yellow, green, blue and grey colours respectively. The following figures show the range of possible outcomes from these sensitivity simulations. Also shown in the diagrams are the simulation run (blue line) of the base case scenario of São Miguel. The diagrams show that for the variables of installed capacities there are a larger range of possible outcomes. For the average monthly consumer consumption and expected revenues there are a smaller range of possible outcomes.

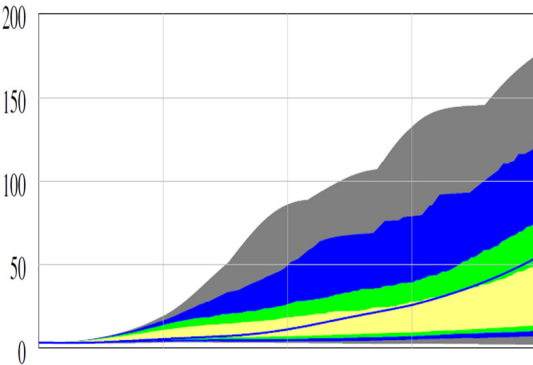




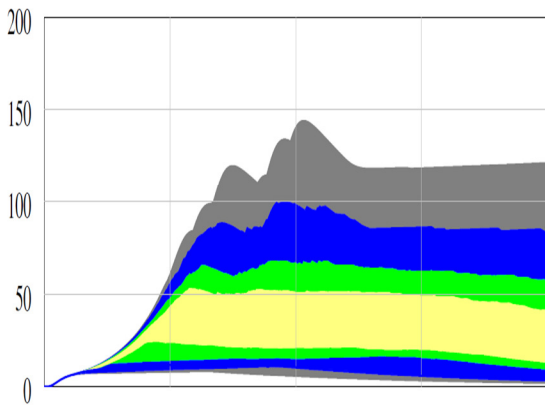
Installed Renewables Capacity[geothermal]



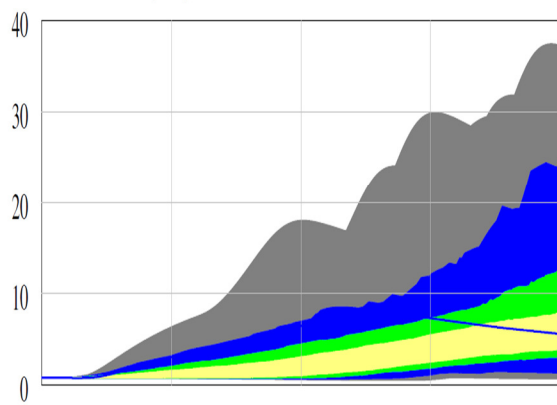
Installed Renewables Capacity[run of river hydro]



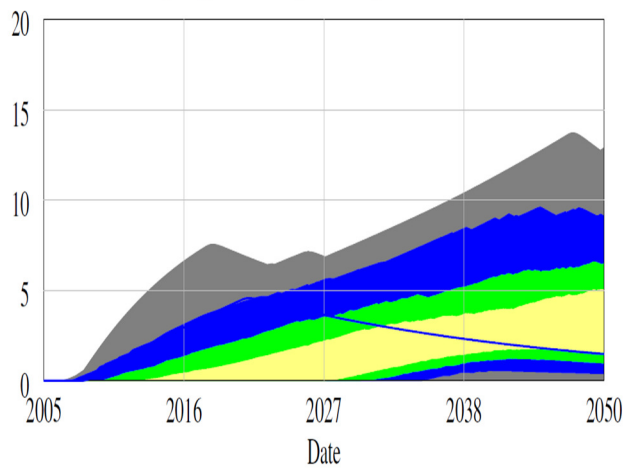
Installed Renewables Capacity[wind]

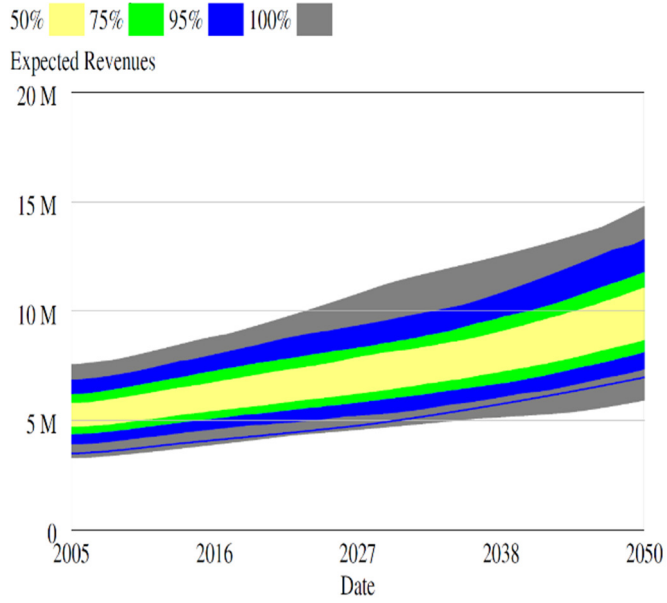
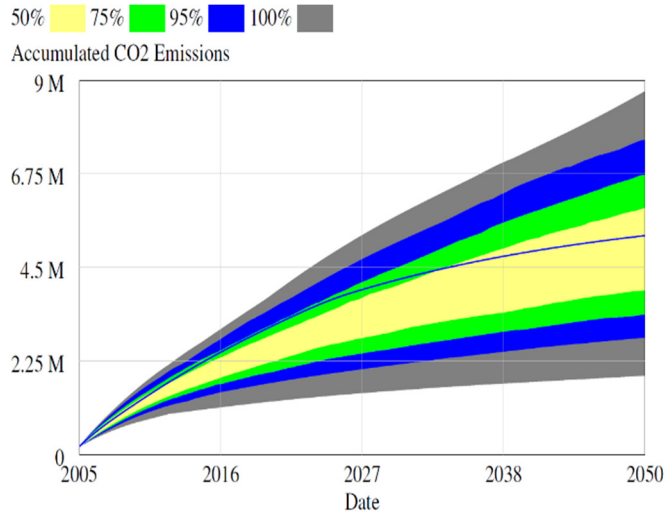


Installed Renewables Capacity[biomass]



Installed Renewables Capacity[micro mini generation]





Appendix C Black box Details

The back box is used in Chapters 5 and 6 for capturing the short-term day/night peak and troughs of the demand profiles. This difference in peaks and troughs is used to decide whether to continue with the current EV policy objectives or to lower it to prior policy levels. The black box implemented within this thesis is very simple and can be extended later to be more comprehensive to capture (auto) correlation of the demand over time. The implementation of the black box involves the following steps:

- a. Using the daily 30 min demand output for São Miguel from EDA for the 2012 to 2015 three-year period to determine the difference of the minimum and maximum daily demand values of the demand within each month (30 days) of the dataset.
- b. The next step is Normalization: Starting from the first month of the dataset, a month at a time, until the end of the dataset, use the largest minimum maximum difference for the month and then divide each of the other minimum maximum difference by this value for the month. At the end of the process all profiles would be normalized.
- c. The three normalized values for each of the months Jan, Feb, ..., Dec for the three years are then called within the Vensim program using the following implementation:
 - i. They are put into a lookup, where the x-axis is the integer number of the point:
Normalised MIN MAX Lookup
x: 1, 2, 3, 4, ..., N
y: 32, 17, 39, 24, ..., 29
 - ii. Then pick an integer at random and use that with the lookup:
Black box index = INTEGER(RANDOM UNIFORM(1,N+1,0))

Finally, use the black box index to pick a demand value:

Demand = Demand Lookup(Demand Index)

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