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A study of residential solar power and battery energy storage adoption dynamics

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ABSTRACT

As the global response to anthropogenic climate change evolves, centralised electricity supply systems have become a key focus for emission reduction efforts. While governments and industry mobilise to decarbonise the electricity sector, substantial opportunities have also begun to emerge at the residential level. Recent dramatic growth in the rate of rooftop solar photovoltaic (PV) adoption in Australia epitomises the opportunity, and the disruption, that can occur in response to falling technology costs, increasing retail electricity prices, and the emergence of more active and engaged electricity consumers.

Residential battery energy storage is now on the threshold of mass-market uptake. When coupled with solar PV, battery technology could enable potentially millions of small-scale electricity end-users to participate in the market as both generators and consumers, reducing total system demand while challenging the business models of incumbent utilities. This development will not only amplify existing operational complexity in Australian electricity markets, but if the technology is poorly integrated, negatively impact the efficient provision of electricity, an essential service that underpins the structure and function of modern economies.

There is a clear imperative for government and industry to proactively manage the integration of residential PV and battery energy storage to avoid adverse or unintended consequences. A number of these risks have received considerable academic and industry attention, particularly from a techno-economic viewpoint. However, there exists a substantial gap in the literature regarding research into battery adoption dynamics from a whole-of-system perspective addressing the multi-causal, socially complex nature of the problem. This dissertation aims to address this gap by identifying the key dynamics that will underpin battery adoption, how they could influence battery deployment rates and how these dynamics will manifest along the broader electricity supply chain.

To most effectively incorporate the substantial uncertainty and complexity associated with consumer-led electricity sector transitions in this regard, a systems thinking methodology supported by a mixed method approach to data collection has been used. To generate meaningful results at an appropriate level of granularity, the state of Queensland in Australia is used as a case study to conceptualise and model battery dynamics. Queensland has many of the preconditions necessary for rapid residential battery uptake, and with a centralised electricity sector worth more than AU$30 billion, understanding the drivers that may underpin disruption to this system is critical.

Casual loop modelling, informed by an extensive participatory data collection exercise involving interviews with nearly 70 energy sector experts, was initially used to map the complex dynamics associated with residential battery adoption. This research found that a range of non-financial and financial reinforcing feedback loops encouraging battery adoption are currently dominant in Queensland. Should battery prices continue to fall as forecast – a necessary precondition for mass-market uptake – the causal loop diagram demonstrates that multiple paths to market targeting a highly motivated consumer-base would make rapid battery uptake highly likely in coming years.

To empirically test the conclusions drawn from causal loop modelling, and to more accurately understand the strength and influence of battery adoption drivers, a stock-and-flow simulation model was created. The model demonstrated that across all scenarios tested, battery adoption in Queensland is likely to achieve mass-market uptake prior to the end of the 30 year simulation period. The base-case simulation found that by 2036, approximately 570,000 batteries would be installed representing 5,444 megawatt hours of capacity. This outcome would see substantial private sector investment, exceeding $8 billion, while achieving material contributions to greenhouse gas emission mitigation equivalent to approximately 6.2 million tonnes of carbon dioxide.

The results of scenario analysis show that rates of battery adoption are a function of complex interactions between endogenous and exogenous variables. Impacts in one part of the supply chain, be it the unilateral action of a market participant, introduction of government policy or a completely exogenous influence such as an extreme weather event, not only increase battery adoption in their own right but can also reinforce several endogenous feedback loops. This affects electricity prices and strengthens non-financial motivations, driving even larger increases in battery adoption. Importantly, the model also shows that proactive efforts to integrate the technology in an efficient manner can drive beneficial outcomes along the supply chain, particularly where batteries are installed to help improve utilisation of the existing network.

The potential risks and opportunities of residential PV and battery energy storage in coming years could be substantial. This dissertation makes an important contribution in this regard. It provides the basis with which to better understand the dynamics that could drive battery uptake while identifying possible leverage points to more effectively integrate the technology. In doing so, this research will help contribute to ongoing efforts to accelerate the transition towards a more sustainable, low-emission electricity supply system.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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Publications during candidature

Peer-reviewed papers (in order of appearance in this thesis)

Agnew S, Dargusch P. (2015) Effect of residential solar and storage on centralized electricity supply systems. *Nature Climate Change,* 5(4): 315-318.

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Conference and workshop papers

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Research Involving Human or Animal Subjects

Due to the requirement for human participation in this study, ethical approval was granted by the University of Queensland's School of Geography, Planning and Environmental Management Ethics Officer on 15 December 2014 (GPEM number 20130063). A copy of the ethics approval letter is included in Appendix A.

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Keywords

Residential battery energy storage, solar photovoltaics, systems thinking, energy policy

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

AEMO	Australian Energy Market Operator
AEMC	Australian Energy Market Commission
AER	Australian Energy Regulator
CLD	Causal loop diagram
CO_2e	Carbon dioxide equivalent
DEWS	Queensland Department of Energy and Water Supply
DNSP	Distribution Network Service Provider
FiT	Feed-in Tariff
GOC	Government Owned Corporation
GW	Gigawatt
GWh	Gigawatt hour
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
kW	Kilowatt
kWh	Kilowatt hour
MW	Megawatt
MWh	Megawatt hour
NEM	National Electricity Market
OECD	Organisation for Economic Co-operation and Development
PV	Photovoltaic
QCA	Queensland Competition Authority
QPC	Queensland Productivity Commission
RET	Renewable Energy Target
SBS	Solar Bonus Scheme
SEQ	South East Queensland
TW	Terawatt
TWh	Terawatt hour
UNFCCC	United Nations Framework Convention on Climate Change
UTP	Uniform Tariff Policy

Chapter 1 Introduction

1.1 Issue overview

In 2012, then United Nations Secretary-General, Ban Ki-moon stated that “energy is the golden thread that connects economic growth, social equity, and environmental sustainability” (Ki-moon 2012, p. 1). This statement was an acknowledgement that in the past century, affordable and reliable energy has underpinned global economic development and delivered substantial human health and welfare advances. In particular, it has been the vast centralised electricity supply systems operating in most modern economies that have enabled some of the world’s most significant technological, manufacturing and social achievements. However, disruption to these electricity supply systems is accelerating as governments, industry and communities grapple with the so-called ‘energy trilemma’ – the challenge of providing secure, equitable and environmentally sustainable energy to an ever growing global population (World Energy Council 2016).

Within this trilemma, the global imperative to reduce greenhouse gas emissions has driven much of the disruption currently impacting energy systems around the world. This is because energy provision is responsible for the largest share of global greenhouse gas emissions, with 82% of total primary energy supply sourced from fossil fuels contributing almost two-thirds of total emissions (IEA 2013a). Within the energy sector, electricity generation is the largest contributor, generating more than 40% of global energy related greenhouse gas emissions (IEA 2016d).

As the anthropogenic causes of climate change are becoming better understood, the need for urgent action is increasing, making the energy sector a prime target for deep emission cuts. This imperative is reflected in the Paris Climate Change Agreement, the international accord designed to strengthen the global response to climate change. The Agreement which entered into force in November 2016 seeks to minimise the threat of climate change by “holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels.” (UNFCCC 2015, p. 2). To achieve the objectives of the Agreement, it is widely accepted that “transformative change in the energy sector” is required (IEA 2016d, p. 21).

While substantial efforts are currently underway aimed at decarbonising centralised electricity supply systems, most mitigation scenarios indicate that the pace of change is too slow, and existing measures insufficient to avoid the worst impacts of climate change (IPCC 2014a). This is because two-thirds of power generation continues to rely on fossil fuels, despite rapid renewable energy deployment in recent years (IEA 2014a). If society's reliance on fossil fuels does not change, energy related greenhouse gas emissions will increase by more than 80% by 2050 (IPCC 2014a). In this scenario, the projected temperature increases, which would likely exceed 2°C by 2100, could result in significant negative climate change impacts (IPCC 2014a, 2014b).

Addressing the risks posed by climate change represents only one element of the energy trilemma. The provision of secure and equitable electricity is an equally challenging task. With the world's population estimated to increase to 9 billion people by 2040, and emerging economies seeking greater access to modern energy services, global energy production will need to double before the middle of this century to meet growing demand (Riesz et al. 2014; Larcher & Tarascon 2015; World Energy Council 2016). This does not include efforts to supply electricity to the 1.2 billion people who currently do not have any access to electricity whatsoever (IEA 2016d).

At the same time, the global economy is expected to grow by 150% putting additional strain on existing energy assets (World Energy Council 2016). This enormous expansion of energy infrastructure must occur within the context of changing societal expectations, the decline of energy resources and shifting geopolitical dynamics. In this rapidly evolving environment, it is clear that if the issues inherent in the energy trilemma are to be addressed, a fundamental paradigm shift is required to help transform the structure and operation of the traditional centralised electricity supply system. However, with so many uncertainties "no path of development of the global energy system can be confidently drawn to 2040" (IEA 2016d, p. 33).

As industry and governments struggle to develop cogent solutions to the challenge, it may be the emergence of a large and engaged residential consumer base that could provide the impetus for transformational change in the electricity sector (Agnew & Dargusch 2017). This development is a relatively new phenomenon, enabled by cost-effective demand-side energy technologies and the liberalisation of energy markets, which could empower consumers to change their relationship with the existing electricity supply system.

The recent multi-billion dollar global boom in residential solar photovoltaics (PV) symbolises both the power of consumer-led transition and the challenge. Global PV capacity increased from 1.3 gigawatt (GW) in 2000 to 303 GW in 2016 (EPIA 2014; IEA 2017). However despite its many benefits, the rapid integration of PV into existing centralised electricity systems has not always been optimal, and in some cases has resulted in negative consequences. These included economic impacts for electricity sector participants, power quality and system stability issues, increasing electricity prices and negative social-equity outcomes (Noone 2013; Rickerson et al. 2014; Karimi et al. 2016; Simshauser 2016).

As Government and industry attempt to respond to the issues associated with residential PV, the emergence of affordable battery energy storage represents the next wave of disruptive change likely to impact the electricity supply system. The implications of this development are substantial. Until recently the cost of storing electricity has been prohibitive in most circumstances. This means that almost all consumers, even those with PV, have been reliant on the existing centralised electricity supply system to ensure adequate supply is available at any given time. As price takers with little leverage, consumers have been largely captive to a small number of incumbent utilities.

Cost-effective battery energy storage changes this paradigm. Consumers with an appropriately sized PV and battery system will be able to shift the times they use electricity, reduce how much electricity they use from the network, or disconnect from the network entirely (Agnew & Dargusch 2015). For those consumers who can afford the technology, it can reduce electricity costs and provide positive security and reliability outcomes while reducing emissions. At a household level, this reflects a confluence of the drivers that comprise the broader energy trilemma. From a system-wide perspective however, the implications of PV and battery energy storage are not so simple.

PV and battery energy storage are classed as disruptive technologies, a term which refers to innovations that drive sudden and often unexpected change to established markets and products (Bower & Christensen 1995; Rickerson et al. 2014). Distributed energy technology of this nature is essentially the “antithesis of the central generation model” (Finkel et al. 2016, p. 2). This is because the technology will allow consumers to compete directly with incumbent utilities eroding their profitability and possibly impacting the operation and structure of the existing electricity supply system. Ultimately, this development could drive a ‘megashift’ which would see the electricity sector being “substantially restructured to accommodate a new reality” (CSIRO 2013a, p. 25).

This megashift will occur at a time when existing centralised electricity systems are already undergoing substantial change as governments and industry respond to the challenges inherent in the energy trilemma. The environment is characterised by policy and regulatory uncertainty, changing social, economic and sustainability drivers, and complicated relationships between public and private actors (World Energy Council 2012). The potential for suboptimal outcomes are markedly increased as policy makers grapple with increasing complexity and shifting priorities.

Failure to proactively manage integration of residential PV with battery storage could result in substantial inefficiencies along the supply chain, including a decline in asset utilisation, asset impairment, increases in electricity costs and broader social and economic impacts (Agnew & Dargusch 2015). Despite these risks, there exists a fundamental gap in the academic literature that considers battery adoption dynamics from a holistic perspective, particularly with regard to the influence of reinforcing feedback mechanisms that may manifest under a range of different scenarios and how they may drive broader system change in response.

This gap exists in part because energy systems, despite being frequently defined and modelled as techno-economic phenomenon, are socially driven and characterised by 'messy' real-world complexity (Miller, Richter & O'Leary 2015). Electricity sector transitions are highly dynamic, face challenges in conceptualisation and stem from multi-causal sources, including interactions between technology, the economy, society and institutional actors (Bale, Varga & Foxon 2015). Trans-disciplinary techniques are required that are "capable of grasping the big picture, including the interrelationships among the full range of causal factors underlying them" (APSC 2012, p. iii). This is especially true for residential PV and battery energy storage where the outcome of the impending sector transformation could largely depend on the actions of the consumer, particularly the choice they make in regard to the type of battery they purchase and the way in which it is used.

As the electricity supply system underpins vital economic and social outcomes, it is becoming increasingly urgent to address this gap. To avoid negative outcomes, it is imperative that governments and policy makers anticipate developments and plan now for the changes that could be triggered by residential PV with battery storage in coming years (Rickerson et al. 2014).

To this end, and to most effectively address the research gap outlined above, a systems thinking method has been applied throughout this thesis. With substantial challenges remaining to the equitable and efficient integration of residential PV and battery energy storage, this study ultimately aims to develop a conceptual framework and apply empirical systems thinking techniques to better understand the dynamic complexity emerging from new consumer-led energy technologies. In doing so, it will provide an important theoretical and practical contribution as electricity systems transition in coming years.

1.2 Research problem and questions

This dissertation is concerned with understanding the dynamics that will underpin PV and battery uptake, specifically the economic, environmental and social factors that could directly and indirectly reinforce battery adoption. This analysis takes place within the context of the rapidly accelerating energy transition – a marked shift to a more sustainable, decentralised electricity supply system – that is occurring as governments, industry and the community respond to the issues inherent in the energy trilemma. In this respect, this thesis will address the following research problem: *What are the key dynamics that will underpin residential solar and battery adoption, how could these dynamics influence deployment rates and what are the implications from a broader energy sector transition perspective?* To answer this problem, four key questions are addressed across four discrete stages of research (Figure 1).

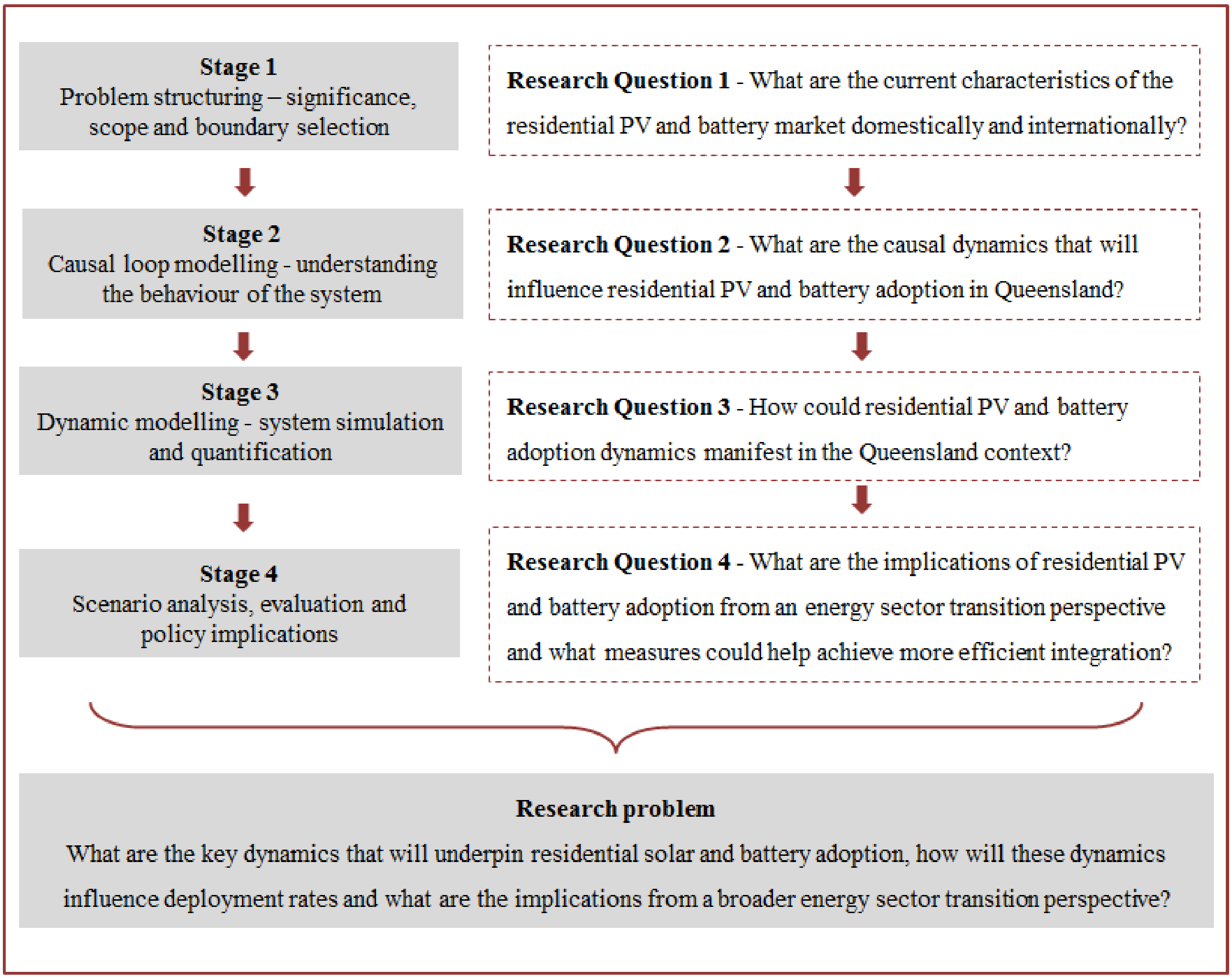


Figure 1 Overview of research approach and research questions

1.3 Research scope

To clarify the scope of research, this dissertation is concerned primarily with:

- Battery technology – Battery energy storage technologies can be deployed at a range of scales and can comprise many different hardware and software configurations (Devine-Wright et al. 2017). A technologically agnostic approach is important in this regard, as advances in battery research are accelerating and it is unknown which technologies will be dominant over the medium to long-term. The research focus in this thesis is therefore primarily concerned with general battery attributes and functionality, noting however that model parameterisation is informed by the current market-leading residential battery chemistry (i.e. lithium-ion).
- Residential sector – The research gap and research imperative being addressed in this thesis relate to *residential* sector dynamics. Specifically, the complexity, lack of homogeneity and the scale associated at the household-level that underpin both the challenge and broader risks inherent in battery adoption. Commercial and utility scale battery energy storage represent promising areas of research, particularly to help improve the utilisation of existing centralised systems, however their deployment and use have different characteristics and drivers and thus have not been considered in this thesis.
- Prosumers – The availability of demand-side energy technologies such as PV and batteries has given rise to a new class of energy consumer referred to as a ‘prosumer’. Prosumers are “agents that both consume and produce energy” (Parag & Sovacool 2016, p. 1).
- Solar PV systems – Household access to embedded generation, such as PV, is a key assumption in this study as residential battery storage in not considered economic without it before 2035 (QPC 2016a). While prosumers can produce their own power from a range of different options (e.g. fossil fuel generators, micro-wind turbines, geothermal etc), this thesis is primarily concerned with rooftop PV. It is currently the most technologically advanced, residential self-generation technology available and is widely deployed in the case-study area. Nearly half a million homes have PV installed in Queensland, comprising nearly a third of dwellings (APVI 2017b; Clean Energy Regulator 2017).
- Modern centralised electricity supply systems – This thesis is concerned with the adoption and integration of PV and battery energy storage in first-world economies that have traditional centralised electricity supply systems. While the potential benefits of distributed PV and battery energy storage in developing countries is enormous and represents a promising area for future research, it is beyond the scope of this study.

1.4 Thesis structure and organisation

This thesis is organised across nine chapters. The first chapter introduces the subject of the thesis with an overview of the key issues and the rationale for investigation. It describes the research problem and research questions. *Chapter 2* provides a detailed review of the specific technology characteristics of both PV and battery energy storage along with an assessment of the current market and the implications associated with the mass market adoption of the technology. *Chapter 3* comprises a journal article published in Nature Climate Change by Agnew and Dargusch (2015), which highlights the imperative to address the research gap and outlines a systems framework that conceptualises at a high-level the issues considered as part of this thesis.

The purpose of *Chapter 4* is to describe the methodology used in the dissertation and the specific research techniques applied to address the research questions. It leads with a literature review of existing energy sector modelling approaches and their suitability for use in analysing energy sector transitions. This provides the context for using systems thinking as the conceptual and organisational framework underpinning the research methodology. The chapter also summarises the specific techniques used across each of the four stages of research.

Based on the results of participatory research and extensive evaluation of secondary data sources, *Chapter 5* presents an analysis of the case-study area of Queensland, Australia. This chapter provides context on both the physical supply system, its position within the National Electricity Market (NEM), and other relevant institutional and regulatory factors that could influence battery adoption. It also considers the factors that underpinned exponential growth in residential PV adoption in Queensland and analyses the state-specific structural drivers and emerging feedback loops that could underpin future battery adoption.

Chapter 6 describes the method, results and findings that were generated from development of a dynamic hypothesis. Key variables were mapped and the causal relationships between them defined to inform the creation of a causal loop model that described the dynamics that could influence the uptake of residential battery energy storage in the case-study area. Building on these results, *Chapter 7* describes the design, development and validation of a stock-and-flow simulation model for use in assessing residential PV and battery energy storage adoption dynamics. It includes general model assumptions and a detailed description of the model's stock and flow structure including key data inputs and equations. This chapter also includes the results of model testing and validation.

Chapter 8 describes the results of model simulations, including the outcomes of sensitivity analysis and scenario analysis, which are used to more clearly understand the important causal relationships and the possible leverage points within the system. It concludes with a discussion on policy implications stemming from the research findings. The last chapter, *Chapter 9*, summarises the key research outcomes, describes the limitations of the study and recommends areas for future research. It is followed by the appendices which includes supplementary material, relevant data sets generated throughout the study and a full version of the stock and flow model including assumptions and sources.

Chapter 2 Context and literature review

Chapter overview

This chapter provides context and a review of the issues associated with residential PV and battery adoption and integration. The chapter starts by characterising PV and battery energy storage technologies, defining commonly used terminology and describing market developments from a global and Australian perspective. This is followed by an assessment of the risks and opportunities of mass market adoption of residential PV and battery energy storage. The chapter finishes with a section outlining the challenges to optimal integration and the imperative to model and understand the system from a holistic perspective.

2.1 Solar photovoltaics

2.1.1 Technology overview

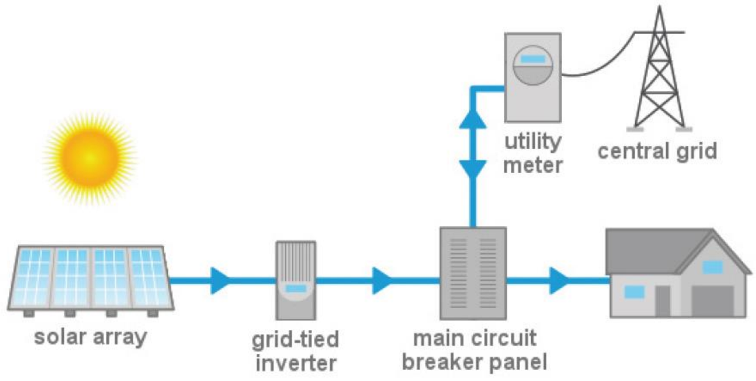
Solar PV has emerged in recent years as a cost-effective, low-emission technology that will change the way in which energy is provided to communities all over the world. PV is a versatile and elegant electricity generation technology which has no moving parts, makes no noise, does not generate waste during operation and is sealed so it can be used in almost any environment. PV is modular and can be scaled to meet load requirements ranging from a few watts to utility-scale generation comprising hundreds of megawatts.

From a broader socio-economic perspective, PV can improve energy security, increase energy sector resilience, improve access to energy, create new industry and jobs and secure energy provision in remote areas (Sener & Fthenakis 2014). It encourages consumers to become actively engaged in managing their energy and provides them with greater choice and control over their electricity bills (Eadie & Elliott 2013).

As a low emissions technology, PV also offers substantial mitigation potential. During operation, a PV array emits no greenhouse gas emissions and during its lifetime pays back the energy and emissions invested in its assembly multiple times (Louwen et al. 2016). Based on lifecycle assessment, average PV emissions equate to less than 50 grams of CO_2 equivalent per kilowatt hour ($gCO_2e\ kWh^{-1}$). For comparison, the global average for centralised electricity supply systems is 532 $gCO_2e\ kWh^{-1}$ (IEA 2013b; Nugent & Sovacool 2014).

PV is classed as a form of distributed generation, which means the power source is located close to the point of consumption (Ackermann, Andersson & Söder 2001). For residential systems, the power that a PV array can generate is measured in kilowatts (kW). Generation is measured as the amount of electricity produced over one hour and is measured in kilowatt hours (kWh). On residential premises, PV arrays range in size from less than 1 kW to around 10 kW, with roof size limiting larger installations.

Almost all PV systems in modern economies are ‘grid-tied’, which means that the dwelling remains connected to the electricity network (Luthander et al. 2015). Power generated by the solar array is first used by the home, with excess exported to the grid. When household demand exceeds power produced by the array, any additional electricity required is provided by the grid (Figure 2).



Source: (Mullendore & Milford 2015)

Figure 2 A typical grid-tied PV configuration

PV technology is based on a concept known as the photoelectric effect, which occurs when electrons are emitted from certain materials when exposed to sunlight (Mertens 2013). While the photoelectric effect was first observed nearly two hundred years ago, it was only in the 1950s that the modern PV cell was developed (Mertens 2013). These cells were made from silicon, a semiconductor material. When photons in the form of electromagnetic radiation from the sun dislodge electrons from their bonds, an electric current is created (IRENA 2013). Early PV cells had very low conversion efficiencies and were expensive, costing one thousand times more than modern PV cells (Mertens 2013). In the past few decades however, the technology has rapidly evolved.

There are now two main commercialised PV technology types in the market. Crystalline silicon (c-Si) dominate the market and comprise more than 90% of total installed PV (IRENA 2013; IEA 2016c). There are two main forms of c-Si technology: mono-crystalline modules which are made from a single cut of silicon and have higher efficiencies; and multi-crystalline modules which are slightly cheaper and made from multifaceted crystalline silicon. While efficiencies for c-SI modules have been proven up to 25% for mono-crystalline (and up to 20.4% for multi-crystalline), mass produced modules tend to achieve efficiencies of around 16% (IRENA 2013; IEA 2016c). These modules can operate for a long time, with most manufacturers guaranteeing that they will produce at least 80% of their rated output after 20 years. Some studies have shown that modules actually degrade even more slowly with efficiency losses of only 0.5% per year (Jordan & Kurtz 2013).

Thin-film PV technologies represent the other common PV category and comprise approximately 10% of total market share (IRENA 2013; IEA 2014f). Thin-film PV cells contain thin layers of PV materials such as amorphous silicon and cadmium-telluride on low-cost substrates such as glass, stainless steel or plastic (Kirkegaard et al. 2010). While they have lower average efficiency levels, typically between 7% and 16.8%, thin-film PV cells are cheaper to produce, lighter and more flexible than c-Si cells (IEA 2016c). Multi-junction PV cells are a derivative of thin film technology which use multiple thin layers of different materials to capture a greater spectrum of energy. Multi-junction technology is expensive but highly efficient and can exceed 40% efficiency (Nelson, Gambhir & Ekins-Daukes 2014).

In addition to the two main commercial technologies, there are numerous pre-commercial PV technologies being investigated in laboratories around the world. Perovskite solar cells are one such example. They are characterised by a specific crystalline structure based on organic and inorganic components and can be manufactured more cheaply than traditional silicon-based cells (Green, Ho-Baillie & Snaith 2014). They were first developed in 2009 achieving 3% efficiency. In only eight years, perovskite efficiencies have since increased to more than 22% (Stranks & Snaith 2016). Subject to addressing technical barriers relating to cell stability, perovskites are just one example of PV technology that when commercialised, could further revolutionise the field.

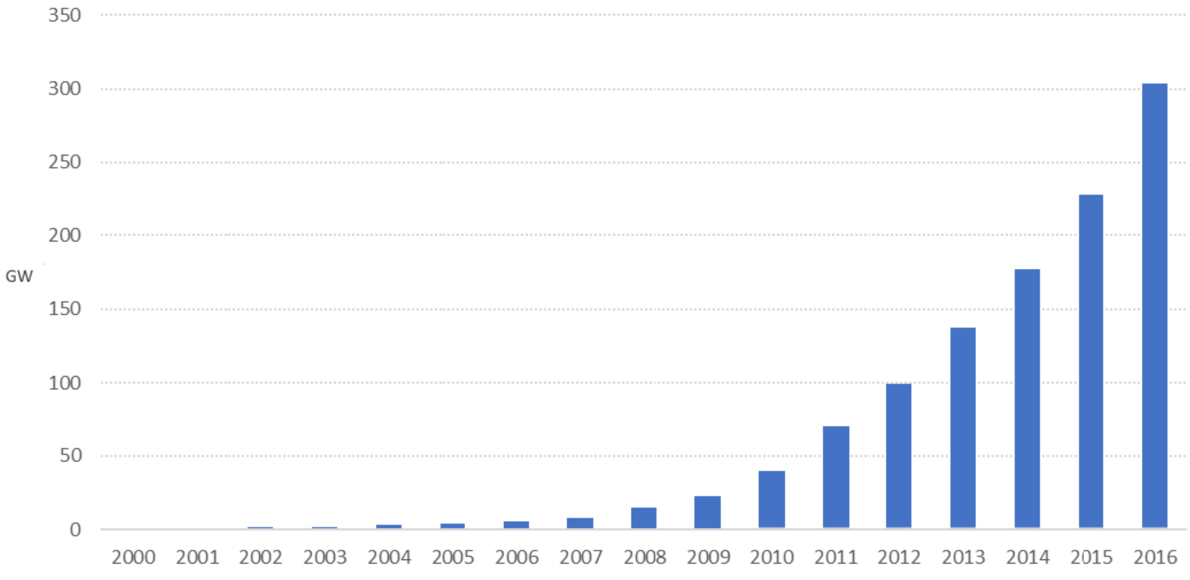
The technological potential of PV in this respect is highly relevant. As PV continues to evolve, it is expected to become cheaper, more efficient and more customisable. For example, advances in printable, organic thin-film PV, mean that PV could be more effectively integrated into buildings at a price that will make it more accessible to a broader cross-section of the community. At scale, these developments will serve to provide consumers with new options to generate more of their own power and ultimately reduce their reliance on existing electricity supply systems. While the research and modelling in this thesis is based on assumptions regarding the performance and cost-curves of currently *commercialised* PV technologies, it is important to remain cognisant that should step-changes occur in technology development, the magnitude of potential impacts could be amplified.

2.1.2 Global market developments

Until recently, the high cost of PV modules has been the primary impediment to sector growth. With PV costing nearly US$100/W in 1975, the technology remained largely unavailable to the public until price declines began to accelerate at the start of the new millennium (Louwen et al. 2016). This was driven by generous subsidies in countries such as Germany, where an uncapped feed-in tariff (FiT) saw expansion of the market, driving growth in manufacturing capacity and development of the broader PV supply chain (Haegel et al. 2017).

Over the following decade, more than 75 countries introduced some form of solar subsidy (Burtt & Dargusch 2015). This, along with economies of scale, lower production costs, cell efficiency improvements, standardisation of technologies and cheaper feedstocks saw PV prices fall below $US0.70/W (Louwen et al. 2016; Reinders, van Sark & Verlinden 2016). During this period, learning rates show the average price of PV dropped by 20% with every doubling of installed capacity[1] (de La Tour, Glachant & Ménière 2013; IEA 2013).

As a result, the global PV market increased exponentially from approximately 1.3 gigawatts (GW) in 2000 to nearly 303 GW by the end of 2016, making a 1.8% contribution to global electricity demand (Figure 3) (EPIA 2014; IEA 2017). At the same time, it is estimated that PV was responsible for avoided emissions of more than 140 million tonnes of CO_2 equivalent (IEA 2014f). Emissions reductions are expected to continue to rise as both a function of increasing capacity and efficiencies in the manufacturing process. For example, a recent study found that for every doubling of installed PV capacity, energy use and emissions costs associated with the PV production decrease by up to 13% and 24% respectively (Louwen et al. 2016).

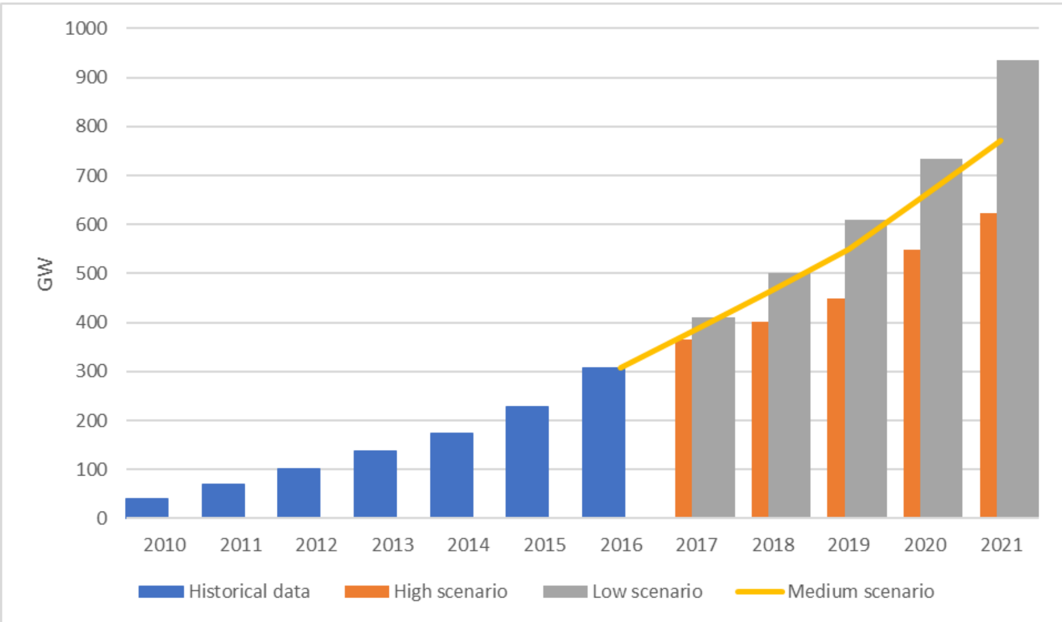


Source: (IEA 2017)

Figure 3 Global growth in PV installations from 2000 to 2016

[1] Learning rates are widely used to predict cost paths and relate production costs to the accumulation of learning, measured by cumulative production (de La Tour et al., 2013).

Despite recent rapid growth, there is no indication that PV saturation is close, as rates of deployment continue to exceed expectations. In 2016 alone, more than 75GW was installed globally, and projections from key industry bodies estimate continued high rates of installation (Figure 4)(IEA 2017; Schmela 2017). While it is unlikely that the cost of PV will see the dramatic falls of the past decade, analysts suggest that downward price trends will continue with PV becoming cost-competitive with traditional energy sources in coming years (National Renewable Energy Laboratory 2014). Should this occur, it is estimated that PV could generate up to 16% of the world's energy by 2050 (IEA 2014f).

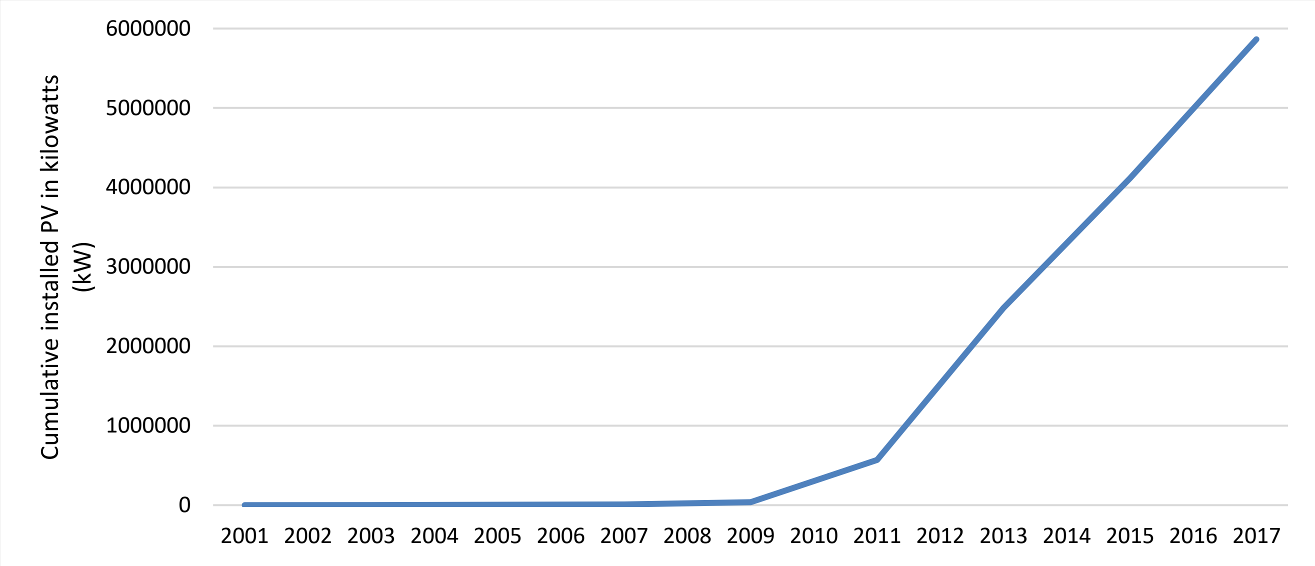


Source: (Schmela 2017)

Figure 4 Global PV uptake scenarios until 2021

2.1.3 PV in Australia

In Australia, PV capacity increased from 17 megawatts (MW) in 2008 to nearly 6GW in 2017 (Figure 5) (APVI 2017a; Australian Energy Council 2017). Currently, residential PV in Australia generates approximately 5,600 gigawatt hours (GWh) per annum, approximately 10% of total residential demand and 2.76% of electricity requirements in the NEM (AEMO 2016b; CEC 2017b).



Source: (APVI 2017a)

Figure 5 PV growth in Australia since 2001

Penetration rates of PV in Australia are some of the highest in the world with approximately 1.65 million installations on more than 15% of Australian dwellings (Finkel et al. 2016; Australian Energy Council 2017). Moreover, due to falling module prices, average PV arrays have increased in size from 1kW in 2009 to just over 5kW in 2017 (IEA2014c; APVI 2017a). Queensland leads the country in PV installations both in terms of total capacity (1.5GW), and the proportion of homes with PV (31% of dwellings) (APVI 2017b). This far exceeds equivalent per capita rates in other leading solar PV markets such as Germany, Italy, California and Hawaii (Finkel et al. 2016). The PV industry in Australia now directly employs more than 5,500 people (CEC 2017b).

Rapid PV adoption in Australia was driven by a confluence of factors. Firstly, Australia has some of the best solar resources in the world. With the highest average solar radiation per square metre of any continent, Australia's annual solar insolation is estimated at 10,000 times its annual energy consumption (Climate Commission 2013). Generous PV subsidies were also introduced in Australia which had two main effects:

- Reduction in upfront capital costs - The Small-scale Renewable Energy Scheme under the Renewable Energy Target (RET) let consumers claim small-scale technology certificates, which could be sold to reduce the purchase price of a PV system (Wood, Blowers & Chisholm 2015).
- Provision of ongoing financial incentives – Most states introduced solar FiTs which paid a premium for electricity generated from a PV system (Table 1). These schemes are classed as either "gross", where households are paid for all of the electricity generated by their PV system, or "net", where households are paid only for the electricity not used by their home and exported back to the network (Martin & Rice 2013).

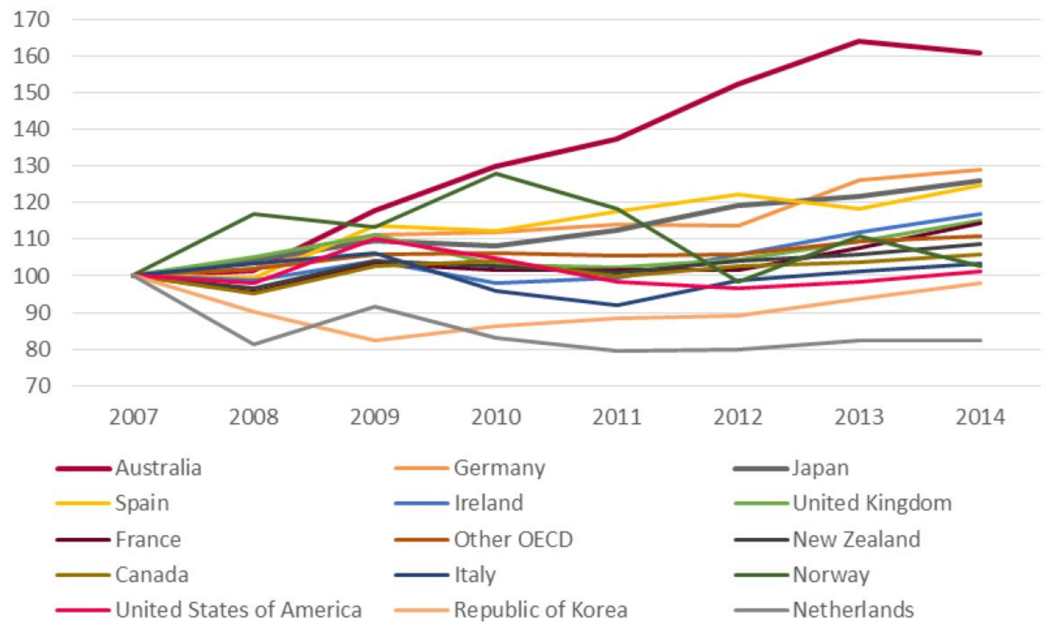
	2008	2009	2010	2011	2012
South Australia	44c	44c	44c	44c » 16c (Oct)	16c
Western Australia	No FiT	No FiT	40c	40c » 20c (Jul) » closed (Aug)	No FiT
Tasmania	1 for 1	1 for 1	1 for 1	1 for 1	1 for 1
Victoria	No FiT	60c	60c	60c	25c
New South Wales	No FiT	No FiT	60c gross » 20c net (Oct)	20c » closed (April)	No FiT
Australian Capital Territory	No FiT	50.5c	50.5c gross » 45.7c (July)	45.7c » closed (May)	No FiT
Queensland	44c	44c	44c	44c	44c » 8c (July)

Note: » represents a change in tariff, 1 for 1 means that the FiT is equal to the price of electricity

Source: Adapted from (Chapman, McLellan & Tezuka 2016)

Table 1 Australian State and Territory Feed-in Tariff Schemes

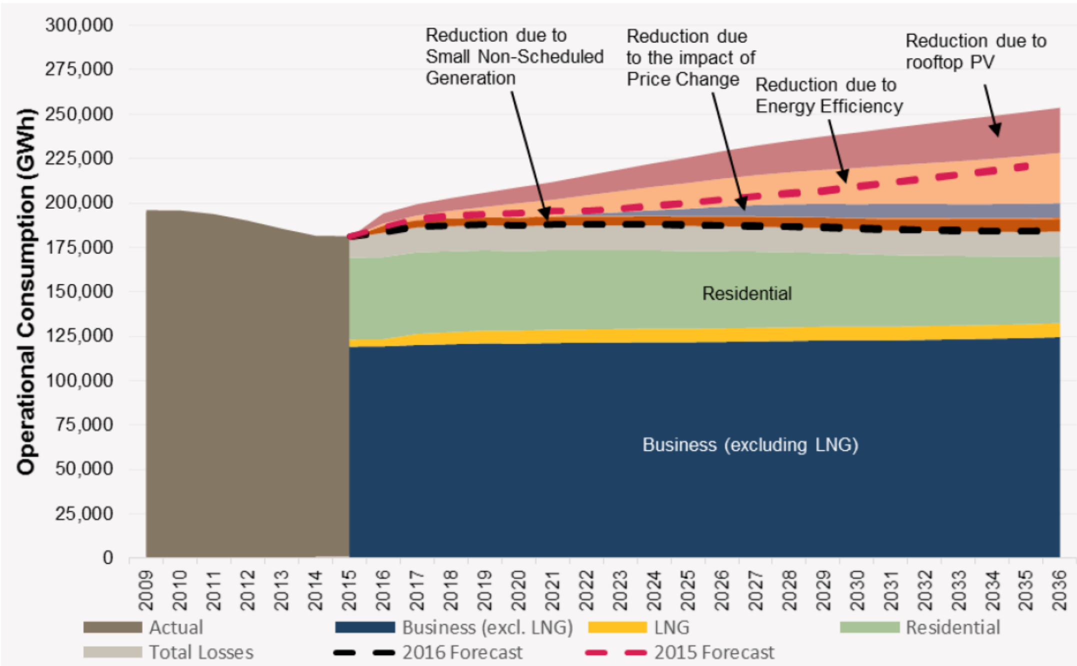
At the same time as subsidies were introduced, electricity prices in Australia increased dramatically (Figure 6) (QPC 2016a). They are now considered amongst the highest in the world (Mountain 2017). This development, along with falling PV system costs meant that PV became a viable proposition for mass market consumers. Exponential growth ensued. The resultant efficiencies of scale saw the cost of PV installations fall further, with Australia achieving some of the cheapest residential install prices in the world (Edis 2015b). Together these factors mean that in most cities in Australia, the cost of electricity from residential PV is almost half the price of grid-sourced power (Australian Energy Council 2017).



Source: (QPC 2016a)

Figure 6 International real electricity retail price indexes (2007 = 100)

With the fundamentals for PV adoption remaining strong, the Australian Energy Market Operator (AEMO) predicts that business and residential PV will increase by approximately 350% by 2036, representing 20GW of capacity and generating 25,000 GWh of electricity (AEMO 2016b). The forecast influence of PV on total Australia operational consumption is shown in Figure 7. This graph shows that in addition to the large demand reductions likely to occur as a result of rooftop PV adoption, energy efficiency and the impact of increasing electricity prices will also serve to reduce residential consumption (AEMO 2016b). This indicates that despite continuing population growth, residential electricity demand from the centralised system could remain flat or decrease over this period. These dynamics, which will be discussed in more detail in later chapters, have important implications for residential battery uptake.



Source: (AEMO 2016b)

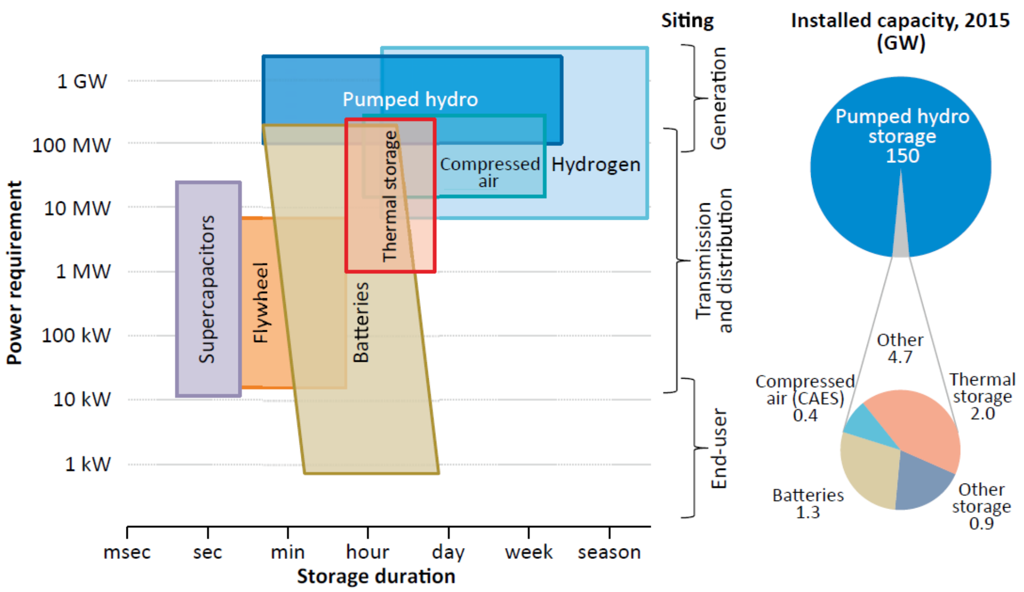
Figure 7 Forecast annual energy consumption for the National Electricity Market across key segments

2.2 Energy storage

2.2.1 Technology overview

Energy storage refers to a "chemical process or physical media that stores energy to perform useful work at a later time" (CSIRO 2015a, p. 9). For modern centralised electricity supply systems, the ability to store energy means that the supply of energy can be decoupled from demand (IEA 2014e). This not only allows for more effective integration of renewable energy sources (where intermittent generation does not always match demand) but can also help realise a range of network operational efficiencies including improved grid stability, flexibility, reliability and resilience (IEA 2014e).

There are several energy storage technologies that can be used in centralised electricity sector applications (Figure 8). However pumped storage hydropower, which involves using off-peak electricity to pump water into a reservoir for later use to generate hydro power, is by far the most common technology comprising 96% of total storage capacity (IEA 2016a).



Source: (IEA 2016d)

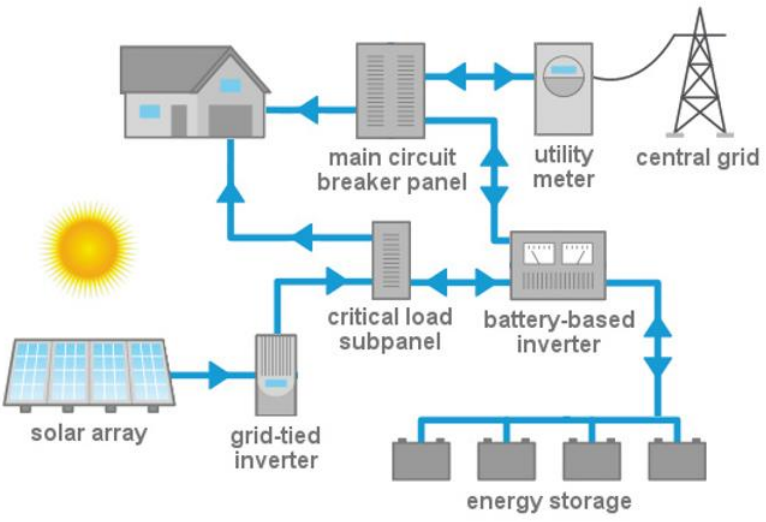
Figure 8 Energy storage technical characteristics and global capacity as at 2015

Despite the many benefits of energy storage and its importance as an enabler to optimise integration of renewables and to help decarbonise centralised electricity supply systems, its uptake has been limited. In 2016, energy storage comprised only 3%, or 150GW, of global electricity capacity (IEA 2016d). This reflects historic energy sector economics, where in the past it was more economically efficient to generate electricity in real-time using existing fossil fuel generators to instantaneously meet demand rather than install costly storage technologies (Marchment Hill 2012).

In recent years however, the interest in energy storage has increased dramatically in response to technology advances, falling costs and the growing imperative to address climate change. The greatest technology focus in this regard has been in relation to *battery* energy storage.

Batteries are a mature technology that have been studied extensively since they were invented by Alessandro Volta more than 200 years ago (IRENA 2015). Batteries are a form of electrochemical storage that release energy via an oxidation-reduction reaction involving the transfer of electrons between electrodes (Salameh 2014). The electrodes, a cathode and an anode, comprise two different materials, typically metals, which when separated in an electrolyte matrix gain or lose electrons. This reaction, when connected to load, creates current and voltage (i.e. power). In primary batteries, the chemical reaction only works in one direction, so that when any of the materials becomes exhausted the battery is flat. Secondary batteries are rechargeable which means that the electrochemical reaction can be reversed by the application of an external electricity supply (Stock, Stock & Sahajwalla 2015).

For residential applications with PV, secondary batteries are used. Typically, any excess electricity generated by the PV array that is not required to meet immediate household load is used to charge the battery. When the battery is full, excess electricity is then exported back to the grid. The consumer decides how and when electricity from the battery is used. Energy management systems now exist that can automatically manage electricity flows between the array, the battery, the household and the grid to optimise consumption and to maximise the financial benefit from the system. A common residential PV and battery configuration is shown in Figure 9.



Source: (Mullendore & Milford 2015)

Figure 9 Common AC grid-tied residential PV & battery configuration

To date, lead-acid batteries have been the most dominant electrochemical-based storage devices used in residential applications (Hoppmann 2013; Koohi-Kamali et al. 2013). Lead acid batteries, in which lead electrodes are sealed in a sulphuric acid electrolyte, are a mature technology and are well proven in small, renewable energy integration applications (Nair & Garimella 2010). While these batteries are well understood, they are primarily used in isolated, off-grid areas due to high costs. They also have some technical constraints which have limited broader uptake for use in residential applications. These include limited cycle-life, poor operation in high or low temperatures, failure from deep and continuous cycling and a negative environmental footprint due to the lead electrodes and acid electrolyte (Nair & Garimella 2010).

In recent years, lithium-ion batteries have entered the market at scale. These batteries are generally defined as one in which lithium ions act as the charge carriers. Most lithium-ion batteries use carbon materials such as graphite for the electrodes and contain organic electrolyte solutions (Horiba 2014). There exist many different lithium-ion cell chemistries e.g. Lithium Cobalt Oxide ($LiCoO_2$), Lithium Iron Phosphate ($LiFePO_4$), Lithium Nickel Manganese Cobalt Oxide ($LiNiMnCoO_2$ or NMC), each with different applications ranging from use in computing devices and appliances, to multi-MW scale installations (Horiba 2014)

Lithium-ion batteries can significantly outperform more mature technologies in regards to delivered energy with high specific power (Dunn, Kamath & Tarascon 2011). For example, lithium-ion batteries can achieve 95% of overall system efficiency compared with 86% for lead-acid batteries in off-grid applications (Pistoia 2014). Lithium-ion also has higher energy densities and longer life-cycle characteristics compared with many other battery technologies. These characteristics, when taken with the potential for improved economics and technology developments, mean lithium-ion batteries are rapidly replacing lead-acid as the dominant energy storage technology in residential applications (Nair & Garimella 2010; Hoppmann 2013; Pistoia 2014; Savvantidou et al. 2014).

A number of common terms are used in industry and academia to help describe the operational characteristics of batteries (CSIRO 2015a; IRENA 2015). These terms, which are described below, are used throughout this thesis and underpin elements of modelling. They include:

- *Battery capacity* and *power rating* – The battery capacity, or stored energy, in a battery is commonly measured in terms of the electricity it can produce in a certain time period represented as kWh or megawatt hours (MWh). The maximum power that a battery can produce at any given time is measured in kW or MW. To illustrate the application of these units, a 10kWh battery could provide 1kW of power constantly for 10 hours, or it could provide 10kW of power for one hour. Battery capacity can also be measured in ampere hours (Ah), which is the number of hours that any given current can be supplied.

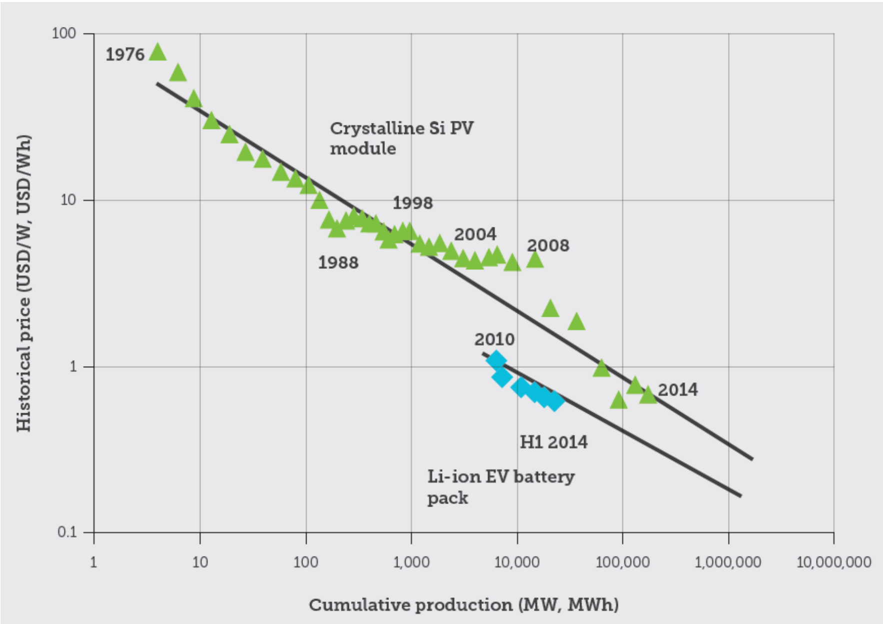
- *Depth of discharge* (DOD) refers to the amount of charge a battery holds and is expressed as a percentage of the battery's total available capacity. For example, if a battery has used 60% of its capacity with 40% remaining, then its DOD is 60%. Should it be fully discharged, the DOD is 100%. Depending on the chemistry, the deeper a battery is discharged the more likely it will degrade faster reducing its operational life. Most battery manufacturers recommend that the DOD does not exceed 80% although some chemistries, particularly flow batteries can be discharged more deeply without consequence.
- *Cycle life* refers to the amount of times a battery can charge and discharge at certain defined operating parameters, such as DOD and ambient temperature, before a material performance loss is experienced. This loss could be defined as a fully charged battery only delivering 70% of its original capacity.
- *Battery lifetime* can either be based on the total number of cycles that can be delivered by a battery or the length of the warranty, which assumes that the battery is used according to operational specifications for a certain period of time.
- *Round trip efficiency* refers to the amount of energy discharged by the battery, relative to the amount of energy provided. Usually there are efficiency losses associated with the charge/discharge process (CSIRO 2015a; IRENA 2015).

Failure to operate batteries within defined system parameters can have substantial implications for cost, performance and life. For example, the depth to which a battery is discharged, how frequently it is discharged and the temperature in which it is operated can all dramatically shorten a battery's life. The above terms also provide a common nomenclature by which the strengths and weaknesses of different battery types can be compared. This is important because there are many types of battery technologies and their use can vary depending on chemistry (e.g. lead-acid versus lithium-ion), design (e.g. redox flow batteries where the electrolyte solution is pumped through a membrane to generate current), application (e.g. starting a car versus supporting grid stability) and specific battery efficiencies and lifecycle characteristics.

2.2.2 Global market developments

Until recently, the application and deployment of residential battery energy storage systems has been relatively limited, with technology cost the most fundamental issue slowing broad market penetration (DOE 2013). For this reason, battery energy storage has only been cost competitive in high value niche markets where purchasers were driven by non-financial motivations and were generally not expecting to see a financial return on the initial investment (Yang et al. 2011; Marchment Hill 2012). In addition to cost, other factors that have hampered uptake include issues associated with reliability, safety, regulatory barriers and limited industry acceptance (Yang et al. 2011; Heymans et al. 2014; Savvantidou et al. 2014).

In the past ten years however, the fundamentals for battery energy storage have changed dramatically. Substantial technological advances were initially made in the mobile phone and computing sectors, and were later followed by similarly important breakthroughs in the electric vehicle industry (AECOM 2015). Since 2008 for example, the energy density of electric vehicle batteries, increased by a factor of four while battery costs fell on average by 14% per year from $USD1000/kWh to $USD410/kWh in 2014 (Nykvist & Nilsson 2015). Between the second-half of 2014 and the second-half of 2015, lithium-ion battery costs fell a further 35% (REN21 2016). Battery costs are now estimated at approximately $US210/kWh, reflecting learning rates of 22%, similar to PV learning rates from more than a decade earlier (Figure 10) (Stock, Stock & Sahajwalla 2015; IEA 2016d).



Source: (Stock, Stock & Sahajwalla 2015)

Figure 10. Learning curves for lithium-ion batteries compared with PV until 2014

In addition to already impressive cost reductions, a number of drivers are coalescing which indicate that battery prices will continue to decline. In the past few years, the private sector has invested billions of dollars in new battery manufacturing capacity which is now starting to come online. Several large battery factories have been constructed in Europe, China and the United States providing a range of battery components for major battery companies including Enphase, SolarEdge, Tesla, NEC and Panasonic (REN21 2016). Tesla's $5 billion battery factory in the United States received particular attention when its construction started in 2014 (Tesla 2014). It is estimated that when the Tesla factory reaches full capacity in 2018, it will produce 35GWh of batteries per year (i.e. more than all lithium-ion batteries produced globally in 2013) while driving down costs by 30% (Tesla 2017).

At the same time, governments are developing subsidy programs to reduce upfront battery capital costs while implementing policy to improve battery integration. For example, US states such as California, Hawaii, New York and Texas have introduced incentive programs for residential battery energy storage (AECOM 2015). Japan's battery subsidy program, with a budget of nearly $US100 million, covers more than half of the price for residential consumers installing lithium-ion batteries (AECOM 2015).

Most notable however was the German government's rebate program which ran from 2013 to 2015 offering up to a 30% reduction in upfront costs of residential battery storage systems to counter the impact of decreasing PV feed-in tariffs (Kelly-Detwiler 2013). This program was relaunched in March 2016 offering a smaller rebate covering up to 22% of costs to reflect the falling price of battery storage (Blackman 2016). The Germany subsidy program has seen more than 50,000 residential solar battery systems installed to date, with estimates suggesting 100,000 systems could be installed by 2018 (Grigoleit, Rothacher & Hildebrandt 2014; Enkhardt 2017). Importantly, it was Germany's decision to implement a solar FiT at the start of the millennium that helped contribute to the global PV boom by increasing manufacturing scale and driving technology innovation (Kelly-Detwiler 2013). It remains to be seen whether German policy initiatives in this regard will enable a similar outcome to occur for battery energy storage.

As a result of the above developments, several forecasts have been made predicting large future price reductions, with some analysists suggesting that battery prices could halve by 2020 (Byrd et al. 2014; Electric Power Research Institute 2014; Koh et al. 2014; AECOM 2015; IRENA 2015). Initially, these bullish forecasts were considered with scepticism by many in the broader electricity industry. However, in early 2015, Tesla announced pricing for new home battery energy storage solutions that were more than seven years ahead of most projections and substantially undercut all previous price expectations (RMI 2015b). In 2016, just over a year later, Tesla upgraded its residential battery offering by doubling the usable capacity and including an integrated inverter while maintaining the original pricing. This represents an effective halving of costs in terms of price per kilowatt hour (Tesla 2016). While the extent of future battery price declines remain uncertain, some estimates suggest that costs could fall to US$100 per kWh by 2040, with the US Department of Energy indicating that they could fall to as low as US$80 kWh (IEA 2016d).

2.2.3 Battery energy storage in Australia

Until recently, residential battery storage in Australia was almost entirely limited to off-grid applications. In 2014, it is estimated that there were close to 5MWh of off-grid battery systems and only 500 grid connected systems in Australia (CEC 2015a). However, a number of factors are emerging that have stimulated the local market and make uptake at scale more likely in coming years.

As previously stated, Australia leads almost all other jurisdictions in terms of proportion of dwellings with PV. With high electricity prices, the cost of electricity generated from PV in many locations in Australia is cheaper than that supplied by the grid, providing a clear financial motivation to maximise PV self-consumption in home (Australian Energy Council 2017). In addition, premium FiT rates which helped stimulate the PV boom have ended or are being phased out, resulting in households receiving a fraction of the value for their exported electricity. In most states this is less than a quarter of the retail tariff (QPC 2016b). Dwellings with PV, and those households considering installing PV will now more than ever be determined to increase self-consumption from their PV systems. At the same time, a range of strengthening non-financial motivations in Australia are likely to encourage battery uptake including environmental values, desire for self-sufficiency, pursuit of reliability and resilience and frustration with incumbent utilities (Agnew & Dargusch 2017).

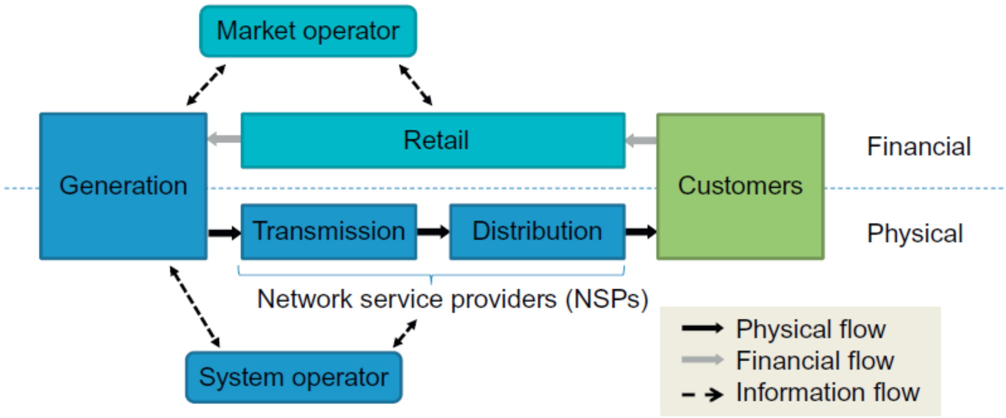
These drivers coupled with falling battery prices have seen rapid battery market development. In 2016, it was estimated that 6750 battery systems representing 52MWh were installed in Australia with nearly one-third of these batteries located in Queensland (Vorrath 2017b). There are currently more than 33 different battery systems with multiple configurations currently available across the country (SolarQuotes 2017). The levelised cost of storage for these systems (i.e. the cost over the systems warranted lifetime to store each kWh of electricity), range from $0.19/kWh to $1.43/kWh (SolarQuotes 2017). The lower end of this range reflects storage costs that have dropped below the retail cost of electricity, which if battery price reductions continue, will make battery energy storage a viable financial proposition for many households in coming years. Indeed, some of the world's largest battery manufacturers such as Tesla and Enphase identify Australia: "as the most prospective market in the world, thanks to its high grid prices, its abundance of rooftop solar, excellent solar resources and the nature of tariffs across the nation" (Edis 2015a, p. 1).

2.3 What are the implications of residential PV and battery adoption at scale?

Numerous industry-led studies in recent years predict that the rise of the engaged electricity consumer along with access to new disruptive technologies such as PV and battery energy storage will cause significant disruption to centralised electricity systems (Kind 2013; Newbury 2013; PWC 2013; Koh et al. 2014; Leitch, Moller & Entchev 2014; PWC 2014; Rickerson et al. 2014; RMI 2014a; Savvantidou et al. 2014). This is because access to distributed generation technology with battery storage means that electricity consumers will no longer be captive to the electricity utilities and will be able to change the way in which they interact with the existing electricity supply system (Severance 2011). This could impact "existing natural monopolies and render incumbent business models unsustainable" (Newbury 2013: p1).

To understand the nature and extent of this disruption, it is first necessary to understand the structure and operation of existing electricity supply systems. In most modern economies, electricity is provided via centralised supply systems in which large generators, typically thermal-based hydro-carbon, hydroelectric and/or nuclear power, supply customers through integrated electricity transmission and distribution networks (McDonald 2008). The transmission network transports electricity over long distances at high voltage for efficient transport. The voltage is then stepped-down by transformers as electricity enters the distribution network. It is then transported to end-use consumers where it is typically on-sold by electricity retailers (AEMO 2010).

Whenever electricity is consumed on the network, for example when a light is turned on, power flows instantaneously from generator to end user. A system and/or market operator typically manages the supply/balance arrangements in an electricity market to ensure security and reliability of supply, while reconciling financial transactions between participants. The generalised functional elements of a centralised supply system are represented in Figure 11 (Riesz et al. 2014).



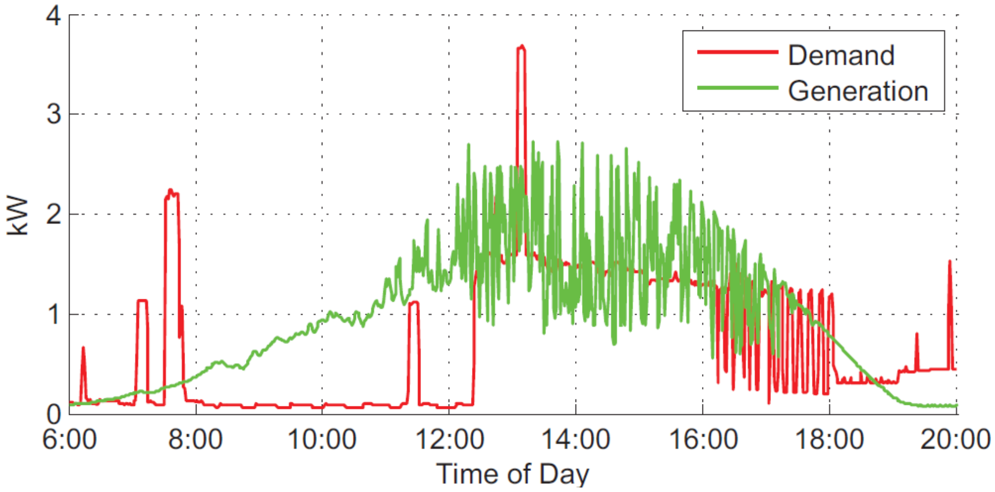
Source: (Riesz et al. 2014)

Figure 11 Generalised functional areas of an electricity supply system

The centralised electricity supply model as described above is well-established and has helped underpin rapid industrialisation during the past century. Its architecture evolved in response to specific developments such as: new generation technologies (e.g. large steam turbines which improved economies of scale by increasing electricity output and reducing marginal cost); the ability to transport electricity over greater distances more efficiently; the ability to increase reliability (as multiple generators connected by transmission networks provide higher reliability than any single power plant); and a desire to locate highly polluting generators away from population centres (DOE 2007).

The relevance and importance of these drivers however is now changing as new technologies emerge, climate change policy evolves, electricity prices increase and consumers become more engaged in the way they access electricity. Together these emerging issues have already begun to influence the social, economic and operational paradigm on which centralised electricity supply system are built. Amongst many other issues for the traditional supply model, these factors introduce new levels of temporal and spatial complexity, which in the past were of little relevance to operators of centralised supply systems (Pfenninger, Hawkes & Keirstead 2014).

In this respect, the rise of residential PV epitomises the speed and the scale of change that can occur in response to emerging drivers and serves as a relevant example to examine the possible impacts of new energy technologies on existing supply systems. The intermittency of PV power for example has given rise to numerous technical integration challenges. PV systems can only generate electricity when they are exposed to sunlight. This means PV power output is limited to diurnal cycles with frequent volatility, from seconds to hours, making it difficult to match load with generation (Pasta et al. 2014). The challenge of matching intermittent supply from PV with varying household demand is illustrated in Figure 12.

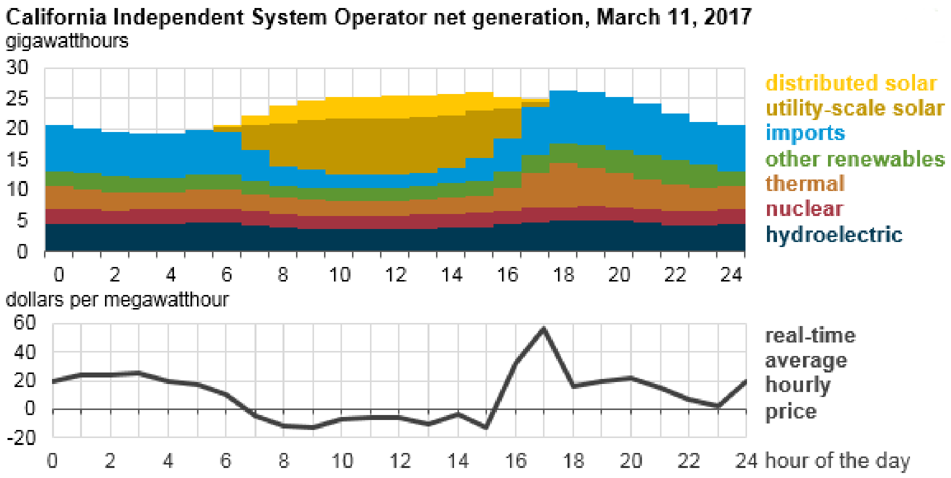


Source: (Muenzel et al. 2015)

Figure 12 Coincidence of intermittent PV generation with demand in an Australian household

To address this issue from a consumer perspective, the majority of residential PV deployed in the past decade has been connected to the existing centralised electricity grid to provide reliability and security of supply (Eltawil & Zhao 2010; Obi & Bass 2016). However, existing electricity networks were generally designed for one-way power flows from the generator to the consumer. Intermittent generation being fed back into the grid from PV systems has caused a range of technical issues such as voltage fluctuations, harmonic distortion and reactive power being sent back to the grid, which has led to power quality degradation (Worthmann et al. 2014; Obi & Bass 2016). It has also increased uncertainty associated with demand forecasting, with some studies showing that concentrations of residential PV can see localised, short-term demand fluctuations of up to 60% due to passing clouds alone (ENA 2014).

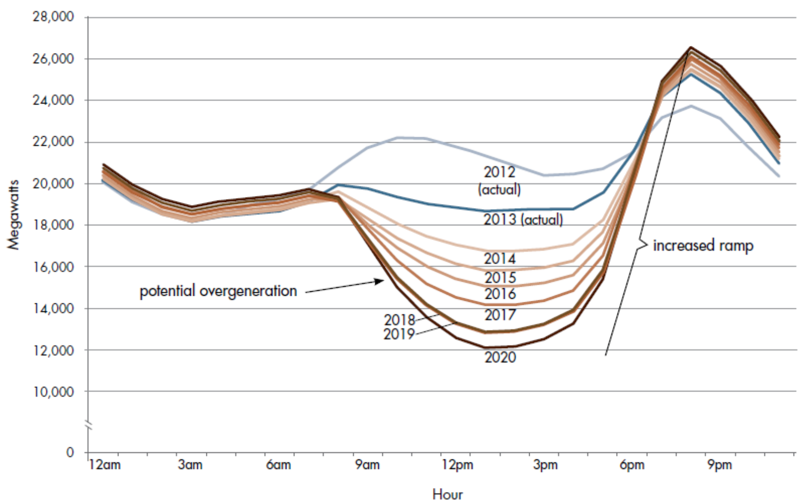
In addition to technical integration issues, PV also influences conventional generation supply dynamics. For example, PV generation hollows out daytime demand reducing the need for conventional generation from the grid. This serves to reduce wholesale electricity costs, and in cases of large volumes of PV generation, has actually resulted in negative wholesale costs (Parkinson 2014; Namovicz 2017). This effect is shown in Figure 13, which illustrates the influence of distributed PV on wholesale prices in California. The top chart shows total generation and the bottom shows wholesale prices during the same period. These effects become a problem if the profitability and competitiveness of generators diminish, resulting in reduced investment in the sector which could impact reliability and security of supply in the longer-term.



Source: (Namovicz 2017)

Figure 13 The influence of PV generation on wholesale prices

The above dynamic also exacerbates existing operational issues associated with worsening peak demand currently being experienced in many countries. Household electricity demand tends to increase in the evening, at the same time as PV generation decreases, requiring electricity utilities to rapidly ramp up their output. Using the Californian example again, this phenomenon is illustrated by the 'duck curve' (Figure 14). It shows that by 2020, 12GW of conventional generation will need to come online and ramp up in less than 3 hours to address peak demand (CAISO 2013). Most baseload generators, such as coal-fired plants, are not designed to operate in this way as they take hours to reach full generation capacity. While peaking plants such as gas generators are used to address this issue they are costly, poorly utilised and can represent substantial additional investment (Obi & Bass 2016).



Source:(CAISO 2013)

Figure 14 Net load in California showing impact of over-generation from renewables such as PV and wind

While PV growth has resulted in a range of technical issues, an additional challenge that has received considerable attention in the literature relates to the so called "death spiral" (Graffy & Kihm 2014; Rickerson et al. 2014; Khalilpour & Vassallo 2015; Simshauser 2016). This refers to the impact of falling demand from the residential sector on traditional utility revenue recovery mechanisms. Electricity prices are typically based on volumetric throughput, however much of the electricity supply sector infrastructure is based on sunk costs. In many modern economies, the network is a regulated monopoly entity where costs are recovered regardless of asset utilisation. This means as electricity volumes decline, electricity prices increase, further increasing the incentive for consumers to reduce their reliance on the grid. These dynamics can result in cost-shifting and a range of negative social equity outcomes (Rickerson et al. 2014; Simshauser 2016).

Many of the issues outlined above have seen significant attention from researchers attempting to develop solutions (Eltawil & Zhao 2010; Eftekharnejad et al. 2013). While technical or policy measures have been developed to respond to some of these challenges, they can entail substantial economic or social costs (ENA 2014). As industry and governments continue to grapple with cost-effective and equitable responses, viable cost-effective battery energy storage systems have begun to enter the market. This development could exacerbate many of the issues associated with PV, particularly if consumers continue to change their electricity consumption behaviour and/or reduce their reliance on the existing electricity network.

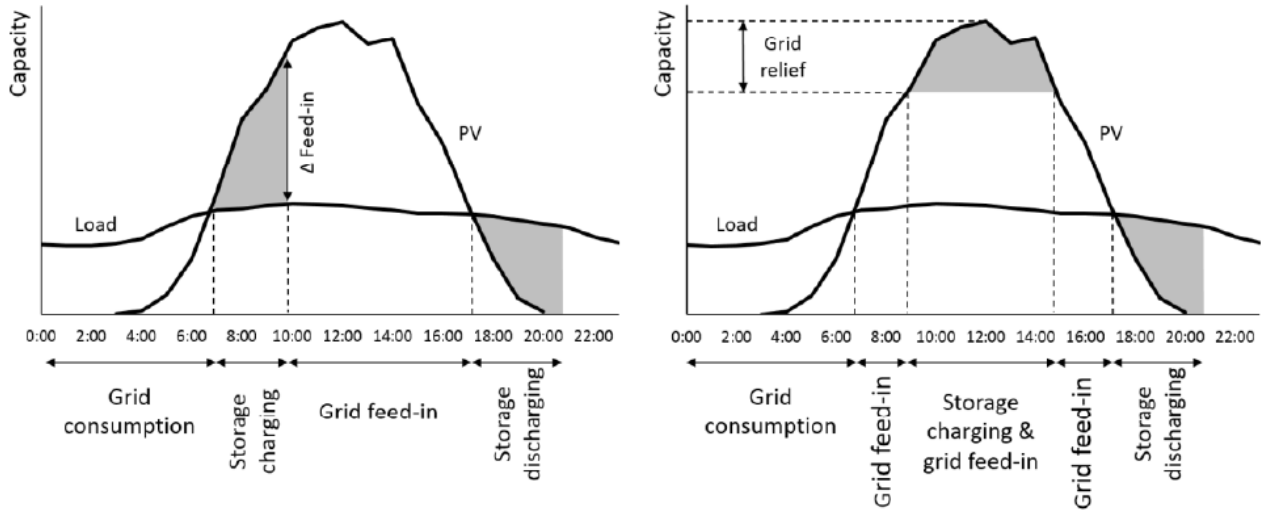
To fully understand the possible implications stemming from residential PV and battery uptake, it is necessary to consider the ways in which these systems are most likely to be deployed. In this respect, there are three basic PV and battery size and functionality configurations that consumers could choose. They could:

- Stay connected to the grid but use their PV to charge small batteries to optimally manage their electricity use so as to lower total electricity bills during peak times.
- Stay connected to the grid but install larger batteries so that they can use most of the power that their PV systems generate in-home. They would only use the grid for emergency backup in case of extended periods of low solar insolation or in case their home energy system fails.
- Disconnect entirely from the grid and meet all their needs from their home PV and battery energy storage system.

A key commonality across all three of these PV and battery configurations, is that grid electricity consumption will be reduced compared with either a PV-only dwelling or a non-prosumer dwelling. Depending on the size of the PV and battery, this reduction could be substantial and could significantly exacerbate the "death spiral" as described above. It also increases the differential in the cross-subsidy that occurs in this scenario i.e. when utilities increase rates, non-prosumers have greater exposure to those increases, meaning they take on a greater share of costs relative to the proportional costs they impose on the system (Picciariello et al. 2015).

To illustrate this magnitude of this issue, current pricing mechanisms in Australia reward reduced consumption regardless of when the reduction occurs, which means prosumer dwellings do not meet the full cost of their network use (AER 2015c). For example, a household installing PV can save approximately $200 in network costs as a result of reduced consumption. However as this reduction is based on PV generated during daylight hours, and not peak times, it actually reflects a real reduction in network costs of only $80, meaning that consumers without PV must meet the $120 difference by paying higher network charges (AER 2015c). Given that PV and battery uptake initially at least will most likely be adopted by wealthier demographics, this could see a potentially regressive effect, whereby lower socio-economic households are locked into a cycle of ever-increasing electricity bills as they become financially responsible for maintaining an under used, capital-intensive electricity network (CSIRO 2013a; Schill, Zerrahn & Kunz 2017).

Batteries poorly integrated into the network could also result in additional technical issues. To demonstrate, a stylised example of two possible charging/discharging regimes is shown in Figure 15. The graph on the left does not have system-oriented charging, which means as soon as the battery is full, it would impose a steeper gradient of PV feed-in back to the grid which could require costly, short-term system flexibility measures to be installed on the network (Schill, Zerrahn & Kunz 2017). At the same time, the battery's ability to soak up and reduce PV intermittency during the day, or to minimise system exports during periods of already low grid demand, are constrained.



Source: (Schill, Zerrahn & Kunz 2017)

Figure 15 Dwelling load, generation and storage profile under non-system oriented charging (left) and system-orientated charging (right)

Notwithstanding the seriousness of the above risks and challenges, it is important to recognise that battery energy storage configured to support the network could realise substantial system-wide benefits. For example, a key functionality of battery energy storage is its ability to store energy in periods of low demand for use during peak demand helping to flatten load profiles (as illustrated in the graph on the right in Figure 15 above). This could offset the additional generation required to service peak load which could lower capital infrastructure investments. Furthermore, as peak load is usually met with expensive fast-start generators such as gas, and as generators are typically dispatched in order from least to most expensive, it could help to reduce wholesale electricity costs (Silva-Monroy & Watson 2014).

Flatter load profiles could also reduce congestion on transmission and distribution networks which would avoid or defer the need for costly system augmentation (Hanser et al. 2017). In terms of future planning, network operators could incentivise batteries in constrained areas as a cost-effective alternative to traditional network infrastructure upgrades (Noone 2013). Furthermore, battery energy storage can reduce power quality issues associated with intermittent PV generation being fed back in the grid and can be used to manage voltage fluctuations and to stabilise local power flows (Hanser et al. 2017). From a system-wide perspective, PV with batteries increase generation diversity and as highly dispersed systems can improve overall reliability and security of supply (Bell, Creyts & Lacy 2014).

In recognition of the potential risks and opportunities associated with PV and battery energy storage technologies, a large body of research already exists in the literature that examines some of these issues. One of the most dominate areas of research relates to technical system optimisation. The volume and depth of these studies reflect the fact that early applications of PV and batteries (primarily lead acid) can be traced back nearly five decades, when even then they were the subject of significant research interest and technical characterisation (Khalilpour & Vassallo 2015).

Initially this research reflected the potential at the time for PV and battery use in off-grid and remote areas (Gordon 1987). In recent years, studies have begun to examine the possibilities for grid-connected applications and interactions with the network (Hiremath, Shikha & Ravindranath 2007; Manfren, Caputo & Costa 2011). Such studies have become highly sophisticated and have been used to: estimate optimal sizing characteristics and design criteria (Schmiegel & Kleine 2014; Weniger, Tjaden & Quaschning 2014); determine appropriate battery chemistries for use in various applications (Hammond & Hazeldine 2015); maximise beneficial battery characteristics such as optimal charge/discharge efficiency, energy density and cycle life (Pedram et al. 2010); and determine optimal operational scheduling for use in grid-connection applications (Lu & Shahidehpour 2005; Ratnam, Weller & Kellett 2015a).

In the past decade, the number of techno-economic studies has also increased, examining issues associated with battery system costs, the influence of subsidies such as feed-in tariffs, and the impact of adoption on electricity prices (Ru, Kleissl & Martinez 2013; Bruch & Müller 2014; Hoppmann et al. 2014; Mundada, Shah & Pearce 2016). Many techno-economic studies also look to quantify the benefit from PV and storage based on maximising self-consumption as the primary value proposition or by leveraging incentives deriving from other network benefits (Mulder et al. 2013; Luthander et al. 2015; Fares & Webber 2017; Schill, Zerrahn & Kunz 2017). Furthermore, several studies consider ways to use batteries to minimise residential electricity costs through time shifting while attempting to achieve broader network objectives (Hubert & Grijalva 2012; Nottrott, Kleissl & Washom 2013; Ru, Kleissl & Martinez 2013). The use of different electricity tariff pricing mechanisms such as time-of-use, critical peak pricing and real time pricing have also been modelled to determine their influence on the economic benefits of residential PV and battery energy storage (Lupangu & Bansal 2017).

The studies described above are almost all based on bottom-up optimisation or simulation models with resolutions of one hour or less spanning relatively short time periods (i.e. months to years as opposed to decades). They are data-rich and aim to estimate the best technical or financial configurations for a specific dwelling, the optimal mix of distributed technologies in a specific spatial area, or the best combinations in terms of broader economic or environmental outcomes (Manfren, Caputo & Costa 2011). As primarily linear-based models, they incorporate very little endogenous feedback. In addition, they do not address the diffusion characteristics in the energy system nor the transitional effects on broader system elements (Kubli & Ulli-Beer 2016).

In contrast, several long-term planning studies based on hybrid modelling approaches have also been undertaken to better understand the implications of PV and battery integration from a broader perspective. These include studies that consider the economics of load and grid defection both from the individual and electricity sector perspective (RMI 2014a, 2015a), forecasts of PV and battery uptake to determine demand impacts over the medium to longer term for use in operational electricity sector planning (AEMO 2016b) and national energy policy planning studies (CSIRO 2013a, 2017). In addition, the United States National Renewable Energy Laboratory is planning on including behind-the-meter storage in its Distributed Generation Market Demand model which simulates the potential adoption of distributed energy resources in the United States through 2050 (Sigrin et al. 2016).

Despite the substantial body of work described above, the assumptions underpinning the technology diffusion dynamics for residential PV and battery energy storage in the existing literature are almost entirely predicated on techno-economic factors. This means these models may not accurately account for the many factors that comprise the consumer decision making process, particularly non-financial motivations, nor do they incorporate the differing feedback mechanisms that can reinforce consumer preferences in this regard. Currently diffusion characteristics for residential PV and battery adoption are addressed in the literature primarily in a qualitative way or through industry surveys. Simulation models dealing with "diffusion and transition aspects of the energy system are very rare" (Basu et al. 2011; Kubli & Ulli-Beer 2016, p. 73).

While this is true of residential battery adoption dynamics, it is worth noting that residential PV *without* batteries has received far more attention in the literature. This reflects the significant PV growth seen over the past decade and the maturity of the PV market. The literature that considers PV adoption dynamics is more diverse and includes analysis of specific drivers of PV diffusion such as consumer behaviour and preferences (Bollinger & Gillingham 2012; Sigrin, Pless & Drury 2015; Dharshing 2017; Reeves, Varun & Robert 2017), more holistic modelling approaches such as agent-based modelling (Robinson et al. 2013; Sigrin et al. 2016) and diffusion models based on stated preference data (Islam 2014). The methods used in these studies were considered as part of the broader methodological development for this thesis.

To address the gap for residential PV *and* battery energy storage in this regard, Kubli and Ulli-Beer (2016, p. 73) identify the need for "innovative simulation models addressing the diffusion aspects for distributed generation systems, taking into account the complex interlinkages between technology, actors, the economy and institutions". In recognition of this requirement, a systems thinking framework has been identified as the most suitable methodology to address the research objectives of this thesis.

Chapter 3 Synthesis and significance

Overview of chapter

This chapter represents a synthesis of the project's research objectives and summarises emerging issues including possible implications associated with broad uptake of residential PV with battery storage. The paper also outlines a systems framework that conceptualises at a high-level the methodological approach that is being applied as part of this research project.

Citation

Agnew S, Dargusch P. Effect of residential solar and storage on centralized electricity supply systems. *Nature Climate Change* 2015, **5**(4)**:** 315-318.

3.1 Introduction

A key focus of global climate change mitigation activities has been attempts to decarbonise centralised electricity systems. Although there have been some successes, a majority of mitigation scenarios indicate that the electricity sector must decarbonise more quickly, and more completely, over the next 50 years to avoid the worst impacts of climate change (IPCC 2014).

With the electricity sector contributing nearly 40% of global energy-related greenhouse gas emissions, this represents a significant challenge (IEA 2014a). Modern centralised electricity systems, where electricity from large generators is transported to end-users along extensive transmission and distribution networks, are built on billions of dollars of investment, comprising infrastructure with very long asset-lives, supported by complex regulation. For existing electricity markets around the world, effective solutions to transition to a low-carbon economy in an economically efficient and socially equitable manner remain elusive.

Clean-energy advocates are quick to point to the steep increase in renewables as a panacea for future low-emission growth of the electricity system. Despite impressive double-digit annual growth over the past decade, renewable energy is growing from a low base and must be considered within the broader context of the electricity supply system where fossil fuels over the past 10 years have accounted for more than 75% of new electricity generation (IEA 2014a).

With electricity expected to increase its share as part of the total energy mix, a smoother, more efficient low-emission deployment pathway for the sector must be developed (IEA 2014a; IPCC 2014). In this respect, one of the great emerging challenges for policy-makers and utility owners relates to the recent boom in residential solar photovoltaic (PV) power and the emergence of viable and potentially cost-effective electricity storage.

3.2 The rise and rise of solar photovoltaic power

Following PV module price drops of more than 80% in the past 5 years, global PV deployment has increased from a base of 3.7GW in 2004 to more than 150GW in early 2014, contributing nearly 1% of total global electricity demand (EPIA 2014; IEA 2014a; IEA 2014d; IEA 2014f). In markets in Italy and Germany, PV is meeting 7.5% and 6.5% of demand respectively (EPIA 2014). Recent analysis by the International Energy Agency indicates that PV could generate up to 16% of the world’s energy by 2050 (IEA 2014f).

PVs, with average lifecycle greenhouse gas emissions of 49.9 $gCO_2e\ kWh^{-1}$, compared with a global average for the electricity sector of approximately 532 $gCO_2e\ kWh^{-1}$, is now making material contributions to emissions reductions in some countries (IEA 2013b; Nugent & Sovacool 2014). At the end of 2013, installed PV systems were avoiding approximately 140 million tonnes of CO2 per year (IEA 2014f).

For the residential sector, where a substantial proportion of global PV capacity has been deployed so far, this is highly relevant. On average, 30% of total electricity demand is consumed by the residential sector in Organisation for Economic Co-operation and Development (OECD) countries (IEA 2014b). Although some homes are not suitable for PV for reasons of size or shading, and generation can vary depending on location and siting, it is nonetheless clear that residential PV represents an important emissions mitigation target for policy-makers.

Despite recent growth, there is no indication that PV saturation is close, as rates of deployment continue to exceed expectations with at least 36.9 GW of PV capacity installed in 2013 (IEA 2014d). At the same time, PV system prices continue to fall, with US price reductions in 2013 exceeding 12% (Feldman et al. 2014). These reductions are occurring at the same time as the costs to build new conventional generators increase substantially.

There is also the possibility that PV technology will continue to get cheaper. The average price of PVs has dropped by 20% with every doubling of installed capacity over the past two decades (de La Tour, Glachant & Ménière 2013; IRENA 2013). With analysts in the United States predicting the downward trend for PV pricing to continue, albeit at a slower rate, it is likely that the US Department of Energy will reach its target to drive down the cost of solar electricity to US$0.06 kWh to make solar "fully cost-competitive with traditional energy sources before the end of the decade" (NREL 2014, p. 1).

On the surface, these developments are positive. As an electricity generation technology, PVs have no moving parts, makes no noise, do not generate waste during operation, are sealed so can be used in almost any environment, are modular, and can be scaled up or down to meet load requirements. From a broader socio-economic perspective, PVs can improve energy security, increase energy sector resilience, drive reductions in greenhouse gas emissions, improve access to energy, create new industries and jobs, and provide power to remote communities (Sener & Fthenakis 2014). PV use also encourages consumers to become actively engaged in managing their energy and provides them with greater control over their electricity bills.

Despite these benefits, the rapid rate of PV deployment has caused disruption to centralised electricity supply systems, resulting in operability issues (Passey et al. 2011). Existing electricity systems were designed for unidirectional power flow from generators to consumers; increasing volumes of intermittent generation fed back into the grid from rooftop PV are now having an impact on power quality (Zahedi 2011).

Managing many of the technical issues, such as harmonic distortion, voltage spikes and power output fluctuations, can be costly, but these issues are not insurmountable. More difficult to address are the emerging economic impacts. Residential households with PV participate in the electricity market as both generators and consumers, reducing total system demand, while effectively challenging the business models of entrenched utility providers.

A recent study reported that 94% of energy sector executives surveyed predict a "complete transformation or important changes to the power utility business model" as a result of disruptive technology, the changing role of the consumer, and the emergence of distributed generation including PV and storage (PWC 2013, p. 1). More than 56% stated that the fall in solar prices would have "a high or very high impact on their market" (PWC 2013, p. 9).

3.3 The importance of storage

So far, electrochemical storage in the form of lead–acid batteries has been the most common form of electricity storage for residential PVs. Because of its high costs, it has almost exclusively been used in off-grid applications. Now, with electricity prices increasing in some regions and battery prices decreasing, viable battery storage options are emerging for grid-connected households.

This development is very important from the perspective of global climate change mitigation and sustainable energy supply. Traditional centralised electricity supply systems require instantaneous balancing of supply with demand. Residential battery storage with PVs and smart invertor technology will change this paradigm and allow consumers to shift the times they use electricity, reduce how much electricity they use from the network, or disconnect from the network entirely. Although consumers will choose the configuration most appropriate to their needs, not all options will result in net positive benefits to the system as a whole.

A widespread shift by consumers towards complete grid independence could see network asset use drop, causing electricity prices to increase as network costs are recovered over smaller volumes of electricity (CSIRO 2013a). This represents substantial societal cost. Households that cannot afford to reduce electricity from the grid could be locked into a cycle of ever-increasing electricity bills as they become financially responsible for maintaining an under used, capital-intensive electricity network (CSIRO 2013a).

In contrast, residential battery storage technologies could be configured to support the network and, when deployed in conjunction with subsidies or supportive tariff structures, help to achieve financial outcomes for consumers. For example, time-of-use electricity pricing provides an opportunity for consumers to store electricity when tariffs are cheap and use it during peak periods to avoid higher rates. This reduces demand on the network, resulting in better asset use while reducing system-wide costs. Batteries with smart invertor technology can also be used to help to manage power quality and improve reliability, resilience and diversity of supply across the network. In some instances, carefully managed grid defection on costly-to-maintain networks, particularly in regional and remote areas, could reduce network costs and improve reliability.

3.4 The rapidly evolving storage sector

High costs remain the fundamental issue slowing broad market penetration of residential battery storage (Yang et al. 2011; Heymans et al. 2014). At present, battery storage is only cost-competitive in some high-value niche markets and in instances where purchasers are motivated by non-economic drivers (Yang et al. 2011). At “current cost and performance levels”, the IEA questions the transformative impact of storage, stating that it “falls short of delivering the conceptual flexibility potential when compared with competing options” (IEA 2014a, p. 239). But a number of factors are coalescing that may trigger a rapid decline in the costs of battery storage while accelerating technology development.

Some governments have developed generous policy measures to help to drive demand for battery storage. Pressure to reduce battery costs is also intensifying as battery manufacturing facilities scale up to respond to increasing demand for electric vehicles (EV). The EV manufacturer Tesla has committed to a US$5 billion manufacturing facility that aims to produce 500,000 EV batteries by 2020 while reducing battery costs by 30% by 2017 (Tesla 2014). Tesla’s Model S battery has the capacity to power the average US household for up to 3.5 days (Byrd et al. 2014). With a global EV fleet of 350,000 vehicles in 2013, and estimates of tens of millions of vehicles on the road in coming decades, there are good prospects for reuse of EV batteries in residential applications in the longer term (Heymans et al. 2014; IEA 2014a).

In response to these developments, forecasts suggest that the cost of some battery technologies could halve by 2020 (IEA 2012; EPRI 2014; Pistoia 2014). Investment bank Morgan Stanley states that the storage market is larger than predicted and that battery costs will decline more rapidly than previously thought, with a total of 240GW of residential and commercial storage likely to be deployed in the United States alone (Byrd et al. 2014). In addition, at least two studies have found that PV and storage has already reached grid parity for certain consumers in Hawaii, and with falling battery prices, parity could be achieved in other US markets, such as New York and California, in less than 10 years (Koh et al. 2014; RMI 2014a).

Should battery storage drop in price as forecast, enabling widespread uptake, the impacts could challenge the fundamental assumptions of centralised power system design and the operation of electricity markets (PWC 2014). In early 2014, global investment bank Barclays downgraded the corporate bond market for the entire US electricity sector, suggesting that the industry is unprepared for the threat posed by residential PV and storage (Koh et al. 2014). Barclays states that costs of residential-scale storage are falling quickly, and with PV, this development will "reconfigure the organisation and regulation of the electric power business over the coming decade" (Koh et al. 2014, p. 1). At the same time, Australia's national science agency, CSIRO, predicts that electricity storage could play "a future game-changing role in many aspects of the electricity system" and in one possible scenario it estimates that by 2050, a third of Australian electricity customers could leave the grid entirely (CSIRO 2013a, p. 30; 2013b).

3.5 Managing the transition

With the world's energy systems on the cusp of unprecedented transformation, it is becoming more important to understand system-wide impacts from disruptive technology to ensure that the delivery of secure and reliable electricity is not compromised. For PV and storage, this will be a difficult objective to achieve. The existing electricity system is complex and characterised by multiple disruptive influences and substantial uncertainty. The emergence of the end-user as a primary driver of change is amplifying system complexity.

Comprehending complexity in the electricity sector and addressing issues with long-term consequences have in the past proven difficult. For example, California's well-known attempt to reform its electricity supply system and lower costs in the 1990s led to higher prices and a financial crisis that saw blackouts, the collapse of the state's largest energy company, declining productivity, job losses and public costs in the billions of dollars (Sterman 2001).

Traditional linear approaches to modelling can be limited in understanding and anticipating change in complex systems over time (Hjorth & Bagheri 2006). Such approaches break a system into its component parts to investigate the linear impact of cause and effect while often ignoring the interactions from which the complexity and the behaviour of the system are derived. A 'systems thinking' approach avoids these pitfalls. It can effectively map and quantify multidimensional causal relationships, while incorporating the impacts of feedback loops and time delays (Sterman 2000).

A key strength of a systems approach is its ability to transcend traditional boundaries between the sciences and humanities to connect often disparate variables (Hjorth & Bagheri 2006). This is particularly relevant for consumer-led transformations in the electricity sector, where large numbers of small end-users with differing motivations have the ability to disrupt an essential service that underpins fundamental social, economic and environmental outcomes.

Figure 16 displays a conceptual framework that demonstrates key variables and important feedback loops that could drive a consumer-led boom in rooftop PV and storage. This framework applies to established, centralised, fossil-fuel-based electricity systems in developed world economies where rising electricity prices, deregulation and new technology are empowering end-use consumers to participate in the electricity market.

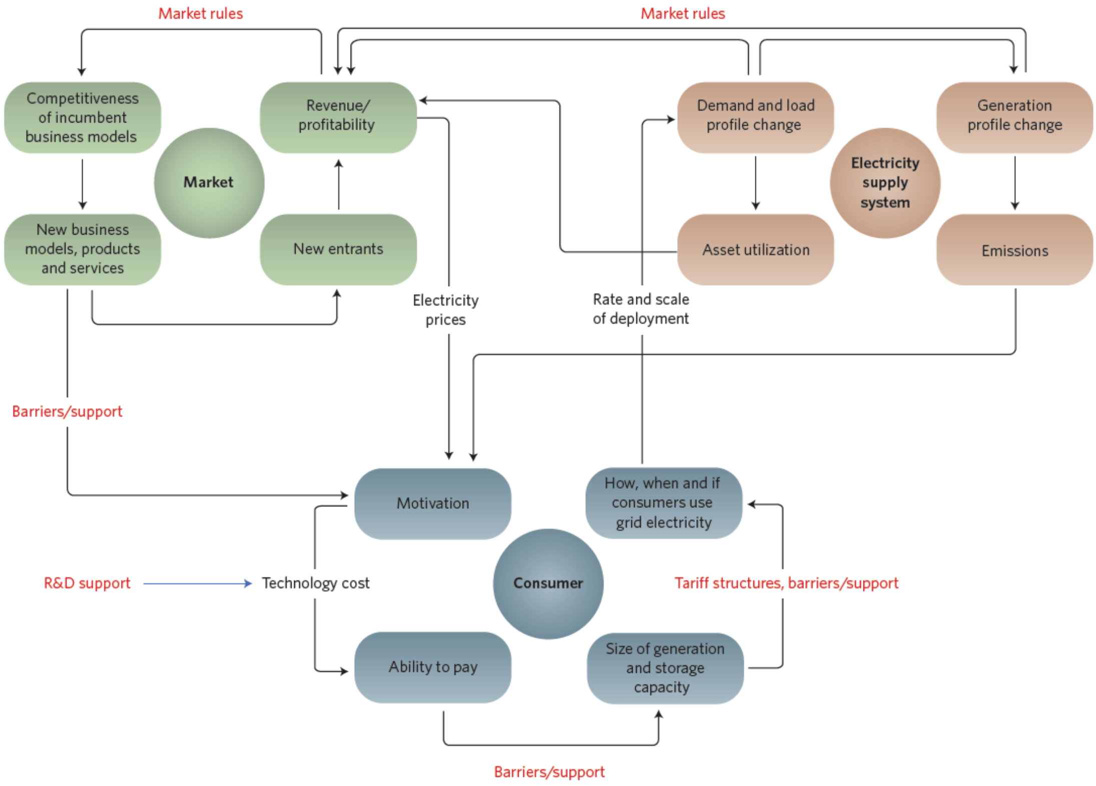


Figure 16 Factors influencing the rate and scale of solar PV and storage deployment

This systems model helps to demonstrate the paradigm shift underway in the residential sector where key feedback loops are encouraging energy self-sufficiency and challenging entrenched business models that are reliant on volumetric sales of electricity. Attempts by incumbents to preserve the profitability of existing business models may end up achieving the opposite by reinforcing consumer drivers for grid independence.

Consumer motivation will be central to determining the rate and scale of storage uptake. Although consumers' financial objectives are one of the most important drivers, the pursuit of energy self-sufficiency, frustration with incumbent utilities, and environmental concerns will also influence behaviour (Balcombe, Rigby & Azapagic 2014). These motivations, along with technology cost and the ability to pay, will drive the type and size of storage that consumers purchase and the way in which they use them. This in turn will determine the system response.

A failure by incumbents to respond to these trends will impact their ongoing competitiveness, allowing new entrants with new business models to cater to consumers' needs. Even with high battery costs, a range of energy service companies around the world are already offering packages that combine storage with other energy efficiency technologies and innovative financing options.

3.6 Where next for residential PV and storage?

Despite the compelling forecasts regarding falling prices and rates of technology improvement, the residential storage market is still very much in its infancy. With sparse empirical data, the extent of future disruption stemming from residential PVs and storage remains uncertain. What is known, however, is that the centralised electricity sector, the form and function of which have remained relatively static for nearly a century, is no longer immune to the power of consumer-led disruption.

For residential storage, this understanding precludes a wait-and-see approach if the problems associated with the PV boom are to be avoided. In this environment, with industry and new entrants mobilising to maintain or build market share, the risks of suboptimal outcomes along the supply chain and for society more broadly are increased.

A systems modelling approach is well suited to help government and industry plan for, and optimise, the looming market transformation. Once the structure of the system is mapped, multiple simulations can be run to determine the impact of interventions anywhere along the supply system from different stakeholder perspectives. This helps in identifying the key leverage points and can determine where policy resistance may occur; that is, where the initial intervention is compromised by the response of the system to the intervention itself (Sterman 2001).

Should they choose, governments will have substantial power to influence this system to achieve stated environmental, social or economic outcomes. But balancing the diverse expectations of different stakeholders is a challenging task, particularly in the absence of any best-practice policy template or roadmap to address issues such as this (Rickerson et al. 2014). Although incumbent utilities have immense economic and market power, the increasing numbers of households with PVs, in some countries numbering in the millions, wield a different but no less effective type of power.

Ultimately, the extent to which PVs with storage confer net positive or negative outcomes over the coming decades will be influenced by the ways in which the market attempts to realise financial value, and the manner in which governments intervene to achieve political or social good objectives. For market participants with differing strategic and commercial objectives, and for governments, particularly those that retain ownership of electricity infrastructure, this will require a fundamental rethink of the form and function of the existing electricity supply system.

Chapter 4 Methods

Chapter overview

The purpose of this chapter is to outline the rationale and epistemological basis for the methodology used in this dissertation and the specific research techniques applied to address the research questions. To help articulate the justification for a systems approach, the chapter leads with a review of common energy modelling approaches. It describes the challenges inherent in modelling energy sector transitions, particularly those involving disruptive demand-side technologies. Systems thinking is identified as the conceptual and organisational framework underpinning the research and its past and current application in the energy sector is reviewed. The second section of this chapter provides an overview of the methodological process applied in this thesis. It describes a mixed methods approach for data collection and analysis, introduces the use of case study research and summarises the specific techniques used across four stages of research.

4.1 Theoretical approach and justification

4.1.1 Characterising energy sector disruption

Centralised electricity supply systems in the past have been relatively immune to sector-wide disruption. The monopolistic nature and relative inertia of the electricity supply system has in many respects underpinned its stability. A relatively small number of institutional stakeholders operating highly technical, capital intensive assets, interact within complex regulatory and financial markets. Participation in the sector has required substantial financial resources and specialised expertise. This has limited competition and with very few cost-effective alternatives, ensured that market structure and function has not changed materially for many years.

The growing global imperative to address the energy trilemma – the provision of secure, equitable and low emission energy – has seen the beginnings of an unprecedented shift in the way electricity is generated, distributed and used (World Energy Council 2016). In this respect, residential PV and batteries typify the dynamic and complex nature of the transition. Distributed technology in the hands of a large, diverse and actively-engaged consumer base, supported by new nimble market participants with access to increasingly sophisticated digital technologies, represent an antithesis of the existing supply system. It is this juxtaposition that underlies the difficulty inherent in understanding and modelling the rate and scale of PV and battery adoption and consequently, the steps required to achieve efficient and optimal integration.

Drawing from complexity science and systems theory, it is possible to more clearly articulate the specific characteristics of the energy sector that make rigorous analysis of disruptive transitions so challenging. Energy systems are classified as complex adaptive systems in which "there is no autonomous control over the whole system, and…self-organised emergent behaviour arises that cannot be predicted by understanding each of the component elements separately" (Bale, Varga & Foxon 2015, p. 152). This is due to several contributing factors:

- agents within energy systems are diverse, with all levels of society, including the public, industry and government, having vested interests regarding energy supply and access;
- agents are heterogeneous in their preferences, they do not have access to perfect information and lack perfect foresight and rationality;
- agents influence, or are influenced within a highly interconnected physical, economic, social and institutional network where decisions taken at any level can have far reaching effects in both time and space;

- these relationships and interactions ultimately shape the characteristics of the system however no one agent has absolute control;
- dynamic equilibrium is rarely achieved due to the influence of multiple feedbacks which means that the system is constantly changing; and
- the emergent nature of the system cannot be predicted based on the past due to the non-linearity of interactions described above (Bale, Varga & Foxon 2015).

With energy sector disruption accelerating, a failure to account for these complex characteristics increases the risk of suboptimal outcomes. It is therefore imperative that fit-for-purpose research methodologies are identified and implemented when addressing specific research problems. With this in mind, the following section reviews common approaches to energy modelling to assess their various strengths and weaknesses.

4.1.2 Overview of traditional energy modelling approaches

Energy models, like models in most other disciplines, are simplified representations of real systems (Hiremath, Shikha & Ravindranath 2007). They allow testing of highly complicated systems, which would be beyond the ability of individual humans to comprehend and would be either impractical or impossible to test in the real world (Hiremath, Shikha & Ravindranath 2007).

Energy modelling has been used for many decades to assist in energy forecasting and policy development. The use of modern macroeconomic energy models originated in the middle of last century, however it wasn’t until the 1970s that energy modelling began to evolve as a distinct field (Herbst et al. 2012). This occurred in response to energy shocks such as the OPEC oil crisis, which prompted governments and industries to recognise the critical importance of longer-term strategic planning for the energy sector (Helm 2002).

Since that time, a vast number of energy models have been developed with diverse methodological designs and data outputs to reflect their specific uses. They range in scale and application from minute-to-minute electricity dispatch models based on highly granular data to long-term energy sector planning models that span decades (Pfenninger, Hawkes & Keirstead 2014). To reflect this diversity, there exist at least nine separate classification systems for energy models based on model purpose, model structure, analytical approach, mathematical approach, geographic scale, sectoral coverage, time horizons and data requirements (Grubb et al. 1993; Hiremath, Shikha & Ravindranath 2007). These different classification systems reflect the fact that energy models have evolved in a multitude of ways based on the target audience (government, utilities, researchers, public), intended use (forecasting, optimisation, planning), spatial coverage (local, national, international), temporal coverage (minutes, hours, days, years), data access (accuracy, availability) and application of analytical theoretical frameworks (top-down macroeconomic approach, bottom-up technical approach) (Herbst et al. 2012).

Despite the increasing diversity of energy models, most have historically been framed based on whether they are "top-down" or "bottom-up", terminology which refers to the level of aggregation (top) or disaggregation (bottom) of data (Bruce, Yi & Haites 1996). Such models differ mainly with respect to "emphasis placed on a detailed, technologically based treatment of the energy system [bottom-up], and a theoretically consistent description of the general economy [top-down]," (Löschel 2002, p. 107; Nakata 2004).

Top-down models apply macroeconomic theory to predict future outcomes based on extrapolation of past trends for analysis of energy-economy interactions (Van Beeck 2000). Econometric methods for example, are frequently used to model the operation of the energy sector as part of the broader economy using aggregated data (e.g. for energy supply and demand) which are then related to production factors, such as labour and capital, to determine the impact on welfare, employment and economic growth (Herbst et al. 2012). Economic equilibrium models focus on long-term effects and are primarily concerned with the conditions that achieve equilibria in either specific elements of the economy such as energy demand and supply sectors, referred to as partial equilibrium, or the entire economy, referred to as general equilibrium (Van Beeck 2000).

In contrast, bottom-up models contain a high level of technical data often with detailed performance and costs parameters (Nakata 2004). They frequently describe specific elements of an energy system in substantial detail by integrating microeconomic and/or technical elements to analyse specific technology or policy combinations (Després et al. 2015). Because of their specific characteristics, the two types of modelling frameworks are generally used to answer different questions. For example, bottom-up models are better at examining complex technology substitution options ("exploration") whereas top-down models are more suited to forecasting wider economic impacts ("prediction") (Bruce, Yi & Haites 1996).

Many of the traditional energy models have been successfully applied to a range of energy sector challenges in the past. However, there remain a number of limitations inherent in these approaches which could limit their effectiveness in addressing emerging issues associated with energy sector transitions.

Linear energy models that rely on historical data to forecast future outcomes do so despite increasing uncertainty and disruption in the energy sector. The rapidly changing energy sector gives credence to the fact that “the future cannot be known as a result of past experiences” (Holt, Pressman & Spash 2009, p. 11). This issue is not a new phenomenon. For example, a review of demand models following the 1970s oil shocks in the US found almost all models systematically underestimated uncertainties and failed to incorporate endogenous feedback such as the ability of the US economy to adopt energy efficient practises in response to high energy prices (Craig, Gadgil & Koomey 2002, p. 94). An additional weakness in this respect, is that trend-based approaches, including many econometric projection models, discourage searches for underlying driving forces and “do not include causality and cannot identify emerging contradictions, both of which can be critical in understanding how the future might unfold”(Craig, Gadgil & Koomey 2002, p. 94).

Failing to account for these factors can result in highly inaccurate modelling outputs that can drive unintended consequences. To illustrate this point, in 2009 modelling undertaken by AEMO for electricity sector planning purposes assumed that electricity demand would continue to grow in line with economic growth as it had in past years. While economic growth increased by 13% between 2008-09 to 2013-14, electricity demand actually fell by 7% in response to energy efficiency, distributed generation and broader economic structural change (Sandiford et al. 2015). AEMO’s modelling results found that electricity demand would increase by 14% during this period which signalled the need for sector expansion. This forecast ultimately underpinned an overinvestment in electricity infrastructure resulting in a corresponding underutilisation of assets which helped to drive up electricity prices (Sandiford et al. 2015).

Another limitation of traditional energy models relates to the assumptions underpinning neoclassical economic theory, which provides the foundation for many top-down energy sector models (Colander, Holt & Rosser 2004; Holt, Pressman & Spash 2009). Based on rationality, selfishness and equilibrium, the theory assumes that individuals have access to perfect information, can accurately quantify benefits and will make rational decisions based on logic (Rai & Benjamin 2013). This means that with individuals able to maximise utility, and firms attempting to maximise profitability, efficient resource allocation occurs in markets that achieve equilibrium which can lead to continual, or limitless, growth. These assumptions, which have been the subject of considerable debate and criticism in recent years, deliver modelling results that provide for optimal sectoral outcomes, or technology configurations which are deployed in an economically rational manner (Colander, Holt & Rosser 2004; Holt, Pressman & Spash 2009).

While modelling based on these approaches may have value from a theoretical perspective, they fail to recognise that decision making at all levels (i.e. individual, business and government) is imperfect and adoption and integration of new technologies often stem from a diverse range of non-financial motivations (Wilson & Dowlatabadi 2007; Kemp & Volpi 2008; Rai & Henry 2016). For new energy technology adoption, this includes the influence of decision heuristics, anchoring, path-dependence, risk aversion, trust-based information networks, and social norms amongst others (Rai & Robinson 2015).

The body of literature that identifies the shortcomings of neoclassical economic theory continues to grow, and while the theory itself remains dominant, there is momentum gaining around new modelling techniques based on "dynamics, recursive methods and complexity theory" (Colander, Holt & Rosser 2004). These developments have seen energy models become far more holistic, so that in addition to technical and economic issues, social and environmental issues are also considered (Ahmad et al. 2016).

In this respect, hybrid models, which link bottom-up approaches with top-down economic models are becoming increasingly popular. These models aim to realise the benefits of combining both aggregated macro-economic data and disaggregated technical elements to better forecast and characterise possible impacts resulting from electricity system change (Pfenninger, Hawkes & Keirstead 2014). In recent years, these hybrid approaches have provided the basis for useful analysis for industry and policy makers, however, they still remain somewhat limited in their ability to represent "the drivers and barriers to long-term change in energy systems"(Bale, Varga & Foxon 2015).

MARKAL, a bottom-up reductionist model is one of the more widely used energy modelling tools, which, along with a number of other common models, such as LEAP, WASP, EGEAS and MESSAGE, adopt a more holistic approach to modelling (Bale, Varga & Foxon 2015; Ahmad et al. 2016). These models have become important for informing policy and strategic business decisions regarding low emission technology adoption in many countries (Dodds, Keppo & Strachan 2015). However, recent reviews have found that even these sophisticated modelling tools "provide normative optimised scenarios in which real implementation bottlenecks are ignored (e.g. uncertainty, heterogeneity of decision makers and market imperfections)" (Dodds, Keppo & Strachan 2015, p. 85). In addition, they tend to ignore causal relationships, the feedback mechanisms that underpin them, non-linearities and system delays (Ahmad et al. 2016).

While the limitations of traditional energy models are becoming better understood, and approaches to energy transition modelling continue to evolve, techno-economic models remain dominant, despite being unable to reflect the full complexity of energy systems and the multitude of interactions between system and actors (Bale, Varga & Foxon 2015). To improve modelling accuracy and usefulness, a greater focus on systemic analysis is required that integrates technological, economic and social behavioural aspects to help achieve a holistic understanding of the interplay associated with adoption dynamics (Kubli & Ulli-Beer 2016). In this respect, and noting the characteristics and complexities associated with energy sector transitions described in the first section of this chapter, the application of a systems thinking methodology has been identified as the most appropriate way to meet the objectives of this study.

4.1.3 Systems thinking

Systems thinking is an approach to analysis that helps to better understand "change and complexity through the study of dynamic cause and effect over time" (Maani & Cavana 2007, p. 7). A system can be defined as a functionally related assembly of interacting, interrelated, or interdependent elements that combine to form a complex whole (Shaked & Schechter 2017). Systems thinking recognises that a system is something more than a sum of its parts; it is an ordered, cognitive endeavour, that balances the focus between the whole and its parts (Cabrera, Colosi & Lobdell 2008; Wright & Meadows 2012).

Systems thinking is not discipline nor content specific but rather provides a conceptual framework and the empirical tools to better understand complexity to help create lasting solutions for difficult problems (Cabrera, Colosi & Lobdell 2008). It is a "structured approach to thinking about complex issues that stimulates new and deeper insights" (Forrest 2008, p. 333). It attempts to see beyond events, which are typically point-in-time snapshots of reality, to uncover the patterns, systemic structures and the mental models that actually drive change in the system (Maani & Cavana 2007).

The concept of 'systems' is not new. For millennia, scholars and philosophers have pondered the structure and order of the world around them. Lao Tsu wrote about systems more than two thousand years ago and Aristotle is credited with the popularised phrase: "the whole is greater than the sum of its parts" (Cabrera, Colosi & Lobdell 2008; Flood 2010). Systems thinking however emerged as a theory in its own right in the early twentieth century when scientists began to question the dominance of reductionism in science, that is, the practise of breaking phenomena down into constituent parts and studying these elements in terms of cause and effect (Flood 2010).

Ludwig Von Bertalanffy, a biologist, articulated this shift in thinking when he wrote that “since the fundamental character of the living thing is its organisation, the customary investigation of the single parts and processes cannot provide a complete explanation of the vital phenomena” (Von Bertalanffy 1972, p. 410). Bertalanffy postulated that models, principles and laws exist that could apply to generalised systems, irrespective of their kind. He saw the systems perspective, with its focus on relationship, as the foundation for a new paradigm in science (Hammond 2003). This type of thinking represented an important shift away from classical science of the time, which was frequently concerned only with one-way causality, the relationship between two variables and the resolution into elementary units (Von Bertalanffy 1972).

In the 1950s, Bertalanffy went on to develop general systems theory, a biological and holistic theory of organisation (Von Bertalanffy 1972). At the same time, work in other disciplines recognised similar phenomenon. For example, the term cybernetics was defined in 1948 as "the scientific study of control and communication in the animal and the machine" and recognised the importance of feedback mechanisms and communication (Wiener 1948, p. 1). Another important systems thinking methodology, system dynamics, emerged in the 1950s. Shaped more by economists and engineers (rather than biologists and physiologists as with cybernetics), it examined dynamic behaviour in complex industrial systems (Forrester 1961; Schwaninger 2006). System dynamics has now been used extensively across many different sectors and has arguably become the most dominant systems methodology in use.

Despite the increasing popularity of systems thinking, there still remains some ambiguity as to how best to define it and how to apply it in various circumstances (Cabrera, Colosi & Lobdell 2008; Monat & Gannon 2015). This is because the field of systems thinking draws from, and is informed by, systems ideas, systems methods, systems theories, systems sciences, and the systems movement (Cabrera, Colosi & Lobdell 2008). Indeed, leading experts in the field acknowledge this ambiguity and recognise that systems thinking can be an: “inconsistent amalgam of logic, heuristics, perspectives, and processes for communicating and thinking about complex issues and problems that newcomers often find confusing” (Forrest 2008, p. 333).

What is common among all theories and methodologies is the idea of systems as organised wholes (Schwaninger 2006). While there are many different approaches to systems thinking, they all share “a worldview focused on complex dynamic systems, and an interest in describing, explaining and designing or at least influencing them” (Schwaninger 2006, p. 583). This reflects emerging agreement from systems thinking theorists that systems are ultimately conceptual constructs and it is these constructs that can be used for engaging with and improving situations of real world complexity (Reynolds & Holwell 2010).

4.1.4 Applying a multi-methodological approach

Since Bertalanffy's seminal work on general systems theory, there has been considerable growth in the field of systems thinking with the emergence of many different system methodologies and theories (Páucar-Cáceres 2002). This includes approaches such as operational research and systems engineering/analysis, systems dynamics, soft systems modelling, cognitive mapping methodologies, critical systems thinking and total systems intervention to name a few (Páucar-Cáceres 2002). These methodologies are generally characterised as hard (i.e. quantitative or positivist) or soft (i.e. qualitative or interpretivist) (Maani & Cavana 2007).

Hard systems thinking approaches assume objectivity and rationality whereas soft systems thinking recognises that the real-world is a complex mess, comprising 'wicked problems' that are difficult for agents to understand and respond to (Byrne et al. 2002). A hard perspective assumes a functionalist view of the world (i.e. the world *is*…), whereas a soft perspective assumes social constructivism (i.e. the world *may be* described as…) (Brown, Cooper & Pidd 2006). In this sense, soft systems thinking ultimately becomes a construct that can be used to examine the 'messes' that exist in the world (Byrne et al. 2002). It acknowledges that the critical perspectives of both science and society are necessary in modelling while recognising that knowledge "is culturally, spatially, and historical relative" (Mingers 2006, p. 4).

These distinctions are important because they recognise both the existence of objective reality, and the fact that efforts to change this reality are generated by individuals motivated by a subjective perception of that reality, referred to as a "mental model"(Kim & Andersen 2012). Ineffective decision making occurs when there is a misalignment between the objective and subjective reality; in this respect systems thinking is used to "improve decision making by making subjective mental models explicit and testable through simulation" (Kim & Andersen 2012, p. 315).

Despite the many different system thinking methodologies available, there is growing support in the literature that system thinking practitioners will be best served by moving beyond single methodologies towards a multi-methodological approach to most effectively incorporate real-world complexity (Mingers & Brocklesby 1997). While soft system thinking approaches can be limited in explicit model creation and simulation due to a reliance on subjective input or intuition, they nonetheless contribute useful insights by eliciting information from-real-world participants (Forrester 1994). At the same time, the contribution of 'hard' quantitative-based simulation models can help provide rigour and clarity to soft systems thinking approaches.

Soft methods therefore can be useful for problem structuring and the development of model architecture (i.e. making sense of the system) while establishing the context within which the hard, or quantitative techniques are used to seek insights and solutions to specific problems (Forrester 1994). For the energy sector, quantitative elements associated with the generation, movement and consumption of electricity and related financial interactions lend themselves to hard system theory. The dynamics that will ultimately control and influence the effects of disruptive technologies on the system are more likely to be related to socio-political influences, more the domain of soft system theory.

When used correctly, these complementary techniques can provide new perspectives, new insights and generate greater understanding without impacting the integrity of the underlying contextual paradigm or by reducing the methodological rigour (Byrne et al. 2002). Indeed, such approaches are recognised as valuable ways to examine complex human-based problems, particularly involving transitional dynamics such as those currently presenting in the energy sector (Seidl et al. 2013).

To capture the full benefits of applying a systems thinking approach, the methodology used in this thesis therefore incorporates both qualitative and quantitative elements. It is based on a staged approach to research that is commonly applied in the systems literature, drawing from both systems thinking theory and the application of a system dynamics methodology. The full method is described in detail in Section 4.2 below.

4.1.5 The suitability of systems thinking for energy sector transitions

Systems thinking is well suited for use in the electricity sector as "energy systems have many of the properties that can be described easily using system dynamics models: for example, nonlinearities (such as resource depletion), stocks and flows (of resources and capital), feedback loops (primarily through price), emphasis on dynamic behaviour, and the need for policy analysis" (Naill 1992, p. 17). Systems thinking has been used extensively in other aspects of the energy sector for several decades and has been useful in analysing a range of energy policy challenges such as global warming, deregulation, conservation and efficiency (Qudrat-Ullah & Seong 2010). It has also been specifically identified by the International Energy Agency as a valuable modelling framework that can assist in energy policy development and planning (IEA 2014a).

The use of systems thinking in the electricity sector can be traced back to the 1970s in the US when a national energy modelling program called Fossil was developed. Based on system dynamics methods, the model incorporated energy sources and demand projections for use in policy analysis (Ford 1997). In those early years, system dynamics models were also used to underpin research into electricity privatisation and deregulation, fuel and resource planning, power sector dynamics and electric vehicles (Ford 1997).

Interest in the field increased rapidly in the 1990s when policy makers and planners recognised the benefits of systems thinking in addressing increasing uncertainty and complexity in response to electricity sector deregulation and market liberalisation (Qudrat-Ullah 2016). This led to a substantial research effort that saw system dynamics models increase in size and sophistication culminating in the development of the IDEAs model, which became the official US department of energy planning model until 1995, and the ENERGY 2020 model, which was used for energy and emissions analysis (Qudrat-Ullah 2016).

Since that time there have been at least 80 studies published which used system dynamics models as the primary methodology for use in electricity sector analysis (Teufel et al. 2013; Leopold 2015). The most common application was for planning models which assessed the impact of policy interventions in regards to issues such as support for renewable energy technologies, market and institutional investment, tariff design, environmental incentives and efficient market operation (Ahmad et al. 2016). Optimisation of physical electricity system operation and planning, such as generation capacity expansions, have also seen considerable attention (Leopold 2015; Qudrat-Ullah 2016).

While systems thinking has been used extensively in a range of electricity sector modelling studies as described above, its application in energy sector transitions is far more limited. A recent literature review that examined the use of systems thinking in energy modelling explicitly identified this gap and concluded that further systems research was required to address: “transformation processes within energy system, and transition issues to renewable energy, energy-consumer centric modelling and modelling-based assessment of alternative energy technology potentials” (Leopold 2015, p. 258).

In this respect, the use of systems thinking to explore issues associated with residential PV and battery adoption is even more limited. Only three related papers were found in the literature. Kubli and Ulli-Beer (2016) developed a system dynamics model to assess the likely diffusion patterns of distributed generation concepts and their impact on network effects in a generic simulation based on a hypothetical region in Europe. Technology adoption was based on net present value (NPV) calculations and elements of diffusion theory. The study found that network effects comprised the main component of the investment decision for distributed generation technologies (Kubli & Ulli-Beer 2016)

Laws et al. (2017) created a system dynamics model to examine the impact of utility rate structures on residential PV and energy storage and their influence on the utility death spiral. PV and battery adoption is calculated using a bass diffusion equation with estimations for adoption rates based on a look-up function which varies linearly based on NPV. The model examines three pricing structures (net metering, wholesale compensation and demand charges) which are applied to three locations (Los Angeles, Boulder and Sydney). The study found that the likelihood of a utility death spiral was unlikely in these scenarios and would require grid-defection at scale driven by a “perfect storm of high intrinsic adoption rates, rising utility costs and favourable customer financials” (Laws et al. 2017, p. 627).

Despite the value of these two studies, particularly from a theoretical perspective, they have a number of substantial limitations. For example, the system dynamics models are highly generic representations of stylised electricity systems. Laws et al. (2017) applied the same model structure in three different locations. While input parameters were varied for each location, the model nonetheless assumes that the structure underpinning electricity price creation is the same. For Sydney at least, the model does not accurately represent the way in which electricity prices are actually set. As retail tariff structure is a key element in their study this appears to be a significant shortcoming.

Furthermore, important variables in both models, such as consumption patterns, PV generation and battery system capacities, are represented in most cases by just one averaged parameter. Kubli and Ulli-Beer (2016) explicitly identify this as a weakness stating the model is “overly aggregated and simplifying”. In addition, both studies appear to be informed only by desktop analysis with no qualitative data collection or analysis used to help inform model architecture and key feedback loops. The way in which consumer decision making processes are represented is also limited.

In contrast to the above studies, Grace (2015) uses a more data driven approach to model and examine the influence of PV and batteries on the Western Australian electricity system. This study finds that exponential PV and battery growth will affect base-load generation and could substantially disrupt the existing network. Unlike Laws et al. (2017), the model shows this would result in an electricity death spiral. While the model includes a far more detailed and accurate representation of the broader electricity supply system, consumer adoption dynamics themselves are far more simple, based on financial feedback only and are based on highly aggregated demand-side data both in terms of dwellings and system sizes.

Notwithstanding the limitations of the above studies, they still make important contributions to help address a substantial gap in the literature. They also demonstrate the applicability of using systems thinking and system dynamics modelling approaches to better understand electricity disruption arising from residential distributed generation. Accordingly, the research approach outlined in this thesis, which is described in detail below, aims to build on this early work. It applies a comprehensive systems thinking methodology to address the research objectives of this project and in doing so aims to provide an important theoretical and practical contribution in its own right.

4.2 Research methodology overview

The research methodology applied in this thesis comprises four distinct yet interrelated stages which correspond to each of the research questions (Figure 17). The specific research approach is based on accepted systems thinking methodologies adapted from Sterman (2000) and Maani and Cavana (2007). It is described in the section below which leads with an overview of the data collection and case study approach, followed by a summary of the methods used in each research stage. Note that this chapter is written to provide an overview of the research approach. More detailed descriptions of the methodology and modelling assumptions are provided in each of the subsequent chapters.

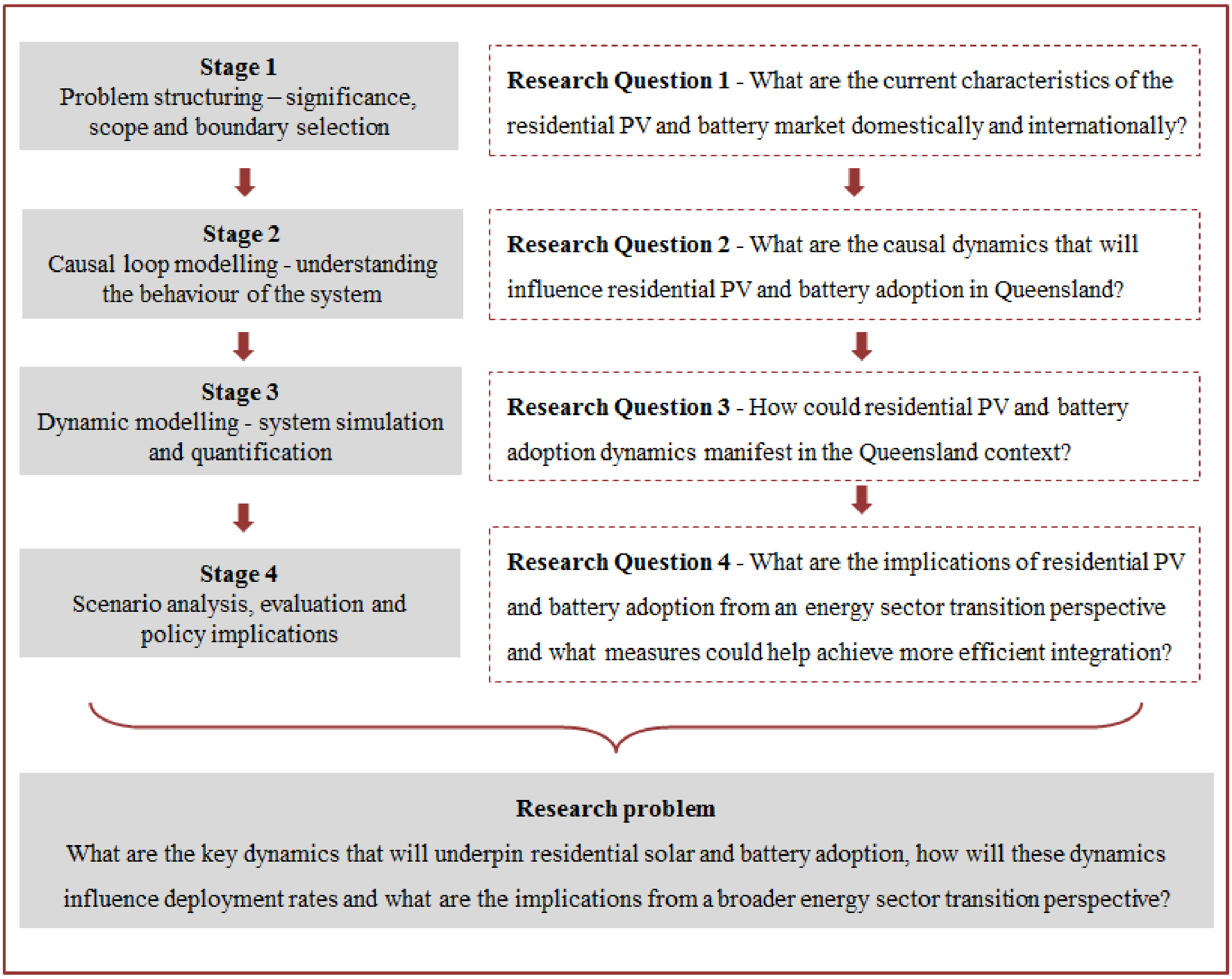


Figure 17 Overview of research stages and their relationship to the research objective

4.3 Case study and data collection approach

4.3.1 Case study

In setting the boundary and scope for this research project, it was decided to focus on one specific case study area so that appropriate levels of granularity could be applied to theory development, testing and modelling. A case study is part of a "research strategy which focuses on understanding the dynamics present within single settings" (Eisenhardt 1989, p. 534). The use of case studies has been extensively evaluated in the academic literature and is considered an appropriate way in which to develop and test theory (Ravenswood 2011). Case study research uses a range of data collection methods, such as interviews, survey analysis, observations, and can include both qualitative or quantitative data to examine issues within a real world setting (Eisenhardt 1989). Chapter 5 provides a detailed description of the case study area. While the state of Queensland is used as the case study area, there are a number of jurisdictions around the world experiencing similar challenges (Rickerson et al. 2014). Despite a diversity in electricity market ownership and structures in these countries, the research findings described in this thesis are broadly applicable.

4.3.2 Mixed methods approach

For research involving issues characterised by substantial complexity and uncertainty, a mixed methods approach to data collection used in conjunction with grounded theory techniques is commonly applied. Grounded theory is defined as the discovery of theory from data that is systematically obtained and analysed as part of the research process (Glaser & Strauss 2009, p. 2). Mixed methods study refers to the use of both quantitative and qualitative data collection, analysis, and inference techniques to achieve greater depth and accuracy in addressing research questions (Johnson, Onwuegbuzie & Turner 2007). Quantitative and qualitative approaches typically involve different data collection methods (e.g. interviews, surveys), data types (numerical and textual) and data analysis (statistical and thematic) to help inform research conclusions based on both objective and subjective representations (Tashakkori & Creswell 2007). Mixed methods study ensures that research is informed by multiple perspectives rather than just single perspective while helping to alleviate a reliance on one form of data collection, for example data-heavy statistical methodologies which can miss the depth that comes from qualitative research (Wheeldon & Ahlberg 2012). The different data collection approaches used throughout this thesis are discussed below.

4.3.3 Participatory data collection

The primary qualitative data collection method used in this thesis involved an extensive stakeholder consultation process. Participatory methods of data collection, such as interviews and workshops, are particularly useful in systems thinking research (Sterman 2000). They allow for the collection of contextualised, site specific information that reflects relevant local economic, political, social and environmental conditions (Chan et al. 2010). Structured correctly, stakeholder interviews and workshops can capture the 'mental models' of individuals and organisations that influence why things work the way they do and represent "a deeper level of thinking that hardly ever comes to the surface" (Maani & Cavana 2007, p. 15). In this way, participatory stakeholder engagement methods can help provide predictive, explanatory and enduring descriptions of the dynamic behaviour in a system (Yearworth & White 2013).

For this study, 68 energy sector experts were interviewed individually, or participated in small group workshops. Stakeholders included regulators and policy makers from national, state and local governments; representatives from the electricity supply chain (including generators, network service providers and retailers); new market entrants; technology developers; PV and battery installers; consumer advocacy groups; and consumer representatives. Due to the requirement for human participation in this study, ethical clearance was obtained from the University of Queensland Behavioural and Social Sciences Ethical Review Committee. To ensure informed consent, an information sheet with specific details about the study was provided to any participants consulted, and a consent sheet was used to record participants' agreement.

A semi-structured interview approach was used that has proven to be effective in systems thinking applications (Sterman 2000). While a script was developed that included a number of pre-set questions, the interviewer was able to deviate from the script at any time to pursue areas of relevance in greater detail. Interview questions were structured to help with problem articulation and to identify key feedback loops and other important causal relationships. This technique is particularly well suited for use in causal loop development as it can help provide predictive, explanatory and enduring descriptions of the dynamic behaviour in a system (Yearworth & White 2013). A dedicated scribe manually recorded meeting outcomes and a representative from the Queensland Government was in attendance for each meeting. All meetings were held in Brisbane, the Queensland state capital, and typically ran for approximately 1 hour.

A large volume of data was generated from the interview process and was analysed using a method adapted from Kim and Andersen (2012), which describes an approach to systematically code qualitative data specifically as part of a broader systems thinking methodology. Coding refers to a technique for organising and interpreting data with the intent of formulating a logical, systematic and explanatory theory that can explain behaviour and actions (Glaser & Strauss 2009).

The first step involved thematic content analysis and open-coding of data for problem definition and identification of the system boundary (Kim & Andersen 2012). This step involved extracting and grouping concepts, or codes, from the interview data according to key words and phrases based on the hierarchy described above. Codes were determined and defined primarily by the research context. In this case, both *in vivo* codes (i.e., descriptions sourced directly from the interviews) and codes based on commonly used terms sourced from the literature were used (Kim & Andersen 2012).

The second step involved identifying key variables and their causal relationships by extracting single units of analysis that relate to the system's structure or behaviour (Kim & Andersen 2012). This involved breaking the data down further into sub-categories, or child nodes, representing a far more granular representation of the system being modelled. Within these sub-categories, specific variables were identified from the data. Memos were used to record key aspects of analysis associated with each variable[2]. They included the initial observation and an explanation describing the variable and its relevance based on the theory that emerged from the interview data. Each memo also detailed the key causal relationships and explicit feedback loops associated with the variable. All variables and memos were reviewed and validated by examining a range of secondary data sources including relevant government, industry and academic research.

The results of this process were used to inform outputs across every stage of research described in this thesis. A more detailed description of the participatory data collection method, including the approach to stakeholder identification, participant engagement, ethics, interview structure and data analysis, is described in Chapter 6.

[2] Memos are commonly used as part of the coding process and are simply a record or product of analysis

4.3.4 Secondary data and statistics

In addition to the data acquired through the interview process, a large amount of information from a wide diversity of secondary sources was also accessed as part of the mixed method approach used in this thesis. These sources included:

- Publicly available data sets from AEMO and the Australian Energy Regulatory (AER) which provided detailed information on a range of electricity sector metrics such as historical and forecast demand, and financial, reliability and network benchmarking data. The national Renewable Energy Certificate registry includes raw data on the number and size of PV installed throughout Australia. Demographic data and trends were accessed from the Australian Bureau of Statistics. Solar insolation data was sourced from the National Renewable Energy Laboratory. Any raw data used in this thesis was aggregated and analysed directly in Excel.
- Regulatory documents including Queensland Government Gazettes, Queensland Competition Authority (QCA) pricing determinations, AER network regulatory determinations and industry annual reports. These references were used to both provide data for use as inputs in model initialisation and also to inform model design. For example, QCA and AER documents include descriptions of the actual methodologies used to calculate electricity prices in Queensland which were then adapted for the model.
- Consumer and industry stated preference data, including government funded annual surveys such as the Queensland Household Energy Survey and academic based surveys such as Romanach, Contreras and Ashworth (2013) and Agnew and Dargusch (2017) were used to more clearly understand consumer relationships with the energy sector and distributed energy technologies. Industry surveys such as PWC (2013) and UtilityDIVE (2015) were also used to gain a broader understanding of drivers from an industry perspective.
- Market statistics and technical system data – analysis of PV and battery technical specifications along with current and historic system pricing from market based sites such as SolarQuotes (2017) were used to help inform model assumptions and structure.

The above list is not exhaustive and is only a representative sample to demonstrate the breadth of data used to help address the research questions. This data was used to not only corroborate the results of stakeholder interviews but also to inform theory creation in its own right, provide quantitative inputs for initialisation of the simulation model, underpin modelling assumptions and inform scenario analysis.

4.4 Stages of research

4.4.1 Stage 1. Problem structuring – significance, scope and boundary selection

Conceptualising and framing the fundamental parameters for a systems thinking model represents one of the most difficult, yet crucial steps in the development of a whole of system model (Kopainsky & Luna-Reyes 2008). It sets the foundation for the entire research process by articulating the specific problem under investigation while identifying major issues and challenges (Sterman 2000). The scope and system boundary (both spatial and temporal) must be clearly specified. In addition, a thorough assessment of the system's existing and historical characteristics is important to provide context and to help show how issues have developed and potentially how the system may respond in the future (Sterman 2000).

To address the first research question and to provide the basis for causal loop modelling, the following elements are addressed in the first stage of research:

- System characteristics and sector context – what are the key technical and operational features of residential PV and battery energy storage? How has the market developed? What have been the challenges and benefits of integration to date? What are the current fundamentals of the residential energy sector, its linkages within the electricity industry and its relationship with broader socio-economic frameworks?
- Problem articulation – what are the problems to be addressed?
- Project scope and boundary – what are the system boundaries? What level of data aggregation is required? Who are the key stakeholders?
- Timeframes – what is the modelling time horizon, both past and future?

To achieve the objectives of this stage of research, the methodology was broadly adapted from Maani and Cavana (2007), Sterman (2000) and Kim and Andersen (2012). While a more detailed description of these methods are provided in subsequent chapters, this stage of research involved a comprehensive review of academic, government and industry literature which was initially used to define and characterise the system under investigation and to "justify the seriousness and clarify the scope and magnitude of the problem/issue identified"(Maani & Cavana 2007, p. 18). The data and analysis undertaken as part of this process was used to help identify key stakeholders, formulate a stakeholder engagement plan and help devise questions used in interviews and workshops. Thematic content analysis and open-coding of data from both the industry review and stakeholder interviews were then used to inform problem definition and identification of the system boundary. Throughout this process, results were verified in separate meetings with key energy experts.

Contribution to research objectives

Stage 1 research outcomes directly address Research Question 1 by describing the current characteristics of the residential PV and battery market domestically and internationally. This stage of research also underpins many other key elements of the thesis, particularly as problem articulation, scope and boundary setting form the foundation on which assumptions are made, data is collected and conclusions made.

Specific inclusion of Stage 1 data and analysis is referenced in the thesis as follows:

- Context – system characteristics and sector context (Chapter 2)
- Synthesis and significance of research from a global perspective (Chapter 3)
- Case study characteristics (Chapter 5)
- Problem articulation, scope, boundary selection (Chapter 6)
- Data inputs and assumptions for stock and flow model (Chapter 7)

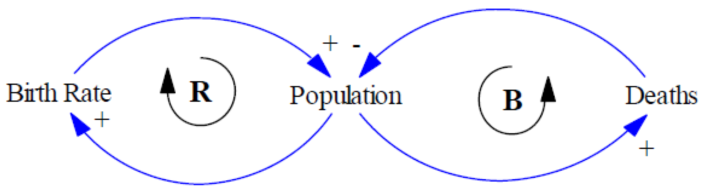
4.4.2 Stage 2. Causal loop modelling – understanding the behaviour of the system

This second stage of research involves theory creation using causal loop modelling, a process that involves taking information from the real world and generating a unifying and coherent hypothesis, effectively a theory of system behaviour (Forrester 1994). This process involves the development of Causal Loop Diagrams (CLD) to graphically reflect system feedback structure by showing the relationships amongst a system's parts and how they interact with each other (Sterman 2000; Hjorth & Bagheri 2006).

CLD development is an important step in conceptualising and understanding complexity as it helps create "a framework for seeing interrelationships…for seeing patterns of change rather than static snapshots" (Senge 2006, p. 68). In this manner, the behaviour of the system as a whole can be better understood. CLDs are frequently referred to as a *dynamic hypothesis*, because they represent a working theory of how a problem arises while providing an explanation that describes the problem in terms of the underlying feedback and stock-and-flow structure of the system (Sterman 2000).

CLDs helps develop an endogenous explanation of system behaviour, which then provides the tools to identify system archetypes and identify leverage points for policy intervention (Maani & Cavana 2007). A strength of CLDs is that they challenge entrenched mental models and test assumptions; in doing so the process can lead to important and sometimes counterintuitive insights about the structure and behaviour of a system (Hovmand 2014). They also form the basis for development of simulation models which can be used to provide a deeper understanding of system behaviour.

CLDs are visually represented by variables (words or phrases) that are linked to other variables that have a cause and effect relationship. The relationship between variables is denoted by an arrow with an assigned polarity in the form of a '+' (same) or a '-' (opposite) to indicate the nature of the cause and effect relationship. A '+' polarity indicates that cause and effect move in the same direction. A '-' polarity indicates that cause and effect move in opposite directions. When linked these variables form part of a feedback loop, which can be reinforcing (R) or balancing (B). Reinforcing loops accelerate change within systems to produce growth or decline, while balancing loops counteract change within systems to produce stabilising behaviour. To illustrate the structure and notations used in a CLD, Figure 18 provides a simplified example demonstrating population dynamics.



Source: (Sterman 2000)

Figure 18 CLD example demonstrating feedback loops

There exist multiple methodologies that can be used to elicit causal structures from qualitative and quantitative data for use in CLD development (Sterman 2000; Maani & Cavana 2007; Kopainsky & Luna-Reyes 2008; Kim & Andersen 2012). Drawing from these studies, the key steps used in CLD design for this thesis included:

1. Identification of the key variables and their causal relationships using data extracted from interviews and other secondary sources. The open-coding techniques used in stage 1 were expanded so that a more granular level of data analysis was achieved and individual variables could be identified. Due to the large volume of variables described, axial coding (which involves reassembly of data into related categories) was also used to simplify concepts and identify the key relationships.
2. Review and validation of identified variables and their relationships using secondary data sources and verification with individual energy experts.

3. Development of a subsystem diagram to visualise the overarching structure of the system particularly the main subunits and their relationship to each other.
4. Translation of data into a CLD that describes the factors influencing residential PV and battery adoption and how these dynamics manifest in the broader system. For this purpose, the CLD was built using Vensim PLE, a software package designed for developing and analysing dynamic feedback models (Ventana Systems 2017).

Contribution to research objectives

Stage 2 research outcomes address Research Question 2 by explicitly describing the causal dynamics that will influence residential PV and battery adoption in Queensland. The method, results and discussion for this stage of research are described in detail in Chapter 6. Stage 2 results were also used to provide the foundation for, and to inform the design of a stock-and-flow simulation model which is discussed in Chapter 7.

4.4.3 Stage 3. Dynamic modelling - system simulation and quantification

Energy system analysis is typically underpinned by quantitative energy models which can provide a powerful tool to support decision making and policy development (Horschig & Thrän 2017). This is also true of systems thinking approaches. As described above, causal loop diagrams represent an important step in conceptualising and understanding the relationship between key variables. However, in complex systems the total impact of feedback loops cannot be established with a CLD alone, particularly where multiple negative and positive loops impact variables (Heath et al. 2011). This is because CLDs do not distinguish levels (stocks) from rates (flows) which can hinder the ability to properly identify the system elements that generate dynamic behaviour (Forrester 1994).

To understand more clearly what is driving system behaviour and the way in which this behaviour will impact the system, a dynamic simulation model must be developed. Specialist systems software, Stella Architect (version 1.1) was used to build the model. Stella Architect provides a graphical interface to help define the integral and differential equations which mathematically represent the model's variables and relationships (ISEE systems 2016).

A stock and flow model comprises a number of elements as illustrated in Figure 19. Each of these elements is described below based on Sterman (2000); Maani and Cavana (2007); Caponio et al. (2015); ISEE systems (2016).

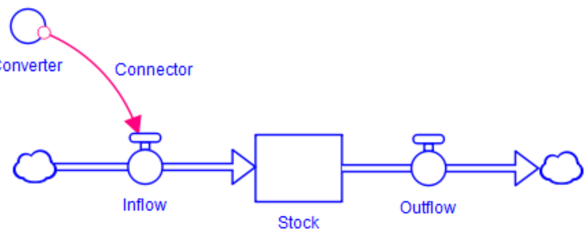


Figure 19 The key building blocks of a stock and flow model

- *Stocks* are entities that represent accumulated quantities, moderated by inflows or depleted by outflows. In Stella they are represented by rectangles. They characterise the state of the system at any point in time. Mathematically, a stock (S) over a specified time (t) period is represented by the equation:

$$\boldsymbol{S_t} = \int_{\boldsymbol{t_0}}^{\boldsymbol{t}} [\boldsymbol{inflow}(\boldsymbol{t}) - \boldsymbol{outflow}(\boldsymbol{t})]\ \boldsymbol{dt} + \boldsymbol{S}(\boldsymbol{t_0})$$

- *Flows* change the volume of the stock during any period of time. In Stella they are represented as valves. Flows, also referred to as rates, comprise both inflows which add to the stock and outflows which deplete the stock. The ‘clouds’ on either sides of flows represent the boundaries of the system.
- *Convertors* control flows by defining inputs such as constants, graphical functions or algebraic relationships. In Stella they are represented as circles. Convertors are also known as auxiliary variables.
- *Connectors* are arrows that link the various components in a stock and flow model and denote causality.

One of the most common ways to build a stock and flow model is by translating it directly from a CLD. For this study, a systematic approach to model design (described in detail in Chapter 7) involved identifying the relevant stocks, flows and convertors based on key elements of the CLD created in Chapter 6. The structure of the model was then built by defining structural relationships between variables using constants, graphical and mathematical functions. Initial values for the model’s stocks and variable parameterisation were based on data sourced from the first two stages of research.

Upon model completion, an extensive testing and validation phase was undertaken. This is a critical element of model development. It helps ensure that the model most accurately represents the system it is based on and, in doing so, provides confidence in modelling outputs and its usefulness in addressing its purpose (Barlas 1994). In this context, validation and testing refers to the process of assessing a model with "empirical reality for the purposes of corroborating or refuting the model" (Forrester & Senge 1980, p. 414). While there is no single approach to validate system dynamic models, a number of structural and behavioural tests were used in this study to validate the model. This included structural confirmation, dimensional consistency, conservation of matter and extreme conditions testing. A discrepancy coefficient, which statistically compares model-generated behaviour to observed behaviour, was also generated for key parameters.

Contribution to research objectives

Stage 3 research outcomes address Research Question 3 to better understand how residential PV and battery adoption dynamics manifest in the Queensland context. This is achieved through the design, development and simulation of a dynamic stock and flow model. The method, assumptions, testing and validation for the model are detailed in Chapter 7. The results of model simulations are included in Chapter 8.

4.4.4 Stage 4. Scenario analysis, evaluation and policy implications

Despite the compelling forecasts regarding battery price declines and rates of technology improvement, the residential storage market is still very much in its infancy. With little empirical data, the extent of future disruption stemming from residential battery storage remains largely uncertain. Within this environment scenario analysis can be used to better understand how battery adoption dynamics could change under a range of different conditions.

Scenarios are hypothetical future events incorporating drivers, trends and policies which are designed to clarify a possible chain of causal events along with their decision points (Amer, Daim & Jetter 2013). For energy sector planning, scenario analysis provide a useful tool to orient and contribute to discussions about energy futures while helping to support strategic decision making in the sector (Cao et al. 2016). Of particular interest is how endogenous feedback mechanisms manifest and drive broader system change when input values and exogenous variables are modified.

To this end, a five-step method for creating and using scenarios has been adapted from Huss and Honton (1987) and Amer, Daim and Jetter (2016). This approach leverages one of the most well established scenario methodologies, the intuitive logic approach, while incorporating elements from a relatively new method that can combine the outputs of causal cognitive maps. To help inform scenario analysis and to understand uncertainty in the model, sensitivity analysis was also applied by varying values of input parameters to determine the relative influence on dependant variables and, more broadly, model output (Saltelli et al. 2008). Detailed descriptions of the methodologies used to underpin scenario and sensitivity analysis are included in Chapter 8.

The final element in this stage of research includes an assessment of the policy implications stemming from the results of model simulation and scenario analysis. The first step in this respect requires clarification of purpose or rationale for intervention. The OECD states that good policy and regulation must serve "clearly identified policy goals, and be effective in achieving those goals" (OECD 2005, p. 3). This is necessary to ensure issues are properly targeted with the right measures to address the problem in the most effective and efficient way (QPC 2016b). In this regard, the scope of research, problem articulation and system boundaries are clearly referenced throughout the thesis. With a stated focus on broader socio-economic outcomes (as opposed to specific commercial or market issues), policy implications in this section are therefore considered through a social-good and economic efficiency framework.

The method for policy analysis is undertaken through a systems thinking lens, which recognises that complex problems rarely have solutions that are complete or final (Rittel & Webber 1973). While it is beyond the scope of this dissertation to outline a comprehensive policy roadmap for PV and battery integration, this section describes and assesses leverage points in the system that represent good targets for policy intervention. The concept of leverage points is well enshrined in systems thinking theory. They refer to measures that address long-term solutions and drive fundamental changes as opposed to actions that merely address the symptoms of a problem at a point in time (Maani & Cavana 2007). Depending on their nature, leverage points can have varying levels of success in achieving change within a system. In this regard, a framework developed by Meadows (1999, p. 3), which describes the places to intervene in a system in increasing order of effectiveness, is used as a reference point to consider policy interventions.

Contribution to research objectives

The outcomes of this stage of research address Research Question 4. The results of simulations and scenario analysis are used to better understand the implications of residential PV and battery adoption from an energy sector transition perspective. This stage of research also considers some of the leverage points and policy measures that could be applied to achieve more efficient integration of the technology. The outcomes of scenario analysis and relevant policy implications are included in Chapter 8.

Chapter 5 Description of the case study area

Chapter overview

This chapter provides a detailed description of the case study area and considers the structural drivers in Queensland that could underpin future PV and battery adoption. The chapter leads with a discussion regarding the existing electricity supply system in Queensland, its relationship to the NEM, and other relevant institutional and regulatory factors. The second section describes the drivers responsible for exponential PV growth in Queensland and considers their relevance in regards to battery adoption. The chapter finishes with a description of the current state of the battery market in Queensland and reviews existing battery adoption forecasts for the State. The data and analysis presented in this chapter is used to help inform all four stages of research, including causal loop development and the structure and parameterisation of the simulation model. Data for this chapter was sourced from an extensive review of industry and government reports, market-based data and the academic literature. Interview data was used to cross-check and where possible validate the results of this analysis.

5.1 Introduction

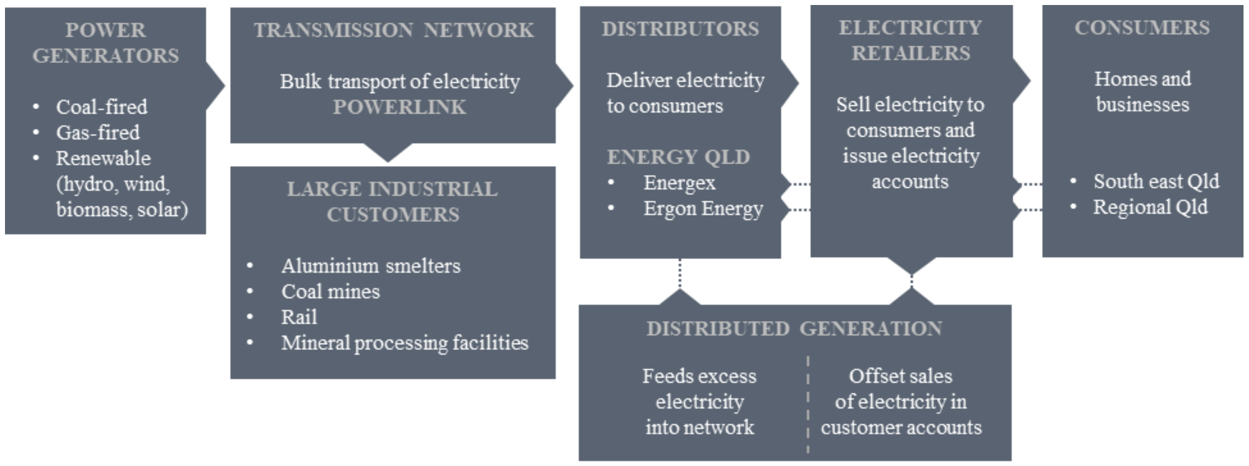
Queensland is the second largest state in Australia, with a land area of 1.7 million km^2, seven times the size of Britain (Queensland Government 2017a). With a population of nearly 5 million people, Queensland has a strong and stable economy with high average wealth per capita compared with global rankings (Queensland Government 2017a). The state also has some of the best solar insolation in the world, with an average of 12 hours of sunshine per day and approximately 263 days of sunshine per year (Queensland Government 2017b).

While the deployment of residential PV and battery energy storage is already occurring in a number of countries around the world, Queensland is considered a global test-bed for battery energy storage uptake (Edis 2015a). With quality solar resources and cheap PV systems by global standards, it has some of the highest per capita PV installation rates in the world. In addition, Queensland has a range of other drivers such as high electricity prices, a poorly utilised and emissions intensive centralised system, and strengthening non-financial motivations which make the state a target market for battery technologies.

The supply of electricity in Queensland has seen significant institutional and structural reform in the past decade. These developments are highly relevant when considering the uptake of distributed generation technologies. Many of the systemic structures which underpin consumers' financial and non-financial motivations occurred during this period and remain dominant today. It is therefore important to understand the environment in which they formed and how they influenced system behaviour, particularly when considering the structure and dynamics that could underpin residential battery storage adoption.

5.1.1 Queensland's electricity supply system

Like any modern centralised electricity supply system, Queensland's electricity sector is comprised of generators, transmission and distribution networks, retailers and end-use consumers. This structure along with the key operational participants in Queensland is illustrated in Figure 20.



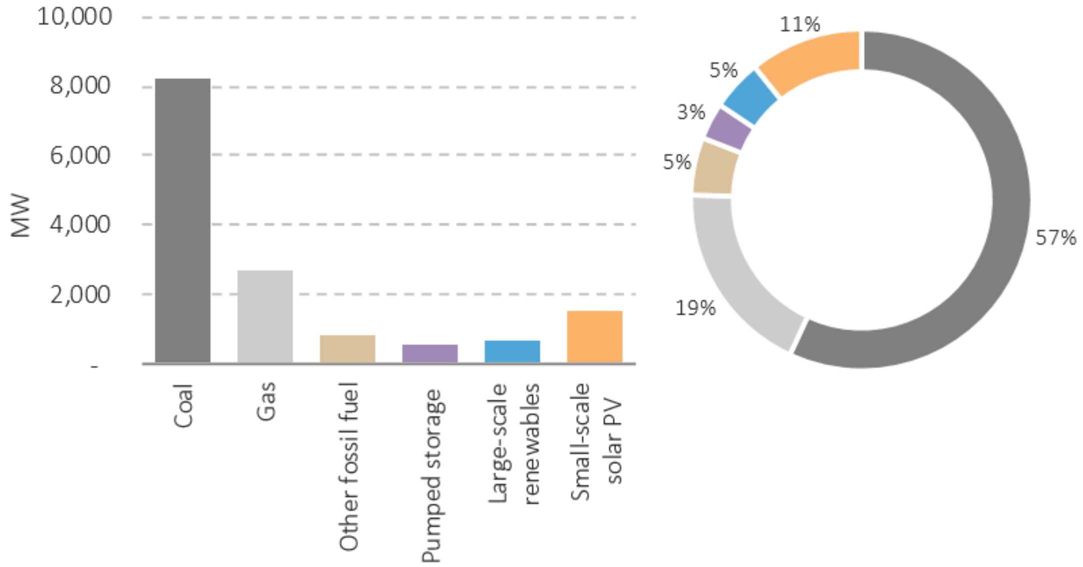
Source: Adapted from Powerlink (2016)

Figure 20 Queensland's electricity supply system

Each component of the above figure is described in more detail below.

- *Power generation*

Queensland has just over 14GW of installed electricity generation capacity with approximately 12.5GW connected to the NEM, comprising 8.2GW of coal and 3.1GW of gas (AEMO 2016a). Queensland has the lowest level of renewable energy capacity in the NEM with approximately 540MW of large-scale grid connected renewable capacity (Mugglestone et al. 2016). The breakdown of Queensland's generation capacity is shown in Figure 21.



Source: (Mugglestone et al. 2016)

Figure 21 Queensland's generation capacity

Due to the state's fossil fuel dominated generation, the emissions intensity of the sector is relatively high at 0.94 kg CO2-e/kWh, compared to a global average of approximately 0.53 kg CO2-e/kWh (IEA 2013b; DOEE 2016). Queensland is the largest emitter of greenhouse gases in Australia. The state contributes approximately 150Mt CO2-e of greenhouse gas emissions per year, with the electricity sector the single largest emitter generating approximately 30% of total state emissions (DOEE 2017).

Two government owned corporations, CS Energy and Stanwell Corporation, comprise 65% of the generation market with the balance made up of private, largely gas-fired owner/operators (QPC 2016b). In 2016, total operational demand in Queensland was just under 50,000GWh and, despite maximum demand exceeding 9GW for the first time, Queensland still has spare generation capacity (AEMO 2016a, 2016b). AEMO predicts that no additional generation capacity will be required in Queensland beyond 2025-26 (AEMO 2016a). This means that PV and battery adoption, which will continue to hollow out demand from the residential sector, will occur in an already highly competitive generation market.

The Queensland Government's commitment to achieve a 50% renewable energy target by 2030, which aims to encourage substantial investment in new renewable energy capacity will exacerbate this issue (DEWS 2017b). As part of this policy, the Queensland Government has also set an aspirational target to achieve 1 million PV systems, or 3,0000MW of PV by 2020. This could be a challenging undertaking, particularly as it would require nearly 500,000 installs in the next three years if the target was to be met by the residential sector. With minimal new funding allocated to meet this target, it appears that the focus of this policy will be utility-scale and commercial PV installations.

- *Electricity networks*

Queensland's electricity transmission network is 1,700 km long and transports bulk electricity to the distribution networks and to large industrial customers that are directly connected to the transmission network (Powerlink 2016). The transmission network is owned by Powerlink, a Government Owned Corporation (GOC) and comprises assets worth approximately $5 billion (Powerlink 2016).

Queensland’s distribution network is owned and operated by two GOCs, Ergon Energy and Energex. In 2016, they were merged to form Energy Queensland to become the largest distribution business in Australia, with AU$24 billion worth of assets (Energy Queensland 2016). Queensland’s distribution network covers an area of 1.7 million km^2 and comprises more than 200,000 km of electricity lines and cables (Energy Queensland 2016).

The regional component of the network, operated by Ergon Energy, is particularly large. It covers 97% of the state making it the most extensive network in the NEM (Ergon Energy 2016). This results in Ergon Energy having the highest cost per customer, spending approximately double compared with other Australian network service providers (AER 2016a). When considering the size of the state’s electricity network it is perhaps not unsurprising that network costs comprise the largest component of retail tariffs in Queensland, contributing approximately 45% of the final cost of electricity for small retail customers (QCA, 2015c).

Electricity network revenues and network prices are regulated in Queensland. As electricity networks are highly capital intensive, it is more efficient for services in a particular geographic area to be provided by a single supplier. This leads to a natural monopoly industry structure, which without regulation could see negative outcomes for consumers such as higher prices or substandard service provision (AER 2016a). To avoid this outcome, the AER is responsible for regulating network prices; it administers Chapters 6 and 6a of the National Electricity Rules which detail the economic regulation framework for electricity networks (AER 2015c). For every five year regulatory period, the AER caps the revenues that a network can earn based on forecast revenue requirements that cover efficient costs including a commercial return on capital (AER 2015c). While the application of this approach to network regulation is necessary in the current environment, it can drive a range of unintended consequences by stimulating overinvestment, artificially increasing electricity prices and influencing negative consumer perceptions of incumbents. These issues are discussed below and explored in greater detail in subsequent chapters.

Finally, and as stated, Queensland’s network companies are all GOCs and pay substantial dividends to government. For the 2015/16 financial year, Ergon Energy paid a final dividend of $1.925 billion, Energex paid $1.295 billion and Powerlink paid $218.3 million (Energy Queensland 2016; Powerlink 2016). Any decline in the value of these network assets, particularly in response to disruption stemming from residential PV and battery adoption, will clearly have broader economy-wide impacts.

- *Electricity retail sector*

In Queensland, the electricity retail sector is the primary point of contact for most residential consumers. Electricity retailers buy electricity from generators and resell to consumers, as well as providing a range of other services such as connections, disconnections and billing. In Queensland there are 16 active retailers servicing more than 1.8 million residential consumers and 200,000 commercial consumers (QPC 2016b).

The retail electricity sector was heavily regulated in the past, however recent electricity market reform has resulted in greater competition and transparency. Since 2007, consumers have been able to choose their own retailer and enter into a market contract where the price is set by the retailer, or remain on a regulated tariff which is set annually by the Queensland Competition Authority (QPC 2016a). For south-east Queensland (SEQ), this reform increased competition and saw 70% of customers adopt market based contracts ultimately resulting in full price deregulation from 1 July 2016 (QCA 2015c).

Competition is more limited in areas outside SEQ, primarily because of the Queensland Government's Uniform Tariff Policy (UTP). This policy requires regulated regional electricity pricing to be based on the cost of supply in SEQ, despite the fact that these prices are well below that in regional areas (QCA 2016c). This differential in pricing occurs due to the high costs of transporting electricity along extensive regional networks to a sparsely populated consumer base. The average cost of supply in some regional areas can be 140% higher than the cost of supply in SEQ (QPC 2016b). In 2014-15, the cost of the UTP was approximately $600 million (QCA 2016a). As it is only provided to Ergon Retail, the one remaining government owned electricity retailer in Queensland, the ability of other retailers to compete against such highly subsidised prices is extremely limited (QCA 2016a).

It is these characteristics amongst others, that help to highlight the enormous potential of PV and battery energy storage in regional areas. When installed to support network objectives, the technology not only offsets the higher cost of electricity provision in regional areas but could also help to reduce the size of the UTP subsidy which reflects a broader benefit to the Queensland tax payer.

While Queensland households have historically been relatively high energy users, consuming on average approximately 7.5MWh per annum, average demand has declined in recent years to 6.1MWh (Simshauser 2016). In regard to tariff structures, almost all residential electricity consumers in Queensland are connected to the standard residential tariff (tariff 11) which includes a volumetric component and a fixed component. Two controlled load tariffs also exist (tariff 31 and 33) which provide cheaper power but they can only be used under certain conditions (e.g. for hardwired appliances such as electric hot water heaters) and at certain times of the day. Tariff 31 guarantees supply for only 8 hours a day whereas tariff 33 guarantees supply for 18 hours a day (DEWS 2017a).

Two new tariffs have been introduced more recently: a time-of-use tariff (tariff 12a) which imposes higher prices during peak times i.e. between 3 and 9.30pm; and a demand tariff (tariff 14) where charges are based on demand (kW) during peak periods but has lower volume (kWh) and fixed costs (DEWS 2017a). Uptake of these new tariffs has been limited with only 250 dwellings subscribing to the time-of-use tariff when it was released (Wardill 2014). Since then it is estimated only a very small proportion of Queensland households have signed up to either time-of-use or the demand tariff (Colmar Brunton 2017). The different pricing structures for all Queensland residential tariffs for 2016-17 are included in Table 2.

Retail tariff	***Fixed charge[a]***	***Usage charge (peak)***	***Usage charge (flat/off-peak)***	***Demand charge (peak)***	***Demand charge (off-peak)***
	c/day	***c/kWh***	***c/kWh***	***$/kW/mth***	***$/kW/mth***
Tariff 11 - Residential (flat rate)	89.572		24.610		
Tariff 12A - Residential (time-of-use)	101.306	55.865	19.859		
Tariff 14 - Residential (time-of-use demand)	60.514		14.984	61.790	11.258
Tariff 31 - Night rate (super economy)			14.423		
Tariff 33 - Controlled supply (economy)			19.960		

Source: (QCA 2016c)

Table 2 Queensland regulated regional residential retail tariffs 2016-17 excluding GST

5.1.2 Structural and institutional reform of the Queensland electricity sector

Prior to the introduction of competition reforms in the mid-1990s, Queensland's electricity supply system was controlled through the Queensland Electricity Commission and regional electricity boards that were responsible for the operation of vertically integrated and publicly owned infrastructure (DEWS 2013). In this environment, the provision of electricity was heavily subsidised but very cheap by OECD standards (DEWS 2013).

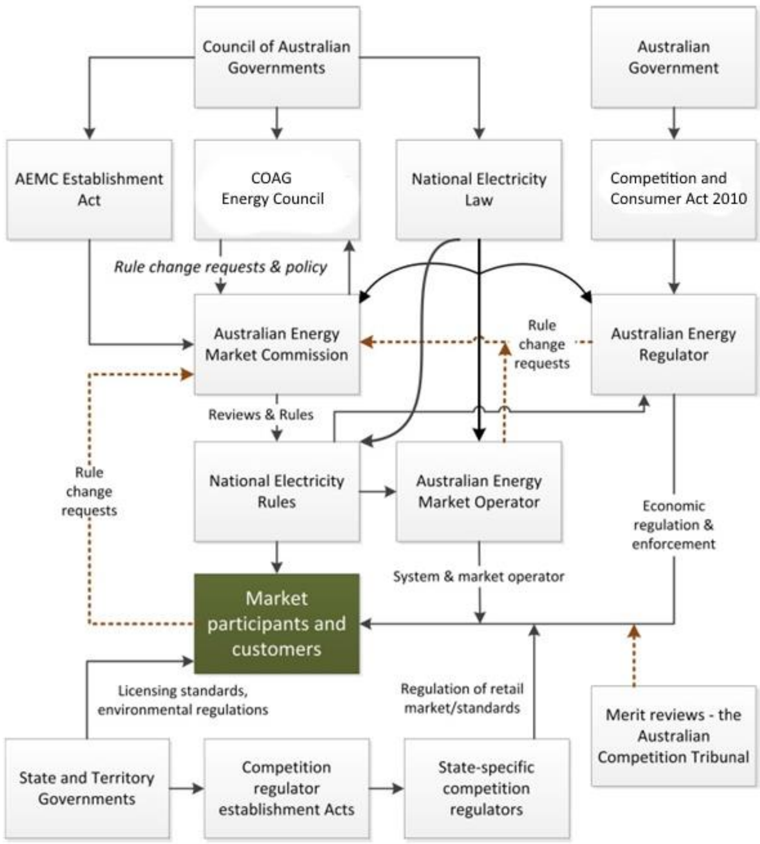
In 1998, Queensland became part of the NEM. The NEM is a wholesale spot market linking five jurisdictions (Queensland, New South Wales, Victoria, South Australia and Tasmania) with approximately $10 billion worth of electricity traded to meet the needs of more than nine million consumers (AEMO 2016c). The NEM has total generation capacity of 45,000MW with about 200 terawatt hours (TWh) of electricity traded each year (AEMO 2016c). Fossil fuels make up nearly 87% of total generation, which makes the emissions intensity of the system high at approximately 0.79 $tCO2_e$/MWh (CCA 2013; BREE 2014).

The NEM is unique in that it is one of the world longest interconnected power systems. The total length of the transmission and distribution network is approximately 800,000 km (AER 2013). Not only is maintenance and augmentation of this network costly, it is relatively inefficient with line losses of 10% across the system representing around 20TWh and 18 $MtCO2_e$ (DOI 2014). The potential benefits of distributed generation technologies, such as PV and battery energy storage, where generation occurs at point of use, are particularly significant in this regard.

A key feature of the NEM is the way in which supply is instantaneously matched to demand through a competitive wholesale pool. This works by way of a spot market where generation capacity is bid into a central dispatch system. The dispatch price is calculated every five minutes and averaged over each half hour to determine the spot price for each NEM region (AEMO 2016c). To determine the order of dispatch, the market operator stacks the bids of all generators and dispatches electricity from the cheapest generator to the most expensive until demand is met. The highest priced bid used sets the dispatch price and all bidders with generation dispatched are paid this price regardless of how they bid (AER 2015c). A consequence of this system is that if PV and battery energy storage are deployed at scale, reducing both average and maximum demand, this could decrease the frequency that higher priced generators bid into the market putting downward pressure on wholesale electricity costs (McConnell, Hearps & Eales 2013).

To demonstrate the volatility in the NEM, the maximum spot price allowed is currently set at $13,800/MWh whereas the market floor price is set at -$1000/MWh (AEMO 2016c). These price caps illustrate the high cost of critical peak demand events when the spot price hits its ceiling, particularly when compared with average wholesale electricity prices. For example, average wholesale prices in Queensland in 2014/15 were $61MWh (AER 2015c). The price at which the market floor is set also highlights the risks to utilities from periods of surplus electricity stemming from over-generation of renewable energy which can reduce prices or see them go below zero.

In addition to the operational and technical complexity associated with provision of electricity throughout the NEM, the underpinning regulatory framework is also highly complex. When taken together, this complexity illustrates the difficulties in understanding and planning for change in the sector. For example, regulation and governance of the NEM occurs through a national framework overseen by the Council of Australian Government’s Energy Council, which includes all Australian states and territories. The Energy Council provides direction to three national energy market institutions: the Australian Energy Market Commission (i.e. the rule maker and market developer), the Australian Energy Market Operator (the system operator) and the Australian Energy Regulator (economic regulator and rule enforcer) (ECRC 2015). The institutional arrangements for the NEM are illustrated in Figure 22 below.



Source: (Productivity Commission 2013a)

Figure 22 Institutional arrangements in the NEM (modified to reflect recent governance changes)

The regulatory framework is enshrined in the National Electricity Law (NEL) which informs the development of the National Electricity Rules (NER) that provide the detailed arrangements that govern the operation of the NEM. The NEL also includes the National Electricity Objective (NEO) which articulates the objective of the NEL to:

"promote efficient investment in, and efficient operation and use of, electricity services for the long term interests of consumers of electricity with respect to – price, quality, safety, reliability, and security of supply of electricity; and the reliability, safety and security of the national electricity system."(AEMC 2017, p. 1)

The NEO is important because it effectively articulates the policy rationale on which the Australian Government considers regulatory intervention in the market. For state-based jurisdictions however, the NEO must be considered in conjunction with state-based policy and legislative frameworks. This is because all jurisdictions in the NEM are able to derogate from national laws so that unique state requirements can be met.

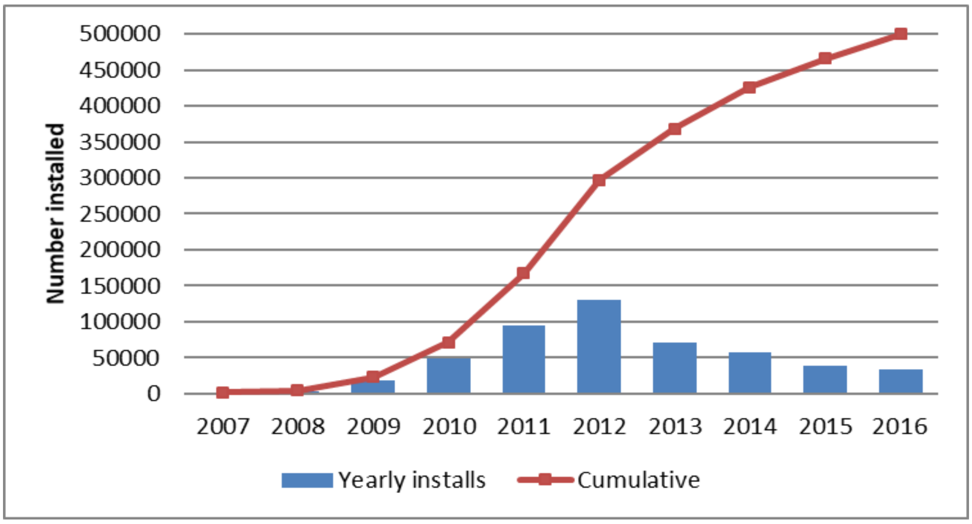
In this regard, the Queensland Government retains a number of specific policy and regulatory roles For example, Queensland administers the *Electricity Act 1994* which amongst other powers enables licensing of generation and network assets, sets minimum service standards for the number and length of power interruptions and provides for setting of notified prices for standing offer customers (Queensland Government 2017c). Small electricity customer disputes (*Energy and Water Ombudsman Act 2006*), electrical safety (*the electricity Safety Act 2002*) and electricity infrastructure planning (*Sustainable Planning Act 2009*) are also the responsibility of the Queensland Government (Queensland Government 2017c).

Furthermore, in early 2017, the Queensland Government released a long-term strategic energy policy with the objective of delivering "stable energy prices, ensure long-term security of electricity supply, transition to a cleaner energy sector and create new investment and jobs" (DEWS 2017b, p. 1). Despite the similarities between this policy statement and the NEO, the inclusion of a sustainability objective in the Queensland policy is worth noting. This is because there is no environmental or emission reduction objectives in the NEO, which has been a significant point of contention since its inception (Finkel et al. 2017). This distinction in policy in Queensland has important implications for the integration of low emission technologies into the existing supply system and development of an efficient transition pathway.

While the Queensland Government has less powers than it did in the past to regulate the sector, its changing role conflicts with public perception, which still sees the state government directly accountable for electricity prices (DEWS 2013). In addition, the role of government as owner of generation, network and retail utilities which return large dividends, can directly conflict with its responsibility to ensure the delivery of an affordable essential service. These factors can reduce consumer confidence in the electricity supply system and strengthen drivers for self-sufficiency and grid independence.

5.2 The rise of residential PV – drivers and implications for battery adoption

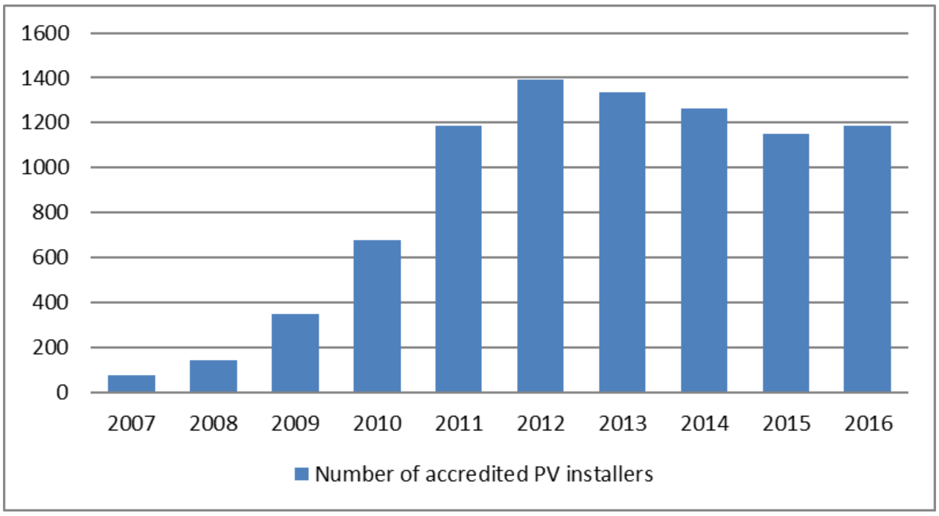
In Queensland, the exponential growth of PV was both unanticipated and unprecedented in terms of the rate and scale of adoption. Within the past 10 years, PV installs increased from less than 1000 in 2007, to just under half a million in 2017, comprising 1.5GW of capacity (Figure 23) (Clean Energy Regulator 2017). Nearly a third of dwellings have PV installed in Queensland making the state the Australian leader both in terms of total capacity and the proportion of homes with PV (APVI 2017b).



Source: data for graph from Clean Energy Regulator (2017)

Figure 23 PV growth in Queensland

The residential PV sector in Queensland is now considered a mature market (QPC 2016b).
At its peak in 2011-12, nearly 1400 solar installers were employed in the sector which included a total of 3520 direct full-time equivalent positions (QCA 2015b). The number of installers has since stabilised following the winding back of subsidy schemes during this period (Figure 24).



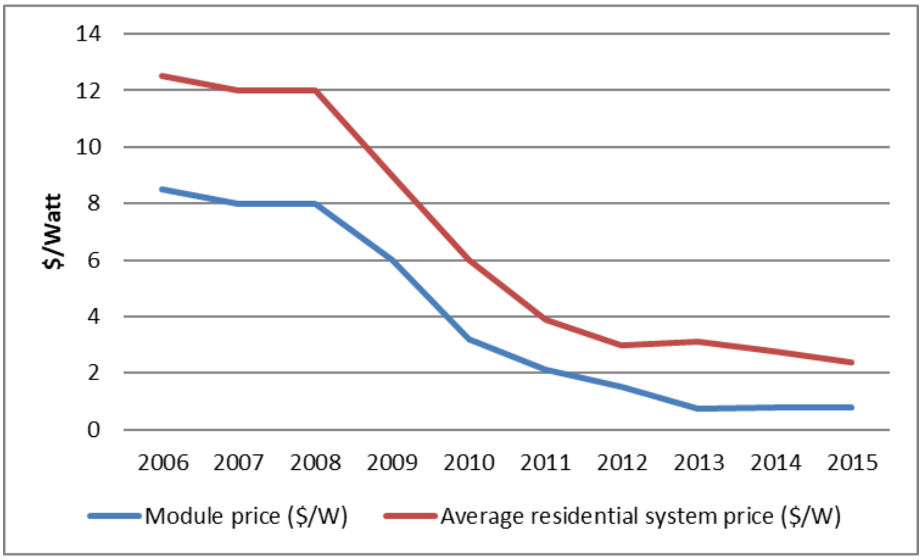
Source: data for graph from CEC (2017b)

Figure 24 Accredited PV installers in Queensland

The rise of residential PV in Queensland, in many ways epitomises the transformation and disruption that new demand side technologies pose. Understanding the factors that drove this growth is highly relevant when considering the adoption of residential battery energy storage. These drivers help illustrate the way in which structure and feedback dynamics can manifest in electricity transitions. Key drivers in this respect include: (1) PV system prices; (2) electricity prices; (3) rebates and subsidies; and (4) the changing role of the Queensland consumer.

5.2.1 PV install prices

Queensland, like many other countries around the world, was the beneficiary of rapid PV price declines. Driven initially by generous subsidy regimes in countries such as Germany, price declines further accelerated in response to technology advances such as better cell efficiencies, process improvements and manufacturing scale (Bazilian et al. 2013). As the local market developed rapidly in Queensland, there were further cost reductions associated with installation (in response to learning effects) and financing (as comfort increased in response to technology familiarisation). To illustrate the magnitude of declines, Figure 25 shows the unsubsidised price declines in module costs and total system costs in Queensland.

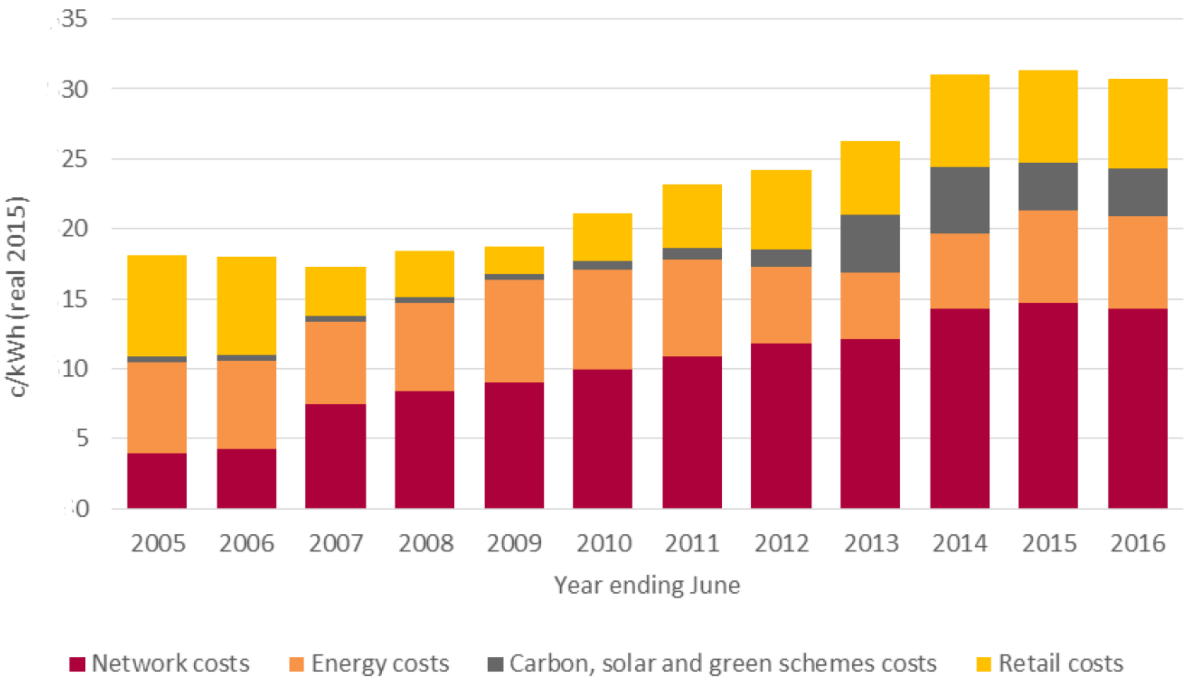


Source: data for graph from APVI (2016).

Figure 25 Unsubsidised module and total system install price declines.

5.2.2 Electricity prices

The retail price of electricity is a key determinant of PV adoption. It directly influences the scale of ongoing savings that consumers accrue from their PV systems. The relative contribution of each component of Queensland's electricity prices is illustrated in Figure 26.



Source: (QPC 2016a)

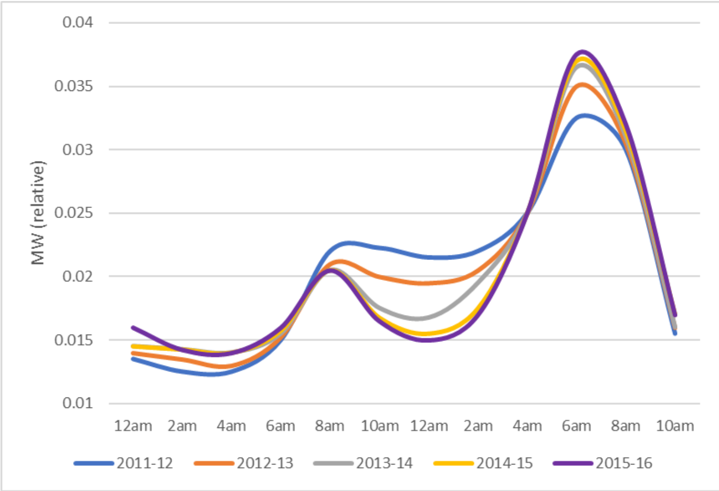
Figure 26 Cost breakdown of primary residential tariff

Prior to 2006, electricity prices in Queensland were low and increased generally in-line with the consumer price index (QPC 2015). However in the subsequent decade, electricity prices increased by nearly 110% (QPC 2015). A key driver was the impact of clean energy schemes. In 2015-16, the cost pass-through associated with the national RET and the Queensland premium FiT, the Solar Bonus Scheme (SBS), made up approximately 11% of a residential electricity bill with 8% attributed to the SBS and 3% to the RET (QCA 2015a). These policies not only provide a direct financial subsidy in their own right, but by helping to increase the price of electricity, further incentivise PV adoption. They are discussed in more detail in section 5.2.3 below.

An even larger contributor to electricity price increases were network costs. Since 2006, network costs increased by 243%, so that they now contribute around 45% to a typical residential electricity bill (QPC 2015). Network cost increases were driven by three main factors:

- Introduction of new reliability standards - In 2004, extreme weather saw severe storms and high temperatures cause network instability and outages. The public backlash resulted in a substantial investment in networks to increase resilience.
- Increasing peak demand - Population growth and the uptake of energy intensive appliances saw a large increase in peak demand requiring additional network investment. Peak demand increased by 104% in the 12 years to 2010, driven in part by a large increase in air conditioner ownership, from 23% to 72% over the same period (Simshauser, Nelson & Doan 2010).
- Cost of capital - The influence of the global financial crisis in 2008 exacerbated network price increases. Network businesses receive a regulated rate of return on their assets based on a Weighted Average Cost of Capital (WACC). In response to the volatility in financial markets impacting debt and equity markets at the time, the WACC for the network businesses was set at 9.72% for the 2010-15 regulatory determination period (QPC 2016a). This return was calculated against a regulated asset base worth approximately AU$15 billion. The large WACC (compared to 6.01% for the following regulatory period) and the corresponding increase in distributor revenues resulted in large electricity price increases (QPC 2016a).

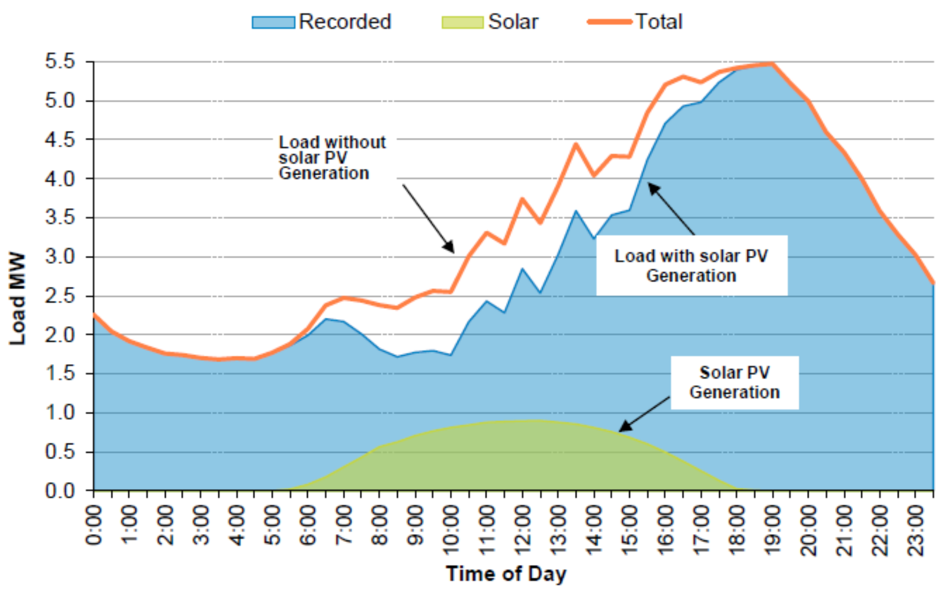
There is also increasing evidence that both the direct and indirect costs associated with integrating PV are influencing electricity prices. With PV growth continuing in Queensland, the 'duck curve' as described in Chapter 2 is becoming more pronounced. For example, since 2011, the net system load profile has seen a material decline during the day due to PV, while peak demand continues to increase (Figure 27).



Source: Adapted from QCA (2017a)

Figure 27 Energex net system load profile based on T11

In some areas this issue is acute. A network feeder in SEQ with 37% PV uptake saw energy demand decline by 22.9% while peak demand increased by 2.8% between 2009 and 2014 (Simshauser 2016). Peak demand represents an increasingly serious issue in terms of network utilisation with Energex estimating that 16% of its network has been built to meet a level of demand that occurs for the equivalent of 88 hours a year, while approximately 6% of Ergon's network is used for less than nine hours of the year (DEWS 2013). These dynamics drive a decline in asset utilisation while pushing up electricity prices. This is because critical peak demand events are the primary factor responsible for increasing network costs. PV has little effect on peak demand, and therefore contributes no material reduction in network costs (Nelson, Simshauser & Nelson 2012). This is illustrated in Figure 28, which shows how peak demand at a residential 11 kW feeder in Brisbane is unaffected by PV.



Source: (Energex 2016a)

Figure 28 Impact of PV at the feeder level at Kallangur on a peak day

Furthermore, high penetrations of PV in Queensland are causing a range of technical issues. Changes to power flow in the network, where PV generation reverses flow along the low voltage network, can require significant augmentation, the cost of which is passed back through to consumers as higher electricity prices (CEC 2015b). Energex has already reported an increase in customer complaints stemming from power quality issues and have forecast that in the next five years the number of distribution transformers likely to have power quality issues will rapidly increase (Energex 2016a). In recognition of these issues, the AER included an allowance of $25.3 million and $26.4 million for Energex and Ergon respectively to manage power quality issues; costs which are passed through to all electricity consumers, including those without solar (QPC 2016b).

5.2.3 Rebates and subsidies

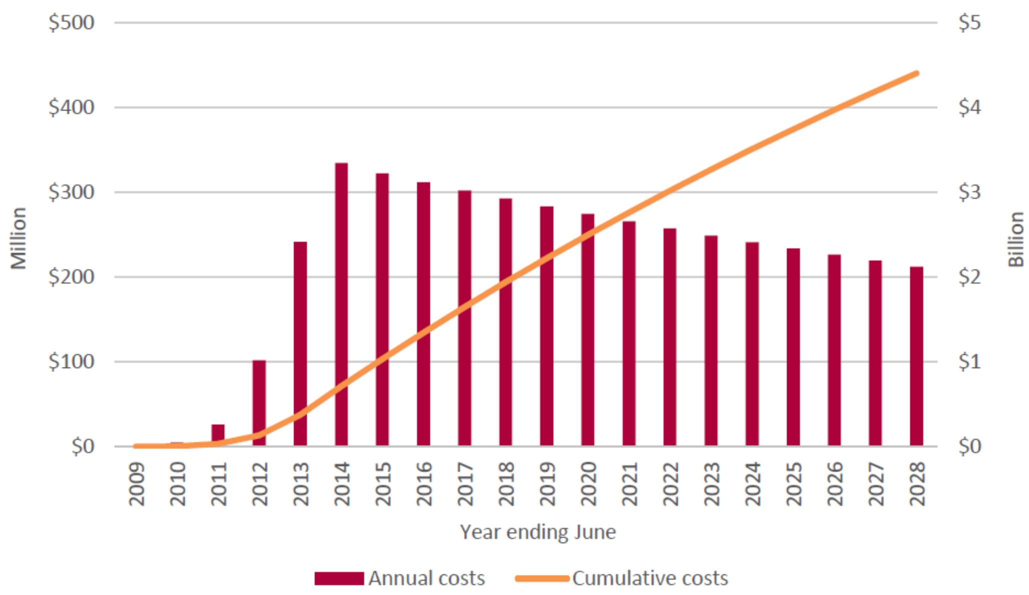
At the same time as electricity prices began to increase in Queensland, subsidies were introduced at both the national and state level aimed at encouraging PV uptake. The two primary incentive schemes included the national RET and the Queensland SBS.

The RET is a legislated, market-based mechanism that requires at least 20% of Australia's electricity supply to come from renewable energy by 2020. Following a review of the scheme in 2014, a revised target requiring 33,000 GWh of large-scale renewable generation was implemented, which if successful, would equate to approximately 23.5% of electricity generation coming from renewables in 2020 (Department of the Environment 2017). The scheme works by placing an obligation on retailers to buy a proportion of their electricity from accredited renewable sources. The RET included a Small-Scale Renewable Energy Scheme, which provided the equivalent of an upfront subsidy for PV in the form of small-scale technology certificates (STCs) based on the deemed generation of a system over 15 years. One STC is worth 1MWh of electricity and the price is either fixed at $40 or can be sold through the open market at the going price.

From July 2009, this scheme involved a multiplier effect so that the value of small-scale technology certificates were increased by 5 times which provided the equivalent of an upfront subsidy of approximately $7,500 (Climate Change Authority 2012). The size of this multiplier gradually reduced back to one from January 2013. Even with this reduction, the capital subsidy for the small scale renewable energy scheme came at a cost to electricity consumers of more than $4 billion between 2011 to 2013 alone (Origin 2014). This cost occurred at a time when module prices were dropping and helped drive rapid deployment, contributing to many of the financial and technical issues experienced by network participants.

The Queensland SBS is a premium net FiT introduced by the Queensland Government in 2008. The stated objectives of the SBS are to: "make solar power more affordable for Queenslanders; stimulate the solar power industry; and encourage energy efficiency" (QPC 2016b, p. 5). The SBS provided 44 cents/kilowatt hour (c/kWh), or roughly double the retail cost at the time, for any electricity not used in the home and sent back to the grid. More than 278,000 participants signed up to the SBS before it was closed to new applications in 9 July 2012 (QPC 2016a). Provided that participants maintain their eligibility, they will continue to receive the FiT until the scheme ends in 2028. For customers who signed up after the closure of the SBS, they were eligible for a transitional FiT of 8 cents/kWh which ran until 2014. After this time, customers in SEQ could negotiate a FiT directly with their retailer, while regional Queensland customers could access a FiT price set annually by the QCA (QPC 2016b, p. 5).

Although the SBS achieved its objective to encourage PV uptake, it did so at an enormous cost and represented a highly regressive intervention from a social welfare perspective (Nelson, Simshauser & Nelson 2012). The scheme is administered through the distribution network businesses with scheme costs passed through to all electricity consumers. This creates equity issues for consumers who do not have PV but are required to pay for the SBS through their electricity bills. In 2015-16, these costs added approximately $89 to a typical residential bill, with total scheme costs estimated to reach $4.4 billion by 2028 (Figure 29) (QPC 2016b).



Source: (QPC 2016b)

Figure 29 Annual and cumulative costs of the Solar Bonus Scheme

The scheme also resulted in a number of unintended consequences. The generous nature of the subsidy saw a rush effect resulting in exponential PV growth. This caused a boom-bust scenario for the industry which resulted in poor industry practices and the installation of substandard systems (Eadie & Elliott 2013). The scheme also encouraged households to maximise their export to the grid (to increase the value of the incentive) which exacerbated many of the technical issues while locking in certain undesirable consumption patterns (i.e. increasing export to the grid) for as long as a household remains subscribed to the scheme.

With rebates and subsidies already being introduced around the world to encourage battery storage uptake, there remain important lessons to be learned from the way in which subsidies were applied for PV and their broader impact on the community. These issues are considered in more detail as part of consideration of policy implications in Chapter 8.

5.2.4 Understanding Queensland electricity consumers

As described above, unprecedented PV growth in Queensland was clearly driven by a number of structural elements relating to technology-specific advances, policy interventions and broader electricity supply sector dynamics. It was however, the Queensland residential electricity consumer that was central to this growth and ultimately responsible for the rate and scale of PV adoption in Queensland. With battery energy storage poised on the cusp of a similar trajectory as PV, understanding the characteristics of the increasingly engaged electricity consumer is crucial.

There exists a substantial body of research that aims to better understand electricity consumers and their relationship with the electricity supply sector (Stern 1992; Wilson & Dowlatabadi 2007; Caird, Roy & Herring 2008; Boughen, Castro & Ashworth 2013; Romanach, Contreras & Ashworth 2013). In recent years, research examining consumer preferences and drivers related specifically to PV adoption has also expanded considerably (Bollinger & Gillingham 2012; Sigrin, Pless & Drury 2015) (Rickerson et al. 2014; Dharshing 2017; Reeves, Varun & Robert 2017). These studies aim to better understand consumer decision making from a financial, social and behavioural perspective using theoretical frameworks such as behavioural economics and diffusion of innovations (Sigrin, Pless & Drury 2015). As there is currently very limited research regarding the role and preferences of the consumer in battery adoption, these studies provide a useful foundation to draw generalised assumptions about consumer drivers.

What these studies find is that consumers are motivated to adopt distributed generation technology for a variety of reasons. In recognising that financial drivers are a key determinant for mass market uptake of demand-side energy technologies, these studies also find that there is substantial evidence to suggest that consumers' "motivations and actions on household energy are more complex than suggested by a rational model of decision making based on information, regulations and economics" (Caird, Roy & Herring 2008, p. 150).

A review of the aforementioned studies revealed a range of common non-financial drivers that could underpin a residential consumer's decision to install PV and battery energy storage. This includes motivations to:

- minimise emissions or reduce environmental impact from energy use;
- reduce reliance on the grid to insulate against possible future price increases while minimising concerns about long-term energy security issues, particularly in regards to those associated with energy commodities that are outside the consumer's control;
- have greater control over all aspects of energy use, including both how it is used, how much is used and how it is produced;
- achieve reliability and resilience outcomes. For example, consumers may seek alternative energy supply solutions to minimise the impact of blackouts or to increase individual household resilience to possible climate change or terrorism impacts on existing centralised electricity supply systems;
- minimise exposure to electricity sector incumbents in response to increasing frustration and dissatisfaction with the broader utility sector. This is stemming from electricity price increases, new rules (particularly where they restrict or penalise distributed generation adoption), perceived profiteering, and broader shifting public perception;
- achieve status and prestige outcomes associated with advanced energy technologies; and/or
- access government subsidies.

For Queensland, many of these non-financial drivers have been reinforced in recent years. For example, the electricity price spike of the past decade, means that electricity costs have become a source of significant concern for many households. The results of a recent ongoing quarterly consumer survey found that the price of electricity remains the number one cost concern for 80% of consumers (Choice 2016). The ability to afford future electricity price rises represents an important motivator to implement measures now, such as installing PV and battery energy storage, to minimise future exposure (QPC 2016a).

Electricity price increases in Queensland have not only served to improve the financial case for new distributed generation technologies but has also underpinned a growing frustration with incumbent utilities and mistrust of the government. In 2015, a national survey found that electricity utilities were one of the least trusted sectors in Australia (Browne 2015). This is supported by surveys in Queensland, one of which found that only 5% of respondents thought the network businesses were acting in the best interests of consumers (Agnew & Dargusch 2017).

The public perception of network overinvestment, commonly referred to as gold plating, has been a key driver in this regard. While it is argued that the growth in network spend was in response to government mandated reliability standards and was based on forecast demand data (that later proved to be incorrect), it is the perception that networks have expanded their assets to increase profits, knowing that the costs will be passed through to consumer, that has prevailed (ECRC 2015).

The impact of this practice has been reinforced by extensive media coverage. A Senate inquiry on the issue found that high network costs had increased the burden on households and businesses as "a result of perverse incentives in the regulatory rules that encourage significant investment in an electricity network that may not be used to the same extent in the future" (ECRC 2015, p. 18). The Inquiry found that these dynamics encouraged consumers to seek out ways to reduce energy consumption and directly encouraged uptake of distributed generation, with access to battery energy storage likely to further change consumer behaviour in this regard (ECRC 2015).

Consumers have also raised concerns that the network businesses discriminate against households with solar by increasing fixed charges and putting barriers in place to connection, such as limiting system size and imposing additional charges (ECRC 2015). The reduction and phase out of some premium FiTs and the perception of unfair pricing for electricity exported back to the grid from solar PV are also factors (ECRC 2015; Solar Citizens 2015).

While some of these claims are unwarranted, they nonetheless create negative perceptions which can have a strong influence on consumer perception and behaviour. A survey for Ergon Energy found that its brand had been damaged in response to a reduction in FiTs wrongly attributed to the company (Ergon Energy 2015). In addition, applications for PV that were declined by Ergon, regardless of the reason also impacted negatively on public perception (Ergon Energy 2015).

Despite these insights, the understanding of consumer behaviour regarding preferences and drivers for battery energy storage in Queensland remains limited. There is only one study to date that specifically examines consumer motivations and how they relate to battery attributes and functionality in Queensland (Agnew & Dargusch 2017). The study used stated preference data and choice modelling to make inferences regarding the specific financial and non-financial factors that could motivate battery uptake. The study involved 268 participants from a primarily early adopter demographic and included a discrete choice experiment (DCE). Estimation of part-worth utilities from the DCE determined the relative importance of battery attributes for each respondent such as cost, size, payback etc. These utilities were then cross-referenced with participants attitudes and beliefs to better understand the influence of non-financial motivations on preferred battery attributes (Agnew & Dargusch 2017).

Several important conclusions were made in the study. A majority of respondents were highly supportive of battery energy storage technology with a high stated intention to install a battery system in coming years. Cost was unsurprisingly the most important individual driver. However, when considered collectively with other battery attributes (i.e. as part of the total system ‘utility’), the study found most respondents preferred medium or larger batteries, which require higher upfront costs with longer payback periods when compared with small, cheaper batteries. These outcomes correlated with respondent’s non-financial attitudes and beliefs regarding support for the environment, negative perception of incumbents, desire for resilience and concerns about future electricity price rises. Interestingly the demographics of the survey sample, while not precisely representative of the entire Queensland population, was characteristic of an early adopter demographic. This result, when considered through the lens of diffusion of innovation theory, reflects the early stage of battery market development but also suggest important implications for technology path dependency.

Prior to this study, the only information on consumer battery preferences in Queensland were found in general energy surveys. For example, a study by Colmar Brunton (2015) which surveyed a representative sample of Queensland consumers on their household energy use characteristics included a small number of questions related to battery storage. The findings indicated that consumers will be motivated to purchase storage to help prevent the impact of rising electricity bills and to achieve self-sufficiency (Colmar Brunton 2015). The primary barriers to uptake were a lack of information, the cost, and a lack of home ownership. The survey also found evidence of rising interest in battery storage but purchase intent was still low (Colmar Brunton 2015).

5.3 Battery energy storage in Queensland – the current state

As discussed previously, many of the preconditions for battery energy storage adoption are already in place in Queensland. However, as is the case globally, the residential battery market is still at the very earliest stages of development. The most recent market data suggests that Queensland has approximately 2000 residential battery systems installed comprising nearly 15MWh of capacity representing 29% of all such installations in Australia (CEC 2017b). While this represents only a tiny fraction in terms of eligible dwellings, a number of recent forecasts suggest that battery uptake will increase substantially in Queensland in coming years.

Modelling undertaken for the Queensland Productivity Commission in 2016 forecast that approximately 130,000 residential *and* commercial battery systems would be installed in Queensland by 2034-35 representing 900MWh of storage (QPC 2016a). This can be compared with a study by AEMO (2015c) which found that residential and commercial storage would reach 2046MWh of capacity by 2034-35 representing more than 300,000 residential and battery systems. The most recent study was undertaken by CSIRO (2017) which projected 10,000MWh of storage in Queensland by 2030, comprising 760,000 residential battery energy systems.

Clearly there is a wide spectrum of results from each of these studies which reflect the variation in underpinning assumptions. In this respect, assumptions were only publicly available for the AEMO and CSIRO studies. The AEMO study listed a number of important limitations. For example, it only considered the uptake of new installations of PV and batteries with no inclusion made for retrofitting existing PV dwellings with a battery. In addition, adoption was based on financial metrics only with no inclusion of non-financial motivations. These limitations suggest that the AEMO forecasts are likely to be conservative.

The CSIRO study is extremely comprehensive and does include assumptions regarding consumer behaviour. However, inclusion of behavioural aspects appeared to be based purely on a logistic curve which incorporated behaviour from an economic point of view, and did not appear to include endogenous feedbacks that might reinforce particular non-financial motivations. In addition, assumptions in the model regarding specific Queensland drivers, such as the impact of the premium FiT over time on battery adoption, appear not to have been taken into account.

This is important because consumers subscribed to the FiT are less likely to install batteries due to loss of income from exported electricity. While the scheme is closed to new applicants, there currently remain more than 200,000 Queenslanders subscribed, which means if they remain eligible, they can continue to receive the FiT until 2028. Finally, the assumptions underpinning saturation in the CSIRO model appear to be very high with one scenario assuming 90% residential uptake (Graham 2015). In many other models, this is typically around 75% (AEMO 2013). This means that the magnitude of PV and battery installs in the CSIRO forecast could be overstated.

In recognition of the potential risks and opportunities associated with battery energy storage should the above forecasts come to pass, Queensland's distributors and retailers are currently undertaking a number of trials to determine the impact of batteries on the sector and to evaluate the specific characteristics of technologies in the Queensland context. Energex, for example, has installed several batteries in SEQ and is looking at their impact on peak demand and power quality in residential areas (Energex 2017). Ergon Energy Retail has installed PV and batteries in 33 homes across regional Queensland to test the efficacy of new business models. This involves customers entering into a long-term contract in which they pay a monthly fee to the retailer but no upfront cost for the system; in return they save money on their electricity bill and the company uses the battery remotely to manage load curtailment (Ergon Energy 2017). These trials are also being used to test battery safety, operation and functionality.

Chapter 6 Causal loop modelling – understanding the behaviour of the system

Overview of chapter

The purpose of this chapter is to describe the use of causal loop modelling to show the structure and dynamics that could underpin battery storage adoption in Queensland. It provides a detailed description of the methodology used to collect data and describes how key variables were mapped, and the causal relationships between them defined, to inform the creation of a causal loop model. The results of this stage of research are then considered in terms of battery diffusion dynamics and how they could influence broader electricity sector outcomes. This chapter also provides the basis for future empirical analysis using a system dynamics simulation model.

Citation

Agnew, S. Smith, C. Dargusch, P. (2017) Causal loop modelling of residential solar and battery adoption dynamics: a case study of Queensland, Australia, *Journal of Cleaner Production* (In Press)

6.1 Introduction

Centralised electricity supply systems are experiencing rapid and material change in response to a confluence of climate policy, technology development and the rise of the ‘engaged’ electricity consumer. The unprecedented growth of residential solar photovoltaics (PV) epitomises this transition. In just over a decade, global PV capacity has increased from approximately 1.3 gigawatts (GW) in 2000 to nearly 230 GW by the end of 2015 (EPIA, 2014; IEA, 2016b).

Despite its many benefits however, the rapid integration of PV into existing centralised electricity systems has not always been ideal. Two-way power flows, voltage fluctuations and intermittent generation have negatively impacted power quality in areas of high PV density (Eltawil & Zhao 2010; Passey et al. 2011; Noone 2013). At the same time, falling electricity volumes have challenged traditional revenue recovery mechanisms resulting in increased electricity prices, cost-shifting and in some cases, negative social equity outcomes (Rickerson et al. 2014; Simshauser 2016).

Residential battery energy storage systems represent the next wave of consumer-led energy technology that could exacerbate electricity sector disruption. Battery energy storage with PV enables consumers to reduce the volume of electricity they use from the network, shift the times they use the network or disconnect from it entirely (Agnew & Dargusch 2015). This represents a paradigm shift for traditional centralised electricity supply systems, which generally require instantaneous balancing of supply with demand.

While high costs in the past have hindered residential battery uptake, recent multi-billion dollar investments in technology development and manufacturing have seen dramatic price declines. In early 2015, electric vehicle manufacturer Tesla announced pricing for new home battery energy storage solutions that substantially undercut all previous price expectations (RMI, 2015b). In 2016, Tesla upgraded its home battery system by doubling the usable capacity and including an integrated inverter (Tesla 2016). The new system, selling at approximately the same price as the original, represents an effective halving of costs in terms of price per kilowatt hour.

Other battery manufacturers have also mobilised and a range of new competitive battery products and services have been released. At the same time, governments have implemented subsidy arrangements while innovative financing approaches have helped reduce high upfront capital costs (AECOM 2015). These developments have seen battery learning rates (i.e. the reduction in cost for every doubling of cumulative installed capacity) exceed 20% since 2010 (IEA 2016a). While the extent to which battery prices will decline remains uncertain it is estimated that costs could decline to $US100 per kWh by 2040, with the US Department of Energy suggesting they could fall to as little as $US80 kWh (IEA 2016d). With these factors coalescing, much like they did for PV more than a decade ago, it is likely that mass market uptake of residential battery energy storage will be possible within the next decade (Byrd et al. 2014; EPRI, 2014; Koh et al. 2014; AECOM 2015; IRENA, 2015).

Should this occur, the implications for the physical electricity supply system, the financial markets that underpin them and future power system design are substantial (PWC, 2014). For example, consumers seeking self-sufficiency will be able to install PV and battery systems that substantially reduce their reliance on the existing network. At scale, this will drive sector-wide demand reductions that will increase electricity prices (as predominately fixed costs are recovered overs smaller volumes of electricity), which in turn encourages more consumers to further reduce electricity demand (Simshauser & Nelson 2012). For those consumers who are unable to change their electricity consumption patterns or install demand-side technologies, rising electricity costs will have a disproportionate and inequitable impact (Simshauser & Nelson 2012) .

At the same time, these dynamics will drive poor asset utilisation and impede future planning and investment, which will weaken the long-term viability of incumbent businesses and the stability of the electricity market. In many modern electricity supply systems, generation and network assets represent multi-billion dollar investments that have been paid for, or heavily subsidised by taxpayers. Poor utilisation, falling dividends and asset impairment can therefore have broader socio-economic impacts.

These risks have received considerable industry attention and an extensive body of research is emerging. Studies include those relating to technical and system optimisation (Castillo-Cagigal et al. 2011; Hammond & Hazeldine 2015; Ratnam, Weller & Kellett 2015a), economic implications (Hoppmann et al. 2014; Ratnam, Weller & Kellett 2015b; Mundada, Shah & Pearce 2016), environmental issues (McManus 2012; Fares & Webber 2017) and policy and regulatory integration (Rickerson et al. 2014; AEMC 2015).

A fundamental gap in the academic literature is an assessment of battery adoption dynamics from a whole-of-system perspective, reflecting the multi-causal, socially complex nature of the problem. This gap exists in part because energy systems, despite being frequently conceptualised and modelled as techno-economic phenomenon, are socially driven and socially embedded systems characterised by 'messy' real-world complexity (Miller, Richter & O'Leary 2015). Traditional econometric models that assume consumer objectivity and rationality fail to incorporate this distinction (Byrne et al. 2002).

Instead, transdisciplinary techniques are required that are "capable of grasping the big picture, including the interrelationships among the full range of causal factors underlying them"(APSC, 2012). In this respect, a "systems thinking" approach is well suited to the task.
Systems thinking is a process for establishing the relationship between system behaviour and system structure (Forrest 2008, p. 333). It provides a conceptual framework and the empirical tools to better understand dynamic complex systems while bridging the gap between the sciences and humanities to connect often seemingly incongruent variables (Hjorth & Bagheri 2006).

In this paper, we use systems thinking theory to identify some of the ambiguous and multi-dimensional problems that relate to the adoption and integration of residential PV with battery energy storage. We develop a dynamic hypothesis using causal loop modelling based on extensive interview data sourced from participants along the electricity supply chain. To our knowledge this is the first time primary interview data collected as part of the study has been applied to map the complex dynamics associated with residential battery adoption. This is an important step in conceptualising and understanding complexity as it helps create "a framework for seeing interrelationships…for seeing patterns of change rather than static snapshots" (Senge 2006, p. 68).

We use the state of Queensland Australia as a case study to model these dynamics. With some of the highest per capita PV installations in the world, a well-established solar industry, ongoing PV growth and high electricity prices, it has many of the preconditions necessary for rapid battery uptake (AEMO, 2014b). As Queensland's centralised electricity sector comprises assets worth more than $AU30 billion, disruption to this system has the potential to result in substantial negative economic, environmental and social impacts. This makes Queensland an excellent target to apply a systems thinking methodology, particularly as the residential battery energy market is currently at an embryonic stage of development and there exists very little market data and limited primary research regarding adoption dynamics.

This paper is structured as follows: Section 2 describes the method used for data collection, an explanation of how the data was used to address the research objectives and a description of the case study area. Section 3 comprises the results used for problem articulation, creation of a sub-system diagram (i.e. an overview of the system architecture) and formulation of a dynamic hypothesis using causal loop modelling. Section 4 concludes with a summary on the broader implications of the research.

6.2 Methods

We apply systems thinking theory to help explain the structure and dynamics underpinning battery energy storage adoption and integration in Queensland. Systems thinking uses feedback theory to develop a testable hypothesis, referred to as a dynamic hypothesis, that explains past and future system behaviour. In the development of this hypothesis, systems thinking works best when it takes multiple perspectives into account by engaging people who work within and manage the system under study (Cabrera, Colosi & Lobdell 2008).

To date, systems thinking has been used to analyse a range of energy policy challenges such as emissions reduction, energy conservation and market liberalisation (Teufel et al. 2013; Leopold 2015; Qudrat-Ullah 2016). Systems thinking is well suited to these applications as "energy systems have many of the properties that can be described easily using system dynamics models: for example, nonlinearities (such as resource depletion), stocks and flows (of resources and capital), feedback loops (primarily through price), emphasis on dynamic behaviour, and the need for policy analysis" (Naill 1992, p. 17). The International Energy Agency (IEA) specifically identifies systems thinking as a framework to help transition to future energy systems. The IEA state that for disruptive technologies such as residential battery energy storage, the use of systems thinking could help to increase efficiency, resilience and the economics of the entire energy infrastructure (IEA, 2014a).

Successful application of a systems thinking approach typically involves a number of stages. These are: 1) problem articulation, 2) formulation of a dynamic hypothesis (causal loop modelling), 3) formulation of a quantitative simulation model, 4) testing and validation, and 5) policy design and evaluation (Sterman 2000; Maani & Cavana 2007). As the objective of our study is to develop a holistic understanding of the dynamics underpinning adoption and integration of residential PV and battery energy storage, we implement the first two stages. This work can then be used to provide the foundation to address the remaining three stages, particularly the design of a stock-and-flow simulation model to empirically model the system.

Problem articulation helps to clarify the purpose of the research while defining the boundary and scope of work (Sterman 2000). Articulating problems can be challenging in the electricity sector, as stakeholders frequently have misaligned or conflicting strategic objectives and therefore assess risk and impact differently. In systems thinking, the term *dynamic hypothesis* refers to a working theory of how a problem arises and provides an explanation "characterising the problem in terms of the underlying feedback and stock and flow structure of the system" (Sterman 2000, p. 95).

Our dynamic hypothesis is the product of two elements. We create a subsystem diagram, which shows the overall architecture of the system and is useful for visualising the main subunits and their relationship to each other (Sterman 2000). Causal loop modelling is then used to create causal loop diagrams (CLD) that explicitly portray the feedback structure between variables. CLDs develop an endogenous explanation of system behaviour that allow system archetypes and leverage points to be identified for policy intervention (Maani & Cavana 2007). A strength of CLDs is that they challenge entrenched mental models and test assumptions; in doing so the process can lead to important and sometimes counterintuitive insights about system structure and behaviour (Hovmand 2014).

In regards to notation used in causal loop modelling, CLDs comprise variables (words or phrases) that have cause and effect relationships. A pair of variables within a CLD are related using an arrow, and this arrow is assigned a polarity in the form of a '+' (same) or a '-' (opposite) to indicate the nature of the cause and effect relationship. A '+' polarity indicates that cause and effect move in the same direction (i.e. if the cause increases, the effect also increases). A '-' polarity indicates that cause and effect move in opposite directions (i.e. if the cause increases, the effect decreases). The cause and effect relationships between pairs of variables form causal chains, and when these chains start and end at the same variable they form a feedback loop. Feedback loops can be reinforcing (R) or balancing (B). Reinforcing loops accelerate change within systems to produce growth or decline, while balancing loops counteract change within systems to produce stabilising behaviour.

To support the development of our dynamic hypothesis, grounded theory techniques were used for data collection and analysis. Grounded theory is the discovery of theory from data that is systematically obtained and analysed as part of the research process (Glaser & Strauss 2009, p. 2). It is a commonly used approach in systems thinking, particularly where substantial complexity exists and can be particularly useful where there is limited quantitative data available. The following sections outline the method for (1) data collection, (2) an explanation of how this data was used in problem articulation and the formulation of a dynamic hypothesis, and (3) a description of the case study area.

6.2.1 Data Collection

The primary data collection process involved expert interviews supported by a review of secondary data including industry and academic literature. For our study, data collection was undertaken in collaboration with the Queensland Government Department of Energy and Water Supply. The data collection approach involved:

- *Stakeholder identification* – a systematic approach to stakeholder identification and prioritisation was adapted from Elias *et al* (2001). This included creation of a stakeholder map that showed key categories along the supply chain. For our study we interviewed regulators and policy makers from national, state and local governments; representatives from the electricity supply chain (including generators, network service providers and retailers); new market entrants; technology developers; PV and battery installers; and consumer advocacy groups and consumer representatives. Based on these categories, and to ensure a representative sample was included in the study, relevant organisations were assessed and participants were identified based on subject matter expertise and authority.
- *Participant engagement method and ethics* – following initial contact, and prior to meeting, study participants were provided with a range of supporting material. This included project context, high-level questions to help frame and stimulate discussion and scenarios of possible future storage uptake to help challenge mental models. This material was tailored for each of the key supply chain categories. A participant consent form was also provided. Due to the requirement for human participation in this study, ethical clearance was received from the University of Queensland's School of Geography, Planning and Environmental Management.
- *Interview approach* – a semi-structured interview approach was used that has proven to be effective in systems thinking applications (Sterman 2000). While a script was developed for the

research team that included a number of pre-set questions, the interviewer was able to deviate from the script at any time to pursue areas of relevance in greater detail. Interview questions were structured to help with problem articulation and to identify key feedback loops and other important causal relationships. This technique is particularly well suited for use in causal loop development as it can help provide predictive, explanatory and enduring descriptions of the dynamic behaviour in a system (Yearworth & White 2013). Experts were either interviewed individually or in small groups according to stakeholder category. A dedicated scribe manually recorded the outcomes of each meeting. To ensure confidentiality and encourage meaningful input, neither participants nor specific organisations were identified. Instead, data was collated and referenced according to stakeholder category.

6.2.2 Data analysis

In total, 68 stakeholders were interviewed. The method used for data analysis was adapted from Kim and Andersen (2012), which describes an approach to systematically code qualitative data for a systems thinking methodology. The high-level hierarchy for our study was structured accordingly to those stakeholder elements along the supply chain that could influence battery adoption dynamics. Effectively, this hierarchy reflected each of the specific stakeholder groups included in the consultation process (Figure 30).

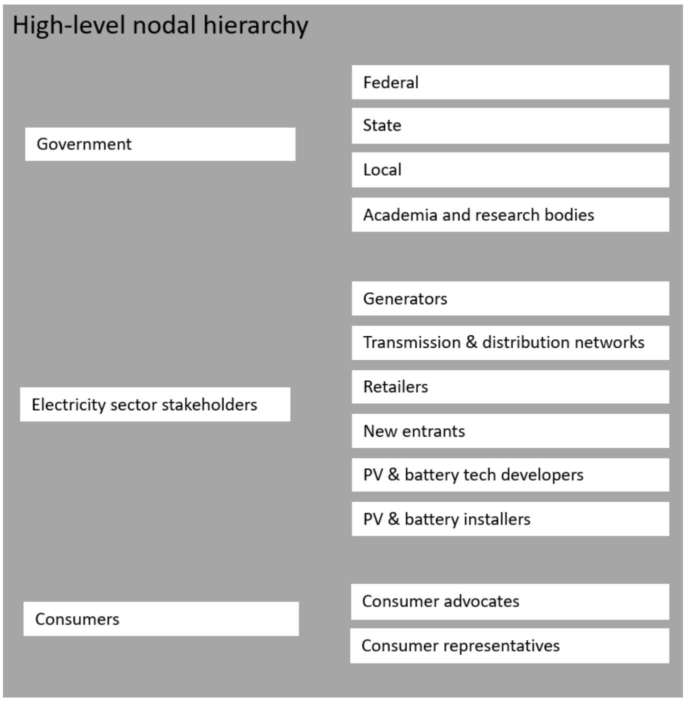


Figure 30. High-level nodal hierarchy based on stakeholder groups

The first step in our approach involved thematic content analysis and open-coding of data for problem definition and identification of the system boundary (Kim & Andersen 2012). This step involved extracting and grouping concepts, or codes, from the interview data according to key words and phrases based on the hierarchy described above. Codes were determined and defined primarily by the research context. In this case, we used both *in vivo* codes (i.e., descriptions sourced directly from the interviews) and codes based on commonly used terms sourced from the literature (Kim & Andersen 2012). The concepts extracted from this analysis were used in problem articulation and boundary setting (see Table 3 in results).

The second step involved identifying key variables and their causal relationships by extracting single units of analysis that relate to the system's structure or behaviour (Kim & Andersen 2012). This involved breaking the data down further into sub-categories, or child nodes, representing a far more granular representation of the system being modelled. Within these sub-categories, specific variables were identified from the data. Memos were used to record key aspects of analysis associated with each variable[3]. They included the initial observation and an explanation describing the variable and its relevance based on the theory that emerged from the interview data. Each memo also detailed the key causal relationships and explicit feedback loops associated with the variable.

All variables and memos were reviewed and validated by examining a range of secondary data sources including relevant government, industry and academic research. The variables and associated memos were then directly translated into a CLD. The CLD was built using Vensim PLE, a software package designed for developing and analysing dynamic feedback models. Throughout its development, the CLD was reviewed and verified by academic and industry stakeholders.

6.2.3 Description of the case study area

The state of Queensland in Australia has more than 1.8 million residential consumers and 200,000 commercial customers serviced by 16 retailers (QPC, 2016b). While there is limited publicly available market data regarding the uptake of residential battery energy storage in Queensland, the status of PV deployment is well reported. PV installations in Queensland increased from less than

[3] Memos are commonly used as part of the coding process and is simply a record or product of analysis

1,000 in 2008 to more than 400,000 in early 2016 equating to nearly 1.5GW of capacity (QPC, 2016b; APVI, 2017b). This growth was driven in part by rapidly falling module costs, generous upfront government subsidies and a premium net feed-in tariff (FiT). The FiT was introduced in 2008 and provided 44 cents/kilowatt hour (c/kWh), or double the retail cost at the time, for any electricity sent back to the grid. Queensland now has the most PV installed of any state in Australia and with PV installed on nearly one third of all homes, has some of the highest per capita installation rates in the world.

Almost all Queensland consumers receive their power from a capital (and emissions) intensive centralised electricity supply systems with large transmission and distribution networks that connect generators with end-users. Queensland's generation fleet is primarily coal (59%) and gas (26%) with two government owned corporations controlling approximately 65% of the generation market (QPC, 2016b). No new generation capacity is likely to be needed in Queensland at least until 2024-25 (AEMO, 2015b). Queensland has an extensive electricity network comprising two government-owned companies that individually manage transmission and distribution. These monopoly businesses are regulated under a revenue cap administered by the Australian Energy Regulator that sets the maximum allowable revenue in every five year regulatory period (QPC, 2016b). Network costs comprise the largest component of retail tariffs, contributing approximately 50% of the final cost of electricity for small customers (QCA, 2015c).

6.3 Results and Discussion

6.3.1 Problem articulation

Analysis of stakeholder input revealed a number of key themes relating to possible problems and issues associated with the integration of residential PV with battery storage. The concepts extracted from this analysis were ordered according to three broad stakeholder groups (Table 3). Study participants acknowledged that mass-market uptake of battery storage will create winners and losers in the market. However, it is the extent to which these dynamics manifest in supply chain inefficiencies (both operational and financial) and the corresponding influence on the end-use consumer (in terms of access to reliable and affordable electricity) that is relevant from a broader socio-economic perspective. How these issues may arise, and the behaviours that could support inefficient integration of battery storage, are considered in more detail in the following sections.

Government	Electricity sector stakeholders	Consumer
• Complexity/pace of reform • Risk of politicised, poorly targeted intervention • Asset ownership and role as shareholder • Ongoing provision of essential service • Consumer protections	• Asset utilisation and impairment • Technical challenges • Revenue recovery • Regulatory impediments • Barriers to competition • Incumbent viability	• Equity • Impacts on vulnerable customers • Consumer protections and safety • Electricity affordability • Complexity and literacy

Table 3 Problems identified by stakeholders that could impede efficient integration of solar with storage.

6.3.2 Subsystem diagram

The subsystem diagram demonstrates the high-level causal dynamics at play between the consumer, the electricity supply sector, the market and government (Figure 31). It shows how consumers, responding to both financial and non-financial motivations, will select home battery systems that will impact on the demand and load profile of the existing electricity supply system. This in turn will change market dynamics prompting a strategic response from existing supply chain participants. The nature of this response, the emergence of new entrants and the extent to which government intervenes to achieve social-good outcomes will in turn influence continued storage uptake and its future impact on the market. While the subsystem diagram helps define the model scope and boundary, the next stage of the process (i.e. the development of a CLD), more explicitly describes the key feedback loops influencing the behaviour of the system.

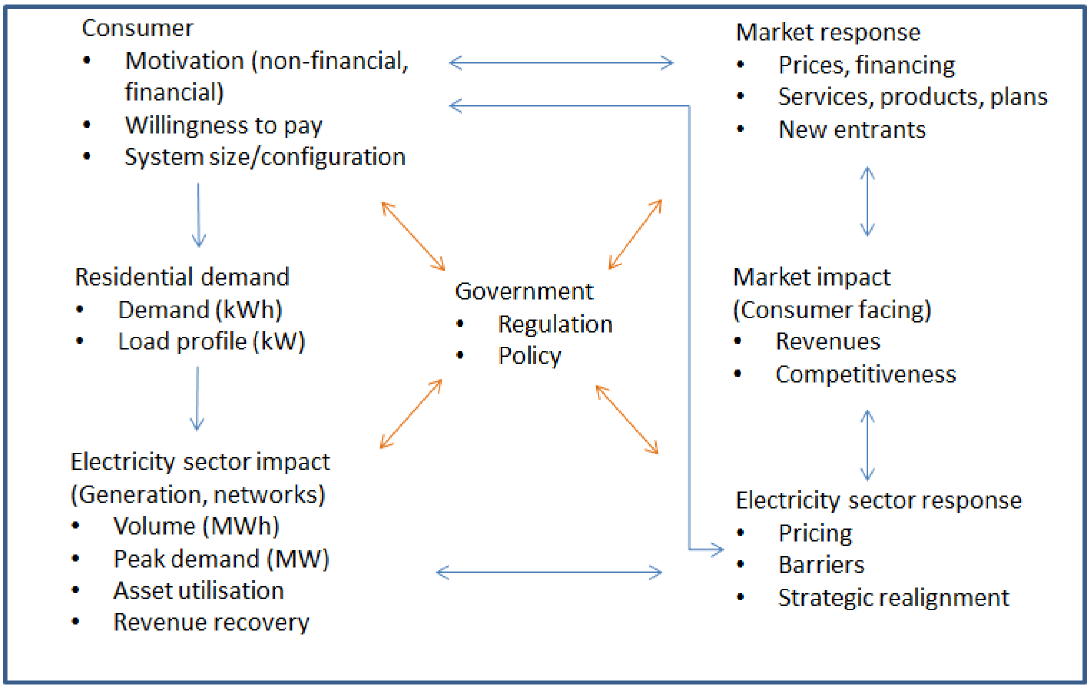


Figure 31 Subsystem diagram - an overview of the model architecture

6.3.3 Development of a dynamic hypothesis - causal loop modelling

The CLD below is presented in three parts, each focusing on a separate component of the final model with an explanation of the key causal dynamics. It is important to note that the final CLD is not designed to replicate the entirety of the electricity supply system but rather to represent the main elements that drive behaviour in the systems of relevance to this study.

<u>Causal loop diagram 1 – solar PV and the building blocks for residential batteries</u>

The first component of our dynamic hypothesis describes drivers for residential PV uptake, the key variables that influence household self-consumption, and its impact on broader grid function (Figure 32). This represents the building block for our dynamic hypothesis because access to embedded local generation such as PV is central to the adoption of residential battery energy storage; without it storage is not considered economic before 2035 (QPC, 2016b).

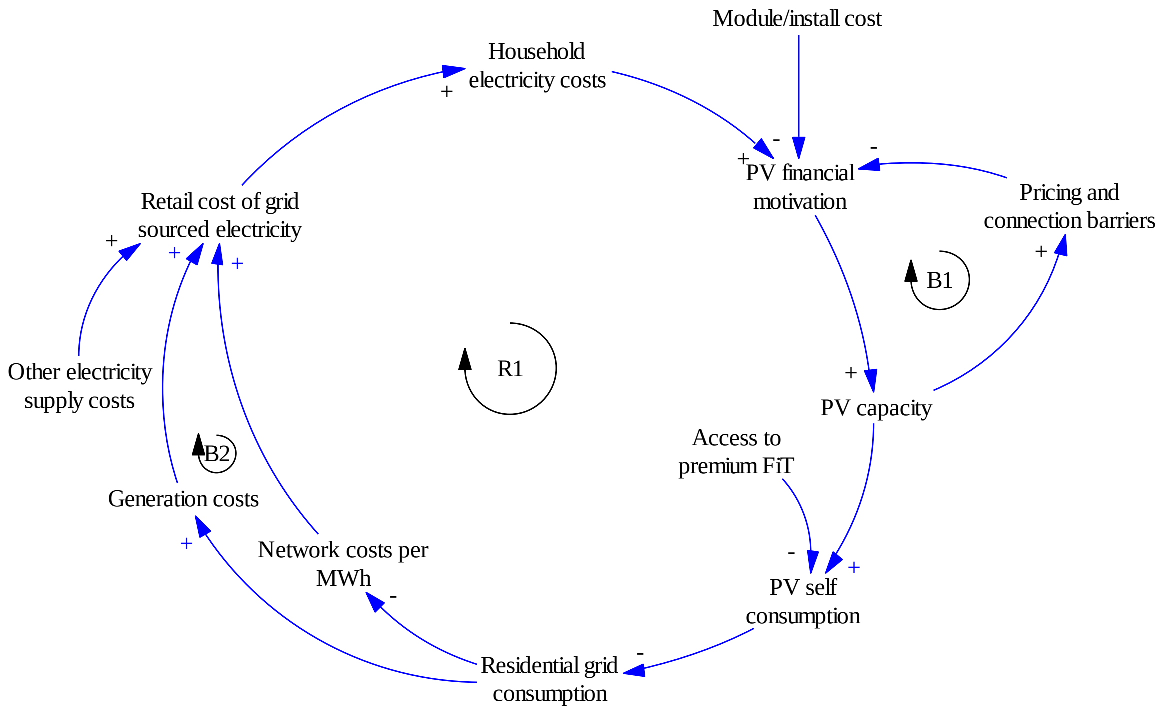


Figure 32 PV dynamics relevant to battery storage uptake in Queensland

One of the key dynamics associated with PV uptake identified by interview participants is its relationship to falling residential network demand, which can in turn drive electricity cost increases (loop R1). This occurs because fixed network costs, which make up the majority of electricity costs in Queensland, are primarily recovered through volumetric charging. Any reduction in demand as a result of PV generation means costs must be recovered over a smaller base. As unit cost of electricity increases, more consumers attempt to reduce their exposure to electricity prices by installing PV or implementing other energy efficiency measures.

At the same time, PV has only a small influence on peak residential demand, the primary driver of network investment. This means while total use of the system declines due to PV uptake, the same level of network capacity is still required to ensure reliability at peak times (CSIRO 2015c). The differential between peak demand and average consumption contributes to poor asset utilisation and inefficiency along the supply chain.

The dominance of this feedback loop (loop R1) over the past decade, along with falling module costs and generous government subsidies has resulted in exponential PV growth. In response to high PV penetrations, reduced demand and a range of technical integration issues, network service providers have introduced PV connection restrictions in certain locations and increased fixed costs to achieve more equitable cost recovery (loop B1). These interventions serve to reduce both the financial case for new residential PV installations and the financial returns for pre-existing PV systems. Whilst utility intervention in this respect is understandable, it serves to increase consumer frustration and mistrust of the electricity sector. These dynamics, which are explored in more detail in the third CLD, may have profound implications in coming years as battery energy storage becomes more affordable.

Study participants noted that whilst loop B1 is strengthening, loop R1 remains dominant and is likely to remain so for some time. This is because there is still a strong financial case to purchase PV, even as subsidies are gradually withdrawn. Module prices continue to fall and electricity prices remain high by global standards. Queensland also has some of the best solar insolation rates in the world. Based on these factors, PV payback periods are forecast to continue to decline in Queensland, falling from 6.5 years in 2018 to 4.8 years in 2035 for a 4kW system (AEMO, 2015c). With up to one million rooftop PV systems forecast for Queensland by 2035, representing as much as 5.3GW of capacity generating approximately 7 gigawatt hours (GWh) per annum, residential PV generation will represent a substantial share of total demand (AEMO, 2015a; QPC, 2016a). Clearly, PV penetration of this magnitude, coupled with mass-market uptake of battery storage will have enormous implications for the existing centralised electricity supply system.

Finally, the inclusion in the CLD of the exogenous variable "access to premium FiT" is worth mentioning. The premium FiT provides 44 c/kWh for any electricity sent back to the grid until the scheme closes in 2028. While access to the FiT is closed to new entrants, more than 60% of PV households still receive 44c/kWh for any electricity not used in their home and exported to the network (QPC, 2016b). For those households receiving a premium for exported electricity from their PV systems, there is less of a financial incentive to use self-generated electricity in home or to charge a battery. This means consumers not subscribed to the premium FiT are far more likely to install storage in the short-term. It also means when the scheme closes in 2028, there could be a spike in battery installations as consumers seek to maximise PV self-consumption. This could be particularly dramatic if battery prices decline as forecast and other drivers continue to strengthen.

Causal loop diagram 2 – the case for residential PV <u>with</u> battery energy storage

The second element of the dynamic hypothesis describes the financial and non-financial motivations that could encourage residential battery energy storage adoption and how these dynamics could impact residential demand and load profiles (Figure 33). Unlike PV which is now considered a mass market technology in Queensland (and its continued diffusion is primarily the function of financial drivers), residential battery energy storage is still at the earliest stages of the innovation adoption curve. The results of stakeholder interviews indicate that while battery prices are decreasing, non-financial motivations are primarily underpinning adoption at present.

Stakeholders identified a range of non-financial motivations including environmental drivers, concerns about future electricity price rises and perceived risks to future electricity supply, e.g. from energy commodity fluctuations, climate change and terrorism. These non-financial drivers correlate with a desire for greater resilience, self-sufficiency and ultimately grid independence (Agnew & Dargusch 2017).

In Queensland, consumer dissatisfaction with incumbent utilities was identified as a particularly strong non-financial driver (loops R7 and R8). This stems from the fact that electricity utilities have been identified as one of the least trusted sectors in Australia (Browne 2015). A recent survey in Queensland found that only 5% of respondents thought the network businesses were acting in the best interests of consumers (Agnew & Dargusch 2017). These negative perceptions stem from rapid electricity price increases driven in part by network over-investment, large increases in fixed charges, barriers to PV connection and perceived unfair pricing of electricity exported back to the grid from PV (ECRC 2015).

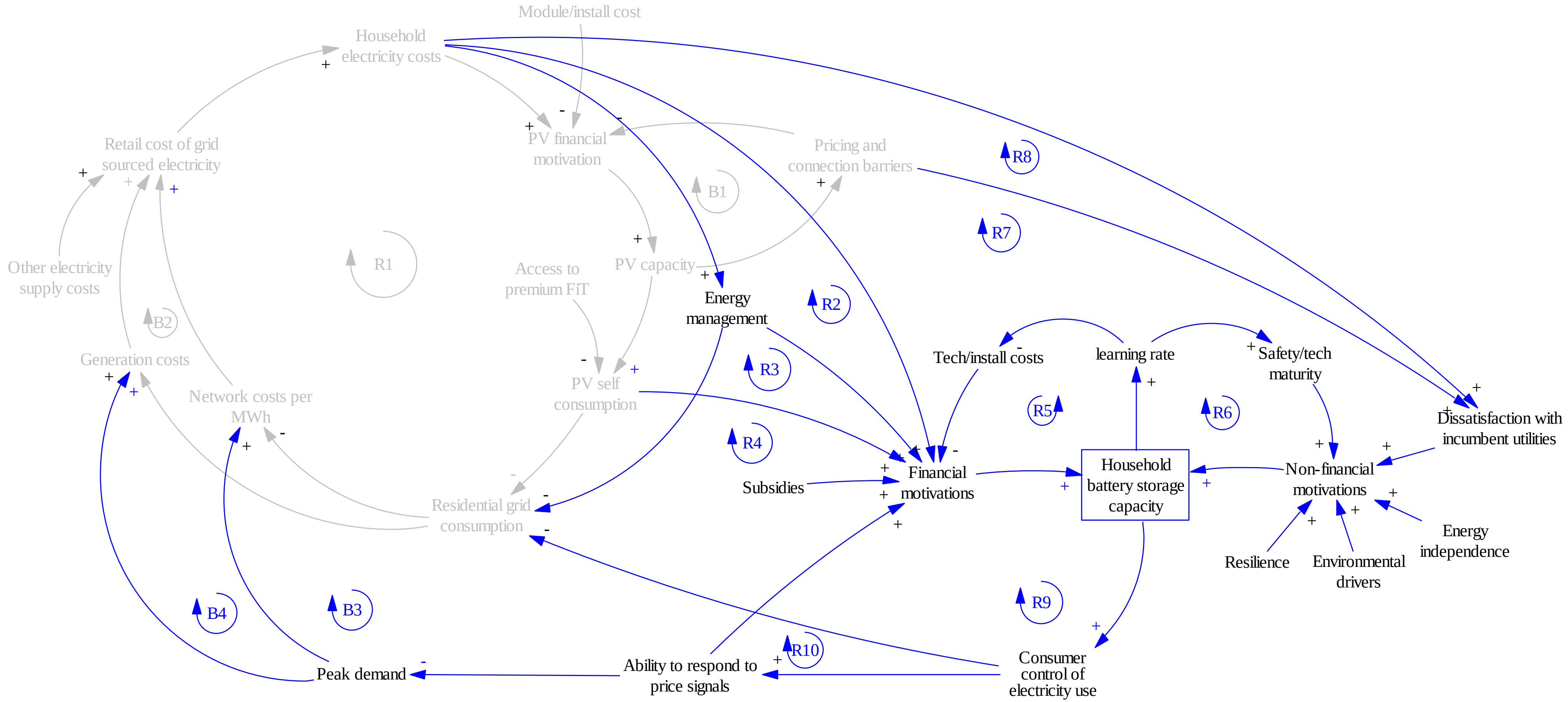


Figure 33 Drivers for residential battery energy storage

As the technology matures (loop R6) and technology costs decline (loop R5), it is likely that the financial feedback loops in the CLD will become more dominant and drive broader consumer uptake. In this respect, study participants identified that a number of key variables would contribute to the financial case for storage. These include:

- Household electricity costs (loop R2).
- The household's energy management potential, that is, the ability of a household to reduce electricity consumption and peak demand (loop R3). This improves the financial case for storage as it reduces the energy (kWh) and peak output (kW) of the battery required. This also has the consequence of further decreasing residential grid consumption, which reinforces loop R1.
- The size of a PV system, a household's generation potential and the value of any feed-in tariff, which will influence any incentive to self-consume or export to the grid (loop R4).
- The ability to leverage and respond to price based signals (loop R10).

Ultimately, it will be the trade-off between financial and non-financial factors and the availability of price based incentives that will determine the type of system installed, the way in which it is used and the way in which it is integrated with the existing network. This in turn will influence the type of control consumers will exercise over their electricity use and the broader impact this has on the total residential demand profile (loop R9). For example, if appropriate price-based signals exist to support the stability and economic efficiency of the network, consumers will have incentives to use their batteries to even out peaks and help manage power quality. This will help balance network costs while having a moderating impact on wholesale generation costs (loops B3 and B4).

What this component of the CLD demonstrates, is the pervasiveness of financial and non-financial reinforcing loops that could encourage battery adoption. Should battery prices halve by 2020 as forecast and payback periods continue to fall, it is likely that a positive financial proposition could exist for mainstream adoption in Queensland within a decade or sooner (Ergon Energy Retail 2015) (Pistoia 2014). Whilst cost will be a key determinant for mass-market battery uptake, study participants acknowledged that the influence of non-financial motivations on consumer purchasing behaviour could bring forward participation in the market in advance of a 'rational' financial case. The impact of these changes and the industry response are considered in the final CLD below.

Causal loop diagram 3 – Market impact and system response

The final component of our dynamic hypothesis describes how residential PV with battery energy storage could interact with the existing electricity supply chain (Figure 34). It shows that vastly different outcomes could be reinforced depending on the response of key stakeholders.

For **generators**, increased uptake of PV with battery energy storage will result in decreased demand and flatter load profiles from the residential sector. With a current over-supply of capacity in Queensland, exacerbated by large inflows of electricity from PV during the day, generators are already operating in a highly competitive market. Whilst residential demand in Queensland represents only 26% of total consumption, reduced electricity volumes and decreased volatility could contribute further to a decline in generator profitability.

Study participants stated that the ability of the generation sector to respond to these issues is currently limited within the Queensland context. There is majority government ownership of the generation fleet in Queensland and limited vertical integration. At the same time, wholesale generation costs are only one component of retail tariffs, yet the sector must compete with distributed generation that is valued against the total delivered cost of electricity to consumers. Finally, the generation sector is not consumer facing, i.e. generation businesses do not interact directly with residential consumers, which limits options for strategic intervention to improve profitability and competitiveness.

Despite the possible risks to the generation sector associated with residential PV and battery energy storage, study participants noted that a response from generators to the challenge was still in its infancy. This may be because generator profitability is currently more contingent on other macro-economic factors, particularly changing electricity demand from the industrial sector and policy driven large-scale renewable energy development.

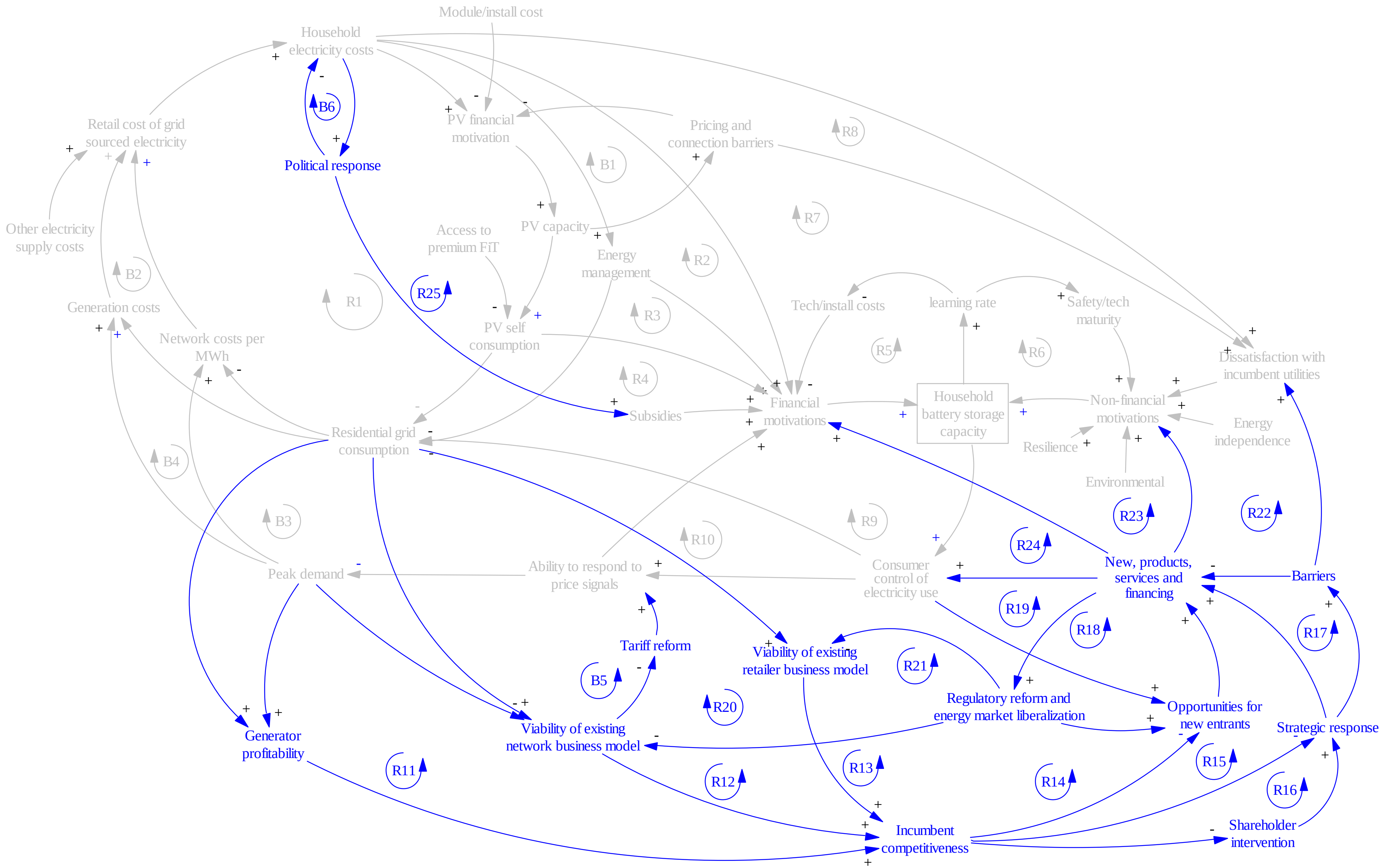


Figure 34 The market impact and response to solar with battery energy storage

For Queensland's **distribution network service providers** (DNSPs), the traditional supply model based on unidirectional flows of electricity and volumetric pricing is already being challenged by the rapid growth in residential PV. Our dynamic hypothesis shows that the emergence of affordable battery energy storage technologies will further test the network business model. This is in part because existing regulated revenue recovery mechanisms encourage DNSPs to pursue conventional approaches to network augmentation (i.e. by building more poles and wires) which in an environment of declining demand ultimately pushes up electricity prices. As the DNSPs are guaranteed a return on revenue, there is little incentive in the short term to change their approach.

Study participants identified a number of factors that question the validity of this approach in the face of increasing residential PV and battery energy storage adoption. For example, under current regulations, the DNSPs must meet minimum service and reliability standards, meaning the networks will need to be maintained even as residential grid consumption declines. With peak demand forecast to exceed average demand growth in Queensland in coming years, this challenge will be compounded as additional network investment may be required to meet peak demand, putting further upward pressure on electricity prices (QPC, 2016a). In the past, consumers have not had access to cost-effective, demand-side technology to respond to these drivers. However, with battery prices declining and new entrants and new business models in the market, consumers will be able to directly compete with DNSPs. The viability of the existing regulated monopoly structure could weaken in this scenario (loop R14). In response to likely political pressure arising from high electricity prices and increasing inequity, such dynamics would necessitate regulatory intervention that could see changes to regulated revenue recovery mechanisms, which could in turn further weaken the existing incumbent business models (loop R18).

As Queensland's network businesses are owned by the state government, any decline in productivity or asset impairment could result in broader budgetary consequences. For example, in the past two years alone the network businesses have paid dividends exceeding $AU1 billion annually to the state government (Queensland Government 2015). Should dividends fall or the value of the companies decrease, government as sole shareholder could directly intervene or even seek sale of the network businesses (loop R16). In either case, this would most likely result in a net loss of value for Queensland taxpayers.

Queensland's DNSPs appear to be aware of many of the risks and are examining ways in which to use batteries to optimise existing network assets while providing choice and control to consumers (ECRC 2015, p. 117). However, despite a number of DNSP-led trials and reviews in this regard, many non-network stakeholders remain skeptical of efforts made to date, particularly as DNSPs continue to support measures that are perceived to be barriers to distributed generation uptake.

As discussed previously, DNSPs have responded to high penetrations of PV and falling demand by introducing PV connection barriers, increasing fixed charges and introducing new fees. Whilst these measures ostensibly improve the cost reflectivity and equity of network tariffs, they may in fact be 'fixes that fails'.

Fixes that fail occur where an initial fix alleviates a problem in the short-term, however unintended consequences of the fix mean that the problem returns after a delay. To demonstrate, between 2012 and 2015 fixed charges in Queensland increased by more than 400% from 26.2 c/day to 106.7 c/day (QCA, 2013b; QCA, 2015a). These charges serve to reduce the value of PV systems already installed while diminishing the financial case for new systems. While a delay in new system installations is achieved, this action substantially increases consumers' non-financial motivations, particularly dissatisfaction with incumbents.

At the same time, increased fixed charges reduce the consumer's ability to proactively and autonomously manage their electricity costs. This could increase electricity consumption and peak demand, which could further increase electricity costs. Over time, these dynamics reinforce consumer desire to reduce reliance on network utilities and when financial motivations align, increase uptake of non-network solutions, ultimately increasing the severity of the original problem. This dynamic is represented as a CLD in Figure 35 below.

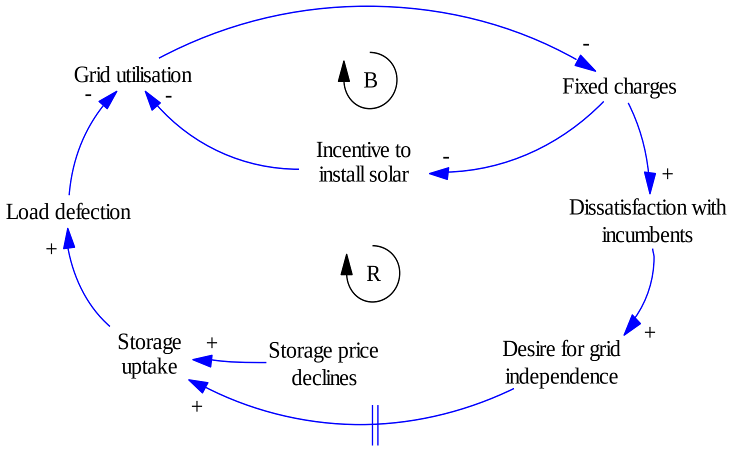


Figure 35 Fixes that fail - the impact of increasing fixed costs on residential solar and storage

While study participants acknowledged the magnitude of the challenge for DNSPs in integrating home battery storage, there was also a broad consensus that effective integration of the technology could provide as much benefit to the networks as it does to the household. Battery energy storage behind the meter could reduce peak demand, increase system resilience, improve power quality and defer network upgrades. These outcomes help ensure that the delivery of power comes at the lowest whole-of-system cost, which ultimately results in lower electricity tariffs. This in turn reduces some of the drivers that underpin consumers' desire for self-sufficiency and grid independence.

The key to unlocking these benefits is capturing and assigning value among all sectors of the supply chain, particularly consumers. Tariff reform could play an important role in this respect, as appropriate price-based signals represent a mechanism to incentivise the use of battery storage to support network objectives (loop B5). Study participants acknowledged however, that a failure to get tariff reform right could result in poorly structured or complex price signals, which risk further alienating electricity consumers. With alternatives to the network monopoly rapidly emerging, network pricing must be competitive with those options whilst maintaining high standards of reliability to keep consumers connected.

To explicitly recognise the changing role of the consumer and influence of new technology, DNSPs may need to fundamentally rethink the form and function of the network if effective integration is to be achieved (loop R15). Study participants identified that this would necessitate cultural and structural change within these organisations. Whilst reform and a strategic restructure of this nature could see a possible decline in DNSPs financial position in the short-term, it would most likely improve their commercial viability in the long-term. This could also help encourage retention of grid-connected consumers and provide more avenues to leverage the most efficient use of existing network assets while paving the way for new and innovative solutions in the future.

Unlike the DNSPs, the consumer-facing **electricity retailers** have had a more immediate imperative that has necessitated a more timely response to the challenges associated with residential battery energy storage. This stems in part from the impact PV has already had on retailer revenues with earnings per electricity customer dropping in recent years; providing a clear indication to the sector that new demand-side technology can impair the profitability of the traditional electricity retailer business model (loop R13). In the next five years, PV with storage could exacerbate these issues with reductions in earnings for Australia’s two largest retailers, Origin and AGL, estimated at more than AU$100 million (Koh et al. 2015). Indeed, AGL has predicted that in just over a decade, approximately a third of households will be partially or fully off-grid (AGL 2014).

In recognition of these developments, and with barriers to competition being removed through ongoing regulatory reform, electricity retailers are now offering a range of new services, products and financing options in an attempt to realise growth opportunities and strategically realign themselves as ‘energy services companies’ (loop R15). For some companies this includes the creation of new divisions within the business that will compete directly with the traditional retail divisions.

While incumbent electricity retailers are rapidly mobilising, continued technology development and new paths to customers have also seen **new entrants** become active in the electricity market. With little or no vested interest in the existing supply model, these companies can be nimble, innovative and consumer-focused.

As ‘change agents’, new entrants appear to give little attention to consequence other than those beneficial results that accrue to their customers (Rogers 2003). This pro-innovation bias means that new entrants could have a disproportionate effect on electricity sector disruption (loops R18, 23, 24). New entrants are targeting early adopters and leveraging consumer distrust and frustration with incumbents as they test the market with a number of products aimed at directly addressing consumer drivers for self-sufficiency.

Innovation theory suggests that the activities of these early adopters could have a substantial impact on future market characteristics. This is because some technologies exhibit path dependence where the influence of systemic factors, expectations and small events can shape how that technology develops (Foxon & Pearson 2008). This means that for PV with battery energy storage, the way in which the market responds to initial conditions, the way in which products and services are targeted (i.e. to support the network or to further reduce reliance on the network) and the support or opposition by incumbents could have a large influence on the market as it matures.

Finally, our dynamic hypothesis considers the role of the **government** and other regulatory agencies. In Australia, most jurisdictions are pursing market liberalisation frameworks, which over time will likely degrade the viability of traditional incumbent business models as competition increases (loops R11, 12, 13). A majority of study participants identified the importance of this regulatory reform work, stating that the current framework designed for traditional electricity supply models was impeding the ability of the market to efficiently deploy new technologies such as home battery energy storage.

Study participants also identified the need for government to assist in accelerating the development of battery safety and technical standards. Rigorous safety standards are a necessary precondition for mass-market uptake, with consumers highly sensitive to safety issues (Agnew & Dargusch 2017). This is particularly pertinent for home battery storage technologies as they can be susceptible to chemical leaks, fires or explosion. Damage to property or individuals could have serious implications for continued uptake of the technology (loop R6). At the same time, there is a growing imperative for governments to reform consumer protection frameworks. Access to battery energy storage will increase the complexity of technology and service offerings. For consumers this may result in contractual issues, miscommunication and misleading behaviour, which could increase mistrust of the sector and impede technology uptake.

Our analysis also considers the impact governments can have when they intervene directly in the market to achieve stated policy outcomes or politically motivated objectives. This can include the introduction of upfront subsidies (loop R25) or other measures such as intervening directly in the setting of electricity prices (loop B6). When poorly planned, targeted or implemented, these interventions can drive unintended consequences, social inequity and industry boom-and-bust cycles. For residential battery energy storage, a lack of market and consumer data, an evolving regulatory framework and unclear policy objectives means artificial stimulus at this time must be carefully calibrated to avoid negative outcomes.

6.4 Conclusion

The recent global PV boom was a precursor, and enabler, of growing consumer-led disruption in modern centralised electricity supply systems. Battery storage is now emerging as the next generation of residential energy technology on the cusp of mass-market penetration. With markets, regulators and incumbents still struggling to integrate large volumes of PV into the existing electricity supply system, the rise of affordable battery storage could compound existing challenges.

Whole-of-system analysis is urgently required to chart an integration pathway in order to avoid adverse social and economic consequences. Our study provides the foundation for this work. Using systems thinking we have mapped key variables and the causal relationships between them that will influence the uptake of residential battery energy storage in the future.

While we use the state of Queensland, Australia as our case study, there are a number of jurisdictions around the world, such as Germany, Italy, Japan and some states within the USA (such as Hawaii and California), that are experiencing similar demand-side pressures particularly rising electricity prices (Rickerson et al. 2014). Like Queensland, these jurisdictions have many of the preconditions for rapid residential battery uptake such as an increasing desire for self-sufficiency and falling system prices, and despite a diversity in electricity market ownership and structures in these countries, our findings remain broadly applicable.

In particular, our analysis shows that mass-market uptake of residential PV with storage will erode the dominance of the traditional electricity supply model. This model, once characterised by a small number of incumbents each with substantial market power in their respective domains, will weaken as technology develops, new avenues for competition emerge and market concentration disperses.

In Queensland, a range of non-financial and financial reinforcing feedback loops encouraging battery storage uptake are currently increasing in strength. Should battery prices continue to fall as forecast - a necessary precondition for mass-market uptake - multiple paths to market targeting a highly motivated consumer-base make large-scale battery uptake highly likely in coming years.

How incumbents and new entrants respond to these changes during the early phase of battery uptake could have lasting effects on the way in which PV with battery energy storage is deployed and used in the future. With feedback loops highlighting the increasing power of the consumer, our model shows that incumbent efforts to maximise revenues under the current regulatory framework by impeding competition or frustrating customer preferences are likely to reinforce drivers for greater battery uptake and disruption to the existing electricity supply system in the longer-term.

Moreover, the current structure and interconnectedness of the existing centralised electricity supply system could amplify these impacts, as individual action by any supply chain participant could have disproportionate impacts on other areas of the supply chain by increasing costs or influencing non-financial motivations for households to disconnect from the electricity grid. These dynamics could lead to adverse societal outcomes, such as the loss of value in publicly owned assets, increased electricity prices, destabilisation of electricity services and social inequity.

The role of governments and regulators will be critical to minimise these negative outcomes while balancing the needs of the consumer to maintain affordable access to an essential service. Responsible stewardship will require a clear articulation of policy intent, a supportive regulatory environment and a forward plan so that the market can develop and respond to regulatory signals. Inherent in this approach must be the recognition that consumers collectively now have the ability to materially impact electricity sector dynamics. For markets and governments, strategically meeting the needs of this emerging consumer-base will be essential in ensuring an efficient transition to a more sustainable, decentralised electricity supply system.

Chapter 7 Design, testing and validation of a system dynamics model

Chapter overview

The main purpose of this chapter is to describe the design, development and validation of a stock-and-flow simulation model for use in assessing residential PV and battery energy adoption dynamics in the case study area of Queensland. This chapter includes four main sections. The first section includes a brief introduction to the model and its development. The second section describes the high-level model assumptions including details on the model run time, PV system parameters, battery system parameters, household electricity consumption and household load profiles. The third section includes a detailed description of the model's stock and flow structure including key data assumptions and equations. The final section includes the results of model testing and validation.

7.1 Introduction

As part of the broader systems thinking methodology outlined in this dissertation, each preceding chapter has made an iterative contribution towards addressing the overarching research problem. Data collection and analysis has thus far been based primarily on qualitative research techniques. This is a necessary and well accepted approach to help articulate the research case, conceptualise the key issues and clarify the relationship between system structure and behaviour. The next stage in the process involves the design and development of an empirically-based system dynamics simulation model to enable a more quantitative analysis of battery adoption dynamics.

As discussed in Chapter 4, the methodology for developing a simulation model is well documented in the literature. The design is typically informed by causal loop modelling which describes the fundamental architecture of the system and underpins the three primary structural elements of a system dynamics model. These include ‘stocks’, which are accumulations that determine the state of the system; ‘flows’, which are changes over time that influence stocks; and ‘convertors’, which control flows by defining inputs such as constants, graphical functions, or algebraic relationships. These elements are linked by connectors which denote causality. In this thesis, specialist systems software Stella Architect (version 1.1) was used to assist in the creation of the simulation model (ISEE systems 2016).

Within the Stella software environment, key elements of the CLD described in Chapter 6, were parameterised and converted into a simulation model resulting in three broad interconnected sub-sectors[4]. They include a PV and battery adoption sector; electricity price sector; and an electricity system impact sector. Within these sectors, the model incorporates several different PV and battery system capacities combined with multiple household load profiles. When arrayed, the model includes a total of 108 specific dwelling configurations. In total, the base-case simulation model comprises 395 variables, 16 stocks, 22 flows, 357 convertors, 47 constants, 332 equations and 32 graphical functions.

[4] Note, not all elements of the CLD from Chapter 6 were replicated in the model; where these have been excluded, an explanation is provided in the assumptions section below.

7.2 General model assumptions

7.2.1 Model run time

The simulation model is designed to run for 30 years in monthly time-steps starting in 2006 and ending in 2036. The base year was selected so that relevant historical developments, such as early exponential PV growth, large increases in electricity prices and changing electricity load consumption profiles are reflected in the model. Inclusion of these dynamics provides a sound basis for structural model testing and validation. In addition, initial data inputs used in the model from this period are relatively accurate ensuring that the model has a strong empirical foundation.

The 30-year length of the simulation was selected to ensure that possible prosumer technology price trajectories can be appropriately factored into analysis while providing adequate scope to include the influence of longer-term policy scenarios, such as the introduction of climate change policy and the impacts of the closure of Queensland's premium FiT in 2028 (which currently creates a financial disincentive to install battery systems). At the same time, the length of the simulation period reflects the fact that the existing electricity system is characterised by long-lived assets where structural change can take many decades.

The model's Delta Time (DT) is set to 1, which means values are calculated once every time step, resulting in 372 calculations across all variables in any simulation run. This DT is considered appropriate when considering the nature of the system under investigation and the length of the simulation period (Ford 2010).

7.2.2 PV system parameters

Four PV system size categories were included in the model that reflect common capacities installed in the market i.e. less than 2kW, 2-4kW, 4-6kW, and 8-10kW. The generation potentials of these system categories are calculated based on specific system capacities, assumed to be 1.5kW, 3kW, 5kW and 10kW for each size category respectively, multiplied by solar insolation measured in kWh/m^2/day. Solar insolation data was sourced from the National Renewable Energy Laboratory (2016) which has daily solar data from several locations throughout Queensland.

While the model does have the ability to calculate different PV generation outputs based on insolation from different locations, an average for the state has been calculated based on solar data from the main population centres. This approach recognises that in most cases there are relatively marginal differences in insolation in the main areas of population density across the state e.g. the average insolation in south east Queensland is 5.42 $kWh/m^2/day$, compared with 5.64 $kWh/m^2/day$ in Cairns. Moreover, as Queensland already has some of the highest average insolation rates in the world, helping to make PV financially attractive in almost all regions of the state, these differences in insolation are assumed to have a minimal impact on adoption.

Another assumption related to PV system parameters is the effect of PV panel degradation over the system life. Most PV systems are estimated to degrade over time so that they produce at least 80% of their rated output after 20 years (Jordan & Kurtz 2013). Due to the long run period of the model, the effect of PV panel degradation is included as an auxiliary variable and is averaged over the system life.

7.2.3 Battery system parameters

As very few battery systems have been installed to date there is limited market data to determine the most popular battery sizes. To account for this, three battery system capacities were selected to reflect likely consumer preference and functionality (i.e. 5kWh, 15kWh and 30kWh). The smallest system would cost less in terms of total capital outlay but would have limited functionality due to its size. The medium sized system would help maximise self-consumption of solar power while reducing reliance on the grid. The large system, coupled with an appropriate sized PV system would enable consumers to become almost entirely independent from the grid. In some circumstances, this combination could enable grid defection particularly for low and medium consumption households.

It is important to note that the ability of a dwelling to disconnect from the grid would vary enormously and would depend on existing household energy consumption, peak demand, geographic location, size of PV system, solar insolation and options for backup generation. Except for low to medium demand households, grid defection in the short-term appears to be unlikely, as the cost and the size of a solar system to maintain reliable power would deter many urban households (Wood, Blowers & Chisholm 2015).

For this reason, ‘possible’ off-grid systems in the model are calculated as a function of specific household consumption and load profile combinations paired with minimum system capacities e.g. they require at least a 5kW PV system and/or 15kWh battery to be eligible and have zero grid demand along with unused PV capacity. The model assumes that based on these configurations a dwelling could conceivably disconnect from the network (noting that in reality this would require pairing with smart inverters and/or backup power such as a small generator).

The model assumes that battery operation, i.e. the frequency and depth of battery charging and discharging, is relatively simple. Any PV generation that is not required to meet instantaneous household demand is used to charge the battery. The battery either charges until it is completely full or to a level constrained by the generation potential of the PV system. If the battery is fully charged, any additional PV generation is exported back to the grid. At night, the model assumes the battery is fully discharged. If the PV and battery capacity are unable to meet the household demand then electricity is imported from the grid.

Other relevant battery performance characteristics used in the model are shown in Table 4 (note, these terms were defined in Chapter 2). The data used to inform these parameters were based on an assessment of the operational specifications of currently available battery systems on the market, noting that due to the diversity of different battery chemistries, there can be considerable variation between battery types (Martin 2016; SolarQuotes 2017).

Parameters	Values
Depth of discharge	90%
Battery life (warranted)	10 years
Cycle life	3650 (assumes 1 discharge per day)
End of life capacity (degradation)	70%
Peak output	• 5kW (for the 5kWh and 15kWh systems) • 10kW (for the 30kWh system)

Table 4 Battery performance characteristics

7.2.4 Household electricity consumption and load profiles

Battery adoption and its use is highly dependent on specific household energy usage characteristics (CSIRO 2015b). Residential electricity consumption and load profiles are extremely variable and are a function of factors such as location, socio-economic characteristics, house size, occupancy, appliance use etc. Not only do these elements influence the financial drivers for uptake (including the optimal battery size required to meet the specific requirements of the household at the lowest cost), but they also underpin non-financial drivers such as concerns about exposure to future price increases, resilience and desire for self-sufficiency. Whilst it is impractical to model the enormous diversity of residential load profiles and battery system combinations, the simulation model has been designed to better incorporate this diversity by incorporating several different consumption profiles that represent a range of consumer segments. The assumptions underpinning these elements include:

Household electricity consumption - The simulation model includes three consumption values to reflect low, medium and high-use electricity consumers. The initial 2006 daily consumption values used in the model are 11kWh (4MWh/year), 21kWh (7.6MWh/year) and 30kWh (11MWh/year) respectively. These inputs reflect the fact that Queensland electricity consumers have historically been high electricity users (Simshauser 2014). Due to energy efficiency improvements (as a result of building and appliance standards and household responses to rising electricity prices), these consumption values decline yearly by approximately 1% (AEMO 2016b).

Household load profiles – In Australia, there is a scarcity of rigorous, publicly available, residential load profile datasets (Frontier Economics 2012). In Queensland, this issue is exacerbated as the majority of existing electricity meters are accumulation types which only measure the total electricity volume consumed, unlike digital/interval meters that can measure time of use (Simshauser 2016). This means load profiles in Queensland have generally been developed using pilot interval meter data, distribution substation data or net system load profiles (Frontier Economics 2012; Simshauser & Downer 2014; Simshauser 2016).

Based on a review of existing load profiles used by industry and academia, three general load profiles have been developed for use in the model. These profiles are characterised by:

(1) low daytime use with morning and evening peaks e.g. working households;

(2) moderate daytime use with morning and evening peaks e.g. families with children; and

(3) high daytime use e.g. retirees.

Half hourly demand values (kW) were calculated for each of these profiles based on the three household consumption values described in the section above (i.e. low, medium and high). The three load profiles based on a *low* consumption household are shown in Figure 36. In total nine household consumption profiles have been developed which are used to help determine likely PV and battery configurations, electricity imports/exports and the contribution of batteries to peak reduction.

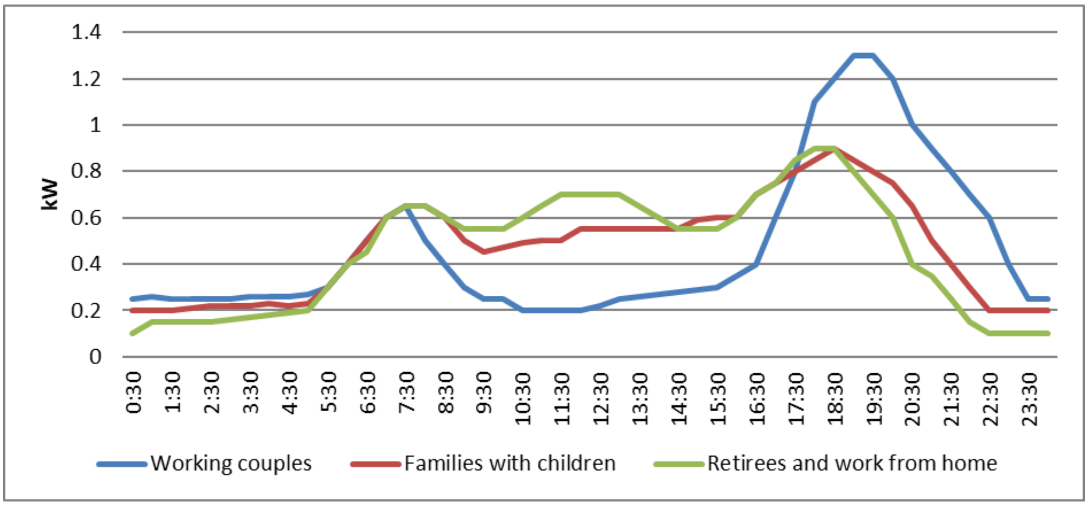


Figure 36 Representative load profiles for Queensland houses based on low electricity consumption

7.3 Model formulation – stock and flow structure and assumptions

This section describes the model's key design and structural elements along with rationale for initial values and other important parameters and equations. The model comprises three high-level sectors – a PV and battery adoption sector, electricity price sector and an electricity system impact sector – with each comprising several sub-sectors. Feedback mechanisms operate both within individual sectors and across sectors. Each of these sectors is described in detail below. Where relevant, representative components of the model are included to visually demonstrate system structure and to illustrate important feedback loops. Full details on the assumptions underpinning the model including all elements of the model's structure are included in Appendix B.

7.3.1 Sector 1: PV and battery adoption

The simulation model calculates system install rates for three stocks including: dwellings with PV only; dwellings with PV with a battery retrofit; and dwellings with new bundled PV and battery. The structure of the PV and battery adoption sector as designed in Stella is shown in Figure 37.

Individual install rates for each system type are calculated as a function of financial and non-financial coefficients, market penetration and market saturation. This approach represents an adaptation of the Bass diffusion model where the relationship between early adopters and later adopters (typically expressed as constants called a coefficient of innovation and coefficient of imitation respectively), is used to describe the rate of new technology adoption (Rogers 2003). In this model however, instead of using constant coefficients, several explanatory variables based on financial and non-financial values are formulated into an adoption fraction, which is loosely based on studies described in Laws et al. (2017) and Islam (2014). This approach aims to ensure that the influence of individual feedback loops between variables across each time step are reflected more accurately in terms of the rate and scale of adoption. It also aims to increase the visibility of the underlying assumptions that make up the install rate so they can be critically examined and/or modified.

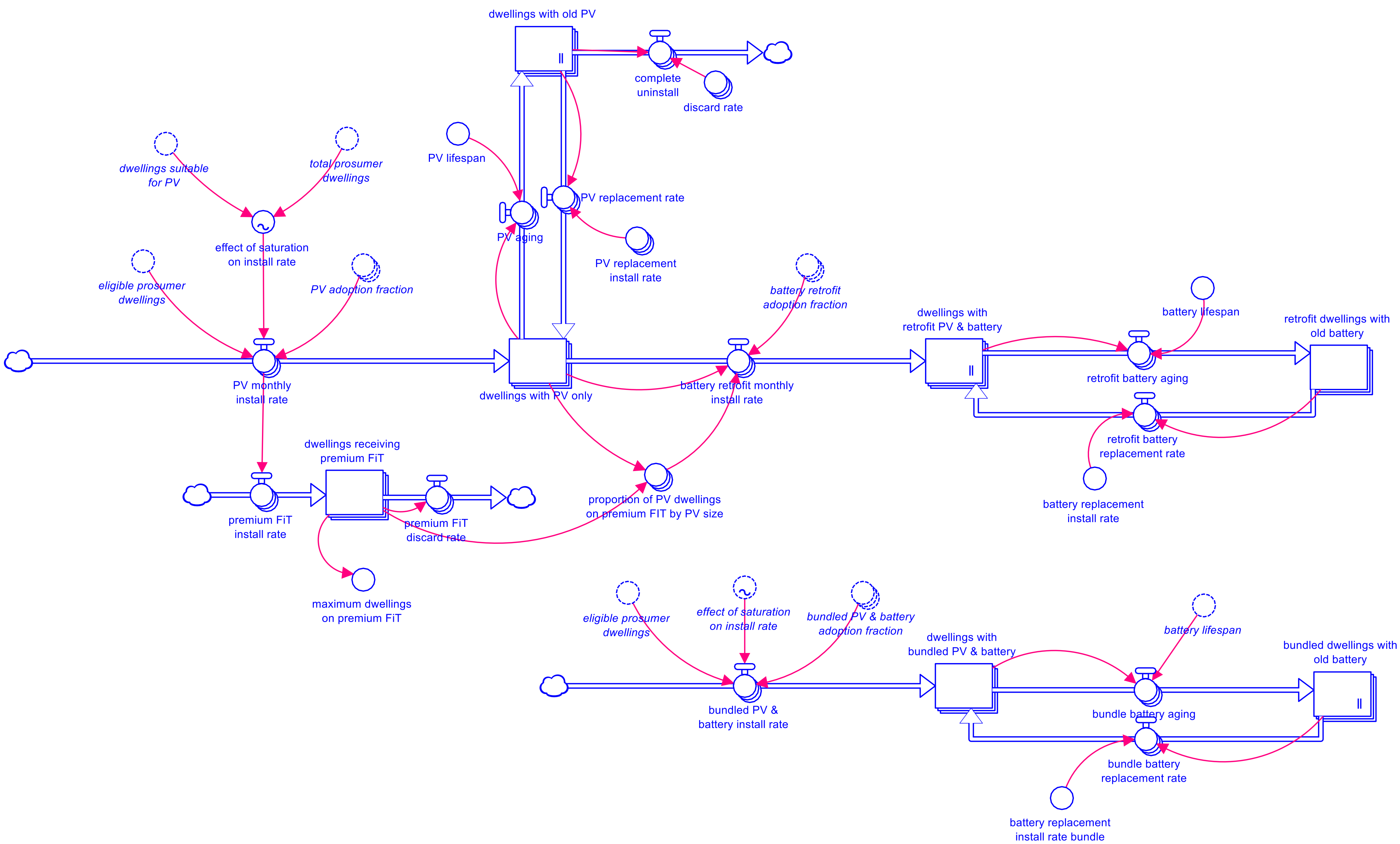


Figure 37 Model structure for PV and battery adoption sector

The generalised equation is represented as:

Actual install rate = eligible dwellings*saturation rate*adoption fraction *[i.e. financial coefficient*non-financial coefficient]*

Where:

- Eligible dwellings are defined as homes suitable for PV.
- Saturation rate shows declining adoption rates as market saturation is approached.
- Financial coefficient represents adoption as a function of payback period.
- Non-financial coefficient represents adoption as a function of non-financial drivers based on diffusion of innovations and utility theory.

Each of the key components of this equation are described in detail below.

1. *Eligible dwellings*

PV and battery adoption rates are both a function of, and dependent on, the number of dwellings in Queensland that are suitable for PV installations[5]. Eligible prosumer dwellings are households that can be physically fitted with PV but do not already have a PV or battery system installed. While PV can be installed on semi-detached homes, townhouses, and/or apartments, they are less common and more expensive due to body corporate restrictions, installation challenges and smaller roof space (IES 2012). For this reason, eligible dwellings are defined as detached homes only. The stock and flow component of this sector is depicted in Figure 38.

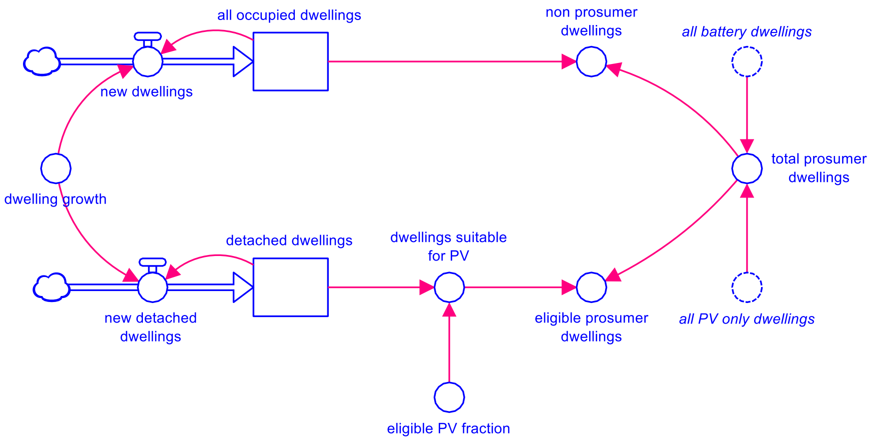


Figure 38 Model structure for eligible dwellings

[5] This is because household access to embedded generation, namely PV, is a key assumption in this study as residential battery storage in not considered economic without it before 2035 (QPC, 2016a).

Key assumptions underpinning this element of the model include the following:

- Dwellings in the model are connected to the existing electricity network. As currently is the case in Queensland, almost all residential dwellings represent one electricity connection point (referred to as a National Metering Identifier).
- Initial dwelling values and dwelling growth rates for the base-case simulation model are based on medium-growth census and electricity connection forecast data (ABS 2016; AEMO 2016b).
- The model assumes that dwellings continue to increase over the simulation period and that dwelling growth is consistent across dwelling classes.
- The convertor "eligible PV fraction" has been included to reflect the fact that not all detached dwellings will be suitable for PV installations due to shading, council restrictions, aesthetic considerations, lack of interest and split-incentive issues for rental properties. The proportion of detached dwellings eligible for PV installations is assumed to be 75% as per AEMO (2013).

This component of the model also calculates the number of all occupied dwellings and non-prosumer dwellings. These stocks and convertors influence several other parameters used throughout the model (e.g. the contribution of total residential demand to electricity prices).

2. Saturation rate

As market saturation approaches, it is assumed that system install rates will slow at an accelerating rate. In the model, this is simply calculated as the number of dwellings with PV divided by the total number of dwelling suitable for PV. As the model assumes that battery adoption requires a PV installation, saturation for battery installs is calculated the same way. The saturation threshold value for the model, i.e. when the effects of saturation would appear, is 50% based on AEMO (2014a), with the rate of decline increasing exponentially to zero when 100% saturation is achieved. This relationship is represented as a graphical function (Figure 39).

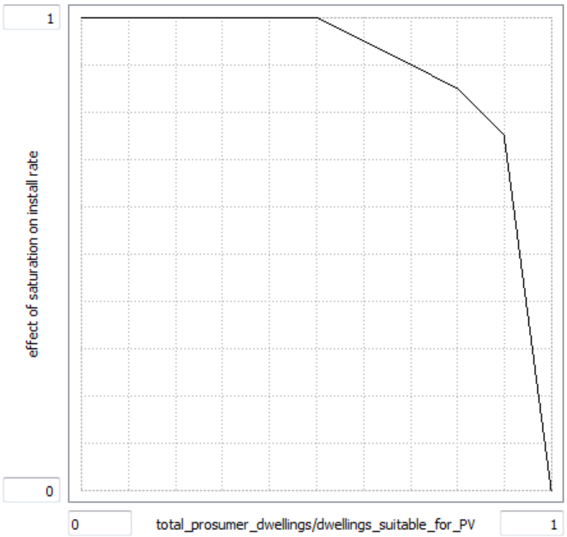


Figure 39 Graphical function used to determine impact of saturation on adoption

3. Adoption fraction

The third component of the 'install rate equation' is the adoption fraction which comprises both a *financial* and *non-financial* coefficient. These are described separately below.

Financial coefficient

The financial coefficient used in the model is primarily a function of payback period, that is, the time taken to recover the cost of an initial upfront capital investment based on ongoing cash flows. While Net Present Value and or Internal Rate of Return are widely accepted in academia and industry as methods to determine the financial benefits of investing in projects, these techniques require a degree of financial literacy and don't reflect the way in which most consumers actually evaluate the financial attractiveness of an investment.

Instead, simple payback is the most commonly used financial measure by solar adopters and consumers more broadly (Kempton & Montgomery 1982; Rai & Benjamin 2013; Rai & Robinson 2015). In one study nearly 90% of study participants used payback periods to calculate the financial attractiveness of PV (Rai & McAndrews 2012). While the use of a simple payback period (i.e. non-discounted payback which fails to factor in the time-value of money) will most likely overstate the financial case for investment, this reflects the way in which a majority of consumers actually make decisions. In this respect it is "perceived gain, not the real gain which matters most" (Kemp & Volpi 2008, p. 16). This distinction is important as one of the primary objectives of this model is to more accurately and realistically reflect the factors that underpin battery adoption in the residential sector.

To model the relationship between the payback period and the adoption fraction, a curve is used which displays adoption as a function of payback based on historical growth rates (Figure 40). This graph was developed to model PV growth for the Clean Energy Council in 2012 and has since been used and adapted by AEMO for national forecasting (IES 2012; AEMO 2013).

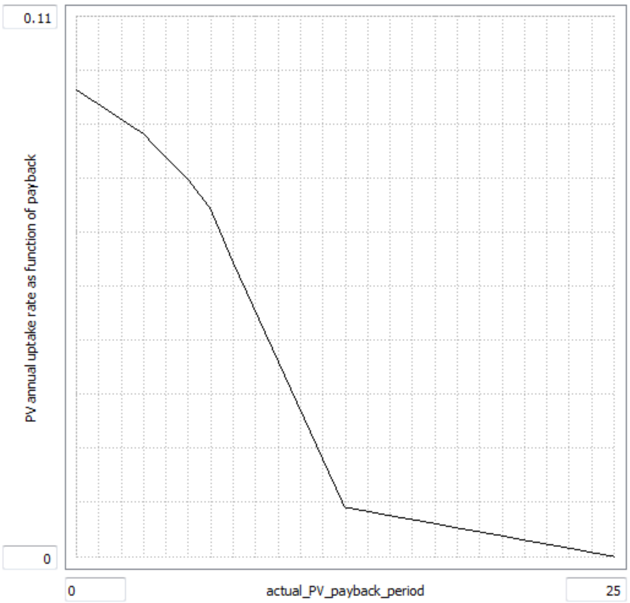


Figure 40 PV adoption rates based on payback

The adoption curve shows that as payback periods increase, adoption rates decrease until payback equals 13 years, reflecting baseline demand of 1% (IES 2012). This declines to zero when the payback period equals 25 years, which is considered the maximum life of a PV system. At lower payback periods, the curve assumes a maximum uptake rate of 9.5%, which is based on the maximum capacity of the solar industry to deploy PV at that time (IES 2012).

For the simulation model, the industry capacity limitation of 9.5% is retained. The data used to inform this curve was sourced from 2011-12, a period characterised by the largest annual rate of PV growth ever in Queensland. During that year the number of solar PV installers peaked at 1391 and nearly 130,000 systems were installed, which was driven by falling module prices, a rush to access subsidies before they were withdrawn and high electricity prices (QPC 2016b; Clean Energy Regulator 2017). It is unlikely such a confluence of drivers will repeat, making the maximum industry capacity an appropriate benchmark for the model.

Despite the curve being specifically designed to determine PV adoption rates, it has also been adapted for use in the model to calculate battery adoption rates. As the battery market is at the earliest stage of development and minimal market data exists, it is difficult to develop an empirical relationship between payback and adoption for batteries. Using uptake rates of analogous technologies such as PV to generate a financial coefficient for battery uptake is considered reasonable because both technologies "are applicable to the same market (electricity consumers), are of a similar order of magnitude of upfront capital cost, and have benefits corresponding to a reduction of energy bills" (CSIRO 2015b, p. 104). This assumption is supported by and has been used in the past for energy sector modelling by AEMO (2015c) and CSIRO (2015b), who recognise that "the uptake of rooftop PV provides the closest indicator of potential storage uptake behaviour" with the relationship between payback and adoption likely to be similar (AEMO 2015c, p. 30). The only modification to the curve for use with battery adoption has been made to reflect the fact that batteries have a shorter lifespan (i.e. batteries are generally warranted for between 10-15 years). This means baseline demand in the battery curve decreases to 1% sooner before decreasing to zero at a payback of 15 years.

Payback period calculations in the model

To inform adoption rates using the above graphical function, the model calculates the payback period for each prosumer dwelling type across each of the household consumption profiles using the following generalised equation:

Payback period = capital costs /ongoing savings

The assumptions underpinning the payback period i.e. the (1) capital costs and (2) ongoing savings for each technology type are described below.

1. Capital costs

The upfront capital investment for PV and batteries comprise the technology cost itself (i.e. the cost of modules for PV and the cost of the battery pack for battery systems), the cost of installation, and the balance of system (BOS) costs which include wiring, racking etc. Any applicable rebate or subsidy is subtracted from total system cost. Note that maintenance costs for both PV and battery systems have not been included in the model. There is a lack of data on the extent to which consumers maintain their systems. As maintenance costs are considered low compared to the capital costs of these systems, they are considered to have a negligible impact on potential adoption (CSIRO 2015b). In addition, no allowance has been made to replace inverters should they fail during the life of the system. These exclusions could introduce an upward bias to the estimated financial returns of installed systems (QPC 2016b).

It is also worth noting that movements in foreign currency can influence battery system costs, particularly as most PV and battery components are imported from overseas. While this element is not explicitly included in the model, sensitivity analysis is used to determine the influence of changing battery costs on adoption.

Finally, this component of the model includes a sector that considers the influence of high upfront capital costs on purchase likelihood. This is important because numerous studies have shown that high upfront costs associated with distributed generation technologies such as PV rank as one of the key barriers to adoption (Allen, Hammond & McManus 2008; Scarpa & Willis 2010; Dharshing 2017). The model recognises this relationship and incorporates a function that reduces adoption for highly capital-intensive systems, even if they have payback periods that would otherwise encourage uptake.

For PV capital costs, the model structure is included below in Figure 41. ‘PV module costs’ are added to ‘BOS and installation costs’ to generate a per watt price. This is then multiplied by system size to generate an unsubsidised installed cost. The influence of rebates and subsidies is then subtracted from the total to generate ‘total PV cost’.

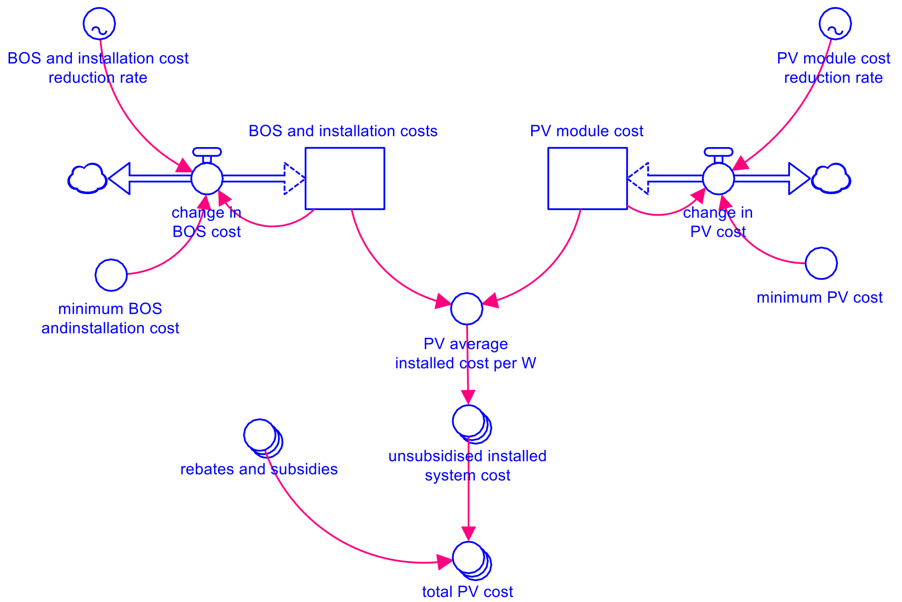


Figure 41 Model structure to generate PV capital costs

For battery capital costs, the model structure is shown in Figure 42. There are fundamental differences in the way in which battery capital costs are calculated compared to PV systems which are demonstrated by the differences in model structure. Furthermore, as battery uptake is at a far earlier stage of diffusion, learning rates associated with battery installation will have a greater impact on cost declines when compared with PV. This endogenous factor has therefore been included separately and is calculated as a function of market penetration.

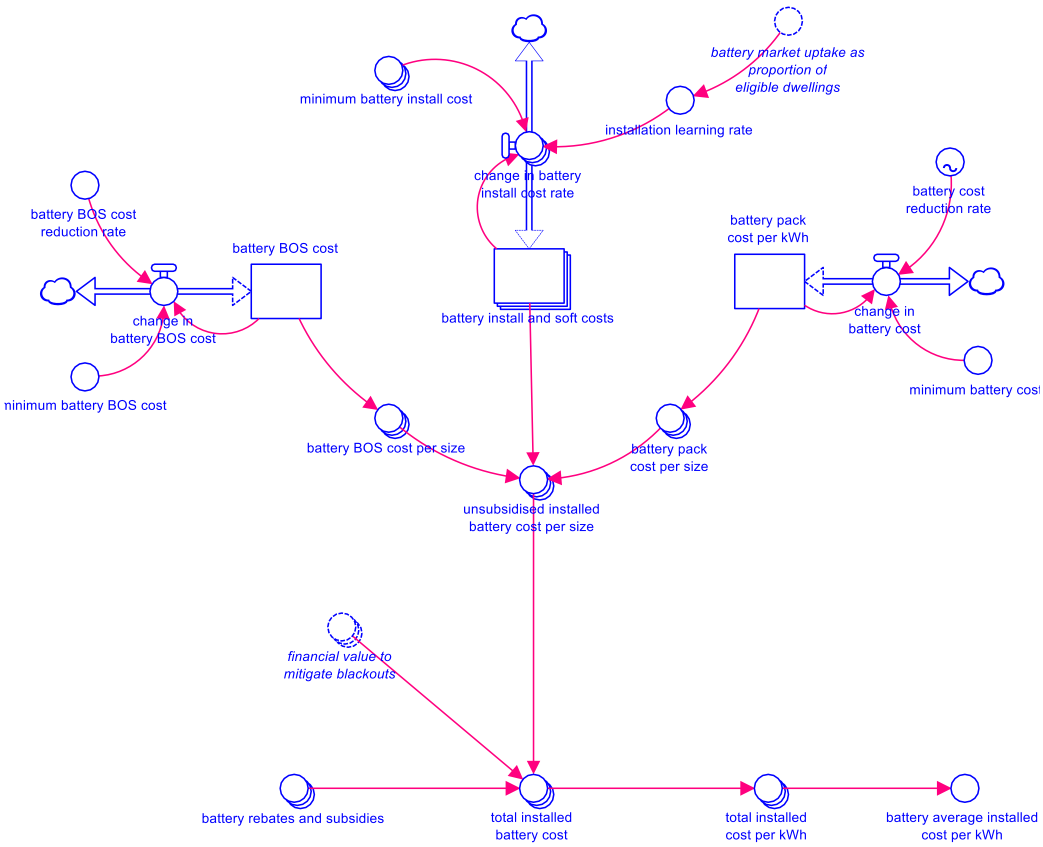


Figure 42 Model structure to generate battery capital costs

For dwellings that already have PV and later retrofit a battery, the model assumes that the capital cost of the PV is a sunk cost. For dwellings that install a new bundled PV and battery system, upfront costs include the addition of the total installed PV system cost and the total installed battery cost. However, buying a PV and battery system at the same time has the potential to lower the total system price as installation and soft costs are generally cheaper. Only one visit to the premises is required, and bundled systems are usually installed with only one inverter, which can account for up to 15% of the total cost of a PV system (Gill 2016). To reflect these savings, the model includes a 10% bundling efficiency coefficient.

As there are no subsidies for batteries in Queensland at present, none are included in the base-case simulation. Subsidies are introduced as part of scenario analysis. In addition, this sector includes the variable ‘financial value to mitigate blackouts’ which recognises that there is a financial value associated with power outages. A study by AEMO (2014c) estimates that the value of customer reliability in response to a loss of power was worth AU$25.42/kWh. As the cost of an outage to a consumer would vary according to the duration and time when the interruption occurred, this value has been used conservatively and scaled accordingly with a cap set on the possible reduction in install prices that it could achieve.

2. Ongoing savings

In addition to the capital cost calculations described above, the second element of the payback equation involves calculating the ongoing savings for each of the system configurations. This is achieved for each of the three prosumer dwelling types by making a number of assumptions about how the systems are used to generate savings. They include:

- Dwellings with PV only – The model assumes that electricity generated by PV meets the daily daytime electricity demand first with any excess exported back to the grid (Figure 43). Ongoing savings in this respect includes the avoided cost of grid sourced electricity (i.e. the amount of electricity used in home due to PV multiplied by the current retail rate) plus the value of any excess PV electricity that is exported to the grid. In Queensland from mid-2008 until mid-2012, consumers could access a premium FiT worth 44c/kWh scheduled to run until 2028. Post mid-2012, new PV consumers can access a voluntary retail FiT - as there is some variation in the value of the FiT depending on the retailer, it has been averaged out across all Queensland electricity retailers and is assumed to be worth 7c/kWh (QCA 2016b).

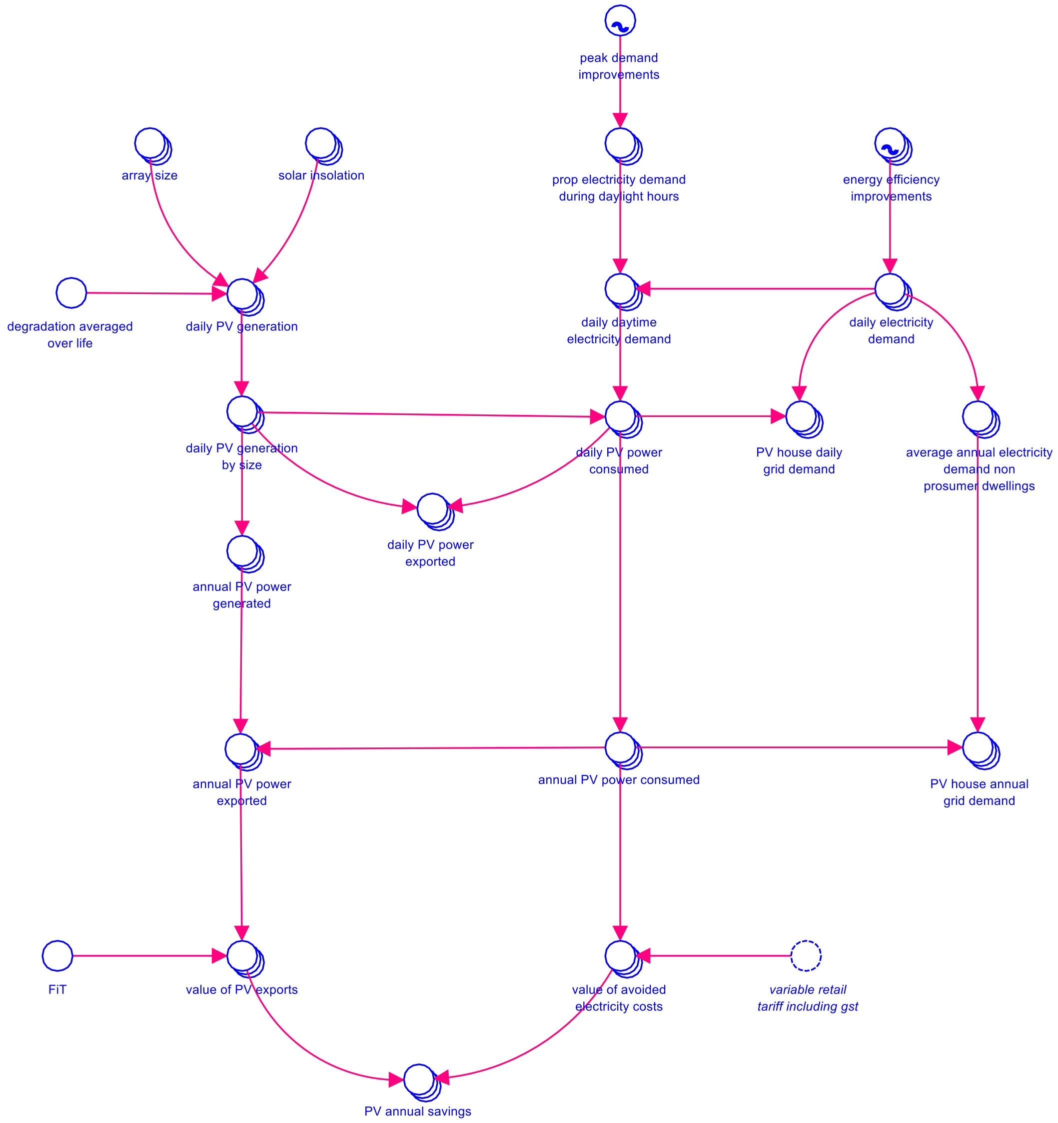


Figure 43 Ongoing annual savings for PV only dwelling

- Dwellings with PV with a battery retrofit – The model assumes that battery systems are retrofitted to existing PV dwellings with the intention of maximising PV consumption in home. As the payback is calculated using only the capital cost of the battery itself (not that of the PV system, as it is considered a sunk cost), ongoing savings are only those savings that occur as a result of the battery install i.e. PV generation that was previously exported and is now used in home (Figure 44).

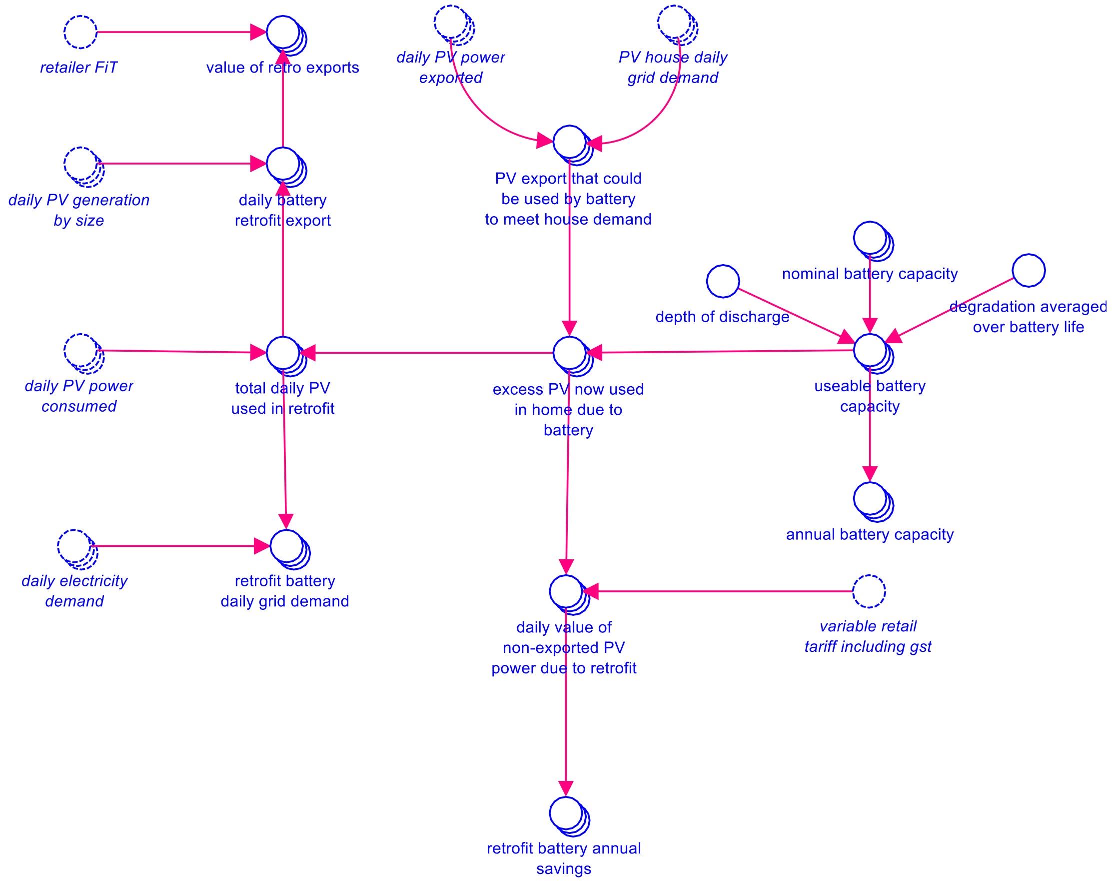


Figure 44 Ongoing annual savings for PV with battery retrofit dwelling

- <u>Dwellings with new bundled PV and battery</u> – Ongoing savings reflect both the value of avoided electricity costs due to the PV and battery bundle and the value of any export back to the grid (Figure 45). Bundled PV and battery systems that maximise in home consumption and minimise exports will ultimately present with shorter payback periods.

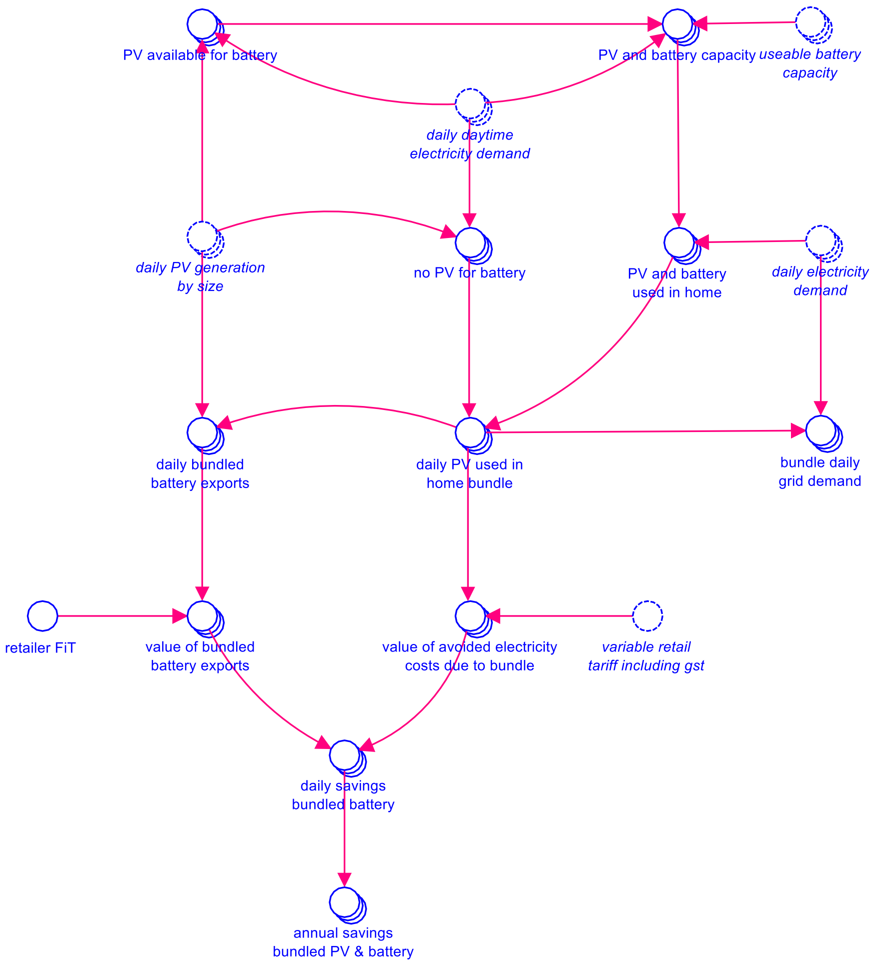


Figure 45 Ongoing annual savings for new bundled PV and battery

Non-financial coefficient

The second component of the adoption fraction includes the calculation of a non-financial coefficient. This is an important element of the model as it deviates from commonly applied neoclassical economic approaches to technology adoption which assumes consumer decision making is based purely on financial considerations. These assumptions deliver modelling results that provide for optimal technology configurations which are deployed in an economically rational manner. However, they fail to recognise that consumer decision making is imperfect and adoption of new technologies often stem from a diverse range of non-financial as well as financial motivations (Wilson & Dowlatabadi 2007; Kemp & Volpi 2008; Rai & Henry 2016).

While there is an increasing body of research focusing on the psychological and social factors that affect consumer decision making in regards to distributed generation technologies, determining the individual drivers that will underpin a decision to purchase a complex product for a large and diverse population remains exceedingly difficult (Wolske, Stern & Dietz 2017). To address some of the complexity in this regard it is useful to consider the role of the consumer through the lens of diffusion of innovation theory. Diffusion in this case refers to the "process of how new technologies spread throughout society over time" (Dong, Sigrin & Brinkman 2017, p. 252).

Models based on diffusion of innovation theory, most notably the Bass diffusion model, are the most common methods used to predict technology adoption (Rogers 2003). These models assume that product adoption follows an s-curve which occurs as a function of both early adopters (represented as an innovation coefficient), later adopters (represented as an imitation coefficient) and market potential (Meade & Islam 2006). The rate of adoption of a new technology is not only dependent on the perceived attributes of an innovation (there are five common attributes referred to in the diffusion literature: relative advantage, compatibility, complexity, trialability and observability) but also the social system in which it is diffusing, the effectiveness of communication channels, and the nature of the innovation-decision itself (Rogers 2003).

A common extension of diffusion curves is to segregate heterogeneous populations based on their propensity to innovate, which is a useful way to conceptualise market growth. First described in Rogers (1962), diffusion can be categorised into five groups based on when individuals are likely to adopt new ideas. These categories include: innovators (first 2.5%), early adopters (next 13.5%), early majority (following 34%), late majority (next 34%) and laggards (final 16%) (Figure 46). Adopters in the early categories are typically better educated, more wealthy and have higher social status than later adopters (Meade & Islam 2006).

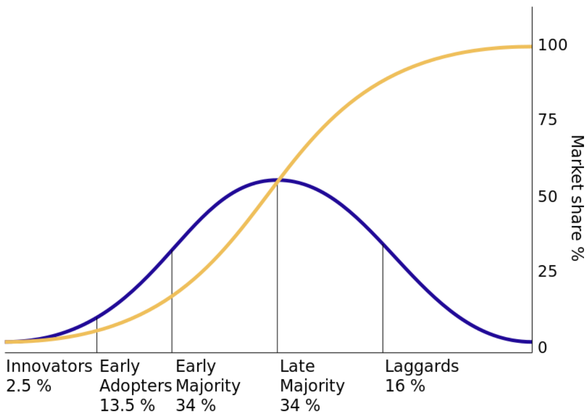


Figure 46 Stylised diffusion curve showing adopter categories (Tungsten 2009)

While diffusion of innovation theory helps to conceptualise likely adoption characteristics, incorporation of non-financial motivations still rests heavily on assumptions. This is because understanding the extent to which non-financial motivations comprise part of the consumer's cognitive choice process when buying a new product can be difficult to ascertain, particularly for disruptive technologies with limited market data. While this makes parameterisation of this element of the model difficult and reliant on rule-of-thumb assumptions, omitting variables that are known to influence system behaviour because empirical data is unavailable is "equivalent to saying they have zero effect – probably the only value that is known to be wrong." (Forrester 1961, p. 57).

With this in mind, the design and structure of the model used in this thesis borrows from elements of random utility and diffusion theory to help underpin assumptions regarding the consumer decision making process and how it could relate to adoption. As there is very little published market data to help quantify the factors influencing consumer buying preferences, variable selection and parameterisation was primarily informed by interview outputs and other secondary data sources described in Chapter 4.

The model structure shown in Figure 47 comprises two main elements which together are used to calculate the 'battery non-financial coefficient'.

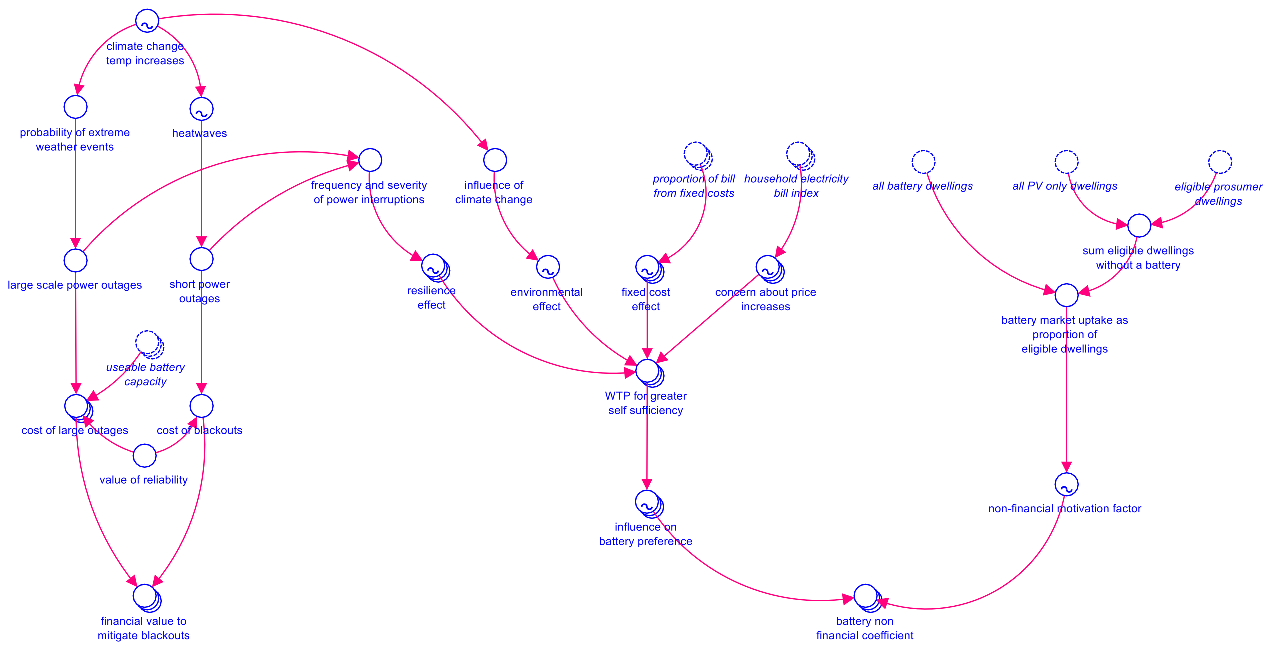


Figure 47 Battery non-financial motivation sector

On the left, the model determines the influence of non-financial factors on battery preference. It does this by nesting several non-financial factors that could contribute to the consumer decision-making process. These include a desire for greater resilience, environmental motivations, concerns about future electricity price increases and the impact of fixed cost increases. Together these factors influence consumers' desires for self-sufficiency and ultimately their willingness to pay for a battery system. The model is structured so that changes in non-financial variables as a result of both endogenous and exogenous factors are assigned a value based on relative importance, which when aggregated, are used to calculate the extent to which a consumer's preference for certain battery types increase or decrease. To reflect the uncertainty associated with the assumptions in this component of the model, it has been designed to generate conservative values. For example, the base-case simulation generates an average value for 'influence on battery preference' that never exceeds 5%.

This value is then multiplied by the second element of the sector, a 'non-financial motivation factor' (shown on the right side in Figure 47), which works as a multiplier to increase the strength of non-financial motivations in the consumer's decision-making process based on the stage of market penetration. This element assumes different adoption characteristics for each group of consumers depending on the stage of technology diffusion based on the categories described by Rogers (1962). It assumes that prior to mass market uptake, innovators and early adopters will place a greater value on non-financial value drivers than later adopters. In other words, in the early stages of product adoption, non-financial motivations make a greater contribution to the willingness to pay for a battery and bring forward investment in the absence of a purely financial case. For innovators, this increases adoption by 5%, which then declines to zero as mass market uptake is achieved. Due to the uncertainty associated with this assumption it has been set at a low level.

It should be noted however that the results from the few studies available, suggest this figure could in fact be much higher. Agnew and Dargusch (2017) showed that non-financial factors could bring forward purchasing behaviour even in the face of longer payback periods, and could increase preference for more costly batteries with larger capacities. Another recent study found that the effects of these motivations can be substantial, suggesting that loss aversion (i.e. a consumer's propensity to strongly prefer avoiding losses compared to acquiring gains), can result in consumers paying a premium of up to 20% above what they rationally should pay to reduce their electricity costs (Vorrath 2017a).

7.3.2 Sector 2: Electricity price

The second main sector in the simulation model is an electricity price module. The price of electricity is a key determinant in PV and battery adoption. As electricity prices rise, they improve the financial case for system installation while also affecting a range of non-financial drivers. In Australia, electricity bills are already considered one of the greatest household cost pressures, and recent increases have contributed to consumer concerns about future price rises (Browne 2015; ECRC 2015). Consumers respond to high prices by reducing electricity consumption, which under the existing regulatory framework, results in higher electricity prices as fixed network costs are spread across smaller volumes of electricity (QPC 2016a).

To capture these dynamics and their effect on battery adoption and the broader electricity supply system, a detailed electricity pricing model has been developed. Electricity retail tariffs comprise a number of components that include energy costs, network supply costs and retailer costs. While there are a number of different tariffs in Queensland, the pricing model is based only on the standard retail electricity tariff (Tariff 11). This is because all Queensland residential consumers are connected to this tariff, and it represents a common cost base to aggregate demand data, apply relevant proportions for each of the building blocks associated with electricity prices, and extrapolate inputs to achieve more accurate retail electricity prices.

In Queensland, the QCA estimates the cost of supply for retail tariffs using an N+R cost build-up approach, in which they treat the N component (network cost) as a pass-through, and determine the R component (energy and retail cost) (QCA 2016c). These elements are passed through to consumers as a fixed cost (for access) and/or a variable charge (based on actual consumption). While the electricity price module is based on these elements (Figure 48), it is important to recognise that past Queensland governments have frequently intervened to unilaterally change electricity prices to achieve specific political objectives. For example, in 2012-13, the government froze Tariff 11 at 2011-12 prices (QCA 2013a). The model includes the effect of such historical interventions by including an annual adjustment that modifies the retail electricity price generated using the building block approach.

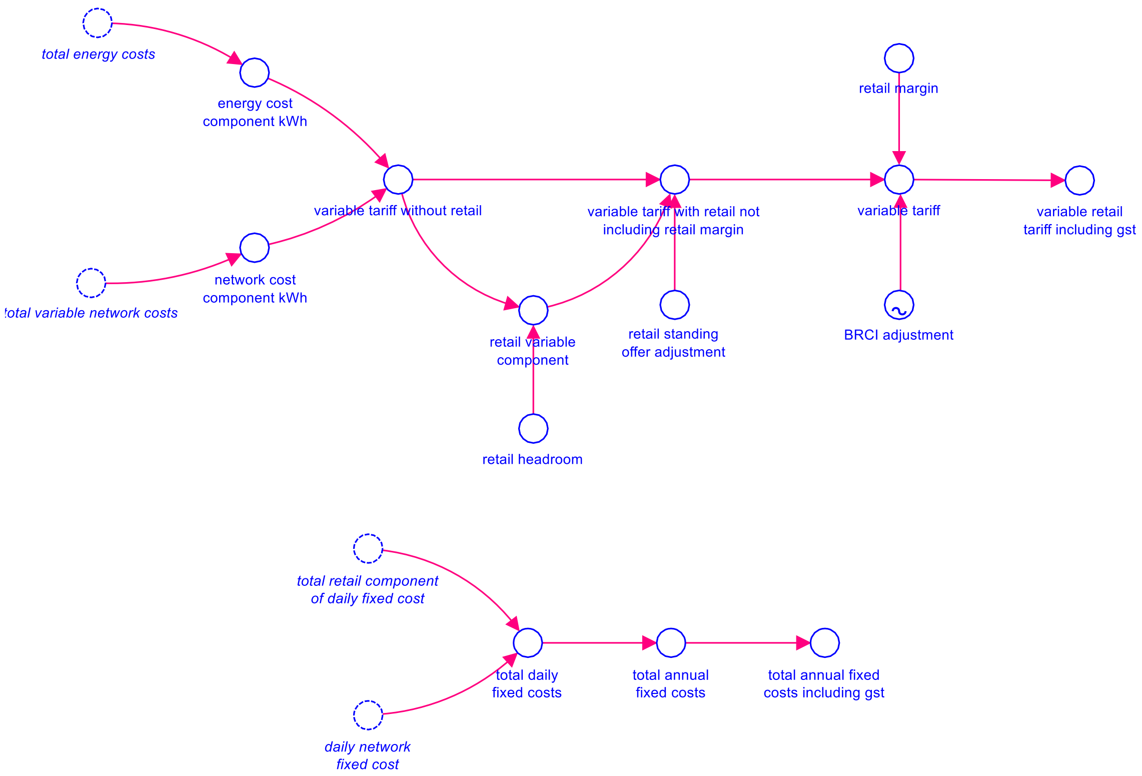


Figure 48 Variable and fixed retail tariff components

Each of the key design principles and assumptions for (1) energy costs, (2) network costs, and (3) retailer costs are described below.

<u>1. Energy costs</u>

Electricity retailers incur several costs when they purchase electricity from the wholesale market to meet end-user electricity demand. These costs comprise three main categories (Figure 49).

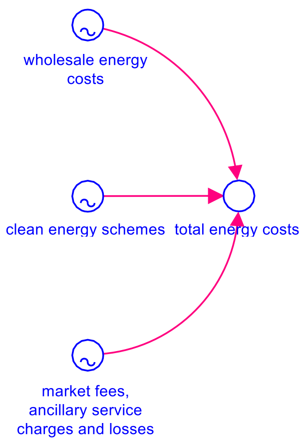


Figure 49 Energy cost components

Wholesale energy costs – Refers to the costs of generating electricity in the NEM. Historical data included in the model is sourced from actual data used in QCA determinations. Future projections are based on government commissioned modelling and assume real wholesale price increases of 2.1% per annum (QPC 2016a). While mass market battery adoption is likely to have some endogenous influences on the generation sector (e.g. generators can realise significant profits from peak volatility often as a result of constraints stemming from the residential sector; battery adoption at scale will likely flatten out some of these peaks and create a more stable generation profile possibly resulting in downward pressure on wholesale prices), the wholesale energy price in the model is categorised primarily as an exogenous variable. This is because wholesale energy prices are more likely to be materially influenced by a range of factors outside the scope of the model including:

- changes in industrial demand (the residential sector in Queensland only consumes around 25% of total generation);
- increasing fuel prices (gas prices in Queensland are now subject to global market dynamics following the commissioning of liquified natural gas trains in Gladstone and as a result have increased dramatically);
- interconnector constraints; and
- extreme weather events (e.g. wholesale energy prices in Queensland spiked during the 2007-08 drought as access to water for cooling towers was severely constrained).

Cost of clean energy schemes – In the past decade, several state and national clean energy policies have been included in the energy cost component of retail electricity bills. For example, the Queensland Gas Scheme introduced in 2005 and phased on out in 2013 imposed costs to encourage investment in gas fired generation. The introduction in 2012 and repeal in 2014 of the Carbon Pricing Mechanism saw a price on carbon included in energy costs. Currently, the national RET is the only remaining clean energy scheme that contributes to energy costs in Queensland. (Note the costs associated with the Queensland SBS are recovered through *network* prices). The historical cost of clean energy schemes in the model are based on the actual data used in QCA calculations. For future projections, costs are assumed to remain at 2016 prices in real terms until the closure of the RET in 2030, at which point the cost returns to zero. The base-case model assumes no carbon pricing mechanism.

Market fees, ancillary services, charges and losses – These costs reflect a relatively small component of total energy costs and are levied on retailers to cover the costs of operating the NEM and paying for services used to manage power system security, reliability and safety (QCA 2016c). Historical data included in the model is sourced from actual data used in QCA determinations with future projected costs remaining at 2016 prices in real terms until the end of the simulation period.

2. Network Costs

Network costs are those associated with the transmission and distribution of electricity and comprise a variable (Figure 50) and fixed (Figure 51) component

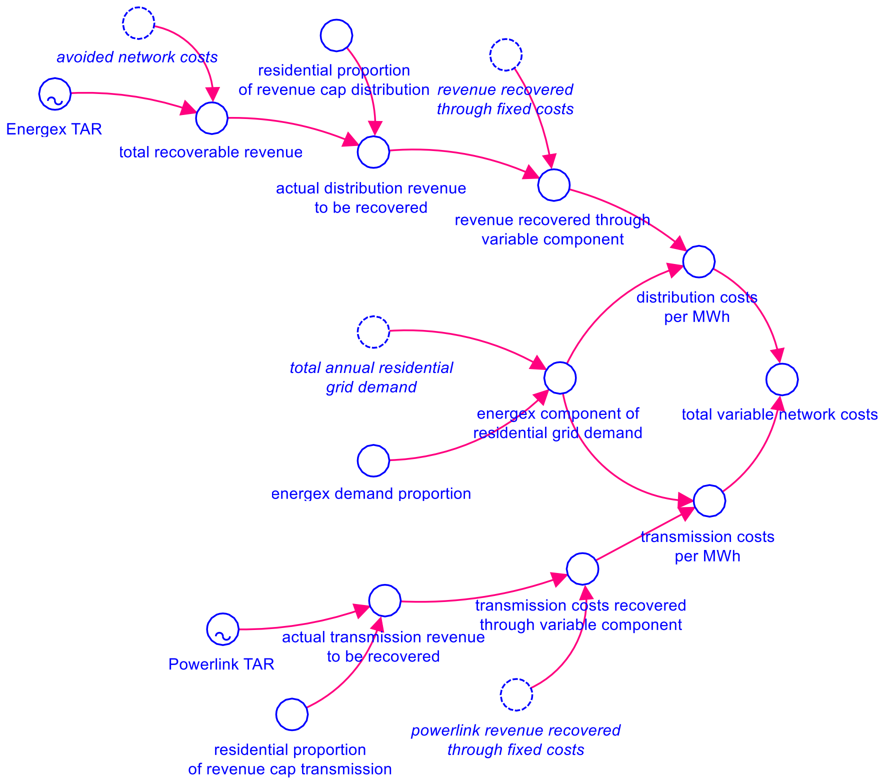


Figure 50 Network variable cost components

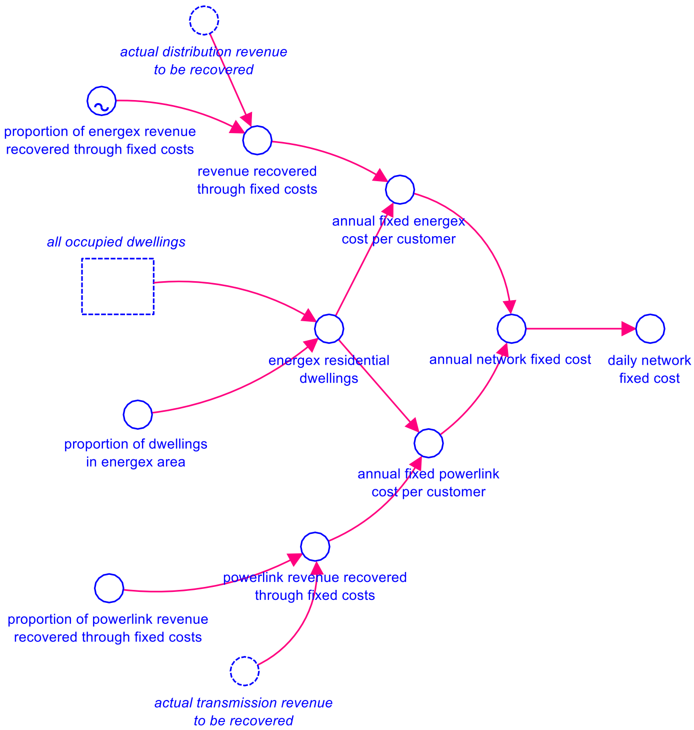


Figure 51 Network fixed cost components

To recover their costs as regulated entities, network businesses are allocated an annual revenue cap from the AER referred to as Total Allowed Revenue (TAR) (prior to 2015-16 this was known as Maximum Allowable Revenue). The TAR is recovered from the various customer classes through network tariffs which are structured to ensure the network business can recover regulated revenue across their entire customer base.

In the model, historical data for the TAR is sourced from AER regulatory determinations. For future projections, data is sourced from the current AER regulatory determination which includes projections of the TAR for Energex until 2020 and Powerlink until 2023. From then on, it is assumed that minimal new network investment will be required to service existing customers in the short to medium term as a consequence of the large network infrastructure augmentation program of the past decade (QPC 2016a). The model therefore assumes that future network costs will only change as a function of population growth (which is correlated with changes in peak demand) and in response to the endogenous influence of PV and batteries which, depending on how they are integrated with the network, will act to put downward pressure on network costs.

As stated, the TAR is recovered from customers through network tariffs. In Queensland, Energex network tariffs are used as the basis for the network component of notified prices for residential customers. These include their own distribution network costs along with a pass-through of Powerlink's transmission network costs (QCA 2016c). As a result of recent rule changes, the revenue to be recovered from each network tariff must reflect the network business' total costs of providing services to the specific consumers assigned to that tariff (AEMC 2014). This is a key assumption underpinning the network pricing component of the model and implies that any change in the amount of revenue generated due to a change in consumption (e.g. from PV and battery energy storage) will be recovered from the customer class that has caused that change in consumption to occur (Harris & Hoch 2013).

Accordingly, the model is structured so that the residential proportion of the distribution and transmission TAR is allocated in the correct proportions to a single residential network tariff. These proportions are calculated using values based on analysis of tariff cost allocations from Energex network pricing proposals and analysis of raw data sourced from AER network benchmarking data (AER 2015b; Energex 2016b).

The model is also structured so that the revenue allocated to the residential network tariff can be split into variable and fixed components. Fixed costs in the past were levied on a relatively arbitrary allocation of fixed and sunk costs and reflected a small component of the two part tariff (Simshauser & Downer 2014). Based on data from QCA determinations, the ratio of fixed to variable costs is calculated and then applied against the TAR so that per dwelling daily fixed charges can be calculated (i.e. the proportion of the TAR allocated to fixed costs divided by numbers of residential dwellings). The variable component is calculated by dividing residential electricity demand by the amount of revenue not recovered through fixed costs to calculate a network cost per MWh. In this way, as residential network consumption changes as a result of PV and battery adoption, variable electricity prices also change reflecting a key feedback loop in the model.

For the base case scenario, the model assumes that in the future, the ratio of fixed to variable costs remain the same as that generated by the model for 2016. This is because a substantial reform process was completed in 2015-16 to improve the cost-reflectivity of tariffs so that nearly one-third of network revenue is now recovered through fixed costs. Only a few years prior, fixed costs generally comprised just over 10% of an average electricity bill (Simshauser & Downer 2014).

While this development reflects a substantial increase in fixed costs, it is important to note that the actual fixed and sunk capital costs of an electricity distribution system typically comprise 70-80% of the total network cost structure (Simshauser & Downer 2014). Scenario analysis is used to consider the impact on PV and battery adoption on further increasing the ratio of fixed costs in the medium to longer term.

3. Retailer costs

In addition to energy and network costs, the other main contribution to retail tariffs are the costs levied directly by the electricity retailer which are also passed through as a combination of both fixed and variable costs. The variable cost elements were included in Figure 48 (on page 142) and the fixed cost elements are shown below in Figure 52.

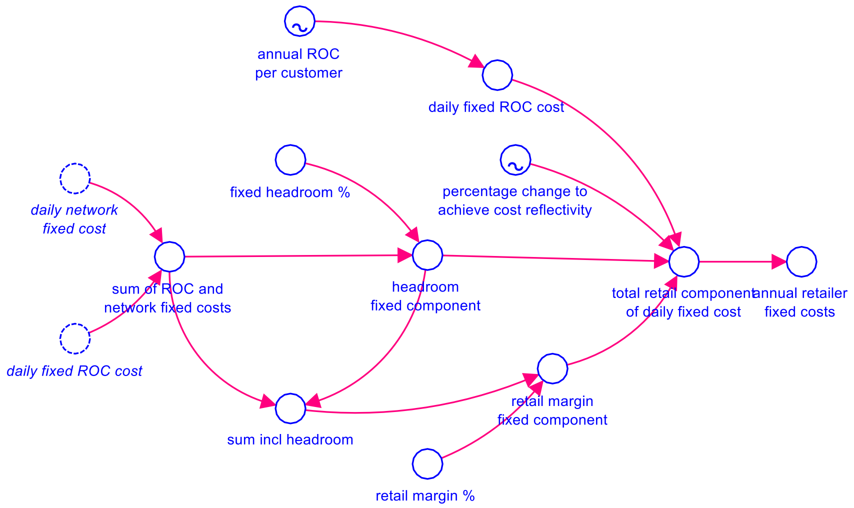


Figure 52 Retailer fixed cost components

The way in which retailer costs have been calculated for notified prices have changed substantially since 2006. Currently electricity retailer costs comprise:

- Retail operating costs (ROC) – Includes costs associated with the services retailers provide to their customers e.g. customer administration, call centres, corporate overheads, billing and revenue collection, IT systems, regulatory compliance, and customer acquisition and retention (QCA 2016c).
- Retail Margin – Represents the return investors expect from providing retail electricity services which can also include costs such as such as depreciation, amortisation, interest payments and tax expenses and is applied against all fixed and variable components including the retail component itself (QCA 2016c).

- Headroom – An allowance for 'headroom' is included in retail tariffs. It is additional to the estimated efficient cost of providing electricity retail services and aims to encourage competition in the semi-regulated market.

The data used to compile historical retailer costs in the model have been sourced directly from QCA determinations. For future projections, the model uses the structure, proportions and values assigned to retailer costs based on QCA (2016c). In summary, this assumes:

- Fixed costs - ROC of $155 per customer remains in real terms throughout the simulation period. Headroom of 5% is applied to all fixed costs. Retail margin of 5.7% is applied to sum of all fixed costs including headroom.
- Variable costs – Headroom of 5% is applied to all variable costs (i.e. energy and network costs). The retail margin of 5.7% is then applied to the total.

7.3.3 Sector 3: Electricity supply system impacts

The third main sector in the simulation model calculates broader electricity supply system impacts that stem from PV and battery adoption. The way in which residential electricity consumers collectively impact the existing electricity supply system is based on changes in how much electricity is used from the network, when it is used and whether any electricity is exported back to the grid. These dynamics directly influence electricity prices, total household electricity costs and the competitiveness of incumbents.

The model comprises five main elements in this regard including:

1) *Total residential grid consumption* – Residential grid consumption is calculated by summing daily consumption values across each of the four dwelling types i.e. non-prosumer dwellings, dwellings with PV only, dwellings with PV with a battery retrofit, and dwellings with new bundled PV and battery (Figure 53). Residential grid consumption for prosumer dwellings will depend on the specific household profile (i.e. daily consumption and load profile) and the capacity of the PV and/or PV and battery combination. Grid consumption for each profile type is calculated and then multiplied by the specific number of households with that description.

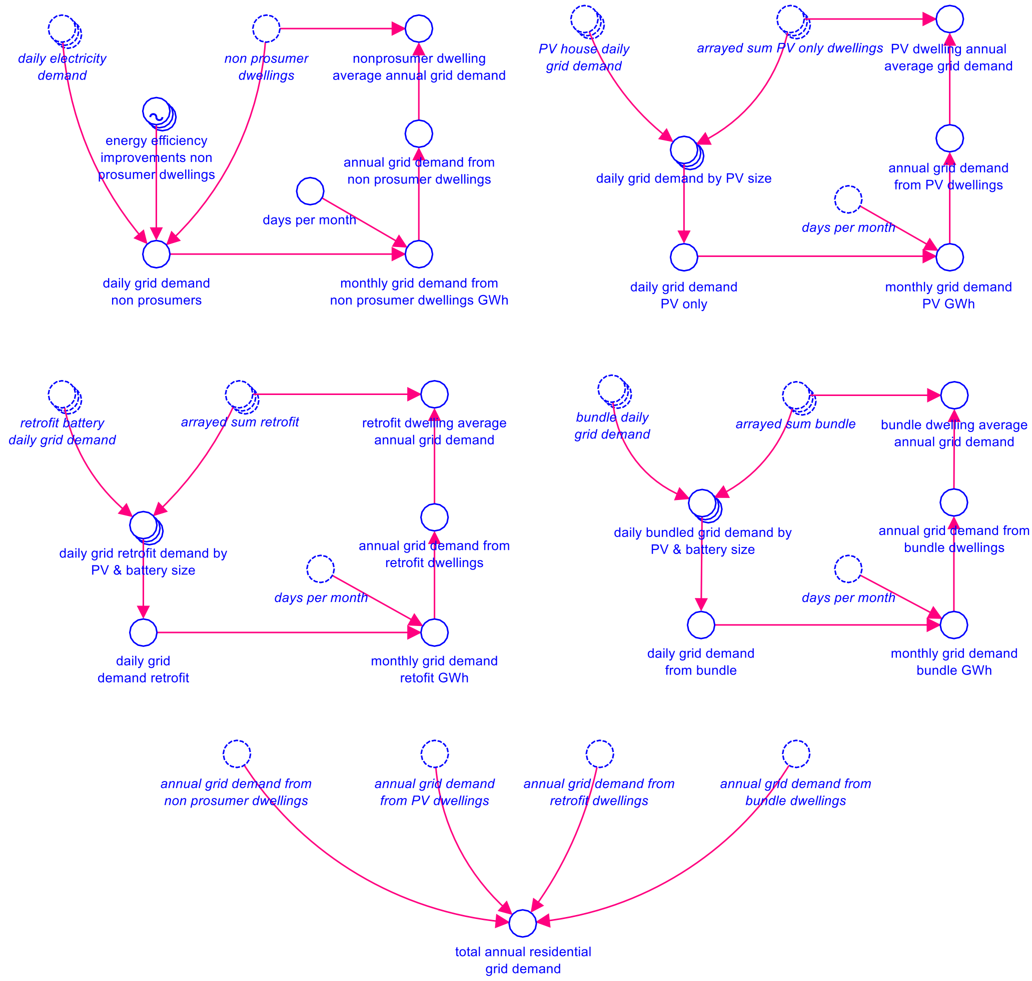


Figure 53 Residential grid consumption

2) *Total PV generation and emissions savings* – Total daily PV generation is calculated by multiplying the capacity of each PV system installed by the average generation for that system type. This figure is then multiplied by Queensland’s centralised electricity emission intensity factor (DOEE 2016). Emissions savings are an important metric to better understand the residential contribution to the emissions intensity of the electricity supply system. As emissions are generated during PV array construction, these lifecycle emissions are subtracted to achieve total emissions savings (Figure 54).

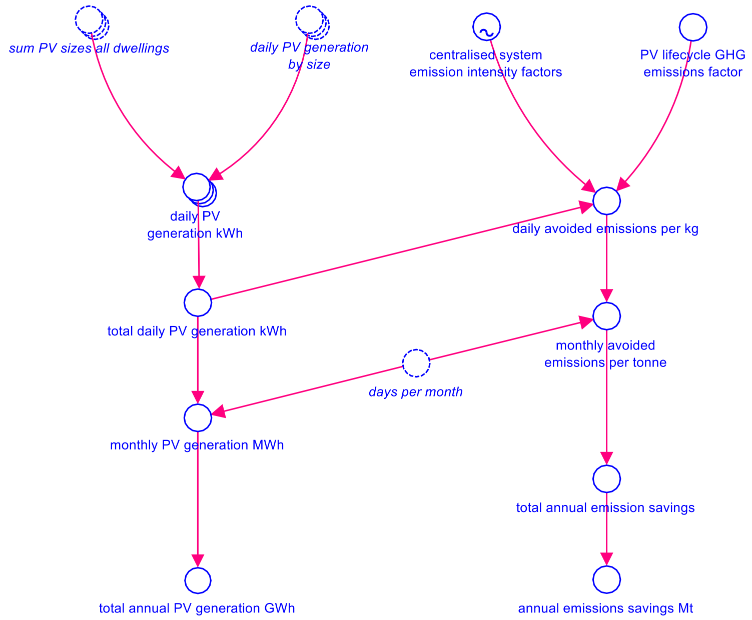


Figure 54 Total PV generation and emissions savings

3) *Annual PV generation used in home and exported* – To reflect the changing way in which consumers use the network, the model calculates the volume of PV used in home and how much is exported (Figure 55). As per above, this is a product of the numbers of each dwelling type multiplied by the export/in-home use for each household profile type.

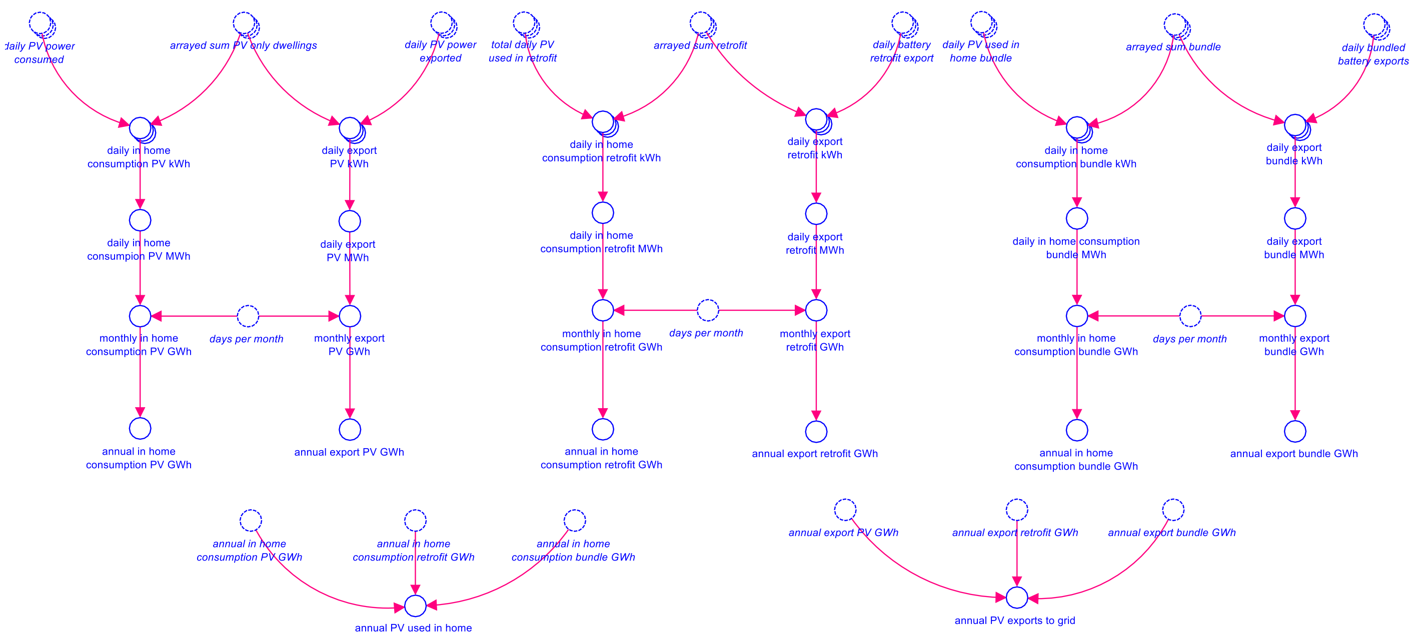


Figure 55 Annual PV used in-home and exported to grid

4) *Electricity bill impacts* – To determine changes in household electricity costs over the simulation period, the model calculates average electricity bill changes for each of the consumers classes (Figure 56). This involves adding variable electricity costs (a function of individual electricity household demand and PV and battery system type, multiplied by the variable retail tariff) with fixed costs and averaging for each consumer class.

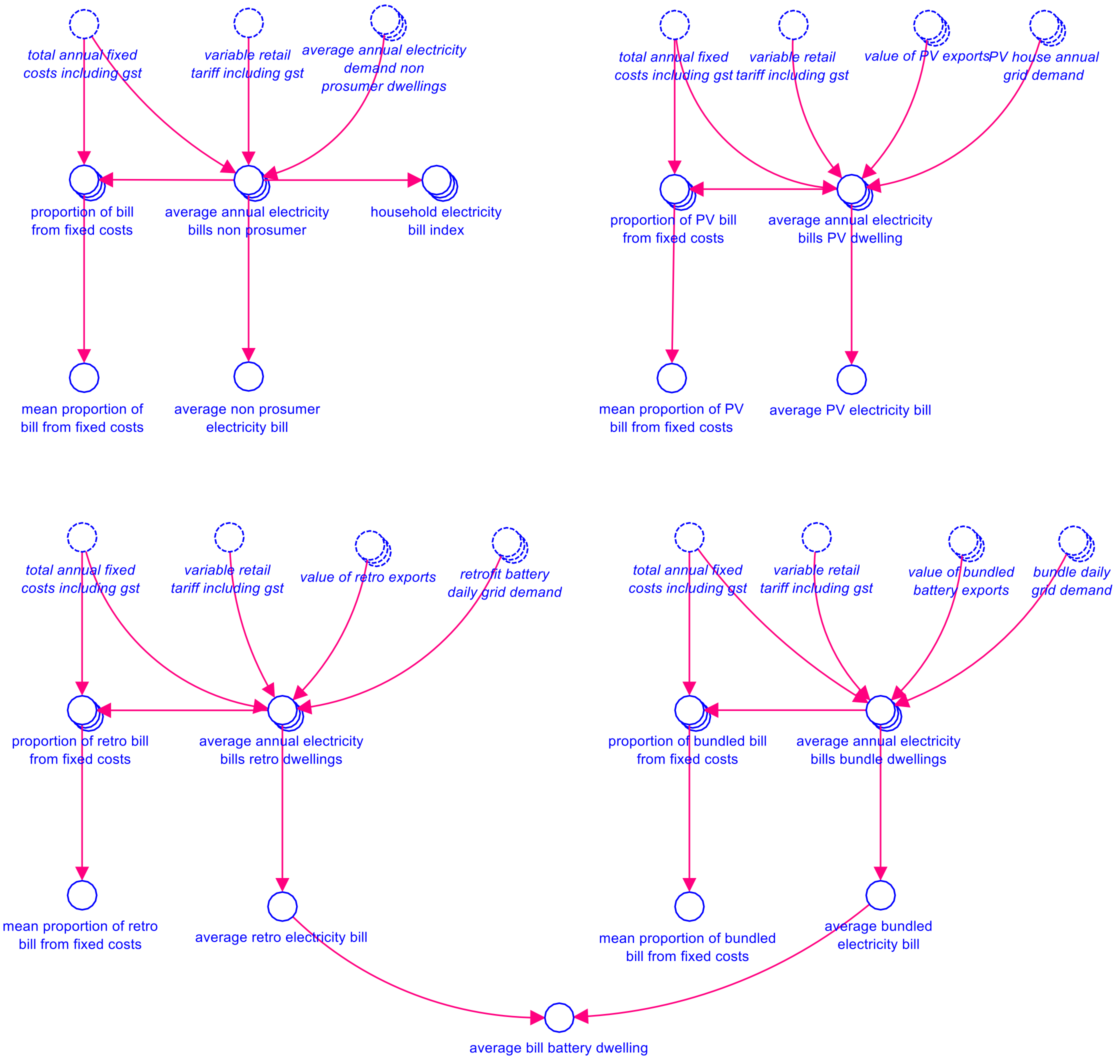


Figure 56 Average electricity bill impacts across all consumer classes

5) *Residential peak demand* – A key benefit of PV and battery energy storage is its potential to reduce the impact of peak demand on network costs. Residential peak demand drives the need for investment in new network assets and the replacement and maintenance of existing network infrastructure (AEMC 2011). In the past, Queensland has had some of the highest demand driven capital expenditure, equating to approximately 50% of total proposed capital expenditure for the state's DNSPs (Ernst & Young 2011). The component in the model that calculates network peak demand and the battery contribution to peak demand reduction is shown in Figure 57.

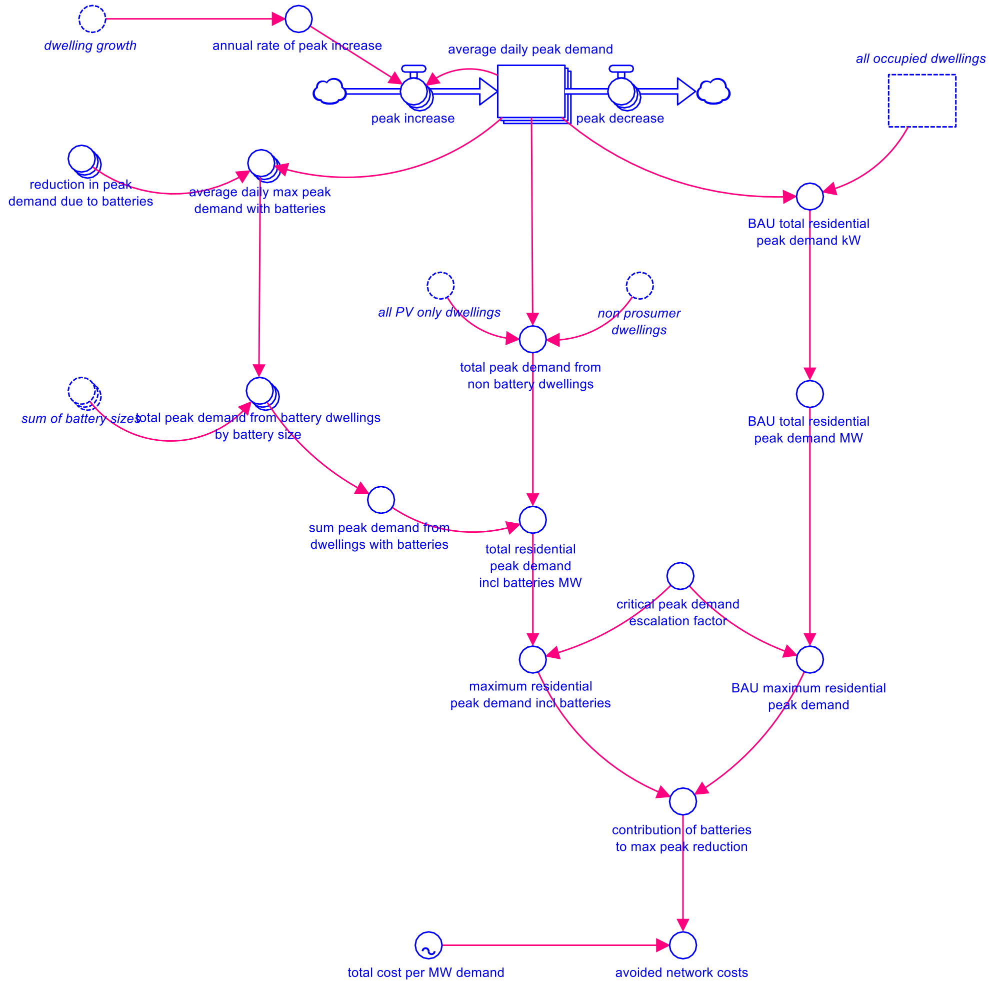


Figure 57 Network peak demand and battery effect on peak reduction

In the model, existing residential peak demand is estimated by calculating the maximum demand for each of the nine different load profiles used in the model. The average of this demand is multiplied by all occupied dwellings to calculate business-as-usual peak demand (i.e. in the absence of batteries and other demand management activities). To determine the impact of battery uptake on peak demand, total household consumption for each load profile is calculated for the peak demand period. This period occurs between 4pm and 8pm based on Energex analysis of overall residential demand in its network area (Energex 2016c).

The model assumes that as evening household load increases and PV generation decreases, battery capacity meets the difference in load. Based on the capacity of each of the battery sizes included in the model, the proportionate reduction in peak is calculated. For example, the model shows that a working household (i.e. a dwelling with medium consumption, low daytime use with an evening peak) with a nominal 5kWh battery would reduce its average household peak demand by half.

To determine the effect of batteries on network costs, the model estimates the value of batteries to the network specifically during *critical* peak periods. This is because network augmentation is generally required in response to critical peak periods, typically experienced during the hottest days of the year which in some cases has seen an increase in peak demand by up to 90% (Simshauser & Downer 2011; Simshauser 2016). To this end, a critical peak escalation factor is applied to average peak demand (a value of 40% is used in the model reflecting a more conservative lower bound). The maximum average peak demand of dwellings with batteries can then be subtracted from the business as usual projection described above to determine the contribution of batteries to peak reduction.

To calculate the financial value of peak demand reductions, attempts have been made by both DNSPs and the AER to specifically calculate the value of network demand augmentation on a $/MW basis so that the overall benefits of demand-side management can be determined (Ernst & Young 2011). Historical $/MW values have been used in the model and directly sourced from DNSP benchmarking datasets from AER (2016b). Future projected values are assumed to remain at 2016 prices (AU$286,224/MW) in real terms until the end of the simulation period.

It should be noted that while the model provides a relatively generalised estimate, determining the impact and the cost associated with peak demand is highly complex, particularly as demand related expenditure is designed to meet localised demand constraints, and not necessarily aggregated system-wide peak demand (Ernst & Young 2011). Reducing network costs associated with peak demand requires identifying the localised area of constraint and determining the cost of solutions to address that specific constraint (Ernst & Young 2011). This could vary considerably depending on whether short or long term drivers of augmentation are considered (Energex 2016c). As part of scenario analysis, the model therefore provides varying estimates of peak demand reductions based on assumptions which estimate the extent that batteries are proactively integrated into the network to reduce constraints.

7.4 Model testing and validation

7.4.1 Overview

While there is no single approach to validate system dynamic models, two main types of test have been developed and are commonly applied. These tests are based either on a model's *structural* validity to ensure the structure of model is an appropriate representation of the system, and its *behavioural* validity to ensure the model is able to produce an acceptable output behaviour (Forrester & Senge 1980; Barlas 1989). On this basis, the following tests were used to validate the model:

- Structure confirmation test – This test involves comparing model equations with the relationships that exist in the real system (Forrester & Senge 1980). The process used to undertake this type of analysis is generally qualitative in nature, as the process involves comparing "the form of the equations of the model, directly with the form of the relationships that exist in the real system" (Barlas 1996, p. 191). For the simulation model, this was achieved by assessing the model structure in terms of (1) the relationships between key variables as defined by stakeholders during the development of the dynamic hypothesis; (2) ensuring that the positive and negative polarity as described in the final CLD were replicated in the model and (3) ensuring that reinforcing and balancing loops produced empirical outputs accordingly. In addition, an internal consistency test was undertaken that involved checking the right-hand and left-hand side of all equations to ensure that units in the simulation are consistent (Barlas 1996).

- Conservation of matter test – All stocks in the model were checked to make sure they obeyed the conservation of matter law, which requires that any change in a stock must equal the sum of inflows minus the sum of its outflows. This was calculated by summing each inflow and outflow after the first time step, subtracting the two values and adding it to the initial stock value. The simulation was then run to determine the value calculated by the model.

- Extreme conditions test – This involves assigning extreme input values to parameters and then comparing the model output with the predicted behaviour of the real system should it experience the same conditions (Forrester & Senge 1980). This test is useful for uncovering flaws in model structure, particularly as formulations can appear plausible until tested with very high or low inputs. The test also ensures that the model will behave rationally even under a wide range of conditions which increases the model's usefulness, particularly for dealing with policy issues that move the system out of historical ranges (Forrester & Senge 1980). The extreme conditions test was applied in the simulation model by changing the values by 25% and 175% of the original value. Results were generated for three dependant variables including total number of batteries, residential grid demand and electricity prices.

- Discrepancy coefficient – This is a quantitative system behaviour test that compares model-generated behaviour to observed behaviour. It is a summary measure to statistically evaluate the behaviour of system dynamic models and represents the sixth step in a procedure that includes (1) trend comparison, (2) period comparison, (3) mean comparison, (4) variance comparison and (5) testing for phase lag (Barlas 1989).

  The discrepancy coefficient (U) is given by (Barlas 1996):

$$U = \frac{\sqrt{\sum(S_i - \bar{S} - A_i + \bar{A})^2}}{\sqrt{\sum(A_i - \bar{A})^2} + \sqrt{\sum(S_i - \bar{S})^2}}$$

  Where:
  A = historical data (i.e. $A_1, A_2 \ldots A_N$)
  S = simulated data (i.e. $S_1, S_2 \ldots S_N$)

  The discrepancy coefficient ranges from 0 (representing a perfect prediction) to 1 (representing the worst prediction) with values between 0.4 and 0.7 implying good to average models (Barlas 1989). In the simulation model, the discrepancy coefficient was calculated for three variables including PV installs, electricity prices and residential demand. These variables are supported by historical trend data and represent key leverage points within the model. Battery installs were not included as there are very few installs currently and no historical data.

7.4.2 Model test and validation results

All structural elements tested within the simulation model behaved as expected. Feedback loops in the model demonstrated appropriate polarity with simulations run to empirically prove the existence of reinforcing and balancing loops. In addition, each stock was assessed to ensure that they did not violate the conservation of matter test, units were assessed for consistency and equations were checked to ensure they correctly represented the relationships assigned to them based on the consultation and CLD development stage.

Extreme conditions test

The extreme conditions test was applied against three key parameters to demonstrate the robustness of the model. A summary of the results, with the outputs at the end of the simulation period provided for each of the parameters tested are presented in Table 5. Graphs that demonstrate trends over time in response to the extreme conditions test are presented in Appendix C. Across all tests, the system responded as expected and the observed behaviour was explainable and rationale.

	Variables		
	Total batteries (dwellings)	Residential demand (GWh/year)	Electricity prices ($/kWh)
Base run	570742	8903	0.3357
Battery payback			
Low	968620	8102	0.3478
High	103032	10315	0.3161
Total network recoverable revenue			
Low	258559	9811	0.2233
high	693418	8627	0.4488
Non-financial motivations			
Low	189040	10006	0.3201
High	802101	8235	0.3471

Table 5 Values for extreme conditions test at end of simulation period

Trend analysis and results of discrepancy coefficient calculations

Trend analysis and calculation of the discrepancy coefficient found that the simulated behaviour trends agreed with the historical data for each of the four variables examined. All discrepancy coefficients were less than 0.3, which is considered a very good result (Barlas 1989). Full working for the discrepancy coefficient including outputs for each of the six steps required to calculate it, are included in Appendix D. Specific test results include:

- *Total PV installations* – Comparison of total number of PV installations returned a discrepancy coefficient of 0.11 (Figure 58). Historical data was sourced from postcode data for small-scale PV installations from the Clean Energy Regulator (2017).

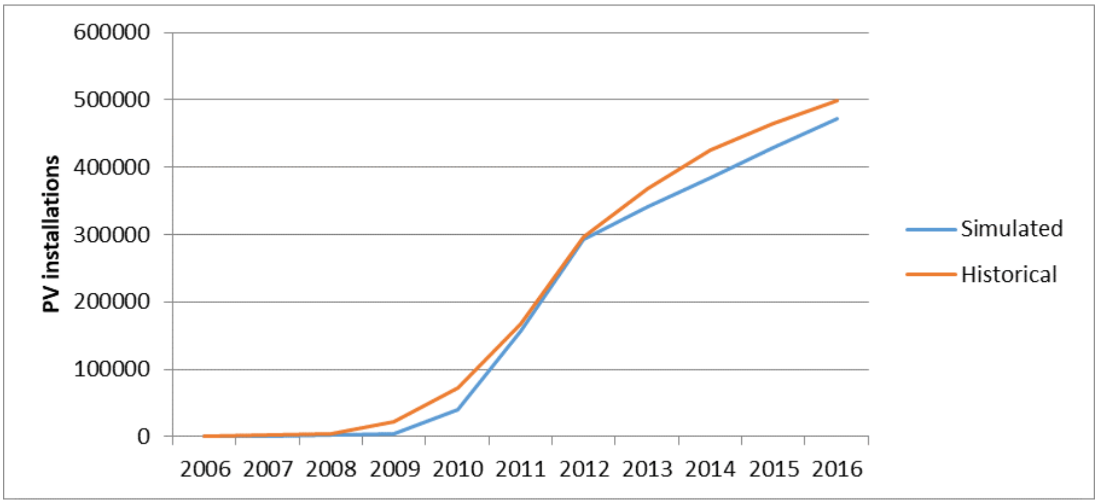


Figure 58 Total PV installs – trend analysis

PV system types – As total PV installs comprise four different system sizes, the model was run to ensure that the trends were consistent with historical data (Figure 59). The model fit was very good with discrepancy coefficients less than 0.28 for all system types. Note, that specific system size data is only available from 2010 and was sourced from APVI (2017c).

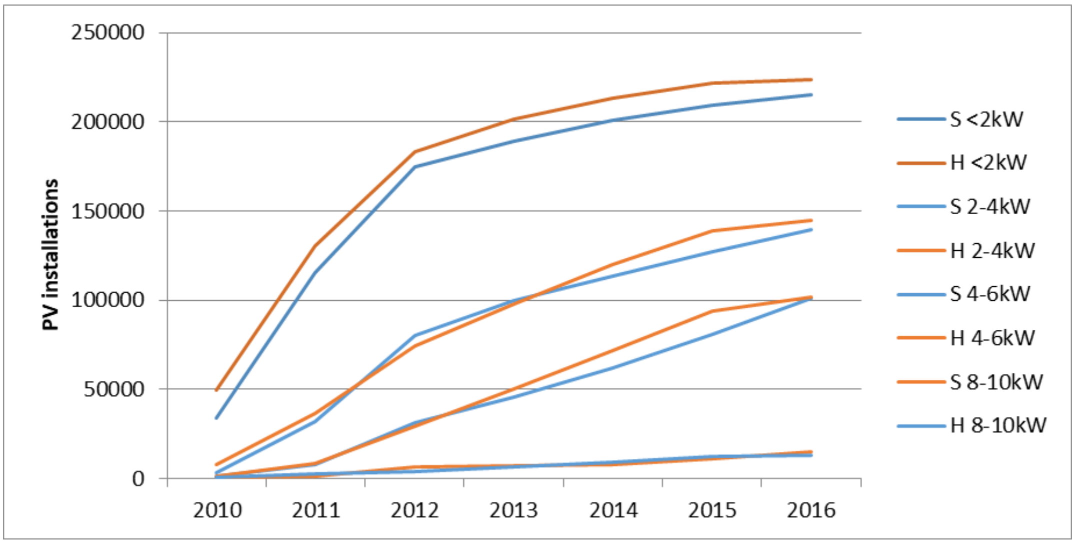


Figure 59 PV installations by size – trend analysis

- *Retail electricity price* – Trend analysis and the discrepancy coefficient for the retail electricity price is calculated against historical data based on the building block approach developed by the QCA (Figure 60). This data was taken from annual final QCA determinations from 2006 until 2017 and excludes GST. The discrepancy coefficient calculated was 0.24 demonstrating very good fit. The main variation in simulated output relates to period from 2013-14 to 2015-16 when the QCA established a transitional path to rebalance the fixed and variable components of Tariff 11 so that each component was cost-reflective by 1 July 2015.

Figure 60 Retail electricity prices based on building block approach – trend analysis

- *Residential demand* – comparison of residential demand against historical data returned a discrepancy coefficient of 0.27 demonstrating a very good fit (Figure 61). Historical values were obtained from datasets sourced from AER (2016b) and AEMO (2017).

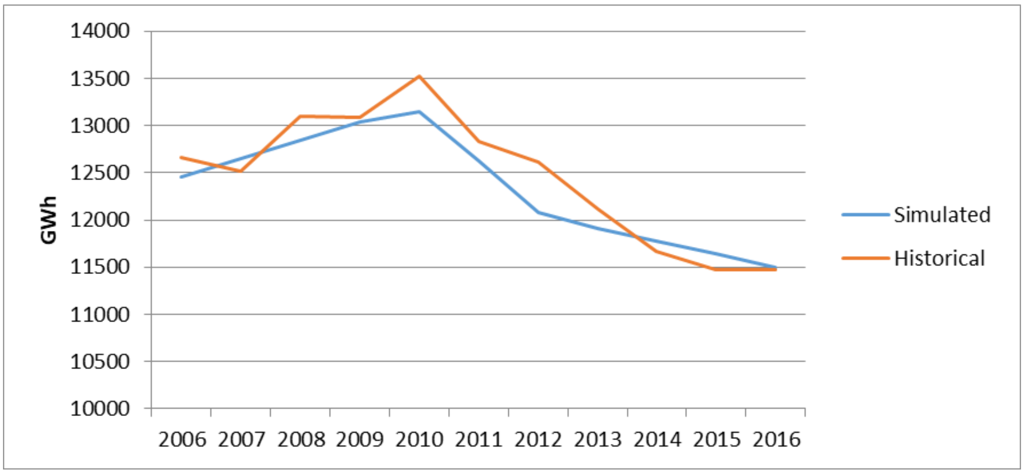


Figure 61 Residential demand – trend analysis

In view of the results of model testing and validation, the structure and behaviour of the simulation model is considered appropriate for use in addressing the research objectives of this dissertation.

Chapter 8 Understanding PV and battery adoption dynamics

Chapter overview

The purpose of this chapter is to describe and discuss the results of model simulations, including the outcomes of sensitivity analysis and scenario analysis. It aims to build on the earlier qualitative analysis to more accurately describe the key causal relationships and the possible leverage points within the system that will influence battery adoption dynamics. The chapter leads with an overview of the approach used, the results of sensitivity analysis, and the rationale and assumptions underpinning scenario development. The second part of the chapter presents the results of all simulation runs. The chapter concludes with a discussion on the implications of residential PV and battery adoption from a broader energy sector transition perspective. This includes consideration of policy measures that could help achieve more efficient integration of the technology.

8.1 Introduction

Sensitivity analysis along with scenario analysis and planning are used in this thesis to enable deeper and more insightful evaluation of the outputs of model simulation. They are both well accepted methods for use with system dynamics models and have been used extensively in the past for energy sector modelling. An overview of these approaches, along with the way in which they are applied to help address this study's research objectives, are detailed below.

8.1.1 Sensitivity analysis

Sensitivity analysis is used to help understand uncertainty in a model by varying the value of input parameters to determine their relative influence on dependant variables and, more broadly, model output (Saltelli et al. 2008). The need for sensitivity analysis stems from the inherent uncertainty in any scientific model. This occurs because modellers effectively design an 'arbitrary enclosure' which by necessity is bounded by assumptions to represent an otherwise open, interconnected system (Saltelli et al. 2008).

Sensitivity analysis is particularly well suited for use with system dynamics models as they generally reflect complex systems and involve considerable uncertainty (Tian et al. 2016). In this respect, sensitivity analysis can help identify variables that have the greatest impact on the dynamic behaviour of the model while helping to better understand key leverage points for policy intervention (Maani & Cavana 2007).

For this study, the sensitivity analysis method is based on an approach designed specifically for use with system dynamics models as described by Maani and Cavana (2007). It involves four steps:

1. Select parameters most likely to influence model behaviour and/or variables with values underpinned by more uncertain or imprecise assumptions.
2. Individually modify selected parameters by a percentage (e.g. 10%) and run a simulation for each.
3. Based on the output of the sensitivity analysis, identify variables that drive significant change in the model.
4. Analyse the results to determine if such change is justified or whether the assumption underpinning the parameters requires modification.

Based on the above approach, a total of 12 parameters were tested as part of the sensitivity analysis process with values for each parameter adjusted by ±10%. To assess the results of the sensitivity analysis, the number of dwellings with batteries was used as the dependent variable. At the end of the simulation period, the percentage change in battery dwellings was calculated for each adjusted parameter against the base case.

8.1.2 Results of sensitivity analysis

The results of sensitivity analysis showing input parameters ranked in order of influence on battery dwelling numbers are presented in Figure 62.

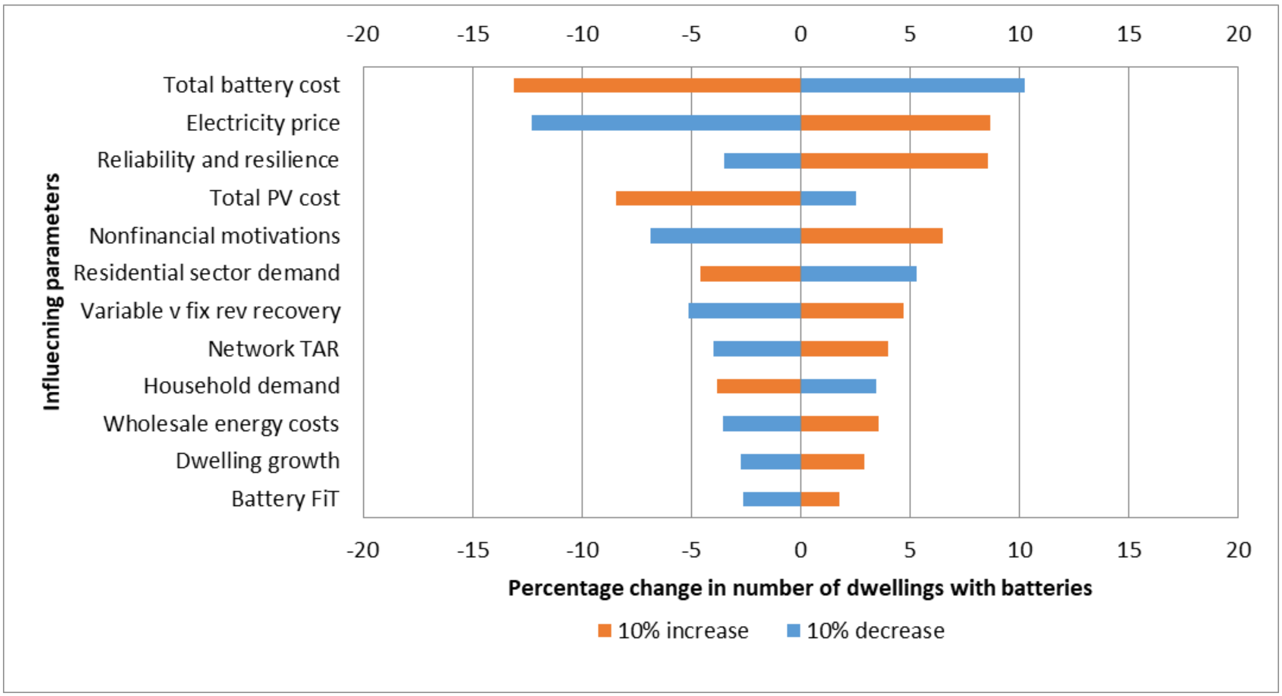


Figure 62 Results of sensitivity analysis

Unsurprisingly, the sensitivity analysis shows that the electricity price and total battery cost - the two main contributing factors to battery payback - have the greatest influence on battery adoption. A 10% increase in electricity prices results in an 8.7% increase in dwellings with batteries, while a 10% decrease results in a 12.3% decrease. This result reflects a confluence of several reinforcing loops in the model. As consumers install batteries, grid demand declines and unit costs of electricity increase, which improves the financial viability of PV and battery energy storage. Rising electricity prices also influence non-financial motivations, such as a desire to reduce exposure to future electricity price increases. As the market increases in size, learning effects put downward pressure on total battery install costs. In contrast, if electricity prices decrease, these reinforcing loops will operate to discourage battery adoption.

Interestingly, there is a large asymmetry associated with the 'total battery costs' and 'total PV costs' result. Higher battery costs have a greater negative influence on battery adoption when compared with an equivalent reduction. This is likely both a function of consumer sensitivity to higher upfront battery costs and a reduction in dominance of the reinforcing loops described above. For PV, a 10% increase in costs results in an 8.5% decrease in battery adoption while a 10% decrease in PV costs results in an only 2.5% increase in battery adoption. Unlike battery costs, this result reflects the fact that PV prices are already extremely low. This means that continued price drops have less of an impact on battery adoption whereas an increase in costs are more likely to materially impact battery payback, particularly on already marginal systems making them ineligible for adoption.

The influence of reliability and resilience on battery adoption is also interesting. This variable is informed by both financial motivations (i.e. the model uses a 'value of reliability' metric developed by AEMO to determine the financial value consumers place on reliable access to electricity) and non-financial motivations, which cumulatively act to increase battery adoption. As the existing electricity system already provides relatively reliable electricity, improvements in reliability do not result in an equivalent decrease in battery adoption.

For the rest of the parameters tested, the results are mostly symmetrical, with the differences between parameters reflecting their relative influence on battery adoption. These results have been used to inform the development of scenarios described below.

8.1.3 Scenario analysis

Scenario analysis is used in this thesis to help better understand how battery adoption dynamics change under a range of different conditions. Of particular interest is how endogenous feedback mechanisms manifest and drive broader system change when input values and exogenous variables are manipulated. Scenario analysis has been used extensively in the energy sector since the 1970s when it was pioneered by Royal Dutch Shell to respond to increasing complexity in the energy supply chain (Wack 1985; Riesz et al. 2014). It can be defined as the process of designing "informed, plausible and imagined future environments" to better understand complexity and uncertainty (Chermack & Lynham 2002, p. 376).

Scenario analysis is particularly useful when addressing new challenges that deviate from established organisational norms. The complexity and uncertainty associated with disruptive technologies such as PV and battery energy storage make scenario analysis highly relevant in this respect. It provides a framework that focuses on the dynamic interactions within the changing environment and as such helps stakeholders understand the forces that are driving change (Wack 1985). In this way, scenario analysis challenges mental models, helps improve decision making and enhances human and organisational understanding of a system (Chermack & Lynham 2002).

Due to the complexity in the energy sector, energy-based scenario analysis is typically supported by modelling to better incorporate qualitative and quantitative elements (Cao et al. 2016). Although there are several scenario analysis methodologies described in the literature with no single agreed upon approach, many of the methods share common characteristics (Amer, Daim & Jetter 2013).

The method of scenario analysis used in this thesis was adapted from two approaches and involves a five-step process. The primary method draws upon one of the most well established scenario methodologies, the Intuitive Logic Approach, which was originally used by Shell (Huss & Honton 1987). Comprising a number of logical steps, the approach is able to accommodate highly complex and qualitative relationships.

Methodological elements have also been drawn from an approach described in Amer, Daim and Jetter (2016) called Fuzzy Cognitive Mapping. This is an intuitive scenario building method designed for use with quantitative analysis and is based on causal cognitive maps, an approach well suited for use in systems thinking (Amer, Daim & Jetter 2016).

Accordingly, the steps used to develop the scenarios in this study include:

1) Analysing the nature of the problem and identifying strategic concerns – This step is necessary to clarify the purpose and scope of the scenario analysis. Problem articulation is a key step in a systems thinking approach and has been well covered in previous chapters
2) Identifying and prioritising key uncertainties and causal relationships – This step identifies relevant parameters to be included and modified in scenario analysis. The results of the participatory data collection process and the creation of a dynamic hypothesis using causal loop modelling as described in Chapter 6, provides the foundation from a qualitative perspective. Expert stakeholder input in this regard is useful to facilitate debate, discussion and consensus regarding the main issues and the various combinations of input vectors to be included in the analysis (Amer, Daim & Jetter 2016). The sensitivity analysis as described above represents an additional measure to help identify the relevant parameters from a quantitative perspective.

3) Defining the scenario logic – Scenario logic includes the "organising themes, principles, or assumptions that provide each scenario with a coherent, consistent and plausible logical underpinning" (Huss & Honton 1987, p. 22). Based on the outcomes of step 2, a brief narrative describing each scenario was developed and is listed in Table 6 below.
4) Parameterising the simulation model – Based on the outcomes of step 3, the model was modified for each scenario by changing key parameter inputs with data and assumptions sourced from the literature and/or the CLD development process.
5) Analysing scenario implications – This step involves analysing the outputs of each scenario to determine the magnitude of system change, the key issues that emerge and the resilience of the system in response to future uncertainty. This can then be used to inform policy analysis and planning interventions to address the scope of the study identified in Step 1.

Using the above method, four scenarios were developed, including the base case. The scenario logic and key assumptions are described in Table 6. These scenarios represent a spectrum of possible future outcomes ranging from the relatively conservative base-case scenario to a more pessimistic climate change scenario. Due to the highly interconnected nature of the system under investigation, only a small number of parameters were modified in each scenario to generate meaningful results.

Table 6 Overview of scenarios used in the simulation model

Scenario	Scenario description
Base-case	The base case reflects a business-as-usual scenario. It assumes all exogenous inputs are based on 2016 values as per the assumptions described in Chapter 7. It assumes no new PV or battery subsidies, no new emissions policy and no climate change impacts. PV module and battery price reductions are based on generally accepted trajectories as described in the literature. There is no strategic response from incumbents in response to battery adoption. Battery integration is not coordinated and makes minimal contribution to a reduction in network costs through peak reduction in constrained areas.
Scenario 1 – proactive battery integration	In response to falling demand and declining asset utilisation, government and industry develop a subsidy scheme that provides rebates for small battery systems with eligibility subject to network control of batteries during periods of high peak demand. The rebate can only be used for a small battery (i.e. 5kWh) and is worth 50% of the system cost to a maximum of $1000. This scenario assumes network utilisation is significantly improved and that 100% of peak demand savings from battery adoption flow through to reduce network costs. This serves to balance rising electricity prices, which along with improved reliability and system resilience, helps moderate non-financial motivations.

Scenario 2 – barriers to battery adoption	With continuing PV uptake reducing network demand, the variable cost of electricity rising in response, and the spectre of increasingly rapid battery adoption exacerbating these issues, network utilities decide to restructure their tariffs to more accurately reflect the costs associated with distributing electricity (this could be in response to government pressure to address social equity issues arising from the 'death spiral', or as a strategic decision to impede distributed energy technologies which challenge the network monopoly business model). At the end of the current regulatory period ending in 2020, network utilities transition over a five year period to a network tariff in which 75% of residential revenue is recovered through fixed costs to more closely reflect the actual fixed and sunk capital costs that comprise the total network cost structure.
Scenario 3 – climate change impacts (worst-case)	As global temperatures continue to increase and the effects of climate change become more evident, a carbon price is introduced in Australia from 2020 to reduce the country's emissions. This increases electricity prices, which occurs at the same time as severe weather events begin to impact the resilience of the existing electricity supply system. Consumers turn to batteries and larger PV systems to manage these risks and maintain a more reliable supply of electricity. The influence of climate change in the model is a function of temperature increases. For this scenario, the temperature follows a linear trajectory reaching a global average increase of 1.5°C by 2036. A number of recent studies suggest that based on current trajectories, this could be a conservative estimate (King & Henley 2016; Henley & King 2017). The model assumes a carbon price starting in 2020 that increases wholesale electricity costs by $25, rising to $70 by 2036. This estimate is informed by Australian Government modelling that was used to forecast carbon price trajectories for the Carbon Pricing Mechanism (Australian Government 2011).

8.2 Results and discussion

The outputs of the base-case simulation model and the results of scenario analysis provide a clearer understanding of the key adoption dynamics that may influence residential PV and battery uptake. In doing so, the model helps identify a number of important relationships that could develop in coming years with substantial implications for industry, government and society more broadly. This section examines these relationships and draws a number of conclusions which form the basis for additional analysis in Section 8.3 that considers policy implications aimed at ensuring more efficient integration of the technology.

8.2.1 The base-case

PV and battery adoption rates and characteristics

The base-case simulation results demonstrate that battery adoption over the simulation period will increase rapidly. Adoption appears to follow s-shaped growth, with battery uptake increasing slowly until 2020 at which point it begins to accelerate. Early-majority market penetration, as per Bass diffusion adoption categories, occurs from 2029 (Figure 63). By the end of 2036, approximately 570,742 battery systems have been installed representing 5,444 MWh of capacity. The majority of battery dwellings comprise installations with new bundled PV and battery systems (~390,000) compared with dwellings that had batteries retrofitted to existing PV systems (~180,000). Total PV installations across all prosumer dwellings exceed 1 million and comprise 4,434 MW of capacity.

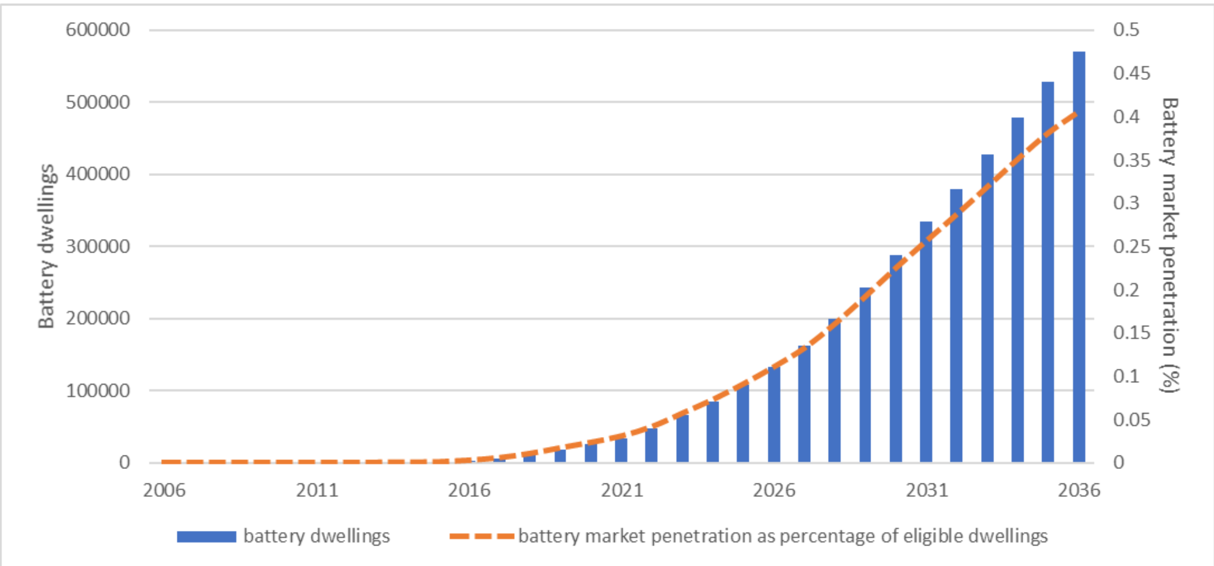


Figure 63 Battery adoption and market penetration

To better understand the rate and scale of battery adoption, it is worthwhile comparing it with the growth of residential PV from a decade earlier. While the base-case simulation shows that battery adoption is likely to be substantial in coming years, the rate of PV uptake was even higher, achieving similar penetrations as those projected for batteries over the entire 30-year simulation period in less than 10 years (Figure 64 shows the rate of PV adoption from 2006 to 2016).

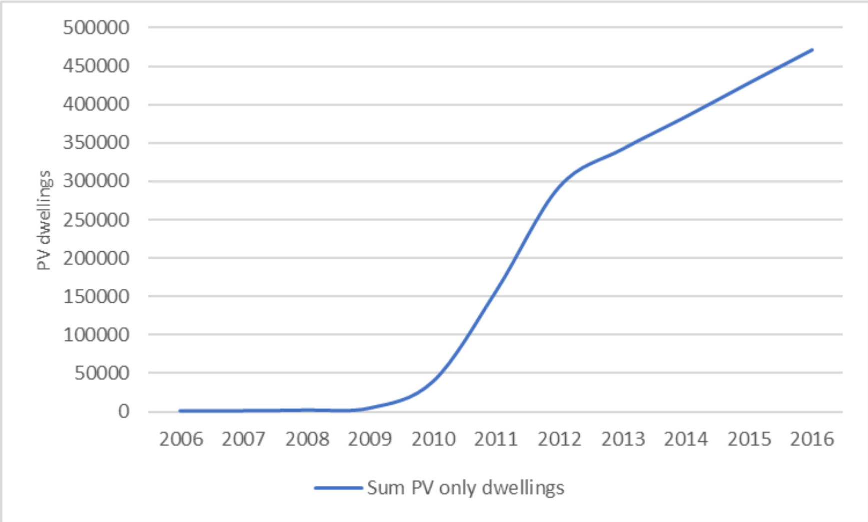


Figure 64 PV adoption between 2006 and 2016

As previously discussed, exponential PV growth was underpinned by a confluence of events including generous subsidy arrangements, rapidly falling PV prices and increasing electricity costs, which all created strong reinforcing loops encouraging rapid uptake. In contrast, the base-case simulation model represents a business-as-usual scenario; it assumes no subsidies and includes relatively conservative estimates for key initial variables. In addition, the influence of non-financial motivations is relatively muted in this scenario. The model shows that depending on market penetration, non-financial motivations will influence battery adoption throughout the simulation period by between 5-9%.

In regards to the types of battery system installed, the simulation model shows that 15kWh batteries are most common (~288,000 installs), followed closely by 5kWh systems (~240,000 installs) and then 30kWh systems (~43,000 installs) (Figure 65). For off-grid systems, and noting the challenges associated with accurately modelling uptake as discussed in Chapter 7, the model shows that 138,000 dwellings could be classed as possible off-grid systems by 2036 representing approximately one quarter of all battery dwellings.

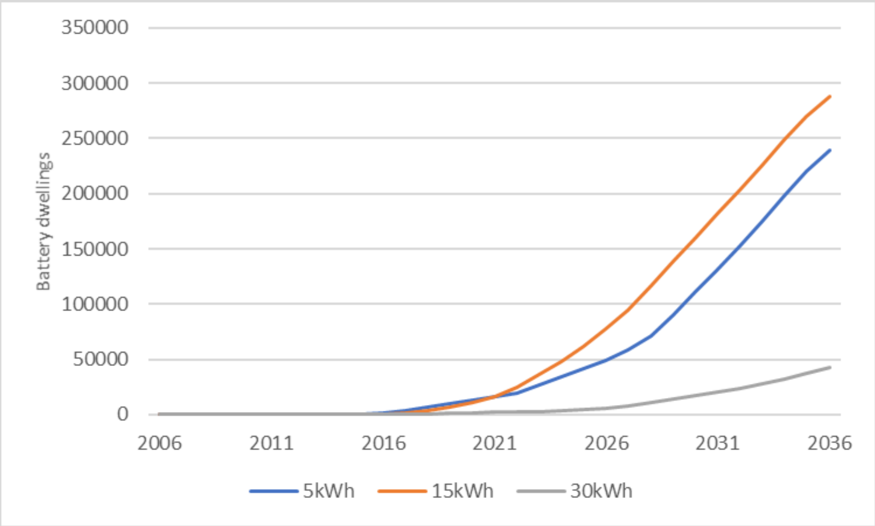


Figure 65 Number of dwellings by installed battery capacity

It is important to consider the above results for battery system sizes in conjunction with data outputs for PV system size. This is because both the financial and non-financial drivers for battery adoption are highly dependent on the amount of electricity that can be generated on site. The numbers of installed PV systems across all sizes is shown in Figure 66. In Queensland, dwellings with PV systems that were less than 2kW were initially the most popular, due in part to the structure of historical subsidies and higher system costs at the time (Australian Energy Council 2017). With module prices falling, it is now financially viable for many of these households to upgrade to larger PV systems by installing more panels, or if considering a battery, installing a totally new PV and battery bundle. Moving forward, the base-case simulation shows a marked preference for 4-6kW PV systems which comprise almost half of all PV installs by 2036. This finding reflects a continuation of the current trend in actual installs which shows that 5kW systems are now the most common PV installs in Queensland (KPMG 2016).

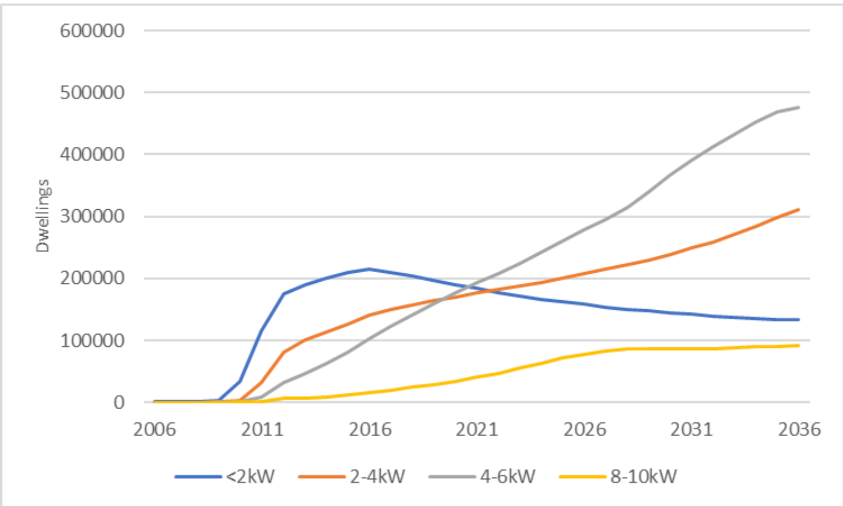


Figure 66 Number of dwellings by installed PV capacity

In terms of the most popular PV and battery system combination, nearly half of all installs by 2036 will include a 5kW PV system and a 15kWh battery. The attractiveness of this combination reflects the falling price of PV and batteries and the rising price of electricity, which effectively make it cheaper for most consumers to generate their own electricity rather than import it from the grid. It is also a function of non-financial motivations. The model shows that as willingness to pay for greater self-sufficiency increases, the preference for smaller battery systems declines by just under 10%, whereas the preference for larger systems increases by 13%.

For these, the grid would be used primarily as backup, most likely for short periods throughout the year. By 2036, the model shows that dwellings with a 5kW PV and 15kWh battery, averaged across all different load profiles and consumption types, will use only 0.16MWh/year of electricity from the grid. In contrast, dwellings with the smallest PV (2kW) and battery combination (5kWh) across all different load profiles and consumption types, would use 3MWh/year from the grid on average.

- *Financial drivers for battery adoption*

The importance of financial drivers for mass market uptake of new energy technologies is well documented (Boughen et al., 2013; Caird et al., 2008; Rickerson et al., 2014; RMI, 2014; Romanach et al., 2013; Stern, 1992). For residential PV and battery energy storage, the simulation model not only demonstrates the pervasive nature of feedback loops that reinforce financial drivers, primarily on the upside, but also the sensitivity of battery adoption to both exogenous and endogenous influences.

The base-case model shows that payback periods for PV and battery systems continue to improve in coming years. Currently the payback period for many PV and battery system configurations is less than 15 years with some as low as 7 years, depending on household load profile and consumption. At the end of the simulation period, the average payback for bundled PV and battery systems is approximately 6 years with some combinations achieving paybacks of less than 4 years. Table 7 shows the payback for bundled PV and battery systems based on battery size (values have been averaged out across load profile, electricity consumption and PV size).

	Payback period (years)		
	5kWh	15kWh	30kWh
2006	111.8	113.7	167.6
2011	30.5	39.2	70.0
2016	10.3	11.4	19.2
2021	6.5	7.3	11.5
2026	6.4	6.9	10.4
2031	6.0	6.3	9.1
2036	5.2	5.3	7.4

Table 7 Average payback period for bundled PV and battery systems

As previously described, the payback period in this model is effectively a function of the *total installed system cost* and the *ongoing savings* that it generates. Within each of these elements, there exist several factors which help characterise the dynamics underpinning battery adoption. These are considered individually in more detail below.

Firstly, the model shows that total installed system costs are one of the key factors underpinning PV and battery adoption. As Figure 67 shows, the decline in the unit costs of fully installed PV systems ($/W) and batteries ($/kWH) have already been dramatic.

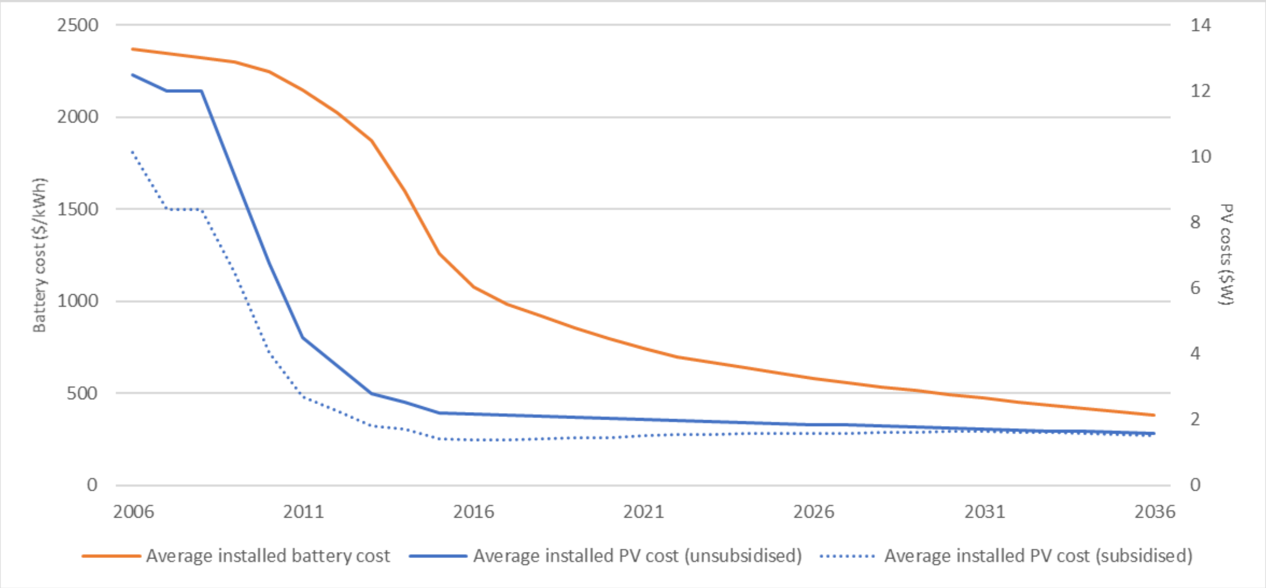


Figure 67 PV and battery fully installed and unsubsidised average cost reductions

While further large decreases in price for PV installs are less likely[6] there remains considerable scope for reductions in battery prices. In Queensland, battery system costs are currently the function of exogenous drivers, with battery packs, PV modules and inverter costs subject to global technology, manufacturing and market developments. While the rate of decline of battery system costs represent a source of considerable uncertainty, the exogenous battery cost assumptions in the model generate a price trajectory that is well within the bounds of industry expectations.

Indeed, and as discussed in Chapter 2, there are in fact a number of factors coalescing globally that suggest battery price reductions could possibly exceed the rate of decline used in the model. New manufacturing capacity and advances in complementary technologies, such as electric vehicles, are driving technology and manufacturing improvements which are seeing efficiencies of scale further reinforcing battery price declines. At the same time, demand for residential batteries is increasing in many jurisdictions, encouraging competition and innovation and further driving system cost price reductions. The availability of government rebates or market-led subsidies could also have a substantial impact on upfront battery system costs (the influence of rebates in this respect is considered as part of scenario analysis).

In addition to hardware costs, soft costs such as installation, customer acquisition and permitting, also make an important contribution to total installed battery system costs. Soft costs contain an endogenous component, with cost reduction rates influenced by learning as a function of market penetration. The simulation model shows soft costs initially reducing by 5% per annum. As the rate of adoption increases, soft costs decline further and reach a maximum rate of reduction of 10% per annum before slowing as mass-market penetration is achieved.

To understand the causal dynamics at play in this regard, it is worth examining the soft cost reductions achieved for PV installations in the past decade. PV soft costs in Australia are now some of the lowest in the world. In 2014, they were $2.19 per watt less compared with those in the USA (RMI 2014b). The reason for this differential can be traced back to the early expansion of the Australian PV market. High demand for residential PV, driven initially by subsidies, saw a rapid increase in PV installers, rising from 961 in 2009 to 4,246 in 2012 (RMI 2014b). This market concentration underpinned high levels of competition and transparency and, as the market size

[6] This assumption is predicated on existing learning curves for c-Si technologies. There exist a number of new PV technologies that are still in development that promise substantial cost and efficiency benefits. However as these have not yet been proven commercially, their specific characteristics and related input values have not been included.

increased, Australian PV installers had to innovate to stay competitive. By reducing the time for installs and introducing efficiencies in other areas of their businesses, soft costs fell from $5 per watt in 2008 to $1.20 per watt in 2013 (RMI 2014b).

For battery energy storage, these developments are highly relevant. While the residential battery market is still nascent in Queensland and the extent of soft cost reductions remain uncertain (the relationships defined in the model and the initial values used are necessarily conservative), it is possible that battery soft cost reductions could be far more rapid as battery penetration increases in the market. Queensland already has a mature distributed generation energy market, which has become highly sophisticated following the rapid growth of PV in recent years, and is well placed to leverage past learnings and apply them to battery installations.

The value of possible *ongoing savings* that accrue from the use of a PV and battery system is the other major component used to assess the financial viability of a system. In this respect, the results of simulation demonstrate that there are multiple variables and feedback loops in the model that influence this value. These include exogenous and endogenous parameters nested within electricity prices, household demand and load profiles, residential peak demand and total residential sector consumption. These elements are considered in more detail below.

Firstly, the model shows that electricity prices increase from 27.11c/kWh in 2016 to 33.57c/kWh at the end of the simulation period, reflecting a 25% increase. The model shows that this price rise is driven in almost equal parts by the impact of falling demand on network revenue recovery, and increasing wholesale energy prices. The contribution of batteries to a reduction in network peak demand has a slight moderating influence on electricity price rises.

The structures and endogenous feedback loops that underpin the impact of falling demand on network revenue recovery have been discussed in detail in earlier chapters. The simulation model clearly demonstrates the impact of these relationships and shows how individual decisions to install PV and batteries at the household level, when taken as an aggregate, have widespread impacts along the electricity supply system.

To demonstrate, the model shows that approximately 1 million PV systems are installed by 2036, comprising nearly 4434MW of capacity. Total generation from prosumer dwellings in 2036 is 8,340GWh with approximately half used in homes with the remainder exported back to the grid.

Despite total numbers of dwellings forecast to increase by almost two-thirds by the end of 2036, grid demand from the entire residential sector drops to 8,903GWh per annum, down from 11,500GWh per annum at the end of 2016 (Figure 68).

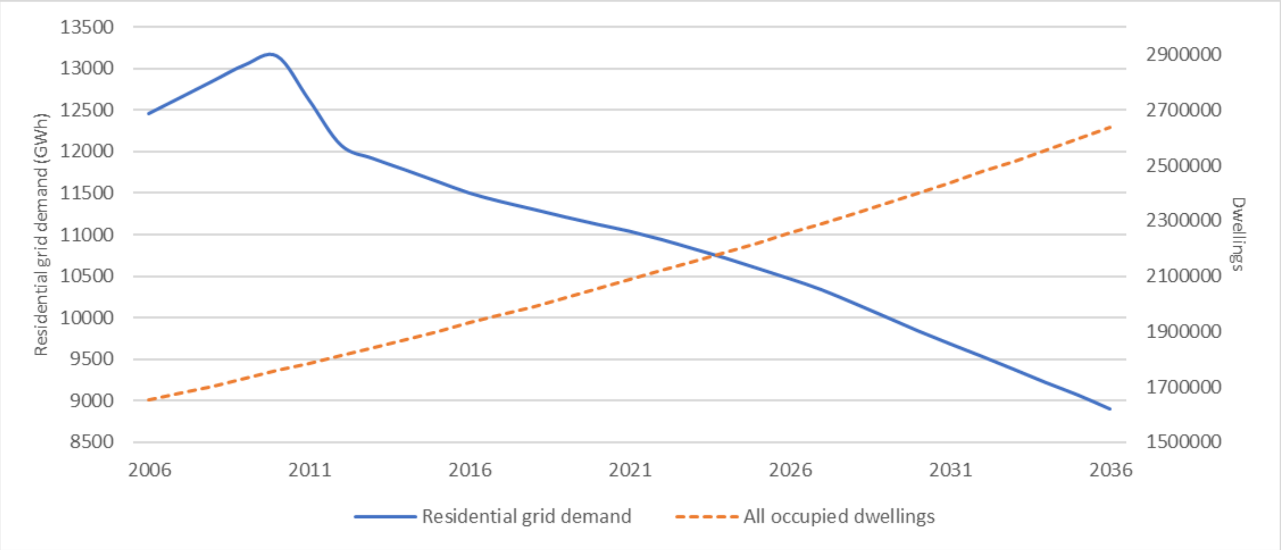


Figure 68 Residential grid demand compared with dwelling growth

While it is clear that PV dwellings contribute to reduced residential grid demand in their own right, dwellings with batteries substantially exacerbate this trend. For example, at the end of the simulation period, dwellings with PV only, use more than 3MWh/year of grid power on average. In contrast, dwellings with PV and batteries on average use less than 0.9 MWh/year of electricity from the grid.

The influence of these dynamics on non-prosumer dwellings must also be considered as they could reinforce other feedback loops within the system. For example, should non-prosumer dwellings respond to higher electricity prices by reducing their electricity use (e.g. by installing energy efficiency appliances or changing energy use behaviour), total demand on the network will fall further, adding to the effects stemming from PV and battery adoption. To test this assumption, an additional 10% reduction in non-prosumer household energy consumption was artificially simulated in the model. This resulted in an additional 5% increase in electricity prices but also a similarly large increase in battery adoption.

Wholesale energy price increases were the other major factor to make a substantial contribution to electricity price increases in the base-case simulation. Wholesale energy prices, despite having some endogenous elements, are represented in the model as a primarily exogenous variable. In the highly dynamic electricity generation sector, wholesale prices are susceptible to a multitude of forces outside the control of any individual agent e.g. utilities, government or customers. This means there can be wide unforeseen fluctuations in price (which are explored in greater detail as part of scenario analysis).

A recent example in Queensland demonstrates the volatility in this regard. Wholesale price projections from 2016 based on Queensland Government commissioned analysis were assumed to increase by 2.1% per annum until 2036 representing a 50% increase in real terms over the entire simulation period (the assumption used in the model). However, in January 2017 wholesale prices in Queensland hit record highs, and are on average expected to increase by up to 40% in 2017-18 compared with the year before (Killoran 2017; QCA 2017b). These price increases were caused by tightening supply-demand balance in the NEM stemming from multiple simultaneous changes. Increased demand for gas, the closure of the Hazelwood power Station (one of Australia's largest and cheapest fossil fuel generators), the continued operation of the Portland aluminium smelter in Victoria (which represents a large demand sink on the NEM), and limited new renewable energy capacity entering the market in Queensland resulted in large increases in wholesale electricity prices (QCA 2017b).

While it is anticipated that wholesale prices in Queensland will return to more normal levels in the short-term, this example demonstrates the rate and scale of change that can now occur in the electricity sector. It also highlights the importance of sensitivity and scenario analysis in modelling energy transitions to take account of unexpected developments. Perhaps more importantly, this example also shows that wholesale energy prices are just one more variable that appears to have a higher probability of influencing battery adoption dynamics on the upside, rather than the downside, further strengthening reinforcing financial loops throughout the model.

The other major factor that influences electricity prices relates to the capital investment cost of maintaining and augmenting the electricity distribution and transmission network. As previously stated, the cost of network expansions to meet peak demand are one of the primary drivers of electricity bill increases in Queensland. In this respect, the model shows that in the absence of batteries, critical peak demand for the *residential* sector is estimated at 4854MW in 2016 rising to 8841MW at the end of the simulation period. When the influence of batteries is incorporated, the model shows that residential critical peak is 7543MW in 2036 representing a 1300MW reduction (Figure 69).

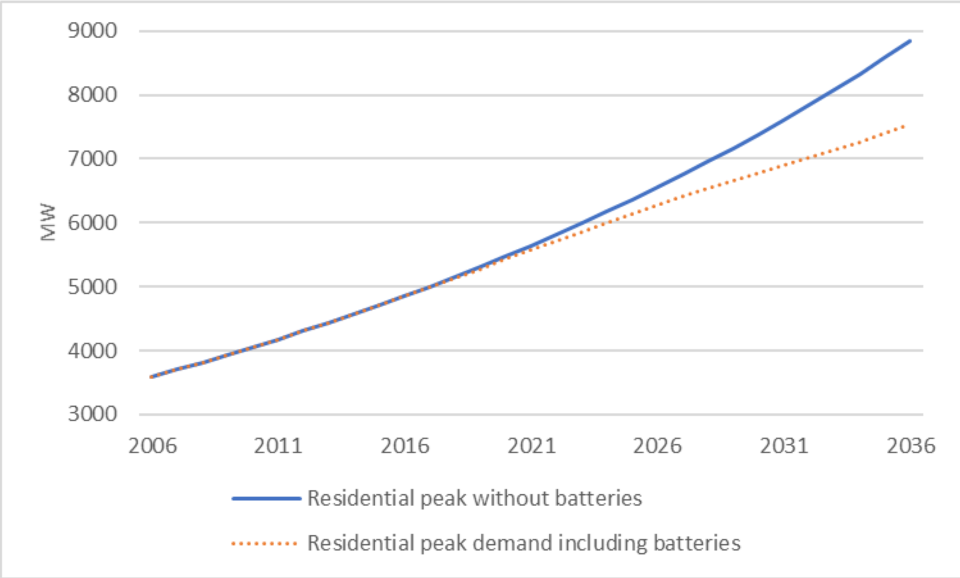


Figure 69 Battery contribution to critical peak demand reduction in the residential sector

Attempts to value this reduction in peak, and the corresponding influence on electricity prices, are subject to a number of assumptions. As explained in Chapter 7, the benefits of network peak demand are generally spatially specific. To achieve maximum network benefit, batteries should be deployed in areas of existing or future network constraint and must include some element of network control. As the base-case simulation assumes there are no incentives to specifically manage peak demand through subsidies, supportive tariffs or regulatory approaches, the full potential of network savings are not achieved in this scenario.

Having said that, due to the large number of batteries deployed across the state, the model assumes that incidental peak demand outcomes would still be achieved. This means that by 2036, battery adoption will contribute to an almost $75 million annual reduction in network prices, resulting in a 2% reduction in electricity prices (approximately 1c/kWh). This dynamic represents an important balancing feedback loop and its potential is examined in more detail as part of scenario analysis.

Access to premium FiTs was a major contributor to the recent residential PV boom as they comprised a substantial component of the ongoing savings achieved for system installation. For those dwellings that still receive the premium FiT, there is limited financial incentive to install a battery, particularly as the premium FiT remains above the retail electricity price. After 2028, when the FiT scheme closes and the incentive falls from 44c/kWh to 7c/kWh, the model shows a more rapid increase in retrofit battery installs as households on the premium FiT rush to install batteries to maximise their self-consumption. This is because at current FiT rates, the price differential when compared with the retail price of electricity makes it far more beneficial for battery households to maximise self-consumption rather than to export back to the grid.

- *Broader system implications*

The simulation model also generates outputs for a number of additional system wide impacts resulting from PV and battery adoption including:

- Equity issues - The model shows that amount of electricity used from the grid, and the size of household electricity bills vary substantially between the different consumer classes. For example, non-prosumer dwellings have average electricity prices of approximately $2235 a year in 2036, whereas the average household bill for dwellings with PV only is $914 per year. For dwellings with PV and battery the average household bill is $424 per year (with the fixed electricity cost comprising the main component). Equity issues arise as prosumer dwellings not only have smaller household bills but also indirectly contribute to increases in electricity prices for non-prosumers. To demonstrate, the simulation model shows that in 2036, an average dwelling with PV and battery using less than 1MWh from the network per year not only pays approximately 80% less on average than a non-prosumer household, but also contributes to demand reductions which collectively result in a 10% increase in electricity prices.
- Emissions reductions - The reduction in use of grid sourced electricity represents greenhouse gas emissions savings of 6.2Mt $CO_{2\text{-}e}$. While there remains considerable uncertainty regarding the true cost of carbon, with accepted values ranging from US$33 to US$220 (Moore & Diaz 2015), this represents a saving of at least $200M.
- Private investment and industry development - Total private sector investment over the simulation period for all prosumer dwelling types is approximately AU$8.7B, which would contribute to broader economic benefits including employment, industry and regional development, and local R&D outcomes.

8.2.2 Scenario analysis

This section describes the results of scenario analysis. In addition to the base-case, three scenarios have been evaluated by comparing and contrasting model output across key variables. The scenarios include proactive battery integration (Scenario 1), barriers to battery adoption (Scenario 2) and climate change impacts (Scenario 3).

All scenarios saw an increase in the numbers of battery dwellings across the simulation period. Scenario 3 had the highest number of installs with a total of 843,164, followed by Scenario 1 with 654,959, the base-case at 570,742 and Scenario 2 with 300,486 (Figure 70). For the base-case and scenarios 1 and 3, the shape of the curve is similar and reflects strong reinforcing feedback. This effect is less clear with Scenario 2, however the rate of battery growth does begin to accelerate past 2030 as falling PV and battery system prices improve financial viability, even in the face of continuing low electricity prices.

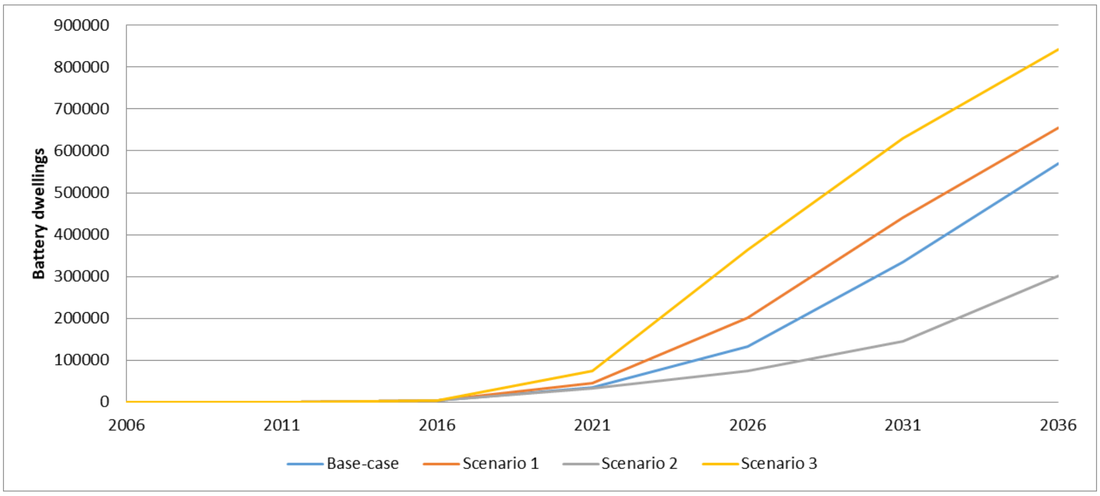


Figure 70 Number of battery dwellings by scenario

While the total numbers of dwellings represent an important value in its own right, broader system impacts also relate to the capacity and combinations of installed system types across each scenario. To demonstrate, Figure 71 shows total installed battery capacity for each scenario. Table 8 and Table 9 on page 179, break down the proportion of different battery and PV sizes between scenarios.

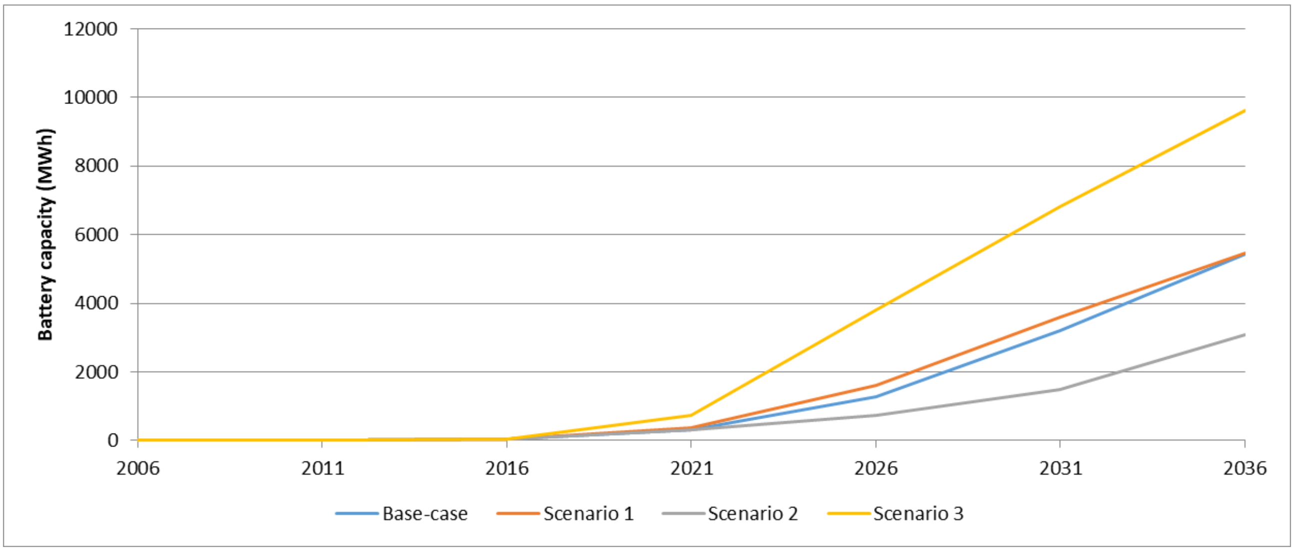


Figure 71 Total installed battery capacity by scenario

The trends shown in Figure 71 and the data in the tables below help illustrate the influence of the different drivers and indicate the existence of strong leverage points for policy interventions. Scenarios 1 and 3 have the highest number of battery installations and similar battery adoption curves, despite the contrary nature of the assumptions underpinning these scenarios. The difference becomes clearer when the proportions of battery sizes installed and the effect on total capacity in each of the scenarios are examined.

Scenario 1 had a much higher proportion of smaller battery systems (55%) than Scenario 3 (24%) which has far more medium and larger battery systems. The dynamics underpinning these results are important. Scenario 3 sees climate change policy initially drive higher electricity prices which reinforce feedback loops that encourage greater self-sufficiency. Residential demand falls more quickly at the same time as the impacts of climate change are felt. With blackouts becoming more common and prices continuing to rise, consumers become more frustrated with incumbents leading to a situation where both financial and non-financial reinforcing loops dominate.

In contrast, financial incentives in Scenario 1 initially encourage smaller systems. A higher proportion of small systems not only result in less total grid reduction from the residential sector but when used strategically to reduce network constraints, creates a balancing feedback loop that helps keep electricity price rises in check. This serves to reduce non-financial motivations for self-sufficiency as batteries integrated to support the network create net benefits in terms of resilience and reliability, further reducing desire for larger battery systems.

The model shows that the total cost of the subsidy that underpins the results in Scenario 1 is substantial, costing approximately AU$360M over the simulation period (although when taken over 20 years it equates to a more moderate AU$18M per year). This cost however, must be considered in terms of the benefits that this subsidy accrues across the system. The model shows that the subsidy delivers a total reduction in network costs of AU$399M which helps to moderate increasing electricity prices, while minimising the impact of broader equity issues. Moreover, while the total cost of the subsidy appears high, it is relatively modest when compared with the cost of the Queensland Solar Bonus Scheme which is expected to exceed AU$4B over its 20 year life.

	Proportion of installed battery sizes		
	5kWh	15kWh	30kWh
Base-case	42%	50%	8%
Scenario 1	55%	39%	6%
Scenario 2	33%	59%	8%
Scenario 3	24%	65%	11%

Table 8 Proportion of installed batteries by size and scenario

	Proportion of PV sizes on battery dwellings			
	<2kW	2-4kW	4-6kW	8-10kW
Base-case	7%	27%	50%	16%
Scenario 1	7%	29%	50%	15%
Scenario 2	6%	20%	48%	25%
Scenario 3	1%	23%	63%	13%

Table 9 Proportion of installed PV on battery dwellings by size and scenario

As already noted, the number of dwellings with PV and battery systems and the size of those systems also influence the amount of electricity sourced from the grid. In this respect, the outputs from the simulation model shows that residential demand across all scenarios will continue to fall (Figure 72).

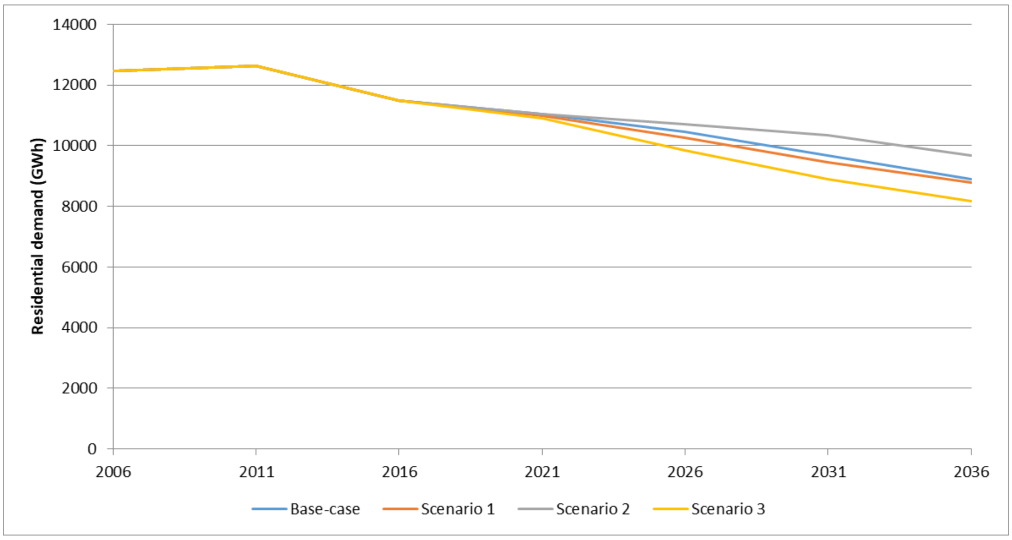


Figure 72 Residential grid demand by scenario

While the influence of residential demand on electricity prices has already been well covered, scenario analysis enables a closer examination of some of the other factors that could influence electricity prices. Variable electricity price trajectories across all scenarios are shown in Figure 73.

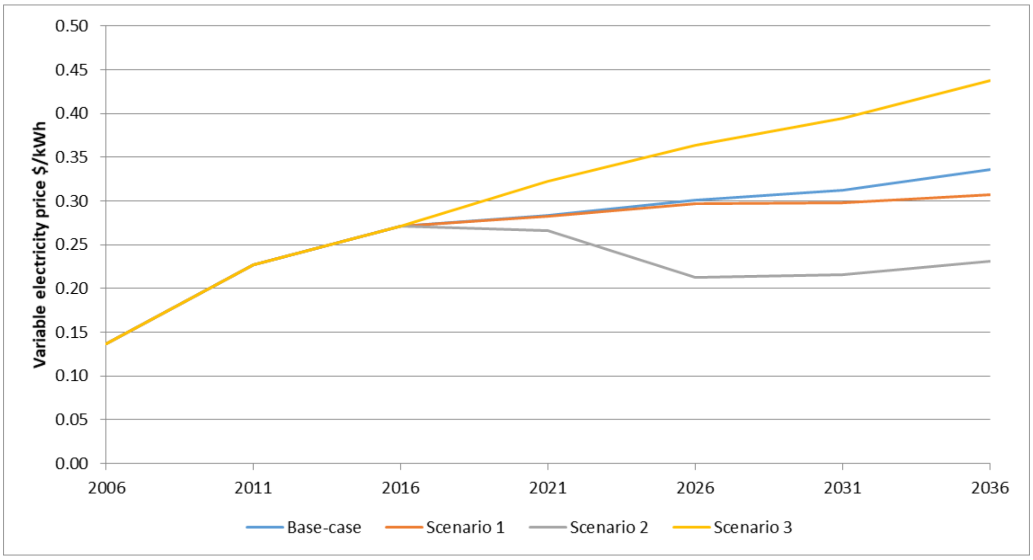


Figure 73 Residential variable electricity prices by scenario

As the above graph clearly shows there is a substantial difference in electricity prices across each of the scenarios. The results for the base-case primarily demonstrate the behaviour of the endogenous feedback loops already inherent in the system. The other three scenarios each help to demonstrate the influence of different assumptions underpinning the system structure. Scenario 1 shows that when batteries are deployed to strategically manage the network, cost savings can be achieved which are then passed on through to electricity prices. Scenario 3 demonstrates how a confluence of factors stemming from direct energy cost increases and rapid and pervasive battery adoption drive up electricity prices.

In contrast, Scenario 2 demonstrates how changes to tariff structures can dramatically change pricing dynamics which can have flow-on effects throughout the system. In this scenario, a recalibration of variable to fixed costs sees a substantial reduction in the variable unit price of electricity. Low variable and high fixed electricity costs serve to reduce the amount of ongoing savings that can be realised from on-site generation, thereby reducing the incentive for households to install PV and battery systems. Battery adoption will be delayed, with the model showing that nearly 50% less PV and battery systems are installed in Scenario 2 when compared with the base-case.

On the surface, this appears to be a positive outcome, particularly in the short-term as electricity prices stabilise and there is increasing utilisation of the network. However, while the low variable electricity price pushes out the timeframe in which PV and batteries become financially viable, it also serves to increase frustration with incumbents, particularly for those households who have already installed PV systems and have seen the value of their investment diminish. For electricity consumers more broadly, high fixed costs reduce the ability to proactively manage electricity costs through energy efficiency measures as the magnitude of savings is proportionately reduced. These effects are particularly pronounced for low consumption dwellings that would be disproportionately penalised by high fixed costs.

Together these dynamics will underpin non-financial motivations for self-sufficiency and grid defection. In this scenario, with electricity prices remaining low contributing to high system payback periods, PV and battery adoption will unlikely occur at scale. However, as the energy sector transitions and monopoly control and ownership erodes, unforeseen actions or the actions of any supply chain participant could independently result in electricity price rises. If this occurs at the same time as there are improvements in battery technology, battery price declines, or broader market-based innovation, a perfect storm could occur with both financial and non-financial drivers encouraging mass grid defection.

To assess equity issues associated with battery adoption, total household bills are calculated across the scenarios for each dwelling type with a breakdown of fixed and variable costs (Table 10). The base-case and Scenario 3 have the highest household electricity prices for non-prosumers, which acts as both a driver for increased adoption and a source of inequity for consumers unable to install a PV and battery system. Scenario 1 results in a moderate household electricity price increase whilst scenario 2 has the lowest household electricity bill, reflecting both the impact of tariff restrictions and the corresponding low uptake of PV and battery systems.

	Variable	Fixed cost	Average household electricity bills		
	$/kWh	$ per year	Non-prosumer	PV only	PV & Battery
Base-case	0.336	310	$2238	$915	$424
Scenario 1	0.307	289	$2051	$802	$365
Scenario 2	0.231	638	$1965	$910	$613
Scenario 3	0.438	307	$2817	$1235	$557

Table 10 Electricity bill components and average household electricity bills across dwelling categories in 2036

Finally, it is worthwhile considering how the assumptions underpinning each of the scenarios could encourage preferences for possible off-grid systems. The number of possible off-grid systems and their proportion as a function of total battery dwellings in each scenario is shown in Figure 74.

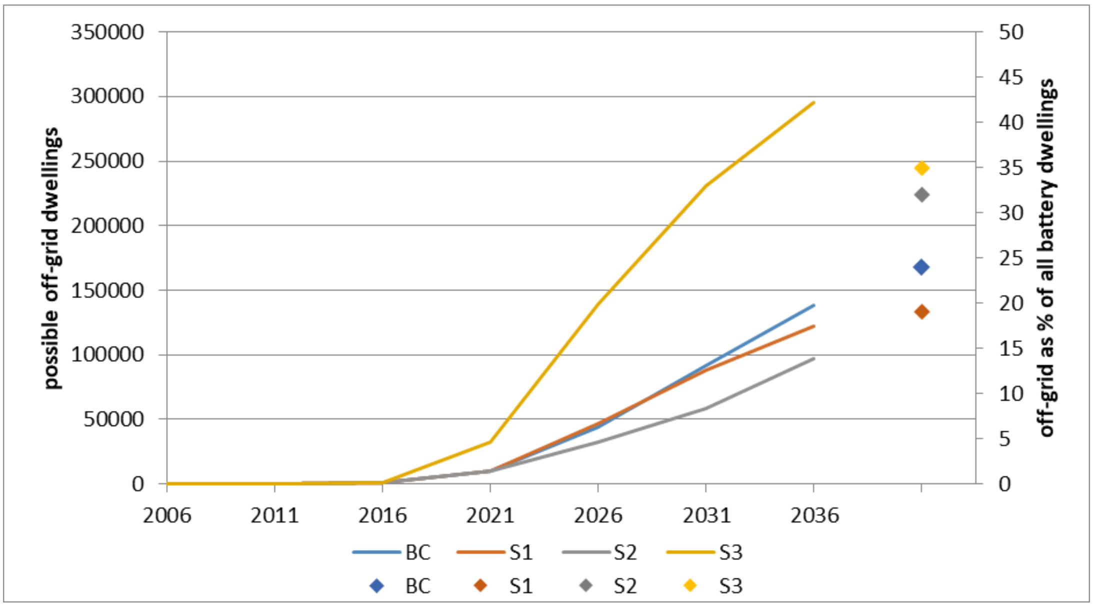


Figure 74 Possible off-grid dwellings by scenario

Not unsurprisingly, Scenario 3 has the largest number of possible off-grid systems. It also has the highest proportion with 35% of all dwellings able to defect. High electricity prices in this scenario along with several strong non-financial drivers, particularly declining network reliability and resilience, underpin this outcome. In contrast, Scenario 1 has the lowest proportion of possible off-grid systems, despite having 15% more batteries in total compared with the base-case. This reflects the influence of the subsidy, which encourages smaller systems, combined with the effect of endogenous feedback loops which keep downward pressure on both electricity prices and non-financial motivations.

Perhaps the most interesting finding from the data in Figure 74, is that Scenario 2 has an almost equivalent proportion (32%) of possible off-grid systems as Scenario 3. While this result was expected to some extent, its occurrence in conjunction with relatively low electricity prices was somewhat surprising. This result may be due to PV and battery payback periods becoming low enough by the end of the simulation period that when compared with total household electricity prices, grid defection becomes a more viable alternative to grid sourced electricity.

The point at which battery market saturation is reached will also be highly relevant in regards to the severity and scale of broader system impacts. Only Scenario 3 shows PV and battery adoption approaching market saturation, and as the ‘worst case’ scenario, this helps illustrate the magnitude of possible impacts. It is interesting however, to consider this finding in conjunction with the well-known systems thinking archetype referred to as ‘limits-to-growth’. Visually represented in Figure 75, this archetype recognises that growth in most systems is eventually constrained as feedback dominance shifts from reinforcing to balancing loops.

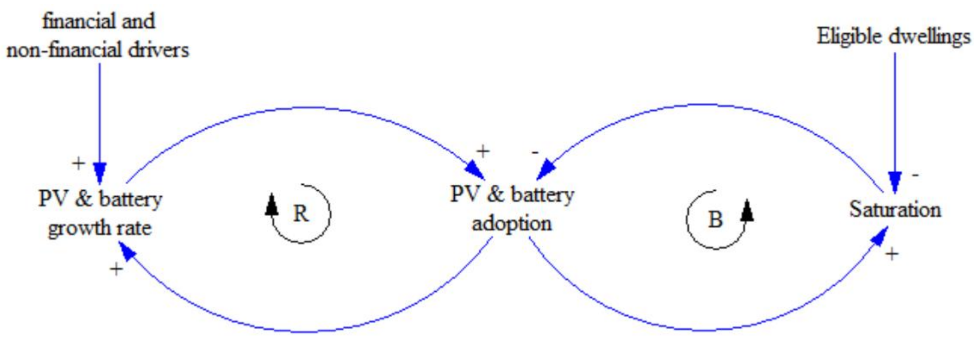


Figure 75 Simplified CLD illustrating limits-to-growth archetype as it applies to PV and battery storage

For residential PV and battery adoption, this dynamic underpins an important observation. Detached dwellings represent just under 70% of total housing stock in Queensland and at maximum saturation, it is assumed that approximately 75% of eligible dwellings will install PV and batteries. This means that even at 100% saturation, just over half of all dwellings would have PV and battery installed. This finding does not diminish the broader system-wide impacts that could arise from mass market uptake of PV and battery adoption. It does however demonstrate the importance of maintaining the existing electricity network and underscores the imperative to ensure that integration of PV and battery technology occurs in the most efficient way possible. It also challenges much of the hype in the popular media which suggests that the wholesale decline of the existing electricity supply system is imminent as a result of mass market PV and battery adoption (Bateman 2016).

8.3 Policy analysis

8.3.1 Key implications

Simulation of the system dynamics model and the outcomes of scenario analysis have reinforced the findings from earlier chapters while eliciting a deeper understanding of the causal relationships, possible unintended consequences, and potential leverage points within the system that will influence battery adoption dynamics. This section evaluates these findings from a policy perspective and uses them as the basis for consideration of possible measures to achieve more efficient integration of the technology.

Firstly, the modelling results support the findings from Chapter 6, which showed that battery adoption is highly likely to occur at scale in Queensland in coming years. Model simulations demonstrate empirically that the structures and dynamics that underpin battery adoption, if not proactively managed, could create path dependence where endogenous feedback loops continue to increase consumer desire for self-sufficiency. This is because battery adoption at scale will drive further declines in residential electricity demand across the electricity supply system, resulting in increased electricity prices as well as strengthening non-financial motivations, which in turn reinforces continued battery adoption. These effects are magnified if consumers are driven to maximise the size of PV and battery installations to specifically reduce their reliance on the network. In the current environment, as depicted by the base-case scenario, the probability of this outcome appears to be strengthening.

The model also quantifies the rate of battery adoption and demonstrates that it will most likely be rapid in coming years with mass market penetration achieved within the simulation period for all scenarios. This was the finding even in the case of the second scenario where reinforcing loops were less dominant. The speed of battery adoption and eventual saturation will have important implications for successful integration. Many of the challenges associated with PV integration in Queensland were related to the rate of uptake and the inability of government or industry to respond in a timely way to unforeseen and unexpected impacts. This resulted in a situation that demonstrated the “folly of making policy on the run” with substantial regressive wealth transfers in addition to many of the technical challenges at the time (Nelson, Simshauser & Nelson 2012, p. 299).

The imperative to proactively address these issues is becoming more urgent. The model shows that based on probable system price trajectories, batteries will become financially viable for many Queensland households well within the coming decade. This is likely to occur even in the unlikely event that electricity prices stabilise at current levels. As system payback periods fall, consumers that install PV and battery systems will benefit from lower total electricity costs while insulating against further price increases and directly addressing any additional non-financial motivations. While this outcome may be advantageous from an individual perspective, the results of modelling demonstrate that this would not necessarily be a beneficial outcome from a whole-of-system perspective.

Social equity issues could be substantial. Most households that install PV and battery systems are likely to stay connected to the grid in the short term, using it both as backup and to generate revenue from any excess PV power they export back to the grid. These prosumer households not only contribute to higher electricity prices but proportionately pay a far smaller amount to use the existing network when compared with non-prosumers.

If left unchecked, the distributional effect of this dynamic will impose a particularly high burden on lower socio-economic households as they spend relatively larger amounts on electricity compared with more wealthy households. In Queensland, households with the lowest income spent approximately 6% of their weekly income on electricity versus only 0.8% for high-income households (QPC 2016b). Moreover, low income households are less likely to be able to install new PV and battery systems to reduce their exposure. This is because they are already budget constrained, more likely to rent (there is a strong correlation between home ownership, household income and PV uptake) and/or live in homes such as apartments that are less suitable for PV and battery installations (QPC 2016b).

Model simulations also show the emergence of other whole-of-system issues. Battery adoption at the rate and scale generated by the model will erode the monopolistic basis of the traditional supply system and further impact already declining asset utilisation. The challenge for incumbents will be to maintain productivity, even as large proportions of residential electricity consumers use PV and battery energy storage technologies to reduce their reliance on the grid. This undertaking will be difficult, particularly because the utilisation of Queensland's electricity networks is already so low. In 2014, Energex's asset utilisation was only 25.7% and Ergon Energy's was 34.2% (QPC 2016a). For multi-billion dollar assets, this is clearly a serious issue in terms of energy productivity and economic efficiency.

The results of simulation indicate that without intervention, the productivity of Queensland's energy supply system will continue to decline as residential PV and battery adoption increases. Moreover, the model shows that this inefficiency could be replicated at the household level. Scenario analysis demonstrates that drivers for self-sufficiency result in a larger proportion of dwellings installing oversized PV and battery systems. As consumers seek to reduce their reliance on the grid, assets at the dwelling level will be built to meet the majority of household consumption, including maximum demand. This means that the same challenges being experienced by the broader network (i.e. oversizing infrastructure to meet demand that only occurs during short periods of the year) will be replicated across possibly millions of dwellings as systems are oversized to meet individual peak requirements resulting in excessive capacity that is infrequently used. This is costly and inefficient from a broader societal perspective, creates substantial redundancies and reduces the collective benefits of a communally used and financed electricity supply system. This dynamic is particularly perverse when taken with the fact that the publicly funded electricity network will become further under-utilised in these scenarios.

8.4 Policy leverage points

To help minimise the risks described above and to enable more efficient integration of residential PV and battery energy storage in Queensland, there is a clear role for government and industry, to anticipate and plan for the potential changes that could be triggered by mass market uptake in coming years. This will involve balancing consumer choice with broader economic efficiency outcomes to maximise "the aggregate or collective wellbeing of the members of the community" (Productivity Commission 2013b, p. 3).

While governments and industry may not have direct control over many of the prosumer drivers discussed in this thesis, they can nonetheless attempt to guide more efficient integration through the use of targeted policy measures (Rickerson et al. 2014). In doing so, it is important that any interventions address the cause of the problem, and not just the symptoms. This has been a problem for energy policy in the past which has "been quite well designed to solve yesterday's problems" (Helm 2002, p. 181). Poor energy policy can make problems worse or at the very least, "introduce new inefficiencies, have unintended impacts and impose compliance and administration costs—which itself imposes costs on the community" (QPC 2016a, p. 72). To avoid these outcomes, it is useful to consider policy analysis through a systems thinking lens, which involves using key leverage points to drive fundamental longer-term changes rather than just addressing the short-term symptoms of the problem (Maani & Cavana 2007).

8.4.1 Subsidies

With modelling results showing that battery system cost factors are a key component affecting the rate and scale of battery adoption, measures used to influence this leverage point are an obvious place to begin. Perhaps the most widely used policy tool in this respect is the provision of government rebates or market-led subsidies (Hsu 2012). Subsidies can comprise several different forms such as capital subsidies, feed-in tariffs, tax concessions or loan guarantees to name a few. Typically, they are used to lower technology adoption costs to achieve stated policy outcomes such as emissions reduction, technology specific outcomes and/or industry development.

Currently there exist only two battery subsidy programs in Australia. The city of Adelaide offers a discount of up to 50% off the cost of a battery up to a value of AU$5000 while the Australian Capital Territory subsidies upfront costs through a competitive tender process (ACT Government 2017; City of Adelaide 2017).

While no such subsidies currently exist for batteries in Queensland, the results of modelling suggest that the use of subsidies to influence battery adoption and integration may only be appropriate in a limited number of circumstances. The model shows that residential PV and battery energy storage systems will become financially viable for most households within the short to medium term without government support. The rationale for government intervention to accelerate battery uptake is therefore questionable when it appears that market development will occur in a timely manner without the need for financial stimulus.

The use of subsidies to support battery adoption also has the potential to reinforce certain systematic structures, such as the common ‘success-to-the-successful’ archetype, potentially exacerbating inherent equity issues already prevalent in the system. In this case, those households already most able to afford PV and battery technology are further incentivised to adopt, resulting in an ongoing financial benefit to the detriment of those households who can’t afford the technology. This situation can be particularly regressive when the costs of subsidies are shared by all electricity users as was done for the SBS. This means non-adopters, who are often low-income households, are directly paying for adopters to implement measures that reduce their electricity costs. This issue is compounded for PV and batteries, the uptake of which strengthens endogenous feedback that directly increase electricity prices. This imposes a further cost on non-prosumer dwellings which further reduces their viability. A simplified CLD illustrating this dynamic is shown in Figure 76.

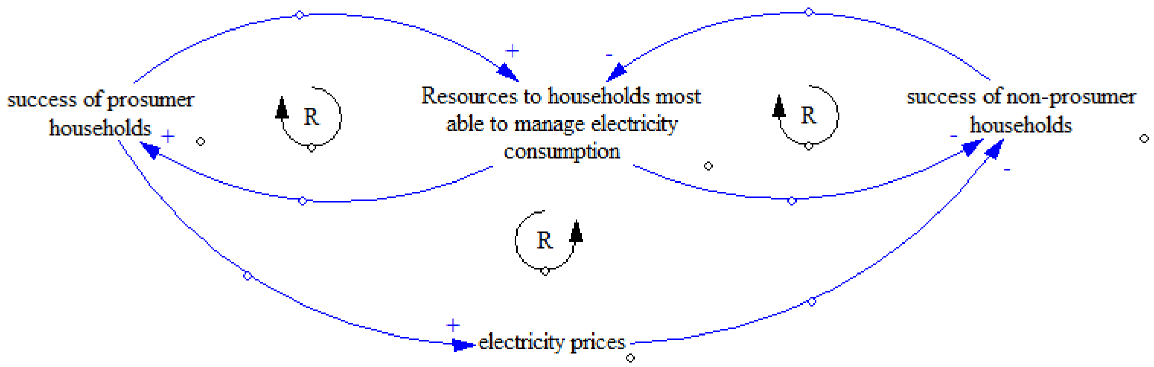


Figure 76 CLD demonstrating the success-to-the-successful archetype

Despite the above issues, the use of subsidies can be appropriate where benefits outweigh the costs and, instead of just addressing symptomatic issues, help modify other leverage points in the system to drive positive longer-term outcomes (Meadows 1999). The assumptions underpinning the use of subsidies in Scenario 1 were based in part on this logic. This scenario demonstrated the potential of using specifically targeted subsidies to change purchasing behaviour and to incentivise management of batteries to achieve network benefits. It also demonstrated the way in which changes to a leverage point can cascade throughout the system to affect both financial and non-financial motivations and in turn realise broader system benefits.

8.4.2 Tariff reform

Another area of policy reform that could help achieve more efficient integration of PV and battery storage relates to the way in which consumers are charged for their electricity. Existing tariff structures in Queensland do not appropriately cost the use of the network for prosumer dwellings[7]. Recent research indicates that Queensland dwellings with PV and high peak load from air

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[7] This is a historical legacy where simple consumption-based pricing was necessary because the metering technology did not exist or was too expensive to enable appropriate allocation of costs (Simshauser & Downer 2014).

conditioners are already the beneficiaries of an implicit subsidy worth 28.1%, whereas dwellings with lower demand and no PV, typically lower socio-economic households, paid network charges 39.5%, or $295 per annum, higher than they should (Simshauser 2016). This differential occurs because prosumer dwellings, despite using less energy, still impose a burden on the grid, representing a cost not only to the DNSPs, but also to electricity retailers who must still provide billing services despite generating far less revenue from prosumers.

Tariff reform could help address these inequities while helping to encourage consumers to use PV and battery technologies to support the objectives of the broader electricity network. An extensive body of research already exists examining tariff design, efficacy, equity and likelihood of consumer adoption (Nijhuis, Gibescu & Cobben 2017). Central to this work is the recognition that consumers are not homogenous and some will place a greater burden on the network than others.

Tariff reform rests on the assumption that all consumers, irrespective of their characteristics, should face cost-reflective, non-distortionary pricing that reflects their use of the network. This not only removes issues associated with cross-subsidisation (where costs are not appropriately assigned between tariff classes reflecting the true cost of supply), but also means that consumers would face appropriate price signals to change their behaviour if they choose (CEER 2016).

Three tariff classes have received the most attention in this respect: time-of-use tariffs where electricity is charged at different rates depending on the time of day (i.e. off-peak, shoulder and peak); critical peak pricing tariffs where very high prices are charged during extreme peak events; and capacity-based tariffs which are priced primarily according to household demand (i.e. a kW charge as opposed to a volumetric kWh charge) (DEWS 2013; QPC 2016a). While the cost-reflectivity and equitability of these tariffs vary, they all represent more sophisticated designs compared with the status quo.

When used in conjunction with residential PV and battery installations, the benefits of these tariff regimes could be substantial. Firstly, prosumers would pay an appropriate and equitable amount for their use of the network, reducing the disproportionate impost of their use of PV and battery technology on non-prosumers. Secondly, these tariffs are designed to incentivise behaviour change to support broader system objectives. Under an appropriate pricing regime, prosumer households could directly respond to price signals by charging and discharging their batteries in response to network cues, saving themselves money and reducing their impact on the network. Over time, and supported by smart invertors and central coordinating services, batteries deployed at scale in conjunction with dynamic cost-reflective tariffs could dramatically increase the efficiency, resilience and utilisation of the network while enabling a far more equitable allocation of costs.

Despite the promise of tariff reform to enable more efficient integration of residential PV and battery systems, there is a major caveat associated with the rollout of new pricing structures. Like so many issues in the energy sector, it is the response of the consumer to new tariffs that will determine their success. In this regard, the relationship between distributed energy technology, retail tariffs and consumer adoption is highly complex. Studies have found that the way in which people understand, use and pay for electricity is the outcome of cultural, technical and social considerations and no single ideal approach to cost reflective pricing currently exists (Graham 2015). Furthermore, behavioural studies are finding that consumers prefer simplicity, such as flat rate tariffs, over all other forms of cost-reflective pricing (Stenner et al. 2015).

Indeed, poorly structured, overly complex price signals or incorrectly incentivised tariffs risk further alienating electricity consumers driving possible unintended consequences. This dynamic – the fixes-that-fail archetype – was identified as part of the participatory research outlined in Chapter 6. The results of simulation and scenario analysis support the existence of this archetype, reinforcing yet again the importance of understanding consumer dynamics in proactively preparing for battery adoption.

8.4.3 Regulatory intervention

Policy measures which aim to modify existing regulatory frameworks to remove impediments to technology uptake can also represent a highly effective target for intervention (Meadows 1999). The Queensland Productivity Commission (2016) specifically acknowledges the importance of ensuring that regulatory frameworks should promote the development of competition for new electricity products or services and not act as a barrier. They note that “energy policy and the associated regulatory framework must be able to adapt to technological change to facilitate a dynamic market response and promote the efficiency and productivity of the electricity sector” (QPC 2016a, p. 65). Reform of this nature not only helps improve the operation of the market but can influence consumer perception of incumbents, particularly with the removal of perceived barriers to battery adoption.

For residential PV and battery energy storage there are many examples where rules and regulatory guidelines have not kept up with new technology developments. In some jurisdictions, outdated network connection rules do not distinguish between a battery and a PV system. This means for example, that if a 5kW PV system is already installed, an application for a 5kW battery inverter could be denied because of the perceived load on the network, despite the fundamental technical difference between the two systems and their respective impacts on the grid (CEC 2017a). Should this barrier persist, consumers may contemplate installing an off-grid system and bypassing the network entirely as the financial proposition for battery systems improves.

At a broader sector-wide level, regulatory frameworks continue to favour existing incumbent business models, impeding new market entrants and acting as a barrier to battery adoption. These include the existing rules in the NEM which support capital investments in network assets such as poles and wires over distributed solutions. While there is a regulatory requirement for DNSPs to consider alternatives to traditional network infrastructure, there is a $5M minimum threshold, which means that lower cost alternatives to poles and wires, such as batteries, do not need to be considered (AEMC 2015).

Even the rules that govern the wholesale market have not changed to reflect the potential of new technology. Existing 30-minute price settlement provisions are due to the technical parameters that existed when the NEM was first designed (i.e. primarily large centralised generators). A shift to shorter settlement times would enable more efficient bidding, improve price signals and enable new technologies and new market entrants to enter and operate in the market (CEC 2017a). The potential of third-party residential battery aggregators in this respect could be significant.

Aggregators represent a new wave of energy market entrants that apply innovative communication technologies to remotely manage large numbers of residential battery systems to directly respond to market based-signals in the wholesale market (AEMC 2015). Australian company Reposit Power has developed a technology platform that can capture additional value from residential PV and battery systems on the consumer’s behalf by trading capacity in the NEM (Reposit 2017). When prices are high, smart inverters discharge electricity back into the grid with the consumer receiving a financial incentive for their participation (Heber 2015).

Aggregated at scale in this way, residential batteries could provide substantial benefits to the network. This includes frequency regulation and voltage support (voltage and frequency must stay within specified ranges or grid instability occurs), spinning reserves (generation capacity immediately able to meet load following unexpected outages), energy arbitrage (when stored energy is sold back to the grid at periods of high wholesale prices) and black starts (when an entire network goes down and power is required to restart operation of large generators) (Fitzgerald et al. 2015).

To realise the full benefit of these approaches to both the network and the individual, further reform is required that encourages new entrants to participate in the market. This requires removal of barriers to competition, an increase in data transparency and access (e.g. by providing detailed technical information for areas of network constraint), and introduction of measures to appropriately value a full range of network benefit such as ancillary services (CEC 2017a). These efforts could help increase the size of the incentive that can be paid to the consumer, increasing the desirability to participate, and improving the benefits to the network.

8.4.4 A portfolio approach

While this discussion on policy measures is not meant to be exhaustive, it aims to demonstrate how a diversity of very different approaches can influence the rate, scale and integration of residential PV and battery energy storage technologies. When taken with the results of modelling, it becomes clear that a portfolio approach will be required to enable efficient battery integration. With no single solution available, a mix of policy interventions must be implemented. These measures will be most effective if they do not attempt to hinder uptake but rather recognise the rapidly emerging primacy of the active and engaged electricity consumer.

For supply side participants in particular, such an approach may seem counterintuitive. This is because actions to remove regulatory barriers, reduce information asymmetry, minimise connection barriers, encourage competition and allocate fair value for the use of batteries on the network will further accelerate adoption, which in the short-term will continue to destroy value along the existing electricity supply chain and reduce the viability of traditional electricity supply business models. While there is no denying the possibility of this outcome occurring, interventions that target structural problems, as opposed to addressing symptomatic issues, have the best chance of achieving long-term success. These actions will result in more efficient use of the network which will increase its resilience, put downward pressure on electricity prices and decrease the emissions intensity of the sector. In contrast, actions taken now to impede battery adoption, while possibly successful in the short-term, will reinforce drivers for grid-defection as the technology further develops and prices continue to fall. For industry, this recognition may necessitate costly structural change in the near term, but will ultimately be required to maintain viability and future competitiveness.

From a broader system-wide perspective, development and implementation of a suite of policy measures to help ensure the most efficient integration of residential PV and battery technologies will be best achieved by, and may be contingent on, a sector-wide paradigm shift. Changing the "mindset or paradigm out of which the system – its goals, structure, rules, delays, parameters – arises" is considered one of the most effective intervention points in a system (Meadows 1999). They are also one of the most difficult to change. The results of modelling, and a confluence of systemic structural issues point to the need for a new reality in the energy sector. This new reality must recognise the imperative and increasing inevitability of a shift away from reliance on fossil fuels toward a smarter, integrated decentralised grid. It needs to acknowledge that consumers are no longer passive participants in the sector but collectively have the power to materially impact electricity sector dynamics.

Achieving this paradigm shift will require governments, industry and consumers to change the way they think about electricity supply and use. With clear articulation of policy intent in this respect and a complementary regulatory reform program, governments can help support industry efforts to identify and unlock shared value along the supply chain. Industry participants must also recognise that the profitability inherent in the monolithic business models of the past can no longer be guaranteed, and future viability will be contingent on broad structural change. If battery adoption at scale is likely to occur regardless, as the results of this research indicate, a positive, proactive approach to integration could see the technology act as a catalyst for a new era of consumer engagement and participation in the electricity market. This could drive productivity improvements and market innovation along the supply chain, realising new sources of profit for the sector and ultimately achieving the best outcomes for individuals and society more broadly.

Chapter 9 Conclusion

Residential PV and battery energy storage systems deployed at scale could help to drive a consumer-led, low emission transformation of modern electricity supply systems. While the benefits are potentially enormous, if poorly integrated, the technology could become one of the most disruptive influences to impact the electricity sector in decades. To help avoid this outcome, this dissertation aims to make a fundamental research contribution by addressing the following research problem: *What are the key dynamics that will underpin residential solar and battery adoption, how could these dynamics influence deployment rates and what are the implications from a broader energy sector transition perspective?* The purpose of this chapter is to articulate the key findings and conclusions that help to address this question. It does this by summarising the results generated from each of the four stages of research described in this thesis. This chapter also discusses the limitations of research along with opportunities for future study. It concludes with a brief discussion describing the implications of this research and its broader contribution.

9.1 Key findings in response to Research Questions

The first stage of research clarified the scope of work, its significance and the specific nature of the problem to be addressed. This involved a review of the specific technology characteristics of both PV and battery energy storage, along with an assessment of the current market and the implications associated with the mass market adoption of the technology. In doing this, it addresses the first research question: "What are the current characteristics of the residential PV and battery market domestically and internationally".

The findings from this stage of research reveal the complex nature of both the technology and the system within which it is to be deployed. It illustrates the dichotomy between the inertia of the existing capital intensive, heavily regulated, monopolistic electricity supply system, and the flexibility and accessibility of new distributed generation technologies. This stage of research shows that while the residential battery market is still at the earliest stages of development, the technology itself is on the cusp of a rapidly declining price trajectory. Should adoption rates begin to accelerate, a failure to proactively manage battery integration could result in substantial inefficiencies along the supply chain, including a decline in infrastructure utilisation, asset impairment, increases in electricity costs and broader social and economic inefficiencies.

The second stage of work addresses Research Question 2: “What are the causal dynamics that will influence residential PV and battery adoption in Queensland?” Based on extensive stakeholder interviews, a causal loop model was used to generate a coherent theory of system behaviour. It also leveraged the findings from a detailed review and evaluation of the case-study area.

This review found that the supply and use of electricity in Queensland epitomises the complexity inherent in the electricity supply system in many modern economies. It also demonstrated that the structural elements that underpinned past exponential PV growth in the state persist, and would likely contribute to the dynamics underpinning future adoption of home battery systems. When taken with the results of causal loop modelling several important findings were revealed.

Many of the preconditions for battery energy storage adoption are already in place in Queensland. If battery prices fall as forecast, multiple paths to market exist in Queensland targeting a highly motivated consumer-base making large-scale battery uptake highly likely in coming years. Causal loop modelling shows how consumers, responding to both financial and non-financial motivations, will select home battery systems that will impact on the demand and load profile of the existing electricity supply system. This in turn will affect market dynamics, necessitating a strategic response from existing supply chain participants. The nature of this response, the emergence of new entrants and the extent to which government intervenes to achieve social-good outcomes will influence continued battery storage uptake and its future impact on the market.

To help quantify the nature of the dynamics inherent in the system, the third stage of research involved the development of a system dynamics model. This stage addresses Research Question 3: “How could residential PV and battery adoption dynamics manifest in the Queensland context?” To address this question, a stock-and-flow simulation model comprising nearly 400 variables was used to empirically simulate adoption dynamics over a 30-year period. The model includes 108 different dwelling combinations comprising several different PV and battery system configurations arrayed with different household electricity consumption and load profiles. Model testing and validation demonstrated that structural elements behaved as expected. Trend analysis along with the calculation of a discrepancy coefficient showed that model-generated behaviour agreed with the trends generated from historical data.

Simulation of the base-case model revealed how battery adoption dynamics could manifest in the system based on a business-as-usual scenario. The results show that battery adoption follows s-shaped growth, with uptake increasing slowly until 2020 when it begins to accelerate with mass market uptake achieved from 2029. At the end of the simulation period, approximately 570,000 battery systems would be installed representing 5,444 MWh of capacity.

Importantly, the results of model simulation demonstrate that the rate and scale of battery adoption in Queensland will be driven by a complex interaction of exogenous and endogenous feedback loops operating throughout the system. Electricity prices increased by nearly 25% in real terms at the same time as module prices fell. Improved payback periods enable consumers to select for systems that address both financial and non-financial motivations, which ultimately sees a preference for larger system capacities. In this respect, the model shows that a majority of consumers are likely to install a 15kWh battery system coupled with a 5kW PV system, a combination that for most dwelling types will see a substantial reduction in grid demand. These dwellings will use on average only 0.16MWh of electricity from the grid compared with nearly 3MWh for the smallest PV/battery combination (i.e. 2kW/5kWh). As more consumers adopt PV and batteries, falling residential demand serves to further increase electricity prices. This highlights a considerable source of inequity, with the model showing that non-prosumers pay proportionately more to maintain the existing electricity network. The declining use of Queensland’s multi-billion electricity supply infrastructure as a result of these dynamics represents a substantial economic inefficiency in its own right.

To build on the results described above and to enable a deeper evaluation of model outputs, the fourth stage of research involved sensitivity and scenario analysis. This work, along with a review of results from a broader policy perspective, address Research Question 4: “What are the implications of residential PV and battery adoption from an energy sector transition perspective and what measures could help achieve more efficient integration?”

Scenario analysis demonstrated that while the number of battery dwellings increases across each scenario, the characteristics of deployment varied enormously. These results not only reinforced the findings from earlier stages of research but also helped demonstrate the strength of various leverage points throughout the system. For example, the climate change scenario shows how changes to exogenous influences would reinforce existing dynamics in the system which underpin consumer preference for self-sufficiency. With the highest numbers of systems installed of any scenario, nearly 850,000 battery systems, the cumulative negative impacts from a system-wide perspective are substantial.

In contrast, where efforts are made to proactively integrate batteries into the existing network as in Scenario 1, the effects were impressive. Despite more than 650,000 battery systems installed, electricity prices are nearly 40% lower than the climate change scenario. Moreover, the disparity between total household costs for prosumer versus non-prosumer dwellings is much lower. With smaller systems installed, network utilisation and resilience is also expected to be far greater.

These results can be compared with Scenario 2 which sees the lowest battery adoption rate of all the scenarios with approximately 300,000 system installs. The actions of incumbents to maintain the status quo by implementing what is effectively a barrier to uptake appears to work in this scenario. However, closer examination of model outputs show that the systems being installed are larger, including a far higher proportion of 'possible' off-grid systems than would be expected under normal circumstances. This scenario shows that by only addressing the symptoms and not the actual structures underpinning consumer drivers for self-sufficiency, the non-financial feedback loops reinforcing battery adoption and possible grid defection are strengthened. If the financial viability of battery systems were to improve independent of, and despite the actions of incumbents, then the likelihood of these dynamics occurring would increase dramatically.

To more clearly understand the implications of the above research from a broader energy transition perspective, the final stage of work included a review of key findings from a system-wide policy perspective. This analysis finds that the substantial complexity inherent in the system under investigation precludes simple solutions. Instead, efforts to achieve efficient integration of residential PV and battery energy storage will be contingent on a portfolio approach. This must include a variety of measures that address consumers' non-financial motivations for self-sufficiency while concurrently incentivising the strategic management of home battery energy storage to achieve beneficial whole-of-system outcomes. Price-based signals that assign fair-value along the supply chain have substantial promise in this regard, along with efforts to remove barriers and increase the efficiency and competitiveness of the market.

To be most successful however, this analysis suggests that industry and government may need to fundamentally rethink the form and function of the network if effective integration is to be achieved. This requires an explicit recognition of the changing role of the consumer and the influence of new technology. This could help encourage retention of grid-connected consumers and provide more avenues to leverage the most efficient use of existing network assets, while paving the way for new and innovative solutions in the future.

9.2 Limitations and suggestions for future research

Despite the compelling nature of the findings presented in this thesis, there exist several limitations. Firstly, as Sterman (2002, p. 525) states: "all models are wrong…because a model is a simplification, an abstraction, a selection". The model developed in this thesis is no different. Its design is restricted by imposed boundaries based on the scope and objectives of this study. It is also not possible to include all variables that exist in reality, nor the possibility of rapid or unforseen step-changes in technology. Instead, the model was designed to incorporate as many of the key elements identified by expert stakeholders during the participatory stage of research that could be practically included. There are a number of specific omissions in this regard that need to be identified, both as limitations inherent in the current study and as suggestions for areas of focus for future research.

As previously stated, the wholesale energy price in the model is categorised primarily as an exogenous variable. While the extent to which residential PV and battery energy storage will have a material impact on the generation sector during the simulation period is unclear, the model would nonetheless benefit from the inclusion of a module that shows the interactions between the residential electricity and generation sectors. Because of the way in which the wholesale generation market is structured and operated in Queensland, this undertaking would entail modelling the operation of the NEM. This would be a highly data intensive undertaking, particularly as it would be ideally modelled in half-hourly time-steps requiring the inclusion of both financial and operational parameters. An interesting focus of future research would be to explore the extent to which existing bottom-up operational models of the NEM could be incorporated into a system dynamics model. This could possibly improve the depth and accuracy of the existing system dynamics model while providing an interesting contribution from a theoretical perspective.

The way in which network effects stemming from PV and battery adoption are calculated in the model do not capture the spatially specific way in which networks actually make decisions when addressing peak demand. This could be improved by designing an additional sector in the model that would more accurately capture the required level of detail on a spatial scale. The application of agent-based modelling in conjunction with the broader system dynamics model could be a useful approach in this respect. Again, this would be an interesting area of future research from both a practical and theoretical perspective. In this case, the specific household characteristics of many different consumer segments could be created within the model and replicated within spatially-defined areas based on different network characteristics. The level of network constraint, when it occurs and the influence of the different consumer segments in response, could be simulated at a more detailed level and as such could more accurately value the contribution of residential PV and battery systems in this respect.

The model also relies on only one electricity pricing structure, Tariff 11. This means the model does not consider the dynamics that could evolve in response to the many new electricity tariffs currently being developed and implemented. The design and inclusion of these dynamics in a detailed system dynamics model would represent a valuable area for future research, particularly as implementation of cost-reflective, dynamic pricing tariffs represent substantial potential in helping to integrate PV and batteries in an efficient way. In this respect, understanding the consumer response to new tariff structures and the likelihood of uptake will be particularly important. The presumed benefits of dynamic tariffs rest heavily on one critical assumption: that consumers will respond 'rationally' to price signals and shift their consumption accordingly (Stenner et al. 2015, p. 4). New research is urgently required that challenges this assumption, particularly as there have been no large-scale systemic studies examining the likelihood of Australian consumers accepting dynamic tariffs nor how they may respond to such tariffs (Stenner et al. 2015).

Another limitation of this research involves its reliance on qualitative assumptions in some sectors of the model. As the battery market is still at such an early stage there is little empirical data. This means parameterisation in some cases has been based on, or extrapolated from limited datasets or qualitative studies. The inclusion of non-financial motivations in the model reflects one of the sectors most heavily dependent on assumptions. As previously stated, omitting variables that are known to influence system behaviour because of a lack of quantitative data is "equivalent to saying they have zero effect – probably the only value that is known to be wrong." (Forrester 1961, p. 57). In recognising these limitations, it is essential that assumptions underpinning the model are visible, open to critical evaluation and can be modified to reflect the specific needs of any stakeholder that uses the model. For this reason, the entirety of the model, including assumptions and equations have been included in Appendix B. As the residential PV and battery market continues to develop, more rigorous and robust methodologies will be able to inform parameterisation and the model can be modified accordingly.

9.3 Concluding remarks

With the challenge to provide secure, equitable and environmentally sustainable energy to an ever-growing global population, the worlds' energy systems are experiencing a wave of transformative change. The emergence of new demand-side technologies, and the rise of the active and engaged electricity consumer represent just one element of this transformation. As was amply demonstrated by the recent boom in residential PV installations, a failure by industry and government to understand the dynamics that underpin technology adoption not only hinders effective integration but can drive suboptimal outcomes along the entire supply chain. With the sector still struggling to respond to the challenges of PV, the emergence of battery energy storage and its potential to enter the residential market at scale, underscore both the imperative and urgency to better understand the dynamics that could underpin adoption so as to avoid the mistakes of the past.

This thesis, and the research approach described throughout, has been drafted specifically in response to this imperative. It not only conceptualises the risks, and the opportunities, associated with the impending transition but provides a model to empirically demonstrate the underlying dynamics. Importantly, the design and development of the model has been informed by an extensive stakeholder interview process. This underpins its usefulness as a practical tool that can be used by policy makers and industry to simulate and test the outcomes of various scenarios to help understand how residential PV and battery energy storage may manifest within the context of the broader electricity sector transition. Moreover, the model's structure and the assumptions underpinning them, are visible and open to scrutiny meaning the model lends itself to be modified, expanded and/or adapted to meet the needs of any client wishing to better understand and plan for the rise of residential PV and battery energy storage.

With the results of research showing that the Queensland residential sector is primed for battery adoption, the imperative now is for government and industry to recognise and respond to the pervasive dynamics that are driving the transition. A key finding from this thesis demonstrates that these dynamics stem in part from the failure of the existing electricity sector to recognise and respond to the changing needs of the residential electricity consumer. Should these needs remain unmet, and consumers turn to grid-alternatives such as PV and battery energy storage, the probability of negative consequences along the supply chain increase dramatically. Instead, proactive measures that address existing systemic issues have the best chance of achieving optimal integration of the technology. This will require broad structural change in the industry - a paradigm shift - that recognises that for the first time, consumers have a viable cost-effective alternative to the existing centralised electricity supply system. For markets and governments, strategically meeting the needs of this emerging consumer-base will be essential in ensuring an efficient transition to a more sustainable, decentralised electricity supply system.

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Appendix A Ethics approval

THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

School of Geography Planning and Environmental Management

15 December 2014

TO: Scott Agnew
FROM: Dr Bradd Witt, GPEM Ethics Officer
CC: Dr Paul Dargusch

RE: Application for Ethics Approval

PROPOSAL TITLE: [GPEM number 20130063] ***Integrating residential solar photovoltaic systems with storage: modelling an optimal deployment pathway.***

In my capacity as the School of GPEM Ethics Officer, I have reviewed the above research proposal for compliance with University and School regulations governing human subjects research.

The proposed research is not subject to higher level review by the University Behavioural and Social Sciences Ethical Review Committee (BSSERC) for the following reasons: 1) the research does not directly involve human subjects from vulnerable or special populations, 2) the research does not involve any risk above "everyday living", 3) the research is not intrusive, and 4) informed consent will be obtained before data collection, participation is voluntary, and participants may withdraw at any time. The research is thus classified as low risk and School level ethics approval is appropriate.

The research proposal, as presented, complies with the National Statement on Ethical Conduct in Human Research and the associated university regulations. You may conduct the research subject to the following conditions. 1) the interviews should be conducted as described in the research protocol, 2) participants should not be personally identifiable in the results without explicit permission of the participant, 3) the data collected is to be kept in a secure location. Should any of the above conditions change, you must refer the amended research protocol back to the GPEM Ethics officer.

If you have questions about the ethics review process, please contact me.

Dr. Bradd Witt (bwitt@uq.edu.au)
Ethics Officer
School of Geography, Planning, and Environmental Management

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Appendix B Model design and assumptions

The following section includes the full version of the system dynamic model described in Chapter 7. Each of the major sectors of the model are included with a description of the sector, the key assumptions, a visual representation of the sector in Stella, and the actual equations directly transcribed from Stella. Figure 77 provides a simplified overview of the entire simulation model. Due to the highly interconnected nature of the model, linked variables between sectors are frequently represented using the 'ghost' icon represented as a . To avoid replication, the assumptions underpinning these variables are only described in the sector from which they originate.

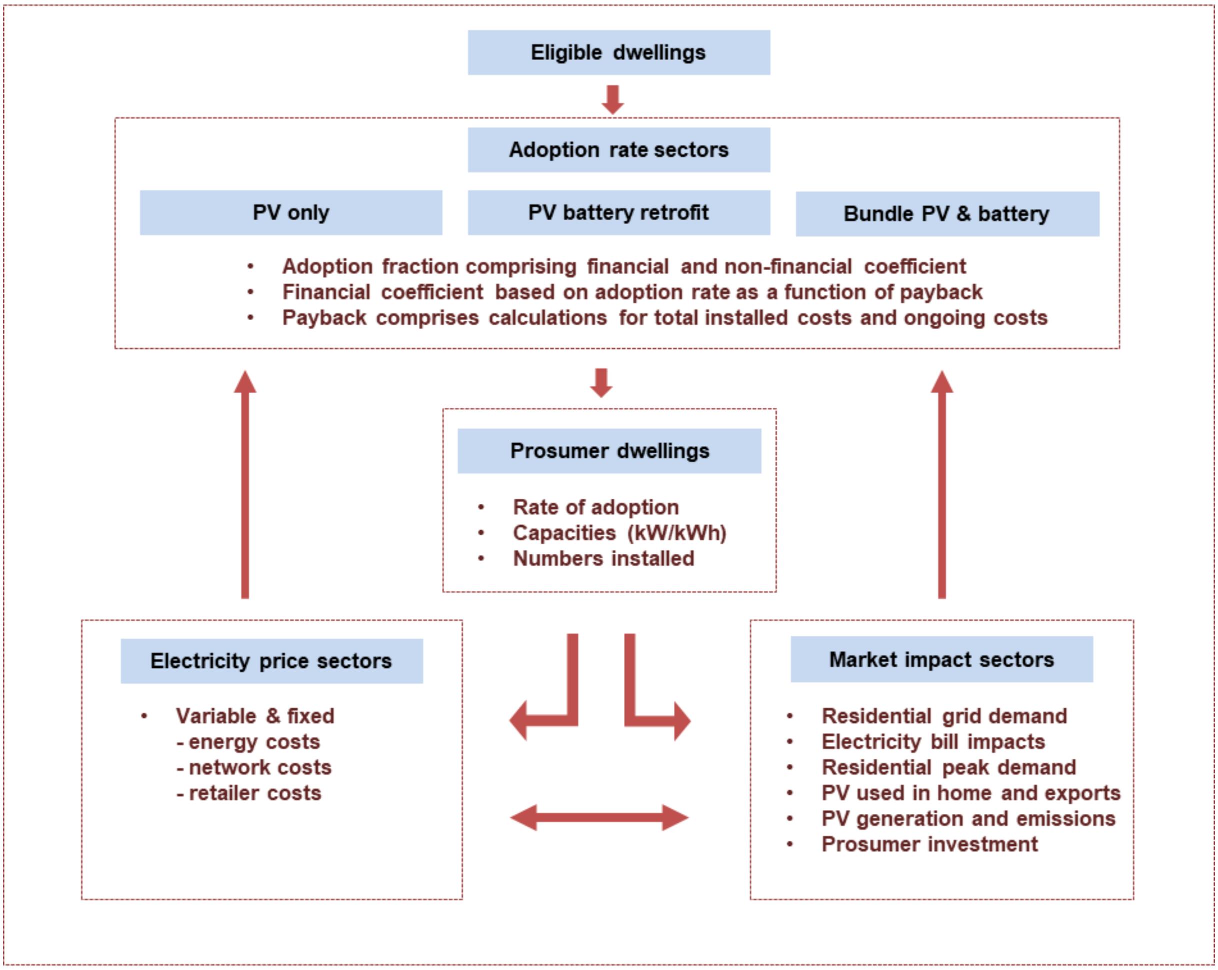


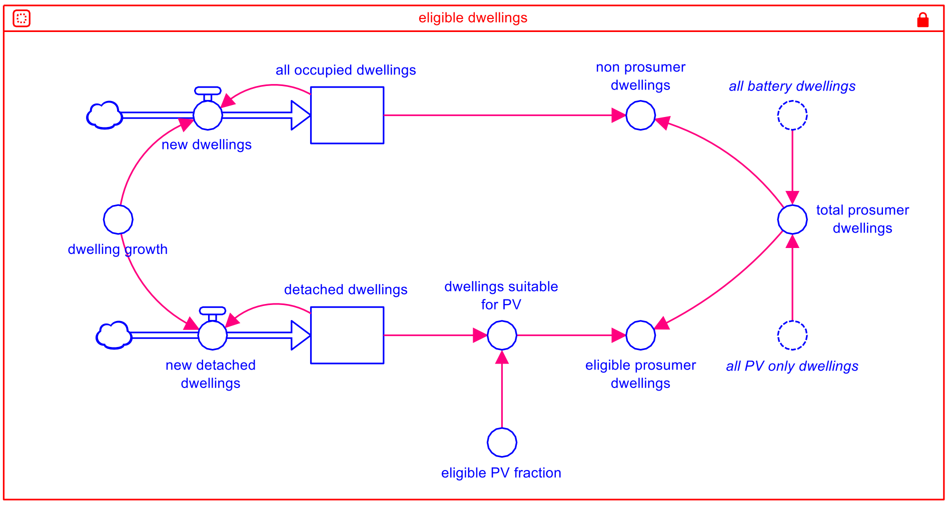
Figure 77 Overview of system dynamics model

1. Eligible dwellings sectors

Key assumptions

- Initial values: 'all occupied dwellings' = 1,625,827 and 'detached dwellings' = 1,154,403 (AER 2015a; ABS 2016).
- 'dwelling growth' (0.0013 per month). Average of ABS data with total dwelling increase in a medium scenario by 1.6% per year between 2011 and 2036 and AEMO forecast active residential NMI connections in Queensland to increase by 1.5% (ABS 2016; AEMO 2016b).
- 'eligible PV fraction' (0.75). Reflects the fact that not all detached dwellings will be suitable for PV installations due to shading, council restrictions, aesthetic considerations, lack of interest and split-incentive issues for rental properties (AEMO 2013).

Representation in Stella



****
Eligible_dwellings:
****

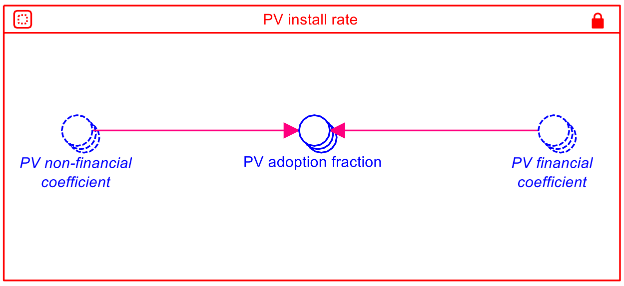
all_occupied_dwellings(t) = all_occupied_dwellings(t - dt) + (new_dwellings) * dt
INIT all_occupied_dwellings = 1625827
INFLOWS:
new_dwellings = dwelling_growth*all_occupied_dwellings
detached_dwellings(t) = detached_dwellings(t - dt) + (new_detached_dwellings) * dt
INIT detached_dwellings = 1154403
INFLOWS:
new_detached_dwellings = detached_dwellings*dwelling_growth
dwelling_growth = 0.0013
dwellings_suitable_for_PV = eligible_PV_fraction*detached_dwellings
eligible_prosumer_dwellings = IF dwellings_suitable_for_PV <= total_prosumer_dwellings THEN 0 ELSE dwellings_suitable_for_PV-total_prosumer_dwellings
eligible_PV_fraction = 0.75
non_prosumer_dwellings = all_occupied_dwellings-total_prosumer_dwellings
total_prosumer_dwellings = all_PV_only_dwellings+all_battery_dwellings

2. <u>PV adoption sectors</u>

2.1. PV adoption fraction

This section includes each of the sectors that comprise the PV adoption fraction. This is a function of a non-financial and financial coefficient.

Representation in Stella



****

<u>PV_install_rate:</u>

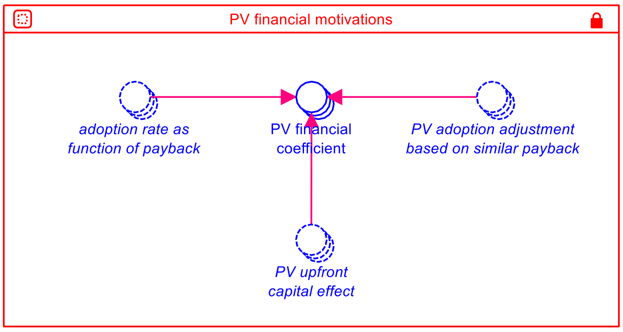
****

PV_adoption_fraction[PV_size, Loadprofile, Electricityconsumption] = PV_financial_coefficient*"PV_non-financial_coefficient"[PV_size]

2.2. PV financial motivations

PV financial motivations is a function of three elements which are described separately below.

Representation in Stella



****

<u>PV_financial_motivations:</u>

****

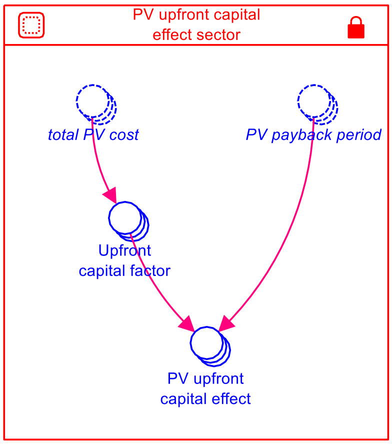
PV_financial_coefficient[PV_size, Loadprofile, Electricityconsumption] = adoption_rate_as_function_of_payback/12 *PV_upfront_capital_effect *PV_adoption_adjustment_based_on_similar_payback

2.3. PV upfront capital effect

Key assumptions

- Consumers have an aversion to high upfront costs which can act as a barrier to adoption (Allen, Hammond & McManus 2008; Scarpa & Willis 2010; Dharshing 2017).
- To reflect this assumption, this variable assumes that adoption rates will be restricted depending on the upfront cost of the system and is based on numbers of households in certain income brackets from ABS (2016). For example, 10% of Queensland households earn $3000 or more a week. Therefore, the model assumes that if the upfront cost of a system exceeds $15,000, then only 10% of households would adopt based on household income.
- If payback periods are below 4 years, then the model assumes adoption will occur without any restriction. This is because once paybacks become short enough, the financial incentive will be high enough that most consumers will access finance.

Representation in Stella



****

PV_upfront_capital_effect_sector:

****

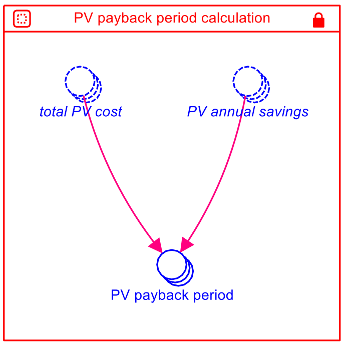
PV_upfront_capital_effect[PV_size, Loadprofile, Electricityconsumption] = IF PV_payback_period < 4 THEN 1 ELSE Upfront_capital_factor[PV_size]

Upfront_capital_factor[PV_size] = IF total_PV_cost[PV_size]>15000 THEN 0.1 ELSE IF total_PV_cost[PV_size]>10000 AND total_PV_cost[PV_size] <= 15000 THEN 0.6 ELSE IF total_PV_cost[PV_size]>7000 AND total_PV_cost[PV_size] <=10000 THEN 0.8 ELSE 1

2.4. PV payback period calculation

Comprises two elements: total PV cost and PV annual savings described below.

Representation in Stella



****
PV_payback_period_calculation:
****
PV_payback_period[PV_size, Loadprofile, Electricityconsumption] = (total_PV_cost[PV_size]/PV_annual_savings)

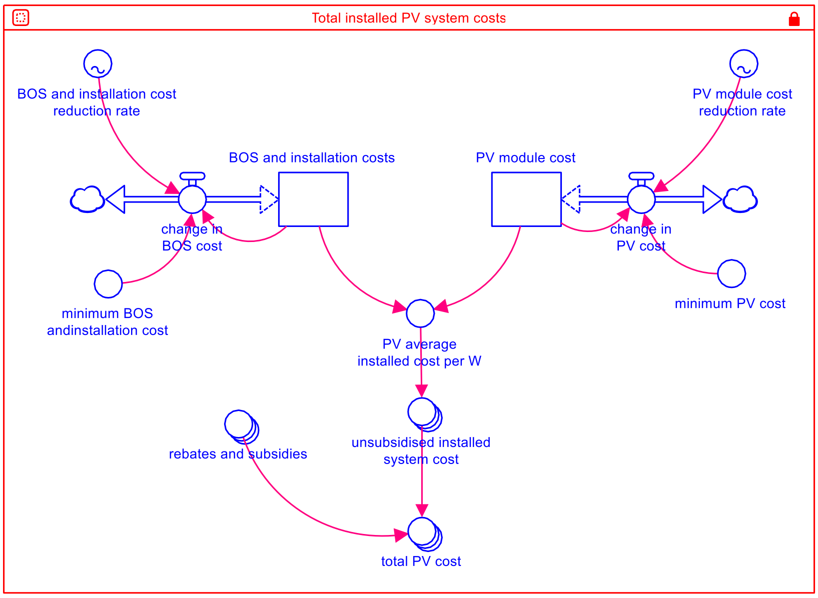
2.5. PV total costs

Key Assumptions

- PV module cost – the initial 2006 value is $8.50/watt (Watt 2007).
- PV module cost reduction rate - is an exogenous variable with past values calculated directly from historic module costs (Johnston & Egan 2016). From 2016, future forecast reduction rates are assumed at 1.5% per annum in real terms based on international and Australian studies (Galanis 2016).
- BOS and installation costs – the initial 2006 value for BOS and installation costs is $4/watt (Watt 2007). BOS costs include inverter, wiring and racking.
- BOS cost reduction rate - is an exogenous variable and, like PV module costs, is calculated directly from historical module costs with future forecast reduction rates assumed to be 1.5% based on cost reductions in inverters and mounts (Galanis 2016; Johnston & Egan 2016). The cost of installation in Queensland is already considered one of the cheapest install rates globally and with substantial efficiencies already realised, continued learning rates are considered minimal (Barbose et al. 2013; CSIRO 2015b).
- Rebates and subsidies – this variable includes rebates from the Photovoltaic Rebate Program worth up to $4000 (between 2006-2007) and the Solar Homes and Communities Plan worth up to $8000 (between 2007 – 2009) (Macintosh & Wilkinson 2010) . From July 2009, the

Commonwealth Solar Credit Scheme rebate is included, where small-scale technology certificates (STC) which are worth $35 (on average) and deemed for 15 years. This scheme involved a multiplier effect so that the value of STCs were multiplied by 5 times from July 2009 to June 2011, 3 times from July 2011 to June 2012, 2 times from July 2012 to December 2012 and returning to normal from January 2013. From 2017. The 15 year deeming period is reduced each year until it reaches 1 in 2030 (Department of the Environment 2017).

Representation in Stella



****
Total_installed_PV_system_costs:
****
BOS_and_installation_cost_reduction_rate = GRAPH(TIME)
(0.0, 0), (12.0, 0), (24.0, 0), (36.0, 0.0208), (48.0, 0.0055), (60.0, 0.038), (72.0, 0.0139), (84.0, -0.026), (96.0, 0.014), (108.0, 0.017), (120.0, 0.00125), (132.0, 0.00125), (144.0, 0.00125), (156.0, 0.00125), (168.0, 0.00125), (180.0, 0.00125), (192.0, 0.00125), (204.0, 0.00125), (216.0, 0.00125), (228.0, 0.00125), (240.0, 0.00125), (252.0, 0.00125), (264.0, 0.00125), (276.0, 0.00125), (288.0, 0.00122), (300.0, 0.00125), (312.0, 0.00125), (324.0, 0.00125), (336.0, 0.00125), (348.0, 0.00125), (360.0, 0.00125), (372.0, 0.00125)
BOS_and_installation_costs(t) = BOS_and_installation_costs(t - dt) + (- change_in_BOS_cost) * dt
INIT BOS_and_installation_costs = 4
OUTFLOWS:
change_in_BOS_cost = IF BOS_and_installation_costs > minimum_BOS_andinstallation_cost THEN (BOS_and_installation_costs*BOS_and_installation_cost_reduction_rate) ELSE 0
minimum_BOS_andinstallation_cost = 0.4
minimum_PV_cost = 0.1
PV_average_installed_cost_per_W = PV_module_cost+BOS_and_installation_costs
PV_module_cost(t) = PV_module_cost(t - dt) + (- change_in_PV_cost) * dt
INIT PV_module_cost = 8.50
OUTFLOWS:
change_in_PV_cost = IF PV_module_cost > minimum_PV_cost THEN (PV_module_cost*PV_module_cost_reduction_rate) ELSE 0
PV_module_cost_reduction_rate = GRAPH(TIME)
(0.0, 0), (12.0, 0.0049), (24.0, 0), (36.0, 0.02), (48.0, 0.04), (60.0, 0.03), (72.0, 0.02), (84.0, 0.09), (96.0, -0.01), (108.0, 0), (120.0, 0), (132.0, 0.0015), (144.0, 0.0015), (156.0, 0.0015), (168.0, 0.0015), (180.0, 0.0015), (192.0, 0.0015),

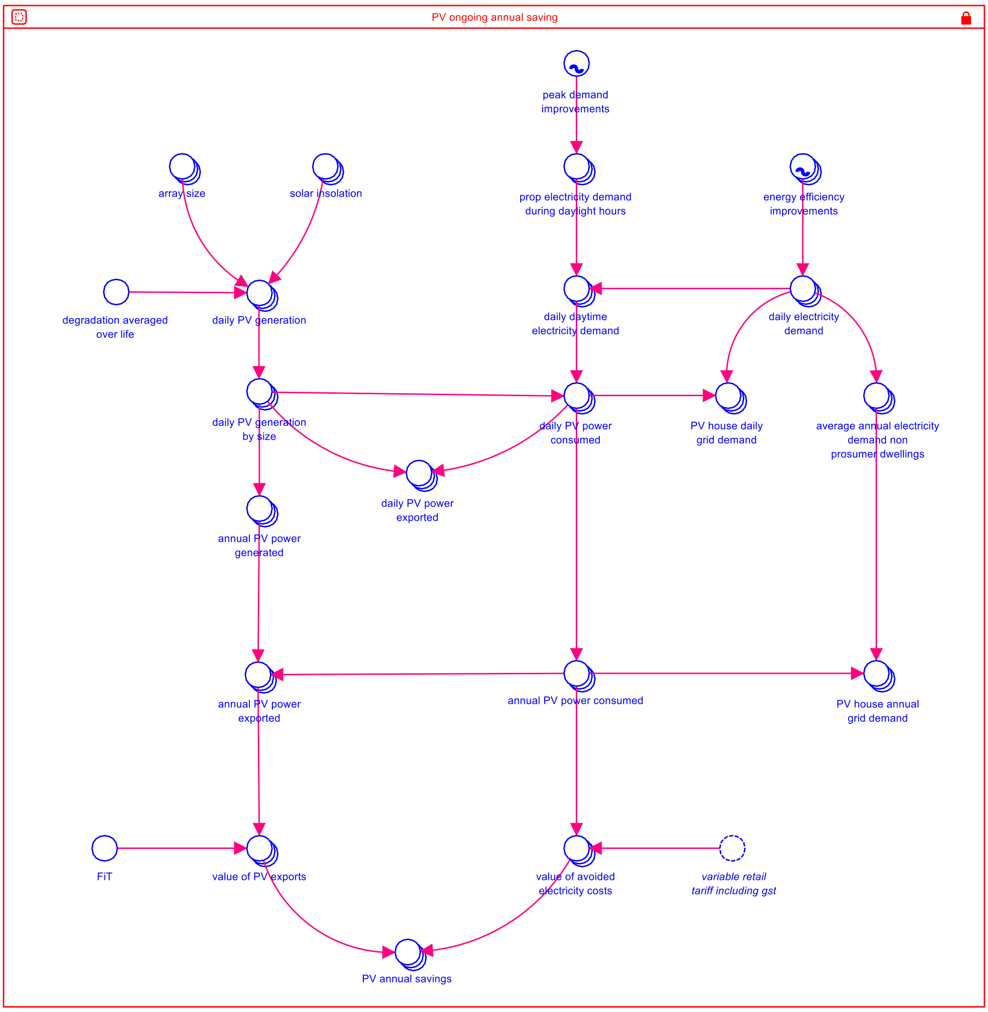
(204.0, 0.002), (216.0, 0.0015), (228.0, 0.0015), (240.0, 0.0015), (252.0, 0.0015), (264.0, 0.0015), (276.0, 0.0015), (288.0, 0.002), (300.0, 0.0015), (312.0, 0.0015), (324.0, 0.0015), (336.0, 0.0015), (348.0, 0.0015), (360.0, 0.0015), (372.0, 0.0015)
rebates_and_subsidies[Less_than_2_kW] = IF TIME <= 12 THEN (4000) ELSE IF TIME > 12 AND TIME <= 42 THEN (8000) ELSE IF TIME > 42 AND TIME <= 66 THEN (5*31*35) ELSE IF TIME > 66 AND TIME <= 78 THEN (3*31*35) ELSE IF TIME > 78 AND TIME <= 84 THEN (2*31*35) ELSE IF TIME > 84 AND TIME <= 132 THEN (31*35) ELSE IF TIME >132 AND TIME <=144 THEN (29*35) ELSE IF TIME > 144 AND TIME <=156 THEN (26*35) ELSE IF TIME > 156 AND TIME <= 168 THEN (24*35) ELSE IF TIME >168 AND TIME <= 180 THEN (22*35) ELSE IF TIME >180 AND TIME <= 192 THEN (20*35) ELSE IF TIME > 192 AND TIME <= 204 THEN (18*35) ELSE IF TIME > 204 AND TIME <= 216 THEN (16*35) ELSE IF TIME > 216 AND TIME <= 228 THEN (14*35) ELSE IF TIME > 228 AND TIME <= 240 THEN (12*35) ELSE IF TIME > 240 AND TIME <= 252 THEN (10*35) ELSE IF TIME > 252 AND TIME <= 264 THEN (8*35) ELSE IF TIME > 264 AND TIME <= 276 THEN (6*35) ELSE IF TIME > 276 AND TIME <= 288 THEN (4*35) ELSE IF TIME > 288 AND TIME <= 300 THEN (2*35) ELSE 0
rebates_and_subsidies[Between_2_and_4_kW] = IF TIME <= 12 THEN (4000) ELSE IF TIME > 12 AND TIME <= 42 THEN (8000) ELSE IF TIME > 42 AND TIME <= 66 THEN (5*31*35+31*35) ELSE IF TIME > 66 AND TIME <= 78 THEN (3*31*35+31*35) ELSE IF TIME > 78 AND TIME <= 84 THEN (2*31*35+31*35) ELSE IF TIME > 84 AND TIME <= 132 THEN (61*35) ELSE IF TIME >132 AND TIME <=144 THEN (58*35) ELSE IF TIME > 144 AND TIME <=156 THEN (53*35) ELSE IF TIME > 156 AND TIME <= 168 THEN (49*35) ELSE IF TIME >168 AND TIME <= 180 THEN (45*35) ELSE IF TIME >180 AND TIME <= 192 THEN (41*35) ELSE IF TIME > 192 AND TIME <= 204 THEN (33*35) ELSE IF TIME > 204 AND TIME <= 216 THEN (28*35) ELSE IF TIME > 216 AND TIME <= 228 THEN (25*35) ELSE IF TIME > 228 AND TIME <= 240 THEN (22*35) ELSE IF TIME > 240 AND TIME <= 252 THEN (18*35) ELSE IF TIME > 252 AND TIME <= 264 THEN (16*35) ELSE IF TIME > 264 AND TIME <= 276 THEN (12*35) ELSE IF TIME > 276 AND TIME <= 288 THEN (8*35) ELSE IF TIME > 288 AND TIME <= 300 THEN (4*35) ELSE 0
rebates_and_subsidies[Between_4_and_6kW] = IF TIME <= 12 THEN (4000) ELSE IF TIME > 12 AND TIME <= 42 THEN (8000) ELSE IF TIME > 42 AND TIME <= 66 THEN (5*31*35+72*35) ELSE IF TIME > 66 AND TIME <= 78 THEN (3*31*35+72*35) ELSE IF TIME > 78 AND TIME <= 84 THEN (2*31*35+ 72*35) ELSE IF TIME > 84 AND TIME <= 132 THEN (103*35) ELSE IF TIME >132 AND TIME <=144 THEN (96*35) ELSE IF TIME > 144 AND TIME <=156 THEN (89*35) ELSE IF TIME > 156 AND TIME <= 168 THEN (82*35) ELSE IF TIME >168 AND TIME <= 180 THEN (75*35) ELSE IF TIME >180 AND TIME <= 192 THEN (46*35) ELSE IF TIME > 192 AND TIME <= 204 THEN (37*35) ELSE IF TIME > 204 AND TIME <= 216 THEN (28*35) ELSE IF TIME > 216 AND TIME <= 228 THEN (25*35) ELSE IF TIME > 228 AND TIME <= 240 THEN (22*35) ELSE IF TIME > 240 AND TIME <= 252 THEN (18*35) ELSE IF TIME > 252 AND TIME <= 264 THEN (16*35) ELSE IF TIME > 264 AND TIME <= 276 THEN (12*35) ELSE IF TIME > 276 AND TIME <= 288 THEN (8*35) ELSE IF TIME > 288 AND TIME <= 300 THEN (6*35) ELSE 0
rebates_and_subsidies[Between_8_and_10kW] = IF TIME <= 12 THEN (4000) ELSE IF TIME > 12 AND TIME <= 42 THEN (8000) ELSE IF TIME > 42 AND TIME <= 66 THEN (5*31*35+176*35) ELSE IF TIME > 66 AND TIME <= 78 THEN (3*31*35+176*35) ELSE IF TIME > 78 AND TIME <= 84 THEN (2*31*35+176*35) ELSE IF TIME > 84 AND TIME <= 132 THEN (207*35) ELSE IF TIME >132 AND TIME <=144 THEN (195*35) ELSE IF TIME > 144 AND TIME <=156 THEN (181*35) ELSE IF TIME > 156 AND TIME <= 168 THEN (167*35) ELSE IF TIME >168 AND TIME <= 180 THEN (153*35) ELSE IF TIME >180 AND TIME <= 192 THEN (139*35) ELSE IF TIME > 192 AND TIME <= 204 THEN (125*35) ELSE IF TIME > 204 AND TIME <= 216 THEN (111*35) ELSE IF TIME > 216 AND TIME <= 228 THEN (97*35) ELSE IF TIME > 228 AND TIME <= 240 THEN (83*35) ELSE IF TIME > 240 AND TIME <= 252 THEN (69*35) ELSE IF TIME > 252 AND TIME <= 264 THEN (55*35) ELSE IF TIME > 264 AND TIME <= 276 THEN (41*35) ELSE IF TIME > 276 AND TIME <= 288 THEN (27*35) ELSE IF TIME > 288 AND TIME <= 300 THEN (13*35) ELSE 0
total_PV_cost[Less_than_2_kW] = (unsubsidised_installed_system_cost[Less_than_2_kW]-rebates_and_subsidies[Less_than_2_kW])
total_PV_cost[Between_2_and_4_kW] = (unsubsidised_installed_system_cost[Between_2_and_4_kW] - rebates_and_subsidies[Between_2_and_4_kW])
total_PV_cost[Between_4_and_6kW] = (unsubsidised_installed_system_cost[Between_4_and_6kW] - rebates_and_subsidies[Between_4_and_6kW])
total_PV_cost[Between_8_and_10kW] = (unsubsidised_installed_system_cost[Between_8_and_10kW] - rebates_and_subsidies[Between_8_and_10kW])
unsubsidised_installed_system_cost[Less_than_2_kW] = IF TIME <= 96 THEN PV_average_installed_cost_per_W*1000*1.5 ELSE IF TIME > 96 THEN PV_average_installed_cost_per_W*1000*1.5*1.2 ELSE 0
unsubsidised_installed_system_cost[Between_2_and_4_kW] = PV_average_installed_cost_per_W*1000*0.95*3
unsubsidised_installed_system_cost[Between_4_and_6kW] = PV_average_installed_cost_per_W*1000*0.81*5
unsubsidised_installed_system_cost[Between_8_and_10kW] = PV_average_installed_cost_per_W*1000*0.9*10

2.6. PV ongoing annual savings

Key assumptions

- The model assumes that electricity generated by PV meets the daily daytime electricity demand first with any excess exported back to the grid.
- Ongoing savings in this respect includes the avoided cost of grid sourced electricity (i.e. the amount of electricity used in home due to PV multiplied by the current retail rate) plus the value of any excess PV electricity that is exported to the grid.
- Four PV system size categories were included in the model that reflect common capacities installed in the market i.e. less than 2kW; 2-4kW; 4-6kW; and 8-10kW. The generation potentials of these system categories are calculated based on specific system capacities, assumed to be 1.5kW, 3kW, 5kW and 10kW for each size category respectively, multiplied by solar insolation based on average of population centres in SEQ (5.42 kWh/m^2/day) and regional Qld (6.03 kWh/m^2/day). Solar insolation data was sourced from the National Renewable Energy Laboratory (2016).
- PV degradation is average over the system life based on Jordan and Kurtz (2013).
- Medium daily electricity demand (21kWh) for 2006 is based on Simshauser (2016). Low (11kWh) and high (30kWh) values are extrapolated.
- Energy efficiency improvements is a graphical function that reflects energy efficiency savings not as a result of PV. Assumes approximately 1% reduction per annum from 2010 based on (Acil Allen Consulting 2015; AEMO 2016b).
- 'Prop of electricity demand during daying light hours' is calculated based on load profiles extrapolated from (Frontier Economics 2012; Simshauser & Downer 2014; Simshauser 2016) and is based on how many kWh are used between 8am and 6pm.
- 'Peak demand improvements' has no value associated as part of this study however it is included in the model for use by stakeholders. This is relevant if future demand management incentives are introduced, or future tariff reform results in peak demand improvements for non-prosumer dwellings which will change when household energy is used and/or reduce electricity prices, which then influences viability of PV and batteries.
- In Queensland from mid-2008 until mid-2012, consumers could access a premium FiT worth 44c/kWh scheduled to run until 2028. Post mid-2012, new PV consumers can access a voluntary retail FiT. As there is some variation in the FiT depending on the individual retailer, it has been averaged out across all Queensland electricity retailers and is assumed to be worth 7c/kWh (QCA 2016b).

Representation in Stella



****
<u>**PV_ongoing_annual_saving:**</u>
****
annual_PV_power_consumed[PV_size, Loadprofile, Electricityconsumption] = daily_PV_power_consumed*365
annual_PV_power_exported[PV_size, Loadprofile, Electricityconsumption] = annual_PV_power_generated[PV_size]-annual_PV_power_consumed
annual_PV_power_generated[PV_size] = daily_PV_generation_by_size[PV_size]*365
array_size[Less_than_2_kW] = 1.5
array_size[Between_2_and_4_kW] = 3
array_size[Between_4_and_6kW] = 5
array_size[Between_8_and_10kW] = 10
average_annual_electricity_demand_non_prosumer_dwellings[Electricityconsumption] = daily_electricity_demand*365
daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] = daily_electricity_demand[Electricityconsumption]*prop_electricity_demand_during_daylight_hours[Loadprofile]
daily_electricity_demand[low_consumption] = 11*energy_efficiency_improvements[low_consumption]
daily_electricity_demand[medium_consumption] = 21*energy_efficiency_improvements[medium_consumption]
daily_electricity_demand[high_consumption] = 30*energy_efficiency_improvements[high_consumption]
daily_PV_generation[PV_size, Location] = solar_insolation[Location]*array_size[PV_size]*degradation_averaged_over_life
daily_PV_generation_by_size[PV_size] = MEAN(daily_PV_generation [PV_size, *])

daily_PV_power_consumed[PV_size, Loadprofile, Electricityconsumption] = IF daily_PV_generation_by_size[PV_size]<=daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] THEN daily_PV_generation_by_size[PV_size] ELSE IF daily_PV_generation_by_size[PV_size] >daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] THEN daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] ELSE 0
daily_PV_power_exported[PV_size, Loadprofile, Electricityconsumption] = daily_PV_generation_by_size[PV_size]-daily_PV_power_consumed
degradation_averaged_over_life = 0.9
energy_efficiency_improvements[Electricityconsumption] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 0.9801), (84.0, 0.970299), (96.0, 0.96059601), (108.0, 0.95099005), (120.0, 0.941480149), (132.0, 0.932065348), (144.0, 0.922744694), (156.0, 0.913517247), (168.0, 0.904382075), (180.0, 0.895338254), (192.0, 0.886384872), (204.0, 0.877521023), (216.0, 0.868745813), (228.0, 0.860058355), (240.0, 0.851457771), (252.0, 0.842943193), (264.0, 0.834513761), (276.0, 0.826168624), (288.0, 0.817906938), (300.0, 0.809727868), (312.0, 0.80163059), (324.0, 0.793614284), (336.0, 0.785678141), (348.0, 0.777821359), (360.0, 0.770043146), (372.0, 0.760)
FiT = IF TIME <30 THEN (0.06) ELSE IF TIME>30 AND TIME <78 THEN (0.44) ELSE IF TIME >=78 AND TIME < 102 THEN (0.08) ELSE (0.07)
peak_demand_improvements = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 1.000), (84.0, 1.000), (96.0, 1.000), (108.0, 1.000), (120.0, 1.000), (132.0, 1.000), (144.0, 1.000), (156.0, 1.000), (168.0, 1.000), (180.0, 1.000), (192.0, 1.000), (204.0, 1.000), (216.0, 1.000), (228.0, 1.000), (240.0, 1.000), (252.0, 1.000), (264.0, 1.000), (276.0, 1.000), (288.0, 1.000), (300.0, 1.000), (312.0, 1.000), (324.0, 1.000), (336.0, 1.000), (348.0, 1.000), (360.0, 1.000), (372.0, 1.000)
prop_electricity_demand_during_daylight_hours[Low_daytime_use] = 0.3*peak_demand_improvements
prop_electricity_demand_during_daylight_hours[Medium_daytime_use] = 0.5*peak_demand_improvements
prop_electricity_demand_during_daylight_hours[High_daytime_use] = 0.6
PV_annual_savings[PV_size, Loadprofile, Electricityconsumption] = (value_of_PV_exports+value_of_avoided_electricity_costs)
PV_house_annual_grid_demand[PV_size, Loadprofile, Electricityconsumption] = average_annual_electricity_demand_non_prosumer_dwellings[Electricityconsumption]-annual_PV_power_consumed
PV_house_daily_grid_demand[PV_size, Loadprofile, Electricityconsumption] = daily_electricity_demand[Electricityconsumption]-daily_PV_power_consumed
solar_insolation[SEQ] = 5.42
solar_insolation[Regional] = 6.03
value_of_avoided_electricity_costs[PV_size, Loadprofile, Electricityconsumption] = annual_PV_power_consumed*variable_retail_tariff_including_gst
value_of_PV_exports[PV_size, Loadprofile, Electricityconsumption] = annual_PV_power_exported*FiT

2.7. PV adoption adjustment based on similar payback

Note this sector is described in the bundled battery adoptions sectors. It is simply a function that reflects the fact that if a PV system has a similar payback period as a PV and battery system, most consumers will install the PV and battery system.

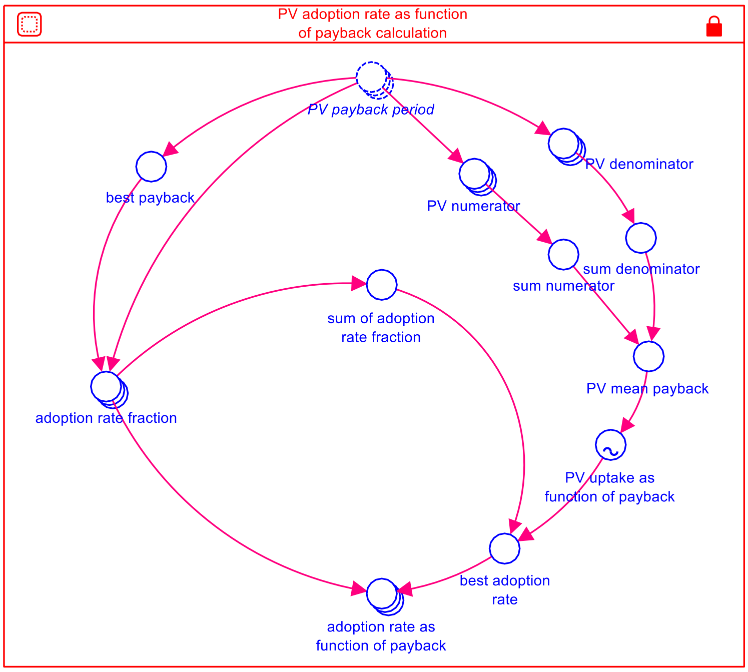
2.8. PV adoption rate as function of payback

Key assumptions

- To model the relationship between the payback period and the adoption fraction, a curve is used which displays adoption as a function of payback based on historical growth rates.
- This graph was developed to model PV growth for the Clean Energy Council in 2012 and has since been used and adapted by AEMO for national forecasting (IES 2012; AEMO 2013).

- The payback function graph represents a relationship based on the average payback across all system types for the entire population (IES 2012).
- As the model incorporates numerous system configurations, this sector calculates the individual contributions of each system to the adoption rate.
- It assumes the biggest contribution to the average adoption rate is from the system with the shortest payback period. It also assumes that a system that takes twice as long to payback would be adopted at half the rate of the system with the shortest payback.
- This means the relationship between the shortest payback and the actual payback of the system in question is used to determine its relative contribution of the total adoption rate, which in turn is used to generate the actual adoption rate for that system configuration type.

Representations in Stella



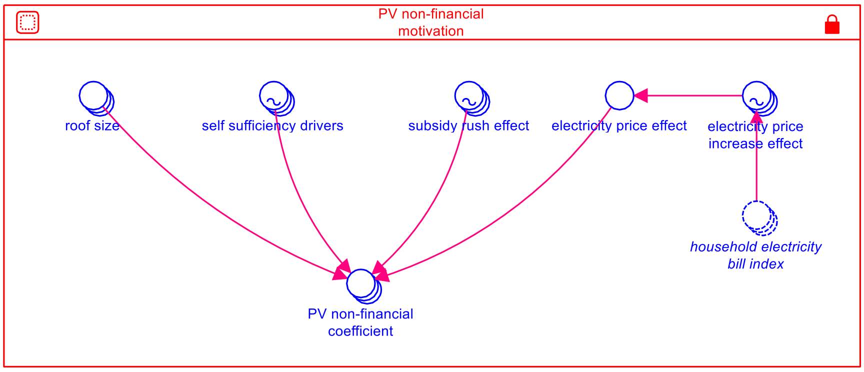
****
PV_adoption_rate_as_function_of_payback_calculation:
****
adoption_rate_as_function_of_payback[PV_size, Loadprofile, Electricityconsumption] = adoption_rate_fraction*best_adoption_rate
adoption_rate_fraction[PV_size, Loadprofile, Electricityconsumption] = best_payback/PV_payback_period
best_adoption_rate = PV_uptake_as_function_of_payback/sum_of_adoption_rate_fraction
best_payback = MIN(PV_payback_period)
PV_denominator[PV_size, Loadprofile, Electricityconsumption] = IF (PV_payback_period) <25 THEN 1 ELSE 0
PV_mean_payback = IF SAFEDIV (sum_numerator, sum_denominator) =0 THEN 25 ELSE SAFEDIV (sum_numerator, sum_denominator)
PV_numerator[PV_size, Loadprofile, Electricityconsumption] = IF PV_payback_period<25 THEN PV_payback_period ELSE 0
PV_uptake_as_function_of_payback = GRAPH(PV_mean_payback)

(0.00, 0.0950), (1.04166666667, 0.0920), (2.08333333333, 0.0890), (3.125, 0.0860), (4.16666666667, 0.08128), (5.20833333333, 0.07671), (6.25, 0.07078), (7.29166666667, 0.0600), (8.33333333333, 0.0500), (9.375, 0.0400), (10.4166666667, 0.0300), (11.4583333333, 0.0200), (12.50, 0.0100), (13.5416666667, 0.0092), (14.5833333333, 0.0083), (15.625, 0.0075), (16.6666666667, 0.0067), (17.7083333333, 0.0058), (18.75, 0.0050), (19.7916666667, 0.0042), (20.8333333333, 0.0033), (21.875, 0.0025), (22.9166666667, 0.0017), (23.9583333333, 0.0008), (25.00, 0.0000)
sum_denominator = SUM(PV_denominator)
sum_numerator = SUM(PV_numerator)
sum_of_adoption_rate_fraction = SUM(adoption_rate_fraction)

2.9. PV non-financial motivations

Key assumptions

- The variable 'PV adoption rate as a function of payback' described above is based on financial factors. Most consumers however consider a range of other non-financial factors when choosing to install a system and may install a system, even if the payback period is long, or choose not to install even if the payback is short (CSIRO 2009).
- The variable 'roof size' recognises that even with attractive payback periods, some dwellings will be constrained by the size of their roof. As data does not exist on the distribution of size of household roofs in Queensland, the following assumptions, informed by Galanis (2016), are made. It is assumed all eligible dwellings will be able to install a system less than 2kW, 95% of homes could install a 2-4kW system, 90% of homes could install a 5kW system and only 50% of eligible homes could install a 8-10kW system.
- The 'self sufficiency drivers' variable is a graphical function that acts as a multiplier based on the assumption that as PV modules become cheaper, consumers are opting for larger systems, even when small systems are cheaper or have better payback periods (Gill 2016).
- 'subsidy rush effect' refers to the rush that occurs at the start and end of subsidy schemes where consumers move forward a decision to purchase a system (IES 2012; Hughes & Podolefsky 2015). For PV, this impact was substantial, particularly for smaller systems which were the beneficiary of the most generous subsidies. A graphical function was created, representing a multiplier based on assumptions from historical data sourced from APVI (2017c).
- 'electricity price effect' is based on studies that suggest that consumers will install PV to avoid possible future perceived electricity price increases (CSIRO 2009; Agnew & Dargusch 2017) . It is a simple index based multiplier that with every *doubling* of electricity prices, PV adoption increases by 10%.



****
"PV_non-financial_motivation":
****
electricity_price_effect = MEAN(electricity_price_increase_effect)
electricity_price_increase_effect[Electricityconsumption] = GRAPH(household_electricity_bill_index)
(0.000, 1.0000), (0.250, 1.0000), (0.500, 1.0000), (0.750, 1.0000), (1.000, 1.0000), (1.250, 1.0250), (1.500, 1.0500), (1.750, 1.0750), (2.000, 1.1000), (2.250, 1.1250), (2.500, 1.1500), (2.750, 1.1750), (3.000, 1.2000), (3.250, 1.2250), (3.500, 1.2500), (3.750, 1.2750), (4.000, 1.3000)
"PV_non-financial_coefficient"[PV_size] =
subsidy_rush_effect*electricity_price_effect*self_sufficiency_drivers*roof_size
roof_size[Less_than_2_kW] = 1
roof_size[Between_2_and_4_kW] = 0.95
roof_size[Between_4_and_6kW] = 0.9
roof_size[Between_8_and_10kW] = 0.5
self_sufficiency_drivers[Less_than_2_kW] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 1.000), (84.0, 1.000), (96.0, 1.000), (108.0, 0.700), (120.0, 0.550), (132.0, 0.400), (144.0, 0.200), (156.0, 0.100), (168.0, 0.100), (180.0, 0.100), (192.0, 0.100), (204.0, 0.100), (216.0, 0.100), (228.0, 0.100), (240.0, 0.100), (252.0, 0.100), (264.0, 0.100), (276.0, 0.100), (288.0, 0.100), (300.0, 0.100), (312.0, 0.100), (324.0, 0.100), (336.0, 0.100), (348.0, 0.100), (360.0, 0.100), (372.0, 0.100)
self_sufficiency_drivers[Between_2_and_4_kW] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 1.000), (84.0, 1.000), (96.0, 1.000), (108.0, 1.000), (120.0, 1.000), (132.0, 1.000), (144.0, 1.000), (156.0, 1.000), (168.0, 1.000), (180.0, 1.000), (192.0, 1.000), (204.0, 1.000), (216.0, 1.000), (228.0, 1.000), (240.0, 1.000), (252.0, 1.000), (264.0, 1.000), (276.0, 1.000), (288.0, 1.000), (300.0, 1.000), (312.0, 1.000), (324.0, 1.000), (336.0, 1.000), (348.0, 1.000), (360.0, 1.000), (372.0, 1.000)
self_sufficiency_drivers[Between_4_and_6kW] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 1.000), (84.0, 1.200), (96.0, 1.400), (108.0, 1.500), (120.0, 1.600), (132.0, 1.700), (144.0, 1.800), (156.0, 1.900), (168.0, 2.000), (180.0, 2.000), (192.0, 2.000), (204.0, 2.000), (216.0, 2.000), (228.0, 2.000), (240.0, 2.000), (252.0, 2.000), (264.0, 2.000), (276.0, 2.000), (288.0, 2.000), (300.0, 2.000), (312.0, 2.000), (324.0, 2.000), (336.0, 2.000), (348.0, 2.000), (360.0, 2.000), (372.0, 2.000)
self_sufficiency_drivers[Between_8_and_10kW] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 1.000), (84.0, 1.200), (96.0, 1.400), (108.0, 1.500), (120.0, 1.600), (132.0, 1.700), (144.0, 1.800), (156.0, 1.900), (168.0, 2.000), (180.0, 2.000), (192.0, 2.000), (204.0, 2.000), (216.0, 2.000), (228.0, 2.000), (240.0, 2.000), (252.0, 2.000), (264.0, 2.000), (276.0, 2.000), (288.0, 2.000), (300.0, 2.000), (312.0, 2.000), (324.0, 2.000), (336.0, 2.000), (348.0, 2.000), (360.0, 2.000), (372.0, 2.000)
subsidy_rush_effect[Less_than_2_kW] = GRAPH(TIME)
(0.0, 1.00), (6.0, 1.00), (12.0, 1.00), (18.0, 1.00), (24.0, 1.00), (30.0, 1.00), (36.0, 1.00), (42.0, 1.00), (48.0, 3.00), (54.0, 3.00), (60.0, 5.00), (66.0, 5.00), (72.0, 5.00), (78.0, 5.00), (84.0, 1.00), (90.0, 1.00), (96.0, 1.00), (102.0, 1.00), (108.0, 1.00), (114.0, 1.00), (120.0, 1.00), (126.0, 1.00), (132.0, 1.00), (138.0, 1.00), (144.0, 1.00), (150.0, 1.00), (156.0, 1.00), (162.0, 1.00), (168.0, 1.00), (174.0, 1.00), (180.0, 1.00), (186.0, 1.00), (192.0, 1.00), (198.0, 1.00), (204.0, 1.00), (210.0, 1.00), (216.0, 1.00), (222.0, 1.00), (228.0, 1.00), (234.0, 1.00), (240.0, 1.00), (246.0, 1.00), (252.0, 1.00), (258.0, 1.00), (264.0, 1.00), (270.0, 1.00), (276.0, 1.00), (282.0, 1.00), (288.0, 1.00), (294.0, 1.00), (300.0, 1.00), (306.0, 1.00), (312.0, 1.00), (318.0, 1.00), (324.0, 1.00), (330.0, 1.00), (336.0, 1.00), (342.0, 1.00), (348.0, 1.00), (354.0, 1.00), (360.0, 1.00), (366.0, 1.00), (372.0, 1.00)

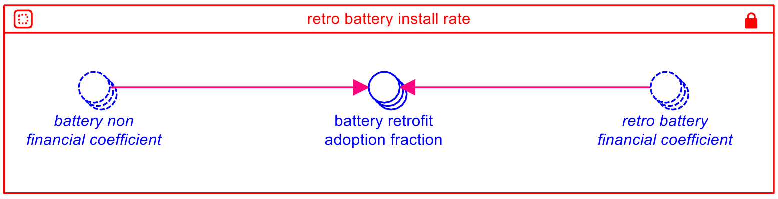
subsidy_rush_effect[Between_2_and_4_kW] = GRAPH(TIME)
(0.0, 1.00), (6.0, 1.00), (12.0, 1.00), (18.0, 1.00), (24.0, 1.00), (30.0, 1.00), (36.0, 1.00), (42.0, 1.00), (48.0, 1.00), (54.0, 1.00), (60.0, 1.00), (66.0, 3.00), (72.0, 5.00), (78.0, 5.00), (84.0, 5.00), (90.0, 1.00), (96.0, 1.00), (102.0, 1.00), (108.0, 1.00), (114.0, 1.00), (120.0, 1.00), (126.0, 1.00), (132.0, 1.00), (138.0, 1.00), (144.0, 1.00), (150.0, 1.00), (156.0, 1.00), (162.0, 1.00), (168.0, 1.00), (174.0, 1.00), (180.0, 1.00), (186.0, 1.00), (192.0, 1.00), (198.0, 1.00), (204.0, 1.00), (210.0, 1.00), (216.0, 1.00), (222.0, 1.00), (228.0, 1.00), (234.0, 1.00), (240.0, 1.00), (246.0, 1.00), (252.0, 1.00), (258.0, 1.00), (264.0, 1.00), (270.0, 1.00), (276.0, 1.00), (282.0, 1.00), (288.0, 1.00), (294.0, 1.00), (300.0, 1.00), (306.0, 1.00), (312.0, 1.00), (318.0, 1.00), (324.0, 1.00), (330.0, 1.00), (336.0, 1.00), (342.0, 1.00), (348.0, 1.00), (354.0, 1.00), (360.0, 1.00), (366.0, 1.00), (372.0, 1.00)
subsidy_rush_effect[Between_4_and_6kW] = GRAPH(TIME)
(0.0, 1.00), (6.0, 1.00), (12.0, 1.00), (18.0, 1.00), (24.0, 1.00), (30.0, 1.00), (36.0, 1.00), (42.0, 1.00), (48.0, 1.00), (54.0, 1.00), (60.0, 1.00), (66.0, 1.00), (72.0, 1.00), (78.0, 3.00), (84.0, 3.00), (90.0, 1.00), (96.0, 1.00), (102.0, 1.00), (108.0, 1.00), (114.0, 1.00), (120.0, 1.00), (126.0, 1.00), (132.0, 1.00), (138.0, 1.00), (144.0, 1.00), (150.0, 1.00), (156.0, 1.00), (162.0, 1.00), (168.0, 1.00), (174.0, 1.00), (180.0, 1.00), (186.0, 1.00), (192.0, 1.00), (198.0, 1.00), (204.0, 1.00), (210.0, 1.00), (216.0, 1.00), (222.0, 1.00), (228.0, 1.00), (234.0, 1.00), (240.0, 1.00), (246.0, 1.00), (252.0, 1.00), (258.0, 1.00), (264.0, 1.00), (270.0, 1.00), (276.0, 1.00), (282.0, 1.00), (288.0, 1.00), (294.0, 1.00), (300.0, 1.00), (306.0, 1.00), (312.0, 1.00), (318.0, 1.00), (324.0, 1.00), (330.0, 1.00), (336.0, 1.00), (342.0, 1.00), (348.0, 1.00), (354.0, 1.00), (360.0, 1.00), (366.0, 1.00), (372.0, 1.00)
subsidy_rush_effect[Between_8_and_10kW] = GRAPH(TIME)
(0.0, 1.00), (6.0, 1.00), (12.0, 1.00), (18.0, 1.00), (24.0, 1.00), (30.0, 1.00), (36.0, 1.00), (42.0, 1.00), (48.0, 1.00), (54.0, 1.00), (60.0, 1.00), (66.0, 1.00), (72.0, 1.00), (78.0, 2.00), (84.0, 1.00), (90.0, 1.00), (96.0, 1.00), (102.0, 1.00), (108.0, 1.00), (114.0, 1.00), (120.0, 1.00), (126.0, 1.00), (132.0, 1.00), (138.0, 1.00), (144.0, 1.00), (150.0, 1.00), (156.0, 1.00), (162.0, 1.00), (168.0, 1.00), (174.0, 1.00), (180.0, 1.00), (186.0, 1.00), (192.0, 1.00), (198.0, 1.00), (204.0, 1.00), (210.0, 1.00), (216.0, 1.00), (222.0, 1.00), (228.0, 1.00), (234.0, 1.00), (240.0, 1.00), (246.0, 1.00), (252.0, 1.00), (258.0, 1.00), (264.0, 1.00), (270.0, 1.00), (276.0, 1.00), (282.0, 1.00), (288.0, 1.00), (294.0, 1.00), (300.0, 1.00), (306.0, 1.00), (312.0, 1.00), (318.0, 1.00), (324.0, 1.00), (330.0, 1.00), (336.0, 1.00), (342.0, 1.00), (348.0, 1.00), (354.0, 1.00), (360.0, 1.00), (366.0, 1.00), (372.0, 1.00)

3. <u>Retrofit battery adoption sectors</u>

3.1. Battery retrofit adoption fraction

This section includes each of the sectors that comprise the battery retrofit adoption fraction. This is a function of a non-financial and financial coefficient.

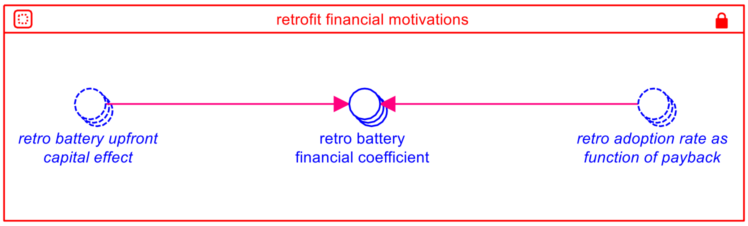
Representations in Stella



****
retro_battery_install_rate:
****
battery_retrofit_adoption_fraction[PV_size, Loadprofile, Electricityconsumption, Battery_size] = retro_battery_financial_coefficient *battery_non_financial_coefficient[Electricityconsumption, Battery_size]

3.2. Retrofit battery financial motivations

This is a function of two elements which are described separately below.

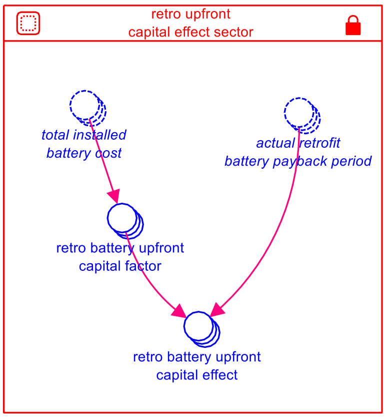


****
retrofit_financial_motivations:
****
retro_battery_financial_coefficient[PV_size, Loadprofile, Electricityconsumption, Battery_size] = retro_battery_upfront_capital_effect*retro_adoption_rate_as_function_of_payback/12

3.3. Retro upfront capital effect

The assumptions underpinning the upfront capital effect for batteries is the same as that described above for PV systems

Representation in Stella

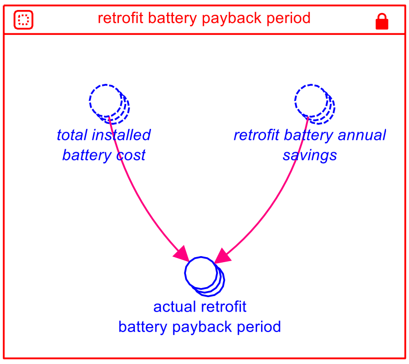


****
retro_upfront_capital_effect_sector:
****
retro_battery_upfront_capital_effect[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF actual_retrofit_battery_payback_period < 4 THEN 1 ELSE retro_battery_upfront_capital_factor[Battery_size]
retro_battery_upfront_capital_factor[Battery_size] = IF total_installed_battery_cost >15000 THEN 0.1 ELSE IF total_installed_battery_cost >10000 AND total_installed_battery_cost <= 15000 THEN 0.6 ELSE IF total_installed_battery_cost>7000 AND total_installed_battery_cost <=10000 THEN 0.8 ELSE 1

3.4. Retrofit battery payback period

Comprises two elements: total installed battery cost and retrofit battery annual savings which are described below.

Representation in Stella



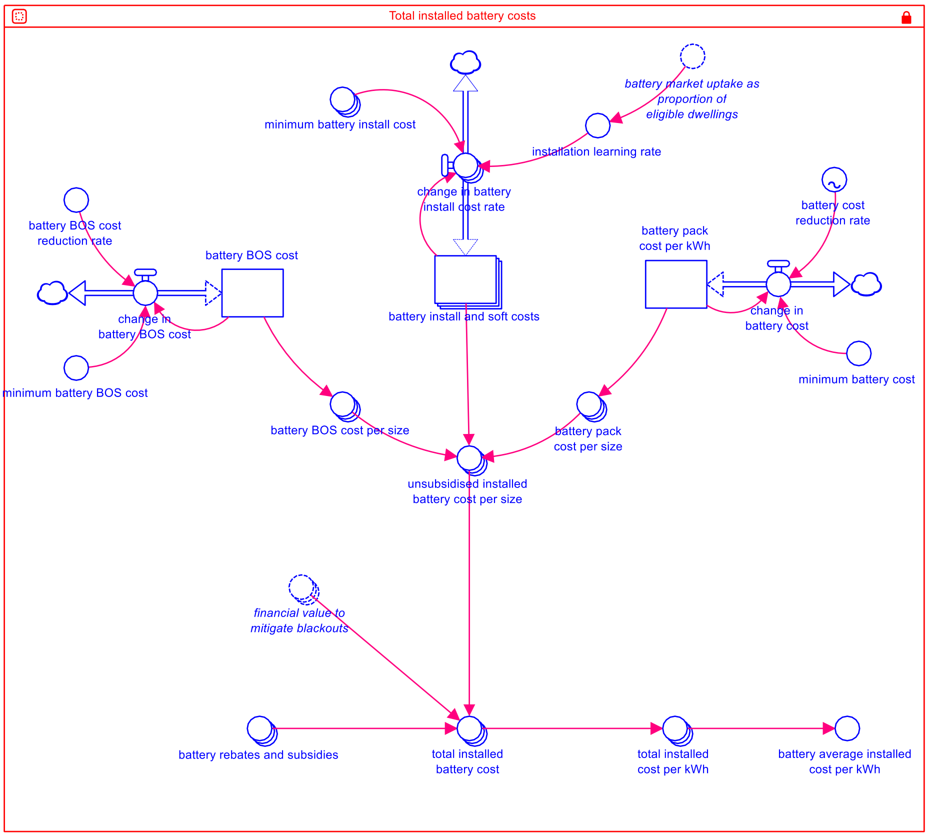
****
retrofit_battery_payback_period:
****
actual_retrofit_battery_payback_period[PV_size, Loadprofile, Electricityconsumption, Battery_size] = SAFEDIV(total_installed_battery_cost[Battery_size], retrofit_battery_annual_savings)

3.5. Total installed battery costs

Key assumptions

- Battery pack cost per kWh – the initial value for 2006 is $1700/kWh based on data extrapolated from historic battery prices (Nykvist & Nilsson 2015).
- Battery cost reduction rate – historic battery cost reduction rates gradually increase from 2011 where they spike with the release of the Powerwall in 2015 and the Powerwall 2 in 2016 (RMI 2015b; Tesla 2016). From 2017, annual reductions are assumed to reduce by 10% per annum until 2021 i.e. a total 50% reduction in 5 years which is well covered in literature (IEA 2012; EPRI 2014; Pistoia 2014). From 2022, more modest annual reductions of 5% per annum are used reflecting the position of batteries on the technology development curve.
- Battery install and soft costs – initial values for 2006 install costs are informed by Galanis (2016) and estimated at $600 (5kWh), $800 (15kWh) and $1500 (30kWh).
- Installation learning rate – the values for installation learning rates are informed by diffusion dynamics which assumes that in the early stages of battery diffusion, installation and soft costs reduce by a larger amount (i.e. 10% per annum). As battery uptake achieves 50% market penetration this then reduces to 5% annum until a minimum battery install cost is reached.
- Battery BOS cost - the estimated initial values in 2006 for BOS costs, which include inverter and battery management systems, are informed by Galanis (2016) and assumed to be $1200/kw.
- Battery BOS cost reduction rate – is assumed to be 3% per annum, double the rate used for PV BOS reduction rates, reflecting the opportunity for cost savings in emerging battery hybrid inverter technology.
- Battery rebates and subsidies – as there are no subsidies for batteries in Queensland at present none are included in the base-case simulation. Subsidies are introduced as part of scenario analysis.
- Note the variable ‘financial value to mitigate blackouts’ is based on research undertaken by AEMO to determine the cost of blackouts to residential consumers. This variable is an extension of the non-financial motivaton section and is described in detail in the relevant section below.

Representation in Stella



****
Total_installed_battery_costs:
****
battery_average_installed_cost_per_kWh = MEAN(total_installed_cost_per_kWh)
battery_BOS_cost(t) = battery_BOS_cost(t - dt) + (- change_in_battery_BOS_cost) * dt
INIT battery_BOS_cost = 1200
OUTFLOWS:
change_in_battery_BOS_cost = IF battery_BOS_cost > minimum_battery_BOS_cost THEN (battery_BOS_cost*battery_BOS_cost_reduction_rate) ELSE 0
battery_BOS_cost_per_size[five_kWh] = battery_BOS_cost*5
battery_BOS_cost_per_size[fifteen_kWh] = battery_BOS_cost*5
battery_BOS_cost_per_size[thirty_kWh] = battery_BOS_cost*10
battery_BOS_cost_reduction_rate = 0.003
battery_cost_reduction_rate = GRAPH(TIME)
(0.0, 0), (12.0, 0), (24.0, 0), (36.0, 0), (48.0, 0), (60.0, 0.004), (72.0, 0.004), (84.0, 0.008), (96.0, 0.008), (108.0, 0.03), (120.0, 0.03), (132.0, 0.008), (144.0, 0.008), (156.0, 0.008), (168.0, 0.008), (180.0, 0.008), (192.0, 0.008), (204.0, 0.004), (216.0, 0.004), (228.0, 0.004), (240.0, 0.004), (252.0, 0.004), (264.0, 0.004), (276.0, 0.004), (288.0, 0.004), (300.0, 0.004), (312.0, 0.004), (324.0, 0.004), (336.0, 0.004), (348.0, 0.004), (360.0, 0.004), (372.0, 0.004)
battery_install_and_soft_costs[five_kWh](t) = battery_install_and_soft_costs[five_kWh](t - dt) + (- change_in_battery_install_cost_rate[five_kWh]) * dt
INIT battery_install_and_soft_costs[five_kWh] = 600
battery_install_and_soft_costs[fifteen_kWh](t) = battery_install_and_soft_costs[fifteen_kWh](t - dt) + (- change_in_battery_install_cost_rate[fifteen_kWh]) * dt
INIT battery_install_and_soft_costs[fifteen_kWh] = 800
battery_install_and_soft_costs[thirty_kWh](t) = battery_install_and_soft_costs[thirty_kWh](t - dt) + (- change_in_battery_install_cost_rate[thirty_kWh]) * dt
INIT battery_install_and_soft_costs[thirty_kWh] = 1500
OUTFLOWS:

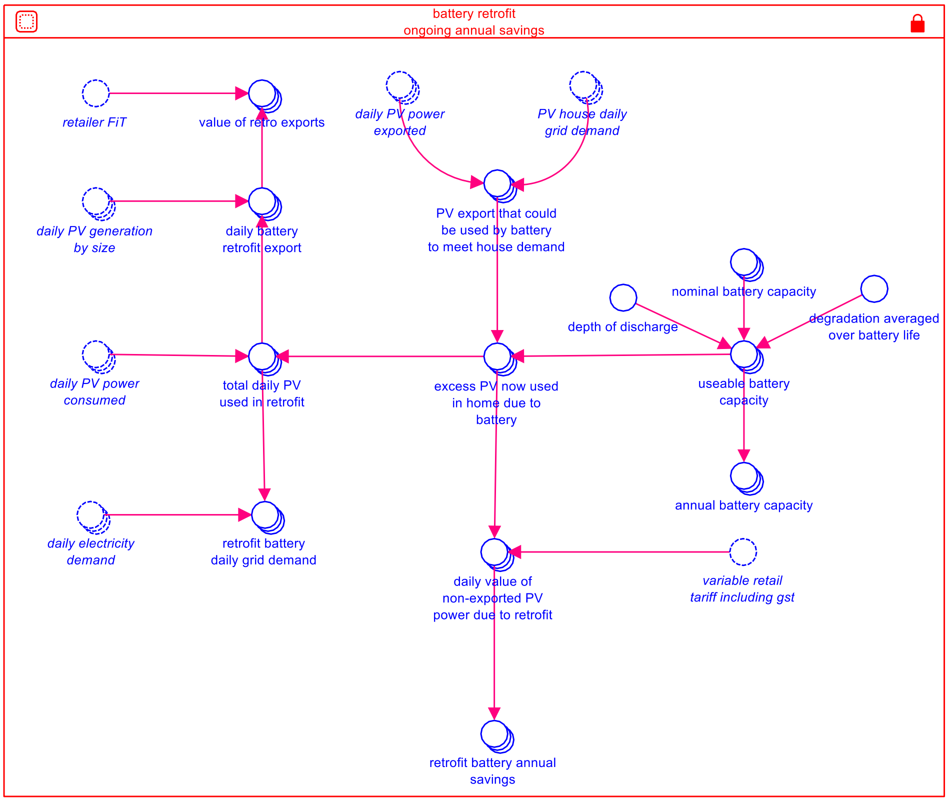
```
        change_in_battery_install_cost_rate[Battery_size] = IF  battery_install_and_soft_costs >
minimum_battery_install_cost   THEN   (installation_learning_rate*battery_install_and_soft_costs)   ELSE 0
battery_pack_cost_per_kWh(t) = battery_pack_cost_per_kWh(t - dt) + ( - change_in_battery_cost) * dt
    INIT battery_pack_cost_per_kWh = 1700
    OUTFLOWS:
        change_in_battery_cost = IF battery_pack_cost_per_kWh > minimum_battery_cost THEN
(battery_pack_cost_per_kWh*battery_cost_reduction_rate) ELSE 0
battery_pack_cost_per_size[five_kWh] = battery_pack_cost_per_kWh*5
battery_pack_cost_per_size[fifteen_kWh] = battery_pack_cost_per_kWh*14
battery_pack_cost_per_size[thirty_kWh] = battery_pack_cost_per_kWh*30
battery_rebates_and_subsidies[Battery_size] = 0
installation_learning_rate = IF  TIME < 108  THEN  0  ELSE IF   TIME >=108 AND
battery_market_uptake_as_proportion_of_eligible_dwellings < 0.005  THEN  0.004  ELSE IF
battery_market_uptake_as_proportion_of_eligible_dwellings >=0.005 AND
battery_market_uptake_as_proportion_of_eligible_dwellings < 0.5  THEN   0.008  ELSE   0.004
minimum_battery_BOS_cost = 100
minimum_battery_cost = 100
minimum_battery_install_cost[five_kWh] = 200
minimum_battery_install_cost[fifteen_kWh] = 400
minimum_battery_install_cost[thirty_kWh] = 600
total_installed_battery_cost[Battery_size] = (unsubsidised_installed_battery_cost_per_size-
(battery_rebates_and_subsidies+financial_value_to_mitigate_blackouts))
total_installed_cost_per_kWh[five_kWh] = total_installed_battery_cost[five_kWh]/5
total_installed_cost_per_kWh[fifteen_kWh] = total_installed_battery_cost[fifteen_kWh]/15
total_installed_cost_per_kWh[thirty_kWh] = total_installed_battery_cost[thirty_kWh]/30
unsubsidised_installed_battery_cost_per_size[Battery_size] =
battery_install_and_soft_costs+battery_BOS_cost_per_size+battery_pack_cost_per_size
```

3.6. Battery retrofit ongoing annual savings

Key assumptions

- The model assumes that battery systems are retrofitted to existing PV dwellings with the intention of maximising PV consumption in home.
- As the payback is calculated using only the capital cost of the battery itself (not that of the PV system, as it is considered a sunk cost), ongoing savings are only those savings that occur as a result of the battery install i.e. PV generation that was previously exported and is now used in home.
- ‘nominal battery capacities’ includes small (5kWh), medium (15kWh) and large (30kWh) battery systems.
- ‘useable battery capacity’ reflects the fact that due to technical restrictions, the ‘nominal battery capacity’ does not reflect the actual kWh that is useable. Accordingly, this variable includes assumptions on battery degradation (~90% averaged over life) and depth of discharge (87.5%) based on common battery specs from (Martin 2016; SolarQuotes 2017).

Representation in Stella



****
battery_retrofit_ongoing_annual_savings:
****
annual_battery_capacity[Battery_size] = useable_battery_capacity*365
daily_battery_retrofit_export[PV_size, Loadprofile, Electricityconsumption, Battery_size] = daily_PV_generation_by_size[PV_size] -total_daily_PV_used_in_retrofit
"daily_value_of_non-exported_PV_power_due_to_retrofit"[PV_size, Loadprofile, Electricityconsumption, Battery_size] = excess_PV_now_used_in_home_due_to_battery*variable_retail_tariff_including_gst
degradation_averaged_over_battery_life = 0.875
depth_of_discharge = 0.9143
excess_PV_now_used_in_home_due_to_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF PV_export_that_could_be_used_by_battery_to_meet_house_demand[PV_size, Loadprofile, Electricityconsumption] < useable_battery_capacity[Battery_size] THEN PV_export_that_could_be_used_by_battery_to_meet_house_demand[PV_size, Loadprofile, Electricityconsumption] ELSE IF PV_export_that_could_be_used_by_battery_to_meet_house_demand[PV_size, Loadprofile, Electricityconsumption] >= useable_battery_capacity[Battery_size] THEN useable_battery_capacity[Battery_size] ELSE 0
nominal_battery_capacity[five_kWh] = 5
nominal_battery_capacity[fifteen_kWh] = 15
nominal_battery_capacity[thirty_kWh] = 30
PV_export_that_could_be_used_by_battery_to_meet_house_demand[PV_size, Loadprofile, Electricityconsumption] = IF daily_PV_power_exported >= PV_house_daily_grid_demand THEN PV_house_daily_grid_demand ELSE IF daily_PV_power_exported< PV_house_daily_grid_demand AND daily_PV_power_exported>0 THEN daily_PV_power_exported ELSE 0
retrofit_battery_annual_savings[PV_size, Loadprofile, Electricityconsumption, Battery_size] = "daily_value_of_non-exported_PV_power_due_to_retrofit"*365
retrofit_battery_daily_grid_demand[PV_size, Loadprofile, Electricityconsumption, Battery_size] = daily_electricity_demand[Electricityconsumption]-total_daily_PV_used_in_retrofit
total_daily_PV_used_in_retrofit[PV_size, Loadprofile, Electricityconsumption, Battery_size] = excess_PV_now_used_in_home_due_to_battery+daily_PV_power_consumed[PV_size, Loadprofile, Electricityconsumption]

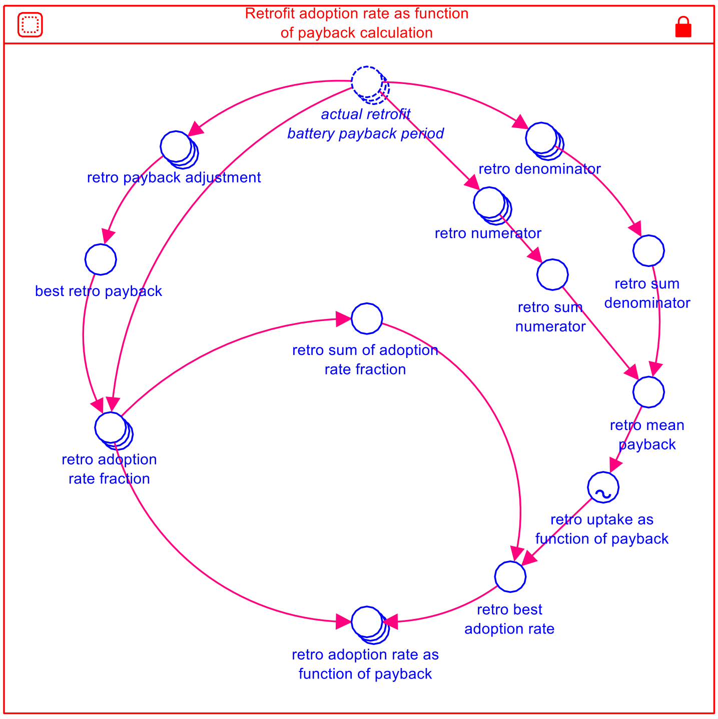
useable_battery_capacity[Battery_size] =
depth_of_discharge*nominal_battery_capacity*degradation_averaged_over_battery_life
value_of_retro_exports[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
daily_battery_retrofit_export*365*retailer_FiT

3.7. Retrofit adoption rate as function of payback calculation

Key assumptions

- To model the relationship between the payback period and the adoption fraction, a similar curve is used to that described above for the PV adoption fraction.
- The only modification to the curve for use with battery adoption has been made to reflect the fact that batteries have a shorter lifespan (i.e. batteries are generally warranted for between 10-15 years). This means baseline demand in the battery curve decreases to 1% sooner before decreasing to zero at a payback of 15 years.
- Using uptake rates of analogous technologies such as PV to generate a financial coefficient for battery uptake is considered reasonable and this assumption is supported by and has been used in the past for energy sector modelling by both AEMO (2015c) and CSIRO (2015b).
- As with PV, the model incorporates numerous battery system configurations. This sector calculates the individual contributions of each system to the adoption rate based on the same logic as that used for PV.

Representation in Stella



****
Retrofit_adoption_rate_as_function_of_payback_calculation:
****
best_retro_payback = MIN(retro_payback_adjustment)
retro_adoption_rate_as_function_of_payback[PV_size, Loadprofile, Electricityconsumption, Battery_size] = retro_adoption_rate_fraction*retro_best_adoption_rate
retro_adoption_rate_fraction[PV_size, Loadprofile, Electricityconsumption, Battery_size] = SAFEDIV(best_retro_payback, actual_retrofit_battery_payback_period)
retro_best_adoption_rate = SAFEDIV(retro_uptake_as_function_of_payback, retro_sum_of_adoption_rate_fraction)
retro_denominator[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF actual_retrofit_battery_payback_period >0 AND actual_retrofit_battery_payback_period<15 THEN 1 ELSE 0
retro_mean_payback = IF SAFEDIV (retro_sum_numerator, retro_sum_denominator) = 0 THEN 15 ELSE SAFEDIV (retro_sum_numerator, retro_sum_denominator)
retro_numerator[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF actual_retrofit_battery_payback_period<15 THEN actual_retrofit_battery_payback_period ELSE 0
retro_payback_adjustment[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF actual_retrofit_battery_payback_period =0 THEN 1000 ELSE actual_retrofit_battery_payback_period
retro_sum_denominator = SUM(retro_denominator)
retro_sum_numerator = SUM(retro_numerator)
retro_sum_of_adoption_rate_fraction = SUM(retro_adoption_rate_fraction)
retro_uptake_as_function_of_payback = GRAPH(retro_mean_payback)
(0.00, 0.0950), (1.00, 0.0924), (2.00, 0.0899), (3.00, 0.0869), (4.00, 0.0830), (5.00, 0.0750), (6.00, 0.0650), (7.00, 0.0550), (8.00, 0.0400), (9.00, 0.0250), (10.00, 0.0100), (11.00, 0.0090), (12.00, 0.0069), (13.00, 0.0049), (14.00, 0.0029), (15.00, 0.0000)

3.8. Battery non-financial motivations

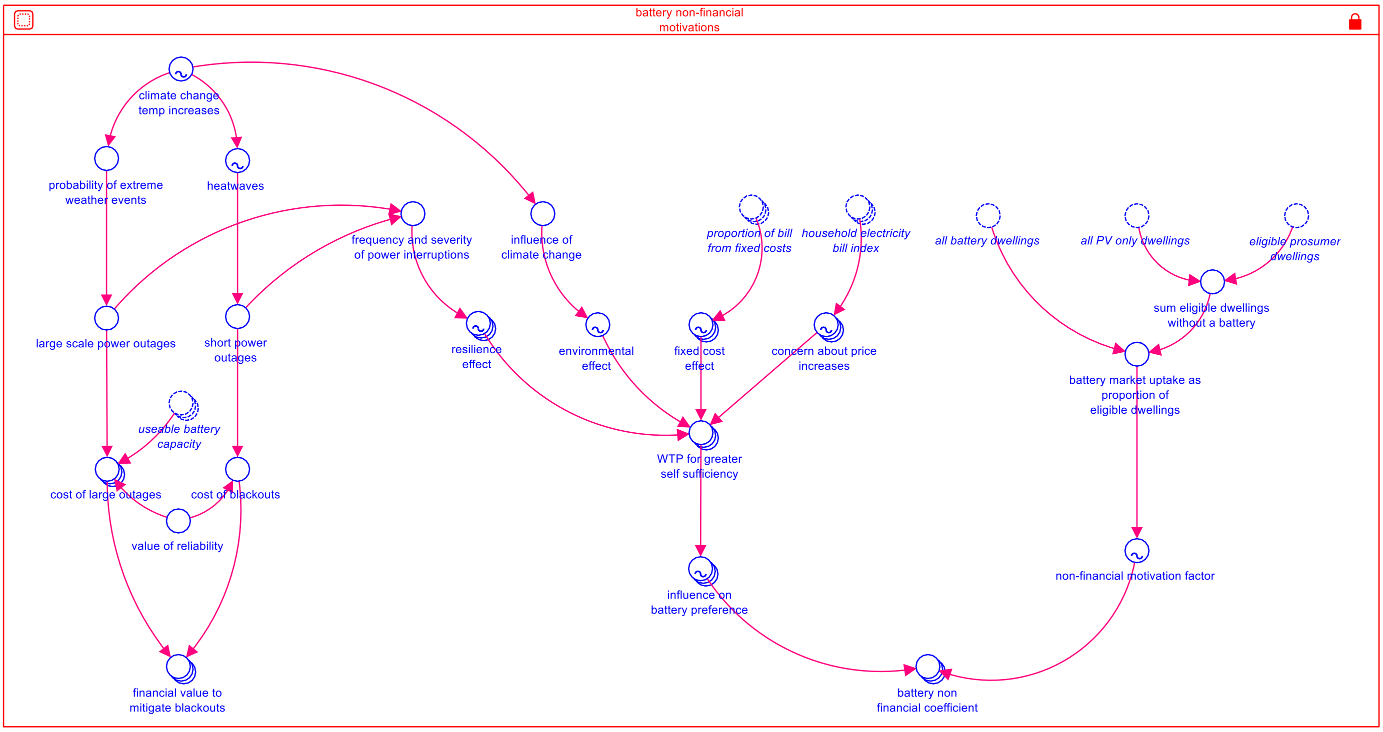
Key assumptions

- Due to an almost complete lack of empirical data regarding non-financial motivations relating to battery adoption, parameterisation of this element of the model necessarily rests on rule-of-thumb assumptions.
- The first part of this model (the structure on the right-hand side) is based on the characteristics of technology adopters based on Rogers (1962). It assumes a ‘non-financial motivation factor’ which effectively works as a multiplier to increase the strength of non-financial motivations in the decision-making process based on the stage of market penetration. For innovators, this increases adoption by 5%, which then declines to zero as mass market uptake is achieved.
- The second part of the model (on the left), is structured so that changes in non-financial variables as a result of both endogenous and exogenous factors are assigned a value based on relative importance. This is based on an index that ranges between 1 and 5 for each variable reflecting the magnitude of the multiplier applied for each factor.
- To determine their impact on adoption, the value of all the non-finanical variables are aggregated and then averaged in ‘WTP for self sufficiency’ (nb WTP = willingness to pay).
- ‘influence on battery preferences’ multiplies the above index against graphical functions for each system size. Effectively as WTP for self-sufficiency increases, preference for smaller batteries decrease while preferences for larger batteries increase. This is then reflected in the model as a multiplier that increases or decreases adoption.

- To reflect the uncertainty associated with the assumptions in this component of the model, it has been designed to generate very conservative values. For example, the base-case simulation generates an average value for ‘influence on battery preferences’ that never exceeds 5%. In the climate change scenario, where non-financial motivations are strongest, this average remains below 20% for the majority of the scenario.
- In regards to each of the specific variables, ‘fixed cost effect’ reflects the fact that as the proportion of total household electricity costs comprising fixed costs increases, it reduces the value of installed PV while reducing the effect of efforts by consumers to reduce household electricity bills through energy efficiency or other measures. These factors all serve to increase frustration with incumbents increasing non-financial motivations to reduce reliance on the grid.
- ‘concern about price increases’ is based on the same logic as that described for PV, namely as electricity prices increases, concern about future prices increases. Research shows that consumers strongly prefer avoiding losses compared to acquiring gains and can be willing to pay a premium of up to 20%, versus what they rationally should pay to reduce their electricity costs (Vorrath 2017a).
- ‘climate change temp increases’ is effectively a proxy for climate change impacts. It is a graphical function that can incorporate possible future changes in average global temperature. For the base-case, it is assumed to remain at the current level (i.e. approximately 1^{o}C above average). The influence of this variable is limited except for the climate change scenario where global temperatures are assumed to increase to 1.5^{o}C.
- The model assumes that as temperature increases the ‘probability of extreme weather events’ (such as cyclones and floods) and ‘heatwaves’ increase, both of which impact the operation of the electricity sector through ‘large-scale power outages’ (loss of supply for significant periods of time) and ‘short power outages’ (i.e. blackouts). This has an effect on both financial and non-financial motivations for consumers considering purchasing PV and batteries.
- The model calculates these effects based on the probability of these events occurring as a function of temperature increases. For example, it is assumed that extreme weather events (with the capacity to knock out significant electricity capacity across the state) currently occur approximately every 6 years. If global temperature increases by 10%, then it is assumed severe weather events will occur every five years. At the same time, as temperatures increase, the likelihood of ‘blackouts’ also increase (extreme heat is a key driver of critical peak demand days). These general assumptions are based on review of IPCC reports (IPCC 2014b) and other climate change studies such as Nierop (2014) and Australian Government (2016).
- ‘climate change temp increases’ impacts three main components of the sector.

- The non-financial variable 'environment effect' assumes that many consumers will consider PV and batteries to reduce their environmental footprint associated with energy use. While this is frequently a stated objective for purchasing low emission technologies, its actual influence in the decision-making process is less clear (Boughen, Castro & Ashworth 2013). For this reason, the variable has been designed to have limited influence on adoption.
- 'resilience effect' assumes that as power outages increase, consumers will be motivated to adopt batteries to hedge against future outages. This was amply evidenced following blackouts in South Australia in 2016, where battery installers saw a 228% increase in inquiries for batteries in the 24 hours after the event (Parkinson 2016).
- 'financial value to mitigate blackouts' is actually a financial motivation and reflects that there is a financial value to consumers associated with power outages. A study by AEMO (2014c) examined the financial value of customer reliability and found that a loss of power was worth approximately AU$25.42/kWh to Queensland consumers. This value has therefore been used to generate a financial cost associated with a loss of power – this is then used to offset a proportion of the 'total installed battery cost'. As the cost of an outage to a consumer would vary according to the type of interruption, the use of this value has been used conservatively and scaled accordingly, with a cap set on the possible reduction in install price that it may achieve.

Representation in Stella



****
"battery_non-financial_motivations":
****
battery_market_uptake_as_proportion_of_eligible_dwellings = all_battery_dwellings/(sum_eligible_dwellings_without_a_battery+all_battery_dwellings)
battery_non_financial_coefficient[Electricityconsumption, Battery_size] = IF TIME > 132 THEN "non-financial_motivation_factor"*influence_on_battery_preference ELSE 1
climate_change_temp_increases = GRAPH(TIME)
(0.0, 0.941), (12.0, 0.941), (24.0, 0.941), (36.0, 0.941), (48.0, 0.959), (60.0, 0.959), (72.0, 0.977), (84.0, 0.977), (96.0, 0.995), (108.0, 0.996), (120.0, 0.997), (132.0, 0.998), (144.0, 1.000), (156.0, 1.000), (168.0, 1.000), (180.0, 1.000), (192.0, 1.000), (204.0, 1.000), (216.0, 1.000), (228.0, 1.000), (240.0, 1.000), (252.0, 1.000), (264.0, 1.000), (276.0, 1.000), (288.0, 1.000), (300.0, 1.000), (312.0, 1.000), (324.0, 1.000), (336.0, 1.000), (348.0, 1.000), (360.0, 1.000), (372.0, 1.000)
concern_about_price_increases[Electricityconsumption] = GRAPH(household_electricity_bill_index)
(0.000, 1.000), (0.250, 1.000), (0.500, 1.000), (0.750, 1.000), (1.000, 1.000), (1.250, 1.500), (1.500, 2.000), (1.750, 2.500), (2.000, 3.000), (2.250, 3.500), (2.500, 4.000), (2.750, 4.500), (3.000, 5.000), (3.250, 5.000), (3.500, 5.000), (3.750, 5.000), (4.000, 5.000)
cost_of_blackouts = value_of_reliability*short_power_outages*4
cost_of_large_outages[five_kWh] = large_scale_power_outages*value_of_reliability*useable_battery_capacity[five_kWh]
cost_of_large_outages[fifteen_kWh] = large_scale_power_outages*value_of_reliability*useable_battery_capacity[fifteen_kWh]
cost_of_large_outages[thirty_kWh] = large_scale_power_outages*value_of_reliability*useable_battery_capacity[thirty_kWh]
environmental_effect = GRAPH(influence_of_climate_change)
(1.0000, 0.000), (1.1250, 1.500), (1.2500, 2.500), (1.3750, 3.500), (1.5000, 5.000)
financial_value_to_mitigate_blackouts[five_kWh] = cost_of_large_outages[five_kWh]+cost_of_blackouts
financial_value_to_mitigate_blackouts[fifteen_kWh] = cost_of_large_outages[fifteen_kWh]+cost_of_blackouts
financial_value_to_mitigate_blackouts[thirty_kWh] = cost_of_large_outages[thirty_kWh]+cost_of_blackouts
fixed_cost_effect[Electricityconsumption] = GRAPH(proportion_of_bill_from_fixed_costs)
(0.000, 1.000), (0.100, 1.000), (0.200, 1.000), (0.300, 1.500), (0.400, 2.000), (0.500, 2.500), (0.600, 3.000), (0.700, 3.500), (0.800, 4.000), (0.900, 4.500), (1.000, 5.000)
frequency_and_severity_of_power_interruptions = IF TIME <=132 THEN 1 ELSE IF TIME >132 THEN (short_power_outages+large_scale_power_outages) ELSE 1
heatwaves = GRAPH(climate_change_temp_increases)
(1.000, 1.00), (1.010, 2.00), (1.040, 2.27), (1.060, 2.80), (1.080, 3.07), (1.100, 3.40), (1.120, 3.73), (1.140, 4.00), (1.160, 4.33), (1.180, 4.73), (1.200, 5.09), (1.220, 5.35), (1.240, 5.56), (1.260, 5.80), (1.280, 5.90), (1.300, 6.03), (1.320, 6.32), (1.340, 6.56), (1.360, 6.88), (1.380, 7.17), (1.400, 7.43), (1.420, 7.69), (1.440, 8.01), (1.460, 8.22), (1.480, 8.41), (1.500, 8.62), (1.520, 8.85), (1.540, 9.14), (1.560, 9.43), (1.580, 9.80), (1.600, 10.12), (1.620, 10.46), (1.640, 10.86), (1.660, 11.23), (1.680, 11.57), (1.700, 11.96), (1.720, 12.44), (1.740, 12.86), (1.760, 13.31), (1.780, 13.78), (1.800, 14.36), (1.820, 14.97), (1.840, 15.52), (1.860, 16.02), (1.880, 16.55), (1.900, 17.00), (1.920, 17.52), (1.940, 18.08), (1.960, 18.58), (1.980, 19.08), (2.000, 19.58)
influence_of_climate_change = climate_change_temp_increases
influence_on_battery_preference[low_consumption, five_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 0.750), (3.000, 0.500), (4.000, 0.250), (5.000, 0.100)
influence_on_battery_preference[low_consumption, fifteen_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)
influence_on_battery_preference[low_consumption, thirty_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)
influence_on_battery_preference[medium_consumption, five_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 0.750), (3.000, 0.500), (4.000, 0.250), (5.000, 0.100)
influence_on_battery_preference[medium_consumption, fifteen_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)
influence_on_battery_preference[medium_consumption, thirty_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)
influence_on_battery_preference[high_consumption, five_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 0.750), (3.000, 0.500), (4.000, 0.250), (5.000, 0.100)
influence_on_battery_preference[high_consumption, fifteen_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)
influence_on_battery_preference[high_consumption, thirty_kWh] = GRAPH(WTP_for_greater_self_sufficiency)
(1.000, 1.000), (2.000, 1.250), (3.000, 1.500), (4.000, 1.750), (5.000, 2.000)

large_scale_power_outages = IF   probability_of_extreme_weather_events <= 1/72 THEN 0 ELSE IF probability_of_extreme_weather_events > 1/71 AND probability_of_extreme_weather_events <= 1/60 THEN 1 ELSE IF   probability_of_extreme_weather_events >1/60 AND probability_of_extreme_weather_events <=1/48 THEN 2 ELSE IF   probability_of_extreme_weather_events >1/48 THEN 3 ELSE   1

"non-financial_motivation_factor" = GRAPH(battery_market_uptake_as_proportion_of_eligible_dwellings)
(0.000, 1.0500), (0.025, 1.0400), (0.160, 1.0300), (0.320, 1.0200), (0.500, 1.0000), (0.550, 1.0000), (0.600, 1.0000), (0.700, 1.0000), (0.800, 1.0000), (0.900, 1.0000), (1.000, 1.0000)

probability_of_extreme_weather_events = IF   climate_change_temp_increases <1 THEN 1/72   ELSE   IF climate_change_temp_increases >=1 AND climate_change_temp_increases <1.1 THEN   1/60 ELSE   IF climate_change_temp_increases>=1.1 AND climate_change_temp_increases<1.2 THEN   1/48   ELSE   IF climate_change_temp_increases >=1.2 THEN   1/36   ELSE 0

resilience_effect[Battery_size] = GRAPH(frequency_and_severity_of_power_interruptions)
(0.00, 1.000), (1.00, 1.370), (2.00, 1.804), (3.00, 2.169), (4.00, 2.694), (5.00, 3.082), (6.00, 3.516), (7.00, 3.790), (8.00, 4.110), (9.00, 4.498), (10.00, 5.000)

short_power_outages = IF heatwaves >= 2 AND heatwaves < 3 THEN 2 ELSE IF heatwaves >=3 AND heatwaves < 5 THEN 3 ELSE IF heatwaves >= 5 THEN   5 ELSE 1

sum_eligible_dwellings_without_a_battery = eligible_prosumer_dwellings+all_PV_only_dwellings

value_of_reliability = 25.42

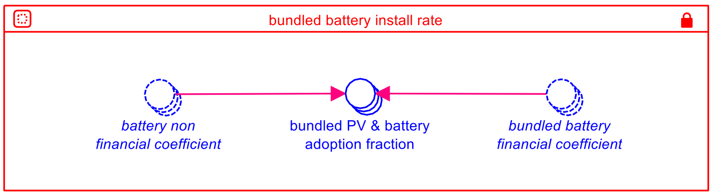
WTP_for_greater_self_sufficiency[Electricityconsumption, Battery_size] = (concern_about_price_increases[Electricityconsumption]+fixed_cost_effect[Electricityconsumption]+resilience_effect[Battery_size]+environmental_effect)/4

4. Bundled battery adoption sectors

4.1. Bundled PV and battery adoption fraction

This section includes each of the sectors that comprise the bundled battery adoption fraction. This is a function of a non-financial and financial coefficient.

Representations in Stella

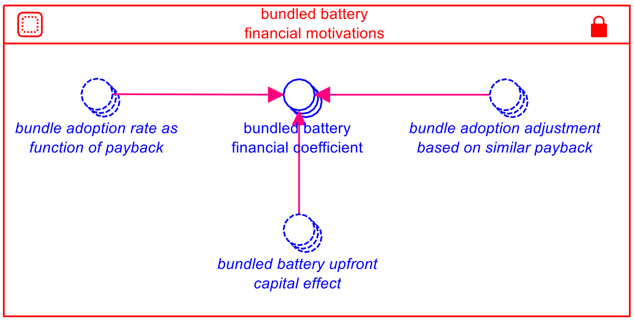


****
bundled_battery_install_rate:
****
bundled_PV_&_battery_adoption_fraction[PV_size, Loadprofile, Electricityconsumption, Battery_size] = bundled_battery_financial_coefficient*battery_non_financial_coefficient[Electricityconsumption, Battery_size]

4.2. Bundled battery financial motivations

This is a function of three elements which are described separately below.

Representations in Stella

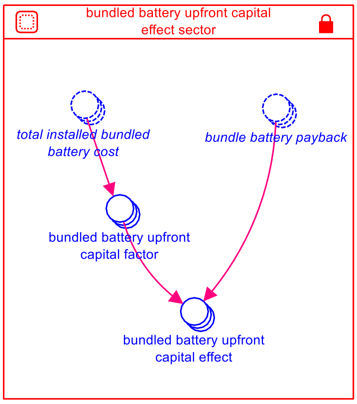


****
bundled_battery_financial_motivations:
****
bundled_battery_financial_coefficient[PV_size, Loadprofile, Electricityconsumption, Battery_size] = bundle_adoption_rate_as_function_of_payback/12 *bundled_battery_upfront_capital_effect +bundle_adoption_adjustment_based_on_similar_payback

4.3. Bundled upfront capital effect

The assumptions underpinning the upfront capital effect for batteries is the same as that described above for PV and retrofit battery systems.

Representations in Stella



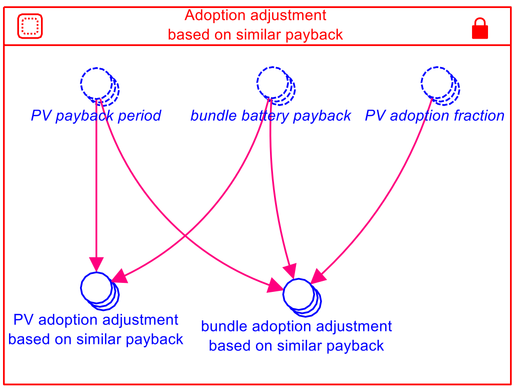
****
bundled_battery_upfront_capital_effect_sector:
****
bundled_battery_upfront_capital_effect[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF bundle_battery_payback < 4 THEN 1 ELSE bundled_battery_upfront_capital_factor[PV_size, Battery_size]
bundled_battery_upfront_capital_factor[PV_size, Battery_size] = IF total_installed_bundled_battery_cost >15000 THEN 0.1 ELSE IF total_installed_bundled_battery_cost >10000 AND total_installed_bundled_battery_cost <= 15000 THEN 0.6 ELSE IF total_installed_bundled_battery_cost>7000 AND total_installed_bundled_battery_cost <=10000 THEN 0.8 ELSE 1

4.4. Bundled adoption adjustment based on similar payback

Key assumptions

This sector assumes that if a PV system has a similar or slightly shorter payback period when compared with a PV and battery system, most consumers will still install the PV and battery system.

Representations in Stella

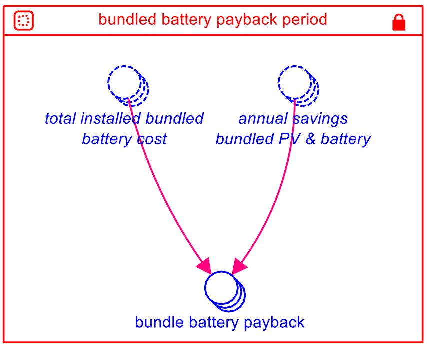


****
Adoption_adjustment_based_on_similar_payback:
****
bundle_adoption_adjustment_based_on_similar_payback[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF bundle_battery_payback>0 AND (PV_payback_period[PV_size, Loadprofile, Electricityconsumption] >= bundle_battery_payback-1) THEN PV_adoption_fraction[PV_size, Loadprofile, Electricityconsumption] ELSE 0
PV_adoption_adjustment_based_on_similar_payback[PV_size, Loadprofile, Electricityconsumption] = IF TIME >132 AND (PV_payback_period >= MEAN(bundle_battery_payback[PV_size, Loadprofile, Electricityconsumption, *])-1) THEN 0 ELSE 1

4.5. Bundled battery payback period

Comprises two elements: total installed bundled battery cost and annual savings bundled PV and battery which are described below.

Representation in Stella



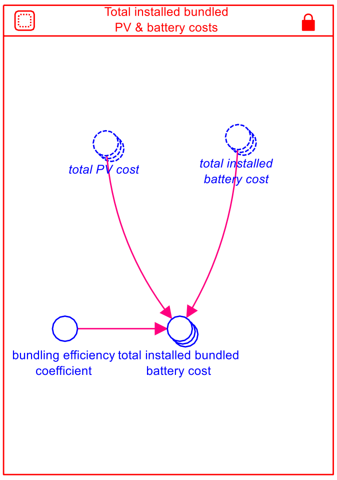
****
bundled_battery_payback_period:
****
bundle_battery_payback[PV_size, Loadprofile, Electricityconsumption, Battery_size] = SAFEDIV(total_installed_bundled_battery_cost[PV_size, Battery_size], annual_savings_bundled_PV_&_battery)
off_grid_install_rate = "monthly_install_rate_possible_off-grid"

4.6. Total installed bundled battery costs

Key assumptions

- 'total installed bundled battery costs' include the addition of the total installed PV system cost and the total installed battery cost.
- However, buying a PV and battery system at the same time has the potential to lower the total system price. Installation and soft costs are generally cheaper as only one visit to the premises is required, and bundled systems are usually installed with only one inverter, which can account for up to 15% of the total cost of a PV system (Gill 2016).
- To reflect these savings, the model includes a 10% 'bundling efficiency coefficient'.

Representation in Stella



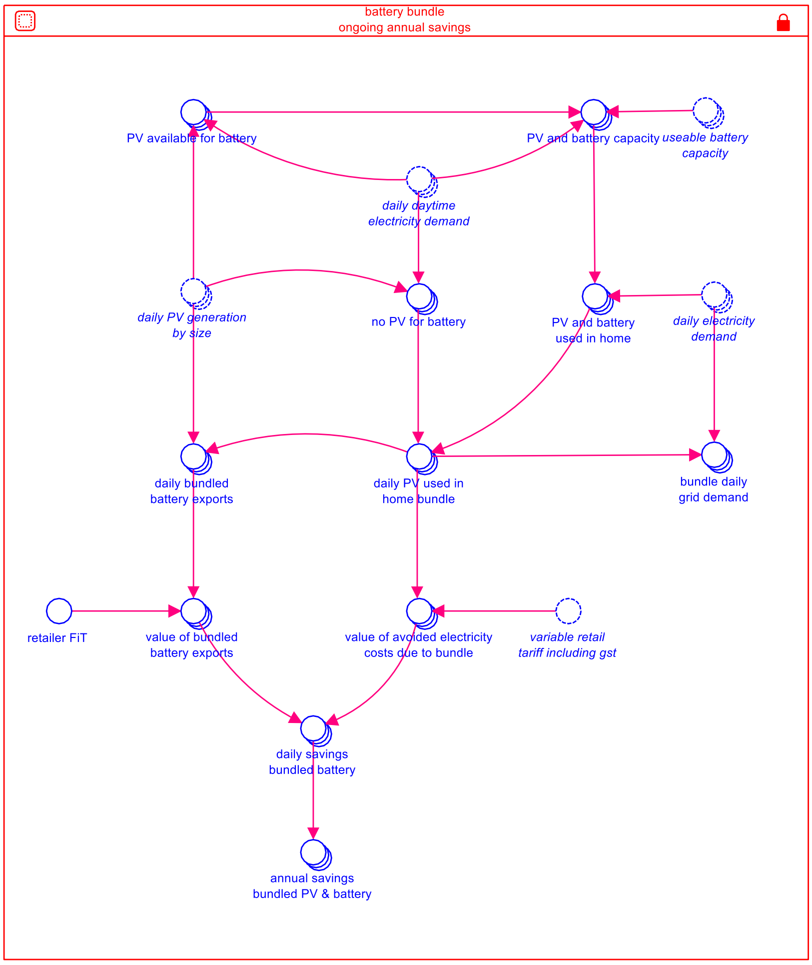
****
Total_installed_bundled_PV_&_battery_costs:
****
bundling_efficiency_coefficient = IF TIME > 120 THEN 0.90 ELSE 1.4
total_installed_bundled_battery_cost[Less_than_2_kW, five_kWh] =
total_PV_cost[Less_than_2_kW]+total_installed_battery_cost[five_kWh]*bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Less_than_2_kW, fifteen_kWh] = total_PV_cost[Less_than_2_kW]
+total_installed_battery_cost[fifteen_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Less_than_2_kW, thirty_kWh] = total_PV_cost[Less_than_2_kW]
+total_installed_battery_cost[thirty_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_2_and_4_kW, five_kWh] =
total_PV_cost[Between_2_and_4_kW]+total_installed_battery_cost[five_kWh]*bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_2_and_4_kW, fifteen_kWh] = total_PV_cost[Between_2_and_4_kW]
+total_installed_battery_cost[fifteen_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_2_and_4_kW, thirty_kWh] = total_PV_cost[Between_2_and_4_kW]
+total_installed_battery_cost[thirty_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_4_and_6kW, five_kWh] =
total_PV_cost[Between_4_and_6kW]+total_installed_battery_cost[five_kWh]*bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_4_and_6kW, fifteen_kWh] = total_PV_cost[Between_4_and_6kW]
+total_installed_battery_cost[fifteen_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_4_and_6kW, thirty_kWh] = total_PV_cost[Between_4_and_6kW]
+total_installed_battery_cost[thirty_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_8_and_10kW, five_kWh] =
total_PV_cost[Between_8_and_10kW]+total_installed_battery_cost[five_kWh]*bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_8_and_10kW, fifteen_kWh] = total_PV_cost[Between_8_and_10kW]
+total_installed_battery_cost[fifteen_kWh] *bundling_efficiency_coefficient
total_installed_bundled_battery_cost[Between_8_and_10kW, thirty_kWh] = total_PV_cost[Between_8_and_10kW]
+total_installed_battery_cost[thirty_kWh] *bundling_efficiency_coefficient

4.7. Battery bundle ongoing annual savings

Key assumptions

- The model calculates how much self-generated electricity is consumed in home depending on each of the different PV and battery system types and load/consumption profile combinations.
- Ongoing savings reflect both the value of avoided electricity costs due to the PV and battery bundle and the value of any export back to the grid.

Representations in Stella



****
battery_bundle_ongoing_annual_savings:
****
annual_savings_bundled_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = daily_savings_bundled_battery*365
bundle_daily_grid_demand[PV_size, Loadprofile, Electricityconsumption, Battery_size] = daily_electricity_demand[Electricityconsumption]-daily_PV_used_in_home_bundle
daily_bundled_battery_exports[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF daily_PV_used_in_home_bundle>0 AND daily_PV_generation_by_size[PV_size] > daily_PV_used_in_home_bundle THEN daily_PV_generation_by_size[PV_size]-daily_PV_used_in_home_bundle ELSE 0

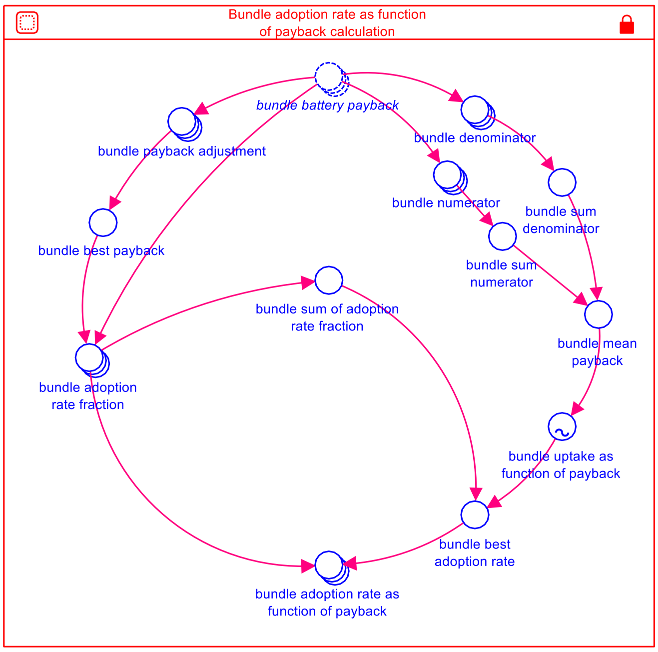
daily_PV_used_in_home_bundle[PV_size, Loadprofile, Electricityconsumption, Battery_size] = PV_and_battery_used_in_home+no_PV_for_battery
daily_savings_bundled_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = (value_of_bundled_battery_exports+value_of_avoided_electricity_costs_due_to_bundle)
no_PV_for_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF daily_PV_generation_by_size[PV_size] <= daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] THEN daily_PV_generation_by_size[PV_size] ELSE 0
PV_and_battery_capacity[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF PV_available_for_battery>0 AND PV_available_for_battery <= useable_battery_capacity[Battery_size] THEN PV_available_for_battery+daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] ELSE IF PV_available_for_battery>0 AND PV_available_for_battery>useable_battery_capacity[Battery_size] THEN useable_battery_capacity[Battery_size]+daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] ELSE 0
PV_and_battery_used_in_home[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF PV_and_battery_capacity>0 AND PV_and_battery_capacity<=daily_electricity_demand[Electricityconsumption] THEN PV_and_battery_capacity ELSE IF PV_and_battery_capacity>0 AND PV_and_battery_capacity>daily_electricity_demand[Electricityconsumption] THEN daily_electricity_demand[Electricityconsumption] ELSE 0
PV_available_for_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF daily_PV_generation_by_size[PV_size] > daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] THEN daily_PV_generation_by_size[PV_size]-daily_daytime_electricity_demand[Loadprofile, Electricityconsumption] ELSE 0
retailer_FiT = IF TIME >132 THEN 0.07 ELSE 0
value_of_avoided_electricity_costs_due_to_bundle[PV_size, Loadprofile, Electricityconsumption, Battery_size] = variable_retail_tariff_including_gst*daily_PV_used_in_home_bundle
value_of_bundled_battery_exports[PV_size, Loadprofile, Electricityconsumption, Battery_size] = daily_bundled_battery_exports*retailer_FiT

4.8. Bundle adoption rate as function of payback calculation

Key assumptions

The logic underpinning this sector is based on that described for the 'retrofit adoption rate as function of payback calculation'.

Representation in Stella



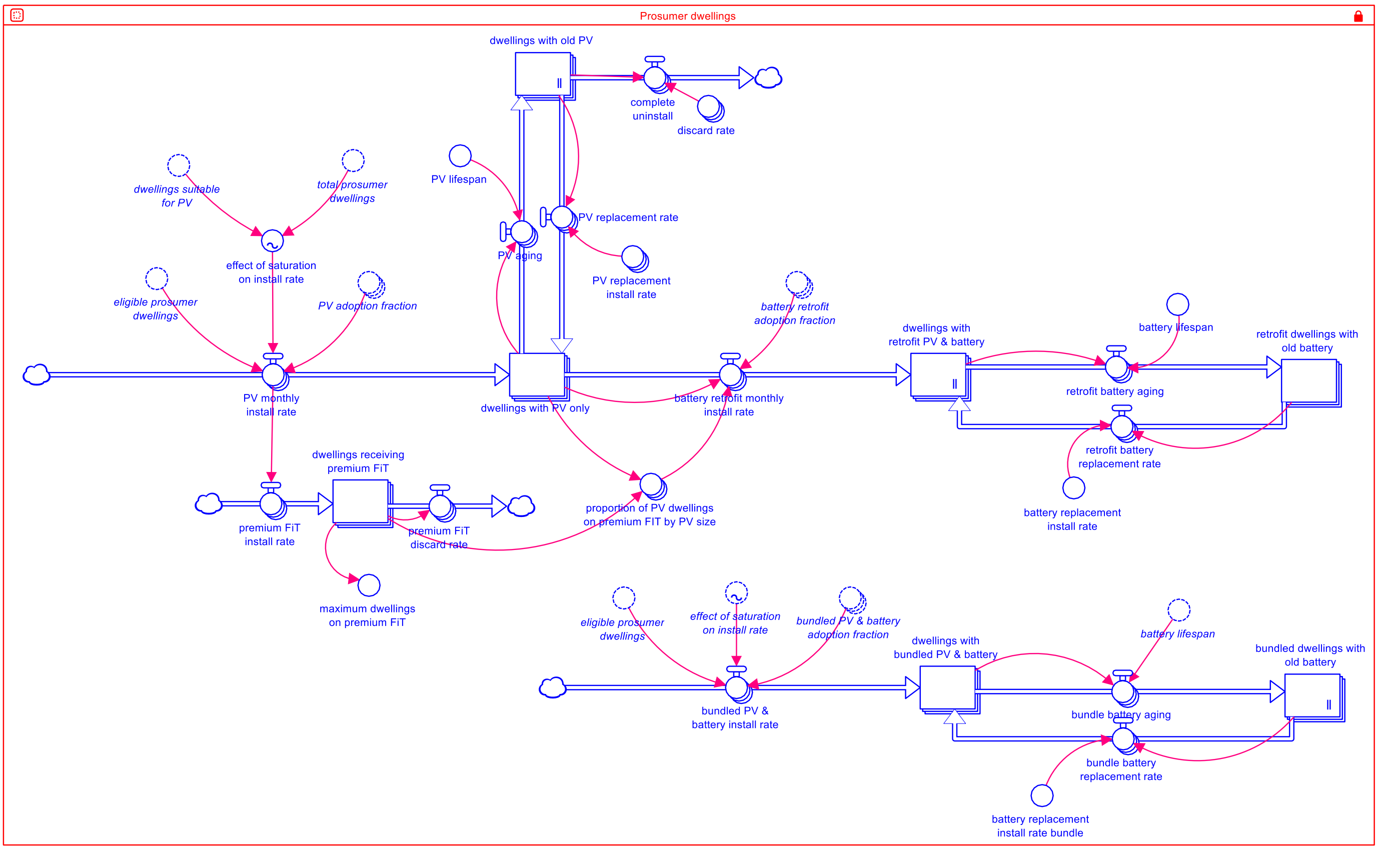
****
Bundle_adoption_rate_as_function_of_payback_calculation:
****
bundle_adoption_rate_as_function_of_payback[PV_size, Loadprofile, Electricityconsumption, Battery_size] = bundle_adoption_rate_fraction*bundle_best_adoption_rate
bundle_adoption_rate_fraction[PV_size, Loadprofile, Electricityconsumption, Battery_size] = SAFEDIV(bundle_best_payback, bundle_battery_payback)
bundle_best_adoption_rate = SAFEDIV(bundle_uptake_as_function_of_payback, bundle_sum_of_adoption_rate_fraction)
bundle_best_payback = MIN(bundle_payback_adjustment)
bundle_denominator[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF (bundle_battery_payback>0) AND (bundle_battery_payback) <15 THEN 1 ELSE 0
bundle_mean_payback = IF SAFEDIV (bundle_sum_numerator, bundle_sum_denominator) =0 THEN 15 ELSE SAFEDIV (bundle_sum_numerator, bundle_sum_denominator)
bundle_numerator[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF bundle_battery_payback<15 THEN bundle_battery_payback ELSE 0
bundle_payback_adjustment[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF bundle_battery_payback =0 THEN 1000 ELSE bundle_battery_payback
bundle_sum_denominator = SUM(bundle_denominator)
bundle_sum_numerator = SUM(bundle_numerator)
bundle_sum_of_adoption_rate_fraction = SUM(bundle_adoption_rate_fraction)
bundle_uptake_as_function_of_payback = GRAPH(bundle_mean_payback)
(0.00, 0.0950), (1.00, 0.0924), (2.00, 0.0899), (3.00, 0.0869), (4.00, 0.0830), (5.00, 0.0750), (6.00, 0.0650), (7.00, 0.0550), (8.00, 0.0400), (9.00, 0.0250), (10.00, 0.0100), (11.00, 0.0090), (12.00, 0.0069), (13.00, 0.0049), (14.00, 0.0029), (15.00, 0.0000)

5. <u>Prosumer dwellings sector</u>

Key assumptions

- ‘effect of saturation on install rate’ is a graphical function. The saturation threshold value for the model, i.e. when the effects of saturation would appear, is 50% with the rate of decline increasing exponentially to zero when 100% saturation is achieved (AEMO 2014a)
- ‘dwellings with PV only’ (1116 total installs in 2006) split among PV size categories based on assumed likely uptake with very high cost key factor limiting large size (Clean Energy Regulator 2017)
- The model assumes zero grid-connected batteries in Qld in 2006 so both battery dwellings stocks are assumed to have initial values of zero.
- The stock ‘dwellings receiving premium FiT’ is used to calculate the numbers of households subscribed to the Queensland Solar Bonus Scheme and is included because the model assumes that as there is no financial incentive to purchase batteries while receiving the premium FiT, these dwellings are excluded from retrofitting batteries.
- This section of the model assumes that all residential PV systems installed in Qld were subscribed from when the scheme started in 2008 until it was closed to new entrants in 2012.
- The ‘premium FiT discard rate’ (0.06 per year) calculates the number of dwellings each year that lose their eligibility (e.g. for moving house) (Rod 2017). When taken with the variable ‘proportion of PV dwellings on premium FIT by PV size’ this is used to determine ex-premium FiT subscribers whom are now eligible to be considered for a retrofit battery installation.
- PV life-span and battery life-span is 25 and 10 years respectively based on accepted industry estimates.

Representation in Stella



****

Prosumer_dwellings:

****

battery_lifespan = 10*12
battery_replacement_install_rate = 1
battery_replacement_install_rate_bundle = 1
bundled_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t) = bundled_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t - dt) + (bundle_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] - bundle_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size]) * dt
INIT bundled_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = 0
INFLOWS:
bundle_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] = dwellings_with_bundled_PV_&_battery/battery_lifespan
OUTFLOWS:
bundle_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] = (bundled_dwellings_with_old_battery*battery_replacement_install_rate_bundle)
discard_rate[Less_than_2_kW] = 0.9
discard_rate[Between_2_and_4_kW] = 0.1
discard_rate[Between_4_and_6kW] = 0.1
discard_rate[Between_8_and_10kW] = 0.1
dwellings_receiving_premium_FiT[PV_size, Loadprofile, Electricityconsumption](t) = dwellings_receiving_premium_FiT[PV_size, Loadprofile, Electricityconsumption](t - dt) + (premium_FiT_install_rate[PV_size, Loadprofile, Electricityconsumption] - premium_FiT_discard_rate[PV_size, Loadprofile, Electricityconsumption]) * dt

INIT dwellings_receiving_premium_FiT[PV_size, Loadprofile, Electricityconsumption] = 0
INFLOWS:
premium_FiT_install_rate[PV_size, Loadprofile, Electricityconsumption] = IF TIME >=30 AND TIME <=84 THEN PV_monthly_install_rate ELSE 0
OUTFLOWS:
premium_FiT_discard_rate[PV_size, Loadprofile, Electricityconsumption] = IF TIME <84 THEN 0 ELSE IF TIME >= 84 AND TIME <= 264 THEN 0.06/12*dwellings_receiving_premium_FiT ELSE IF TIME > 264 THEN dwellings_receiving_premium_FiT ELSE 0
dwellings_with_bundled_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t) = dwellings_with_bundled_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t - dt) + (bundle_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] + bundled_PV_&_battery_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] - bundle_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size]) * dt
INIT dwellings_with_bundled_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = ROUND (0)
INFLOWS:
bundle_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] = (bundled_dwellings_with_old_battery*battery_replacement_install_rate_bundle)
bundled_PV_&_battery_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] = bundled_PV_&_battery_adoption_fraction *effect_of_saturation_on_install_rate*eligible_prosumer_dwellings
OUTFLOWS:
bundle_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] = dwellings_with_bundled_PV_&_battery/battery_lifespan
dwellings_with_old_PV[PV_size, Loadprofile, Electricityconsumption](t) = dwellings_with_old_PV[PV_size, Loadprofile, Electricityconsumption](t - dt) + (PV_aging[PV_size, Loadprofile, Electricityconsumption] - PV_replacement_rate[PV_size, Loadprofile, Electricityconsumption] - complete_uninstall[PV_size, Loadprofile, Electricityconsumption]) * dt
INIT dwellings_with_old_PV[PV_size, Loadprofile, Electricityconsumption] = 0
INFLOWS:
PV_aging[PV_size, Loadprofile, Electricityconsumption] = IF TIME >132 THEN dwellings_with_PV_only/PV_lifespan ELSE 0
OUTFLOWS:
PV_replacement_rate[PV_size, Loadprofile, Electricityconsumption] = PV_replacement_install_rate[PV_size]*dwellings_with_old_PV
complete_uninstall[PV_size, Loadprofile, Electricityconsumption] = dwellings_with_old_PV*discard_rate[PV_size]
dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, low_consumption](t) = dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Less_than_2_kW, Low_daytime_use, low_consumption] + PV_replacement_rate[Less_than_2_kW, Low_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, low_consumption, thirty_kWh] - PV_aging[Less_than_2_kW, Low_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Less_than_2_kW, Low_daytime_use, medium_consumption] + PV_replacement_rate[Less_than_2_kW, Low_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Less_than_2_kW, Low_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, high_consumption](t) = dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Less_than_2_kW, Low_daytime_use, high_consumption] + PV_replacement_rate[Less_than_2_kW, Low_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Less_than_2_kW, Low_daytime_use, high_consumption, thirty_kWh] - PV_aging[Less_than_2_kW, Low_daytime_use, high_consumption]) * dt

INIT dwellings_with_PV_only[Less_than_2_kW, Low_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, low_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, low_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, low_consumption] +
PV_replacement_rate[Less_than_2_kW, Medium_daytime_use, low_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, low_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, low_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, low_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, Medium_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, medium_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, medium_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, medium_consumption] +
PV_replacement_rate[Less_than_2_kW, Medium_daytime_use, medium_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, medium_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, medium_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, medium_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, Medium_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, medium_consumption] = 900
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, high_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, high_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, high_consumption] +
PV_replacement_rate[Less_than_2_kW, Medium_daytime_use, high_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, high_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, high_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, Medium_daytime_use, high_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, Medium_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, Medium_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, low_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, low_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, High_daytime_use, low_consumption] +
PV_replacement_rate[Less_than_2_kW, High_daytime_use, low_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, low_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, low_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, low_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, High_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, medium_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, medium_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, High_daytime_use, medium_consumption] +
PV_replacement_rate[Less_than_2_kW, High_daytime_use, medium_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, medium_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, medium_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, medium_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, High_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, high_consumption](t) =
dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, high_consumption](t - dt) +
(PV_monthly_install_rate[Less_than_2_kW, High_daytime_use, high_consumption] +
PV_replacement_rate[Less_than_2_kW, High_daytime_use, high_consumption] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, high_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, high_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Less_than_2_kW, High_daytime_use, high_consumption, thirty_kWh] -
PV_aging[Less_than_2_kW, High_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Less_than_2_kW, High_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, low_consumption](t) =
dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, low_consumption](t - dt) +
(PV_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, low_consumption] +
PV_replacement_rate[Between_2_and_4_kW, Low_daytime_use, low_consumption] -
battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, low_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, low_consumption, fifteen_kWh] -

battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Low_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, medium_consumption] + PV_replacement_rate[Between_2_and_4_kW, Low_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Low_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, high_consumption] + PV_replacement_rate[Between_2_and_4_kW, Low_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Low_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Low_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Low_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, low_consumption] + PV_replacement_rate[Between_2_and_4_kW, Medium_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Medium_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, medium_consumption] + PV_replacement_rate[Between_2_and_4_kW, Medium_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Medium_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, medium_consumption] = 200
dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, high_consumption] + PV_replacement_rate[Between_2_and_4_kW, Medium_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, Medium_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, Medium_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, Medium_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, low_consumption] + PV_replacement_rate[Between_2_and_4_kW, High_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, High_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, medium_consumption] +

PV_replacement_rate[Between_2_and_4_kW, High_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, High_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, high_consumption] + PV_replacement_rate[Between_2_and_4_kW, High_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_2_and_4_kW, High_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_2_and_4_kW, High_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_2_and_4_kW, High_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, low_consumption] + PV_replacement_rate[Between_4_and_6kW, Low_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_4_and_6kW, Low_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, medium_consumption] + PV_replacement_rate[Between_4_and_6kW, Low_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_4_and_6kW, Low_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, high_consumption] + PV_replacement_rate[Between_4_and_6kW, Low_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Low_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_4_and_6kW, Low_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Low_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, low_consumption] + PV_replacement_rate[Between_4_and_6kW, Medium_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_4_and_6kW, Medium_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, medium_consumption] + PV_replacement_rate[Between_4_and_6kW, Medium_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_4_and_6kW, Medium_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, medium_consumption] = 16

dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, high_consumption](t) =
dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, high_consumption](t - dt) +
(PV_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, high_consumption] +
PV_replacement_rate[Between_4_and_6kW, Medium_daytime_use, high_consumption] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, high_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, high_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, Medium_daytime_use, high_consumption, thirty_kWh] -
PV_aging[Between_4_and_6kW, Medium_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, Medium_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, low_consumption](t) =
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, low_consumption](t - dt) +
(PV_monthly_install_rate[Between_4_and_6kW, High_daytime_use, low_consumption] +
PV_replacement_rate[Between_4_and_6kW, High_daytime_use, low_consumption] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, low_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, low_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, low_consumption, thirty_kWh] -
PV_aging[Between_4_and_6kW, High_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, medium_consumption](t) =
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, medium_consumption](t - dt) +
(PV_monthly_install_rate[Between_4_and_6kW, High_daytime_use, medium_consumption] +
PV_replacement_rate[Between_4_and_6kW, High_daytime_use, medium_consumption] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, medium_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, medium_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, medium_consumption, thirty_kWh] -
PV_aging[Between_4_and_6kW, High_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, high_consumption](t) =
dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, high_consumption](t - dt) +
(PV_monthly_install_rate[Between_4_and_6kW, High_daytime_use, high_consumption] +
PV_replacement_rate[Between_4_and_6kW, High_daytime_use, high_consumption] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, high_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, high_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Between_4_and_6kW, High_daytime_use, high_consumption, thirty_kWh] -
PV_aging[Between_4_and_6kW, High_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_4_and_6kW, High_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, low_consumption](t) =
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, low_consumption](t - dt) +
(PV_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, low_consumption] +
PV_replacement_rate[Between_8_and_10kW, Low_daytime_use, low_consumption] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, low_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, low_consumption, fifteen_kWh] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, low_consumption, thirty_kWh] -
PV_aging[Between_8_and_10kW, Low_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, medium_consumption](t) =
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, medium_consumption](t - dt) +
(PV_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, medium_consumption] +
PV_replacement_rate[Between_8_and_10kW, Low_daytime_use, medium_consumption] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, medium_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, medium_consumption, fifteen_kWh]
- battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, medium_consumption, thirty_kWh]
- PV_aging[Between_8_and_10kW, Low_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, high_consumption](t) =
dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, high_consumption](t - dt) +
(PV_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, high_consumption] +
PV_replacement_rate[Between_8_and_10kW, Low_daytime_use, high_consumption] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, high_consumption, five_kWh] -
battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, high_consumption, fifteen_kWh] -

battery_retrofit_monthly_install_rate[Between_8_and_10kW, Low_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, Low_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Low_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, low_consumption] + PV_replacement_rate[Between_8_and_10kW, Medium_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, Medium_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, medium_consumption] + PV_replacement_rate[Between_8_and_10kW, Medium_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, Medium_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, high_consumption] + PV_replacement_rate[Between_8_and_10kW, Medium_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, Medium_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, Medium_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, Medium_daytime_use, high_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, low_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, low_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, High_daytime_use, low_consumption] + PV_replacement_rate[Between_8_and_10kW, High_daytime_use, low_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, low_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, low_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, low_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, High_daytime_use, low_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, low_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, medium_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, medium_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, High_daytime_use, medium_consumption] + PV_replacement_rate[Between_8_and_10kW, High_daytime_use, medium_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, medium_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, medium_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, medium_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, High_daytime_use, medium_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, medium_consumption] = 0
dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, high_consumption](t) = dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, high_consumption](t - dt) + (PV_monthly_install_rate[Between_8_and_10kW, High_daytime_use, high_consumption] + PV_replacement_rate[Between_8_and_10kW, High_daytime_use, high_consumption] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, high_consumption, five_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, high_consumption, fifteen_kWh] - battery_retrofit_monthly_install_rate[Between_8_and_10kW, High_daytime_use, high_consumption, thirty_kWh] - PV_aging[Between_8_and_10kW, High_daytime_use, high_consumption]) * dt
INIT dwellings_with_PV_only[Between_8_and_10kW, High_daytime_use, high_consumption] = 0
INFLOWS:
PV_monthly_install_rate[PV_size, Loadprofile, Electricityconsumption] = eligible_prosumer_dwellings*PV_adoption_fraction*effect_of_saturation_on_install_rate

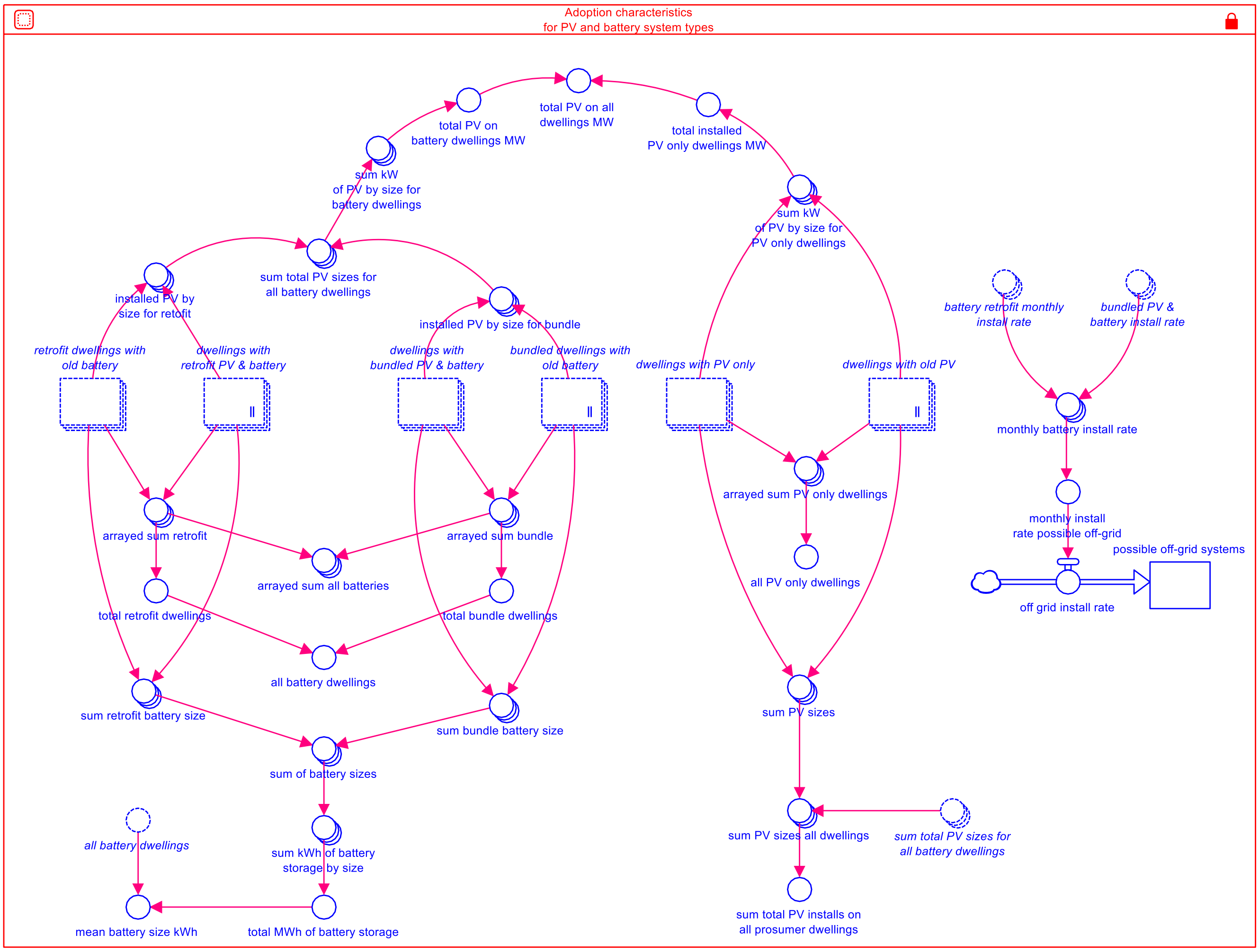
PV_replacement_rate[PV_size, Loadprofile, Electricityconsumption] =
PV_replacement_install_rate[PV_size]*dwellings_with_old_PV
OUTFLOWS:
battery_retrofit_monthly_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
(battery_retrofit_adoption_fraction *SUM(dwellings_with_PV_only)) * (1-
proportion_of_PV_dwellings_on_premium_FIT_by_PV_size[PV_size, Loadprofile, Electricityconsumption])
PV_aging[PV_size, Loadprofile, Electricityconsumption] = IF TIME >132 THEN
dwellings_with_PV_only/PV_lifespan ELSE 0
dwellings_with_retrofit_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t) =
dwellings_with_retrofit_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t - dt) +
(retrofit_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] +
battery_retrofit_monthly_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] -
retrofit_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size]) * dt
INIT dwellings_with_retrofit_PV_&_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = 0
INFLOWS:
retrofit_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
(retrofit_dwellings_with_old_battery*battery_replacement_install_rate)
battery_retrofit_monthly_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
(battery_retrofit_adoption_fraction *SUM(dwellings_with_PV_only)) * (1-
proportion_of_PV_dwellings_on_premium_FIT_by_PV_size[PV_size, Loadprofile, Electricityconsumption])
OUTFLOWS:
retrofit_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
dwellings_with_retrofit_PV_&_battery/battery_lifespan
effect_of_saturation_on_install_rate = GRAPH(total_prosumer_dwellings/dwellings_suitable_for_PV)
(0.000, 1.000), (0.100, 1.000), (0.200, 1.000), (0.300, 1.000), (0.400, 1.000), (0.500, 1.000), (0.600, 0.950), (0.700, 0.900), (0.800, 0.850), (0.900, 0.750), (1.000, 0.000)
maximum_dwellings_on_premium_FiT = ROUND (IF TIME >=30 AND TIME <=83 THEN
SUM(dwellings_receiving_premium_FiT) ELSE 0)
proportion_of_PV_dwellings_on_premium_FIT_by_PV_size[PV_size, Loadprofile, Electricityconsumption] = IF
dwellings_with_PV_only <=0 THEN 0 ELSE dwellings_receiving_premium_FiT/dwellings_with_PV_only
PV_lifespan = 25*12
PV_replacement_install_rate[Less_than_2_kW] = 0
PV_replacement_install_rate[Between_2_and_4_kW] = 0.1/12
PV_replacement_install_rate[Between_4_and_6kW] = 0.1/12
PV_replacement_install_rate[Between_8_and_10kW] = 0.1/12
retrofit_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t) =
retrofit_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size](t - dt) +
(retrofit_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] -
retrofit_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size]) * dt
INIT retrofit_dwellings_with_old_battery[PV_size, Loadprofile, Electricityconsumption, Battery_size] = 0
INFLOWS:
retrofit_battery_aging[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
dwellings_with_retrofit_PV_&_battery/battery_lifespan
OUTFLOWS:
retrofit_battery_replacement_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
(retrofit_dwellings_with_old_battery*battery_replacement_install_rate)

6. Adoption characteristics for PV and battery system types

Key assumptions

- This sector is primarily used to calculate model outputs regarding total numbers of PV and battery dwellings, numbers of system by size, capacity etc.
- Assumptions regarding ‘possible off-grid systems’ are included in this sector. They are based on specific system configurations based on household consumption, minimum PV size (5kW) and minimum battery size (15kWh). To be eligible, these dwellings must have zero grid demand along with unused PV capacity.

Representation in Stella



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Adoption_characteristics_for_PV_and_battery_system_types:

****

all_battery_dwellings = ROUND (total_retrofit_dwellings+total_bundle_dwellings)
all_PV_only_dwellings = SUM(arrayed_sum_PV_only_dwellings)
arrayed_sum_all_batteries[PV_size, Loadprofile, Electricityconsumption, Battery_size] = arrayed_sum_retrofit+arrayed_sum_bundle
arrayed_sum_bundle[PV_size, Loadprofile, Electricityconsumption, Battery_size] = bundled_dwellings_with_old_battery+dwellings_with_bundled_PV_&_battery

arrayed_sum_PV_only_dwellings[PV_size, Loadprofile, Electricityconsumption] =
dwellings_with_old_PV+dwellings_with_PV_only
arrayed_sum_retrofit[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
dwellings_with_retrofit_PV_&_battery+retrofit_dwellings_with_old_battery
installed_PV_by_size_for_bundle[PV_size] = SUM(dwellings_with_bundled_PV_&_battery[PV_size, *, *,
*])+SUM(bundled_dwellings_with_old_battery[PV_size, *, *, *])
installed_PV_by_size_for_retofit[PV_size] = SUM(retrofit_dwellings_with_old_battery[PV_size, *, *, *]) +
SUM(dwellings_with_retrofit_PV_&_battery[PV_size, *, *, *])
mean_battery_size_kWh = SAFEDIV(total_MWh_of_battery_storage*1000, all_battery_dwellings)
monthly_battery_install_rate[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
bundled_PV_&_battery_install_rate+battery_retrofit_monthly_install_rate
"monthly_install_rate_possible_off-grid" = SUM(monthly_battery_install_rate[Between_8_and_10kW, *, *, *])-
SUM(monthly_battery_install_rate[Between_8_and_10kW, *, *, five_kWh]) +
SUM(monthly_battery_install_rate[Between_4_and_6kW, *, low_consumption, fifteen_kWh]) +
SUM(monthly_battery_install_rate[Between_4_and_6kW, *, medium_consumption, fifteen_kWh]) +
SUM(monthly_battery_install_rate[Between_4_and_6kW, *, low_consumption, thirty_kWh])
"possible_off-grid_systems"(t) = "possible_off-grid_systems"(t - dt) + (off_grid_install_rate) * dt
INIT "possible_off-grid_systems" = 0
INFLOWS:
off_grid_install_rate <-- bundled_battery_payback_period:
sum_bundle_battery_size[Battery_size] = SUM(dwellings_with_bundled_PV_&_battery[*, *, *, Battery_size]) +
SUM(bundled_dwellings_with_old_battery[*, *, *, Battery_size])
sum_kW_of_PV_by_size_for_battery_dwellings[Less_than_2_kW] =
1.5*sum_total_PV_sizes_for_all_battery_dwellings[Less_than_2_kW]
sum_kW_of_PV_by_size_for_battery_dwellings[Between_2_and_4_kW] =
3*sum_total_PV_sizes_for_all_battery_dwellings[Between_2_and_4_kW]
sum_kW_of_PV_by_size_for_battery_dwellings[Between_4_and_6kW] =
5*sum_total_PV_sizes_for_all_battery_dwellings[Between_4_and_6kW]
sum_kW_of_PV_by_size_for_battery_dwellings[Between_8_and_10kW] =
10*sum_total_PV_sizes_for_all_battery_dwellings[Between_8_and_10kW]
sum_kW_of_PV_by_size_for_PV_only_dwellings[Less_than_2_kW] =
(SUM(dwellings_with_PV_only[Less_than_2_kW, *, *]) + SUM(dwellings_with_old_PV[Less_than_2_kW, *, *]))
*1.5
sum_kW_of_PV_by_size_for_PV_only_dwellings[Between_2_and_4_kW] = (
SUM(dwellings_with_PV_only[Between_2_and_4_kW, *, *]) +
SUM(dwellings_with_old_PV[Between_2_and_4_kW, *, *])) *3
sum_kW_of_PV_by_size_for_PV_only_dwellings[Between_4_and_6kW] =
(SUM(dwellings_with_PV_only[Between_4_and_6kW, *, *]) + SUM(dwellings_with_old_PV[Between_4_and_6kW,
*, *])) *5
sum_kW_of_PV_by_size_for_PV_only_dwellings[Between_8_and_10kW] =
(SUM(dwellings_with_PV_only[Between_8_and_10kW, *, *]) +
SUM(dwellings_with_old_PV[Between_8_and_10kW, *, *])) *10
sum_kWh_of_battery_storage_by_size[five_kWh] = 4*sum_of_battery_sizes[five_kWh]
sum_kWh_of_battery_storage_by_size[fifteen_kWh] = 12*sum_of_battery_sizes[fifteen_kWh]
sum_kWh_of_battery_storage_by_size[thirty_kWh] = 24*sum_of_battery_sizes[thirty_kWh]
sum_of_battery_sizes[Battery_size] = sum_retrofit_battery_size+sum_bundle_battery_size
sum_PV_sizes[PV_size] = SUM(dwellings_with_PV_only[PV_size, *, *])+SUM(dwellings_with_old_PV[PV_size, *,
*])
sum_PV_sizes_all_dwellings[PV_size] = sum_PV_sizes+sum_total_PV_sizes_for_all_battery_dwellings
sum_retrofit_battery_size[Battery_size] = SUM(retrofit_dwellings_with_old_battery[*, *, *,
Battery_size])+SUM(dwellings_with_retrofit_PV_&_battery[*, *, *, Battery_size])
sum_total_PV_installs_on_all_prosumer_dwellings = SUM(sum_PV_sizes_all_dwellings)
sum_total_PV_sizes_for_all_battery_dwellings[PV_size] =
installed_PV_by_size_for_retofit+installed_PV_by_size_for_bundle
total_bundle_dwellings = SUM(arrayed_sum_bundle)
total_installed_PV_only_dwellings_MW = SUM(sum_kW_of_PV_by_size_for_PV_only_dwellings)/1000
total_MWh_of_battery_storage = SUM(sum_kWh_of_battery_storage_by_size)/1000
total_PV_on_all_dwellings_MW = ROUND
(total_installed_PV_only_dwellings_MW+total_PV_on_battery_dwellings_MW)
total_PV_on_battery_dwellings_MW = SUM(sum_kW_of_PV_by_size_for_battery_dwellings)/1000
total_retrofit_dwellings = SUM(arrayed_sum_retrofit)

7. Retail price sectors

Two broad assumptions must be noted.

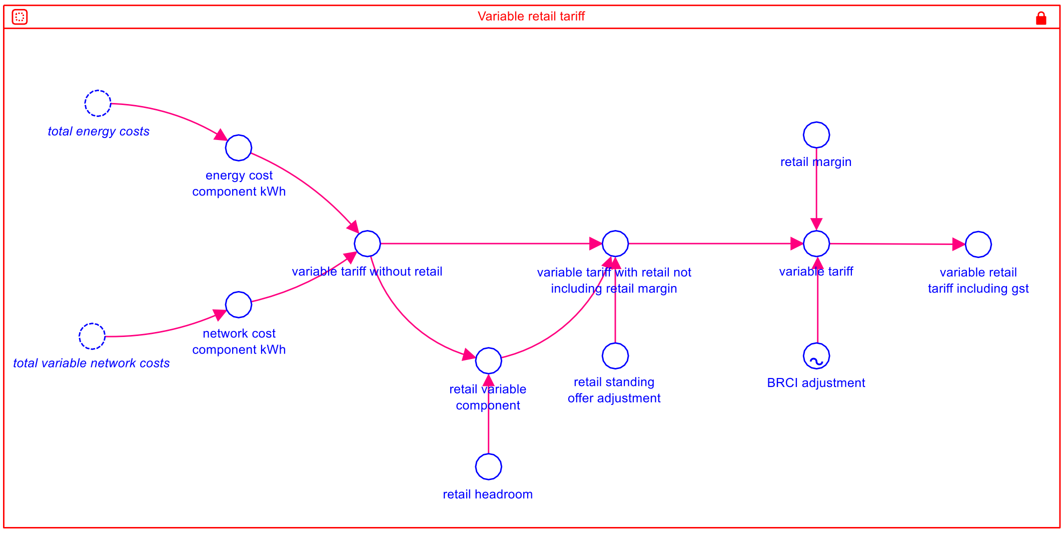
- Firstly, there are numerous components comprising the variable and fixed retail electricity price. The inclusion of various elements and their values were subject to change on a yearly basis depending on the final decision made by the QCA. The values used in this model have therefore been made to best reflect the findings in each QCA determination from 2005-06 until 2016-17 (all of which can be sourced from http://www.qca.org.au/electricity).
- Following the deregulation of the SEQ market, many consumers in SEQ are now on 'market contracts'. To attract customers, retailers can provide discounts, which on average means that market contracts can be approximately 5% less than notified prices (QCA 2016c). As these discounts vary considerably and as not all consumers take advantage of them (for example they are not available to many consumers outside SEQ), they are excluded.

7.1. Variable retail tariff

Key assumptions

- Comprises both 'total energy costs' and 'total variable network costs' which are described separately below.
- Headroom of 5% is applied to all variable costs (i.e. energy and network costs). The retail margin of 5.7% is then applied to the total. From 2016, a retail standing offer adjustment was included in variable retail prices.
- 'BRCI adjustment' is a graphical function that reflects the difference between the building block approach used by the QCA and the final 'variable retail tariff'. This difference frequently occurred as a result of government intervention in electricity price setting to achieve different policy outcomes. From 2015-16, and following a transitional period aimed at achieving cost-reflectivity, it is assumed that for the rest of the simulation period the retail tariff will be based only on the building block approach.

Representation in Stella



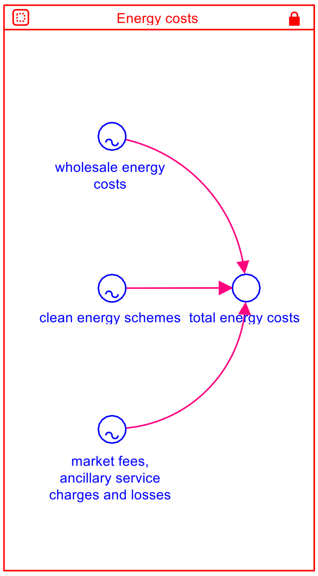
****
Variable_retail_tariff:
****
BRCI_adjustment = GRAPH(TIME)
(0.0, 1.0519), (6.0, 1.0556), (12.0, 1.0593), (18.0, 1.1439), (24.0, 1.1483), (30.0, 1.1528), (36.0, 1.1571), (42.0, 1.1887), (48.0, 1.1926), (54.0, 1.2351), (60.0, 1.2359), (66.0, 1.2129), (72.0, 1.1992), (78.0, 1.2927), (84.0, 1.2836), (90.0, 1.134), (96.0, 1.1277), (102.0, 0.9544), (108.0, 0.9511), (114.0, 0.986), (120.0, 0.9824), (126.0, 0.999), (132.0, 0.9954), (138.0, 1.000), (144.0, 1.000), (150.0, 1.000), (156.0, 1.000), (162.0, 1.000), (168.0, 1.000), (174.0, 1.000), (180.0, 1.000), (186.0, 1.000), (192.0, 1.000), (198.0, 1.000), (204.0, 1.000), (210.0, 1.000), (216.0, 1.000), (222.0, 1.000), (228.0, 1.000), (234.0, 1.000), (240.0, 1.000), (246.0, 1.000), (252.0, 1.000), (258.0, 1.000), (264.0, 1.000), (270.0, 1.000), (276.0, 1.000), (282.0, 1.000), (288.0, 1.000), (294.0, 1.000), (300.0, 1.000), (306.0, 1.000), (312.0, 1.000), (318.0, 1.000), (324.0, 1.000), (330.0, 1.000), (336.0, 1.000), (342.0, 1.000), (348.0, 1.000), (354.0, 1.000), (360.0, 1.000), (366.0, 1.000), (372.0, 1.000)
energy_cost_component_kWh = total_energy_costs/1000
network_cost_component_kWh = total_variable_network_costs/1000
retail_headroom = IF TIME <90 THEN 0 ELSE IF TIME >= 90 THEN .05 ELSE 0
retail_margin = 1.057
retail_standing_offer_adjustment = IF TIME < 126 THEN 0 ELSE IF TIME >=126 THEN 0.00172 ELSE 0
retail_variable_component = IF TIME < 42 THEN 0.0056 ELSE IF TIME >=42 AND TIME < 54 THEN 0.0059 ELSE IF TIME >=54 AND TIME < 66 THEN 0.0067 ELSE IF TIME >=66 AND TIME < 90 THEN 0.0073 ELSE IF TIME >= 90 AND TIME < 138 THEN variable_tariff_without_retail*retail_headroom ELSE IF TIME >= 138 THEN variable_tariff_without_retail*retail_headroom +.0117 ELSE 0
variable_retail_tariff_including_gst = variable_tariff*1.1
variable_tariff = variable_tariff_with_retail_not_including_retail_margin*retail_margin*BRCI_adjustment
variable_tariff_with_retail_not_including_retail_margin =
variable_tariff_without_retail+(retail_variable_component)+retail_standing_offer_adjustment
variable_tariff_without_retail = energy_cost_component_kWh+network_cost_component_kWh

7.2. Energy costs

Key assumptions

- Refers to the costs of generating electricity in the NEM.
- Historical data for 'wholesale energy costs' is sourced from actual data used in QCA determinations. Future projections are based on government commissioned modelling and assume real wholesale price increases of 2.1% per annum (QPC 2016a).
- 'clean energy schemes' include the costs imposed on the generation sector from the Queensland Gas Scheme, the Carbon Pricing Mechanism, the national Renewable Energy Target. Data is sourced from annual QCA determinations. For future projections, costs associated with the RET (the only remaining clean energy scheme) are assumed to remain at 2016 prices in real terms until its closure in 2030, at which point the cost returns to zero. The base-case model assumes no carbon pricing mechanism
- 'Market fees, ancillary services, charges and losses' are levied on retailers to cover the costs of operating the NEM and paying for services used to manage power system security, reliability and safety (QCA 2016c). Historical data included in the model is sourced from actual data used in QCA determinations with future projected costs remaining at 2016 prices in real terms until the end of the simulation period.

Representation in Stella



****
Energy_costs:
****
clean_energy_schemes = GRAPH(TIME)
(0.0, 2.99), (6.0, 2.99), (12.0, 2.99), (18.0, 3.37), (24.0, 3.37), (30.0, 3.64), (36.0, 3.64), (42.0, 4.99), (48.0, 4.99), (54.0, 4.34), (60.0, 4.34), (66.0, 8.37), (72.0, 8.37), (78.0, 8.37), (84.0, 8.37), (90.0, 10.14), (96.0, 10.14), (102.0, 8.13),

(108.0, 8.13), (114.0, 8.72), (120.0, 8.72), (126.0, 8.00), (132.0, 8.00), (138.0, 8.00), (144.0, 8.00), (150.0, 8.00), (156.0, 8.00), (162.0, 8.00), (168.0, 8.00), (174.0, 8.00), (180.0, 8.00), (186.0, 8.00), (192.0, 8.00), (198.0, 8.00), (204.0, 8.00), (210.0, 8.00), (216.0, 8.00), (222.0, 8.00), (228.0, 8.00), (234.0, 8.00), (240.0, 8.00), (246.0, 8.00), (252.0, 8.00), (258.0, 8.00), (264.0, 8.00), (270.0, 8.00), (276.0, 8.00), (282.0, 8.00), (288.0, 8.00), (294.0, 0.00), (300.0, 0.00), (306.0, 0.00), (312.0, 0.00), (318.0, 0.00), (324.0, 0.00), (330.0, 0.00), (336.0, 0.00), (342.0, 0.00), (348.0, 0.00), (354.0, 0.00), (360.0, 0.00), (366.0, 0.00), (372.0, 0.00)
"market_fees,_ancillary_service_charges_and_losses" = GRAPH(TIME)
(0.0, 0.61), (6.0, 0.61), (12.0, 0.61), (18.0, 0.63), (24.0, 0.63), (30.0, 0.71), (36.0, 0.71), (42.0, 0.73), (48.0, 0.73), (54.0, 0.73), (60.0, 0.73), (66.0, 0.84), (72.0, 0.84), (78.0, 0.84), (84.0, 0.84), (90.0, 7.14), (96.0, 7.14), (102.0, 8.31), (108.0, 8.31), (114.0, 5.58), (120.0, 5.58), (126.0, 7.56), (132.0, 7.56), (138.0, 7.00), (144.0, 7.00), (150.0, 7.00), (156.0, 7.00), (162.0, 7.00), (168.0, 7.00), (174.0, 7.00), (180.0, 7.00), (186.0, 7.00), (192.0, 7.00), (198.0, 7.00), (204.0, 7.00), (210.0, 7.00), (216.0, 7.00), (222.0, 7.00), (228.0, 7.00), (234.0, 7.00), (240.0, 7.00), (246.0, 7.00), (252.0, 7.00), (258.0, 7.00), (264.0, 7.00), (270.0, 7.00), (276.0, 7.00), (282.0, 7.00), (288.0, 7.00), (294.0, 7.00), (300.0, 7.00), (306.0, 7.00), (312.0, 7.00), (318.0, 7.00), (324.0, 7.00), (330.0, 7.00), (336.0, 7.00), (342.0, 7.00), (348.0, 7.00), (354.0, 7.00), (360.0, 7.00), (366.0, 7.00), (372.0, 7.00)
total_energy_costs =
clean_energy_schemes+"market_fees,_ancillary_service_charges_and_losses"+wholesale_energy_costs
wholesale_energy_costs = GRAPH(TIME)
(0.0, 52.3), (6.0, 52.3), (12.0, 52.3), (18.0, 49.4), (24.0, 49.4), (30.0, 50.31), (36.0, 50.31), (42.0, 55.49), (48.0, 55.49), (54.0, 58.55), (60.0, 58.55), (66.0, 55.47), (72.0, 55.47), (78.0, 55.47), (84.0, 55.47), (90.0, 69.43), (96.0, 69.43), (102.0, 84.38), (108.0, 84.38), (114.0, 63.73), (120.0, 63.73), (126.0, 75.32), (132.0, 75.32), (138.0, 75.7), (144.0, 77.1), (150.0, 77.5), (156.0, 78.3), (162.0, 79.1), (168.0, 80.5), (174.0, 81.7), (180.0, 82.3), (186.0, 82.9), (192.0, 83.1), (198.0, 83.7), (204.0, 84.3), (210.0, 84.9), (216.0, 85.7), (222.0, 86.9), (228.0, 87.8), (234.0, 88.4), (240.0, 89.0), (246.0, 89.8), (252.0, 90.6), (258.0, 91.2), (264.0, 92.0), (270.0, 92.8), (276.0, 93.4), (282.0, 93.8), (288.0, 94.8), (294.0, 96.0), (300.0, 97.2), (306.0, 98.0), (312.0, 99.4), (318.0, 100.6), (324.0, 101.6), (330.0, 102.8), (336.0, 104.0), (342.0, 105.2), (348.0, 106.0), (354.0, 106.6), (360.0, 107.6), (366.0, 109.0), (372.0, 109.0)

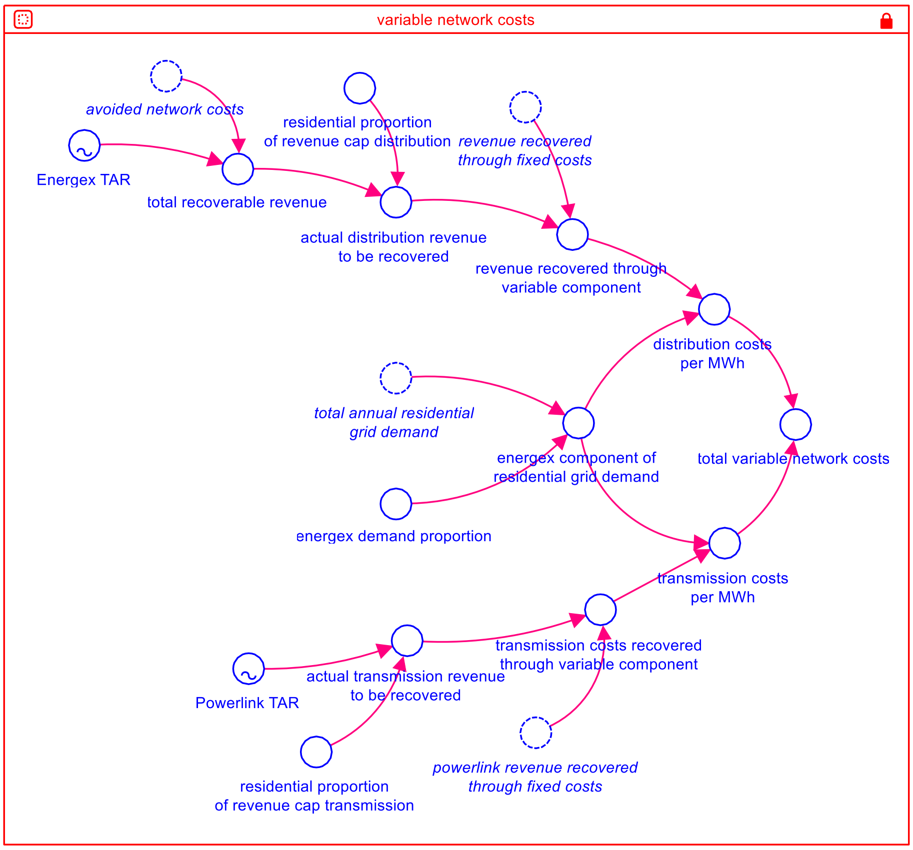
7.3. Variable network costs

Key assumptions

- In Queensland, Energex network tariffs are used as the basis for the distribution network component of notified prices for residential customers. These include their own distribution network costs (Distribution Use of System (DUOS) along with a pass-through of Powerlink's transmission network costs (Transmission Use of System (TUOS) (QCA 2016c).
- To recover their costs as regulated entities, network businesses are allocated an annual revenue cap from the AER referred to as Total Allowed Revenue (TAR).
- The TAR is recovered from the various customer classes through network tariffs which are structured to ensure the network business can recover regulated revenue across their entire customer base.
- The model is structured so that the residential proportion of the distribution and transmission TAR is allocated in the correct proportions to a single residential network tariff. These proportions are calculated using values based on analysis of tariff cost allocations (from Energex network pricing proposals - specifically Standard Asset Classes – non-demand) and raw data sourced from AER network benchmarking data (AER 2015b; Energex 2016b).

- Historical data for the TAR for both Energex and Powerlink is sourced from AER regulatory determinations. For future projections, data is sourced from the current AER regulatory determination which includes projections of the TAR for Energex until 2020 and Powerlink until 2023. From then on, it is assumed that minimal new network investment will be required to service existing customers in the short to medium term as a consequence of the large network infrastructure augmentation program of the past decade (QPC 2016a).
- The model assumes that future network costs will only change as a function of population growth (which is correlated with changes in peak demand) and in response to the endogenous influence of PV and batteries which, depending on how they are integrated with the network, will act to put downward pressure on network costs i.e. ‘avoided network costs’.
- The model is also structured so that the revenue allocated to the residential network tariff can be split into variable and fixed components. The proportions of which are based on data from QCA determinations and calculated in the ‘fixed network costs’ sector below.
- The variable component is calculated by dividing Energex’s proportion of total Queensland residential electricity demand by the amount of revenue not recovered through fixed costs to calculate a network cost per MWh.

Representation in Stella



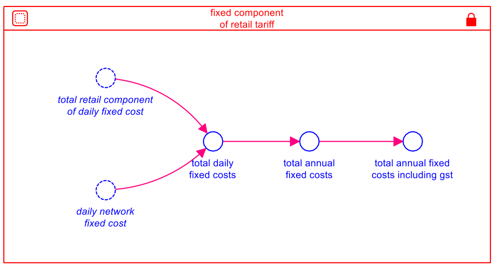
****
variable_network_costs:
****
actual_distribution_revenue_to_be_recovered =
residential_proportion_of_revenue_cap_distribution*total_recoverable_revenue
actual_transmission_revenue_to_be_recovered =
Powerlink_TAR*residential_proportion_of_revenue_cap_transmission
distribution_costs_per_MWh =
revenue_recovered_through_variable_component*1000/energex_component_of_residential_grid_demand
energex_component_of_residential_grid_demand =
total_annual_residential_grid_demand*energex_demand_proportion
energex_demand_proportion = 0.64
Energex_TAR = GRAPH(TIME)
(0.0, 683.8), (6.0, 683.8), (12.0, 683.8), (18.0, 806.5), (24.0, 806.5), (30.0, 875), (36.0, 875), (42.0, 1000.3), (48.0, 1000.3), (54.0, 1135.1), (60.0, 1135.1), (66.0, 1272.7), (72.0, 1272.7), (78.0, 1272.7), (84.0, 1272.7), (90.0, 1700.4), (96.0, 1700.4), (102.0, 1925.4), (108.0, 1925.4), (114.0, 1768.4), (120.0, 1768.4), (126.0, 1701.6), (132.0, 1701.6), (138.0, 1638.8), (144.0, 1638.8), (150.0, 1590.4), (156.0, 1590.4), (162.0, 1577.7), (168.0, 1600), (174.0, 1600), (180.0, 1600), (186.0, 1600), (192.0, 1600), (198.0, 1600), (204.0, 1600), (210.0, 1600), (216.0, 1600), (222.0, 1600), (228.0, 1600), (234.0, 1600), (240.0, 1600), (246.0, 1600), (252.0, 1600), (258.0, 1600), (264.0, 1600), (270.0, 1600), (276.0, 1600), (282.0, 1600), (288.0, 1600), (294.0, 1600), (300.0, 1600), (306.0, 1600), (312.0, 1600), (318.0, 1600), (324.0, 1600), (330.0, 1600), (336.0, 1600), (342.0, 1600), (348.0, 1600), (354.0, 1600), (360.0, 1600), (366.0, 1600), (372.0, 1600)
Powerlink_TAR = GRAPH(TIME)
(0.0, 370.1), (6.0, 370.1), (12.0, 370.1), (18.0, 412.2), (24.0, 412.2), (30.0, 454.3), (36.0, 454.3), (42.0, 525.5), (48.0, 525.5), (54.0, 625.5), (60.0, 625.5), (66.0, 707), (72.0, 707), (78.0, 835), (84.0, 835), (90.0, 882.6), (96.0, 882.6), (102.0, 933), (108.0, 933), (114.0, 986.2), (120.0, 986.2), (126.0, 1042.4), (132.0, 1042.4), (138.0, 710.8), (144.0, 710), (150.0, 730), (156.0, 740), (162.0, 750), (168.0, 750), (174.0, 760), (180.0, 770), (186.0, 770), (192.0, 780), (198.0, 780), (204.0, 800), (210.0, 800), (216.0, 800), (222.0, 800), (228.0, 800), (234.0, 800), (240.0, 800), (246.0, 800), (252.0, 800), (258.0, 800), (264.0, 800), (270.0, 800), (276.0, 800), (282.0, 800), (288.0, 800), (294.0, 800), (300.0, 800), (306.0, 800), (312.0, 800), (318.0, 800), (324.0, 800), (330.0, 800), (336.0, 800), (342.0, 800), (348.0, 800), (354.0, 800), (360.0, 800), (366.0, 800), (372.0, 960)
residential_proportion_of_revenue_cap_distribution = 0.53
residential_proportion_of_revenue_cap_transmission = 0.25
revenue_recovered_through_variable_component = (actual_distribution_revenue_to_be_recovered-revenue_recovered_through_fixed_costs)
total_recoverable_revenue = (Energex_TAR-(avoided_network_costs*0.2))
total_variable_network_costs = distribution_costs_per_MWh+transmission_costs_per_MWh
transmission_costs_per_MWh =
transmission_costs_recovered_through_variable_component*1000/energex_component_of_residential_grid_demand
transmission_costs_recovered_through_variable_component = (actual_transmission_revenue_to_be_recovered-powerlink_revenue_recovered_through_fixed_costs)

7.4. Fixed component of retail tariff

Key assumptions

The fixed component of the retail tariff comprises two elements based on network costs and retail costs. They are described in more detail below.

Representation in Stella



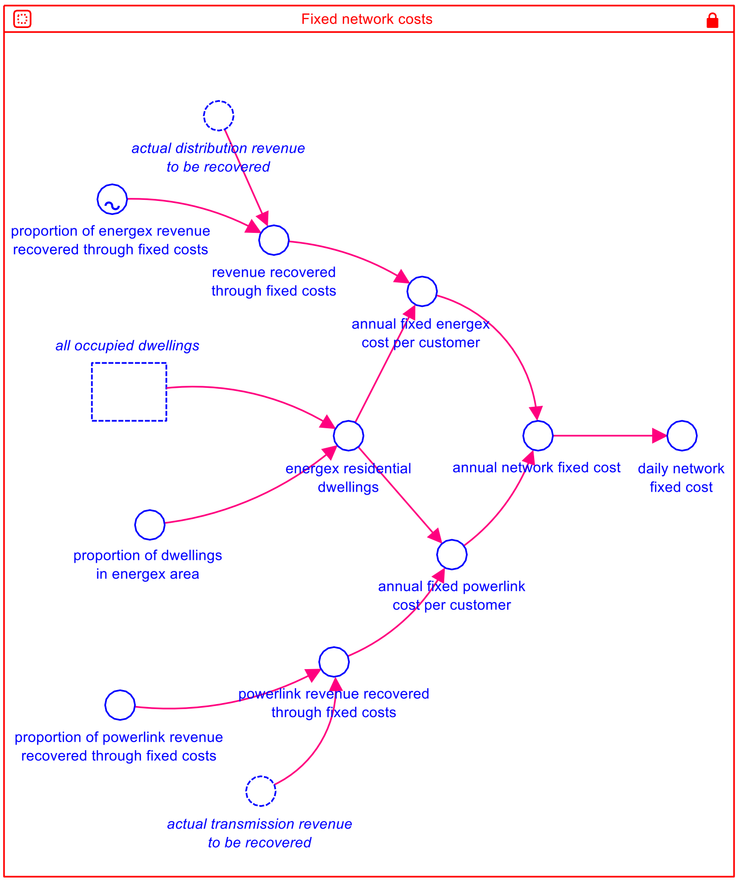
****
fixed_component_of_retail_tariff:
****
total_annual_fixed_costs = total_daily_fixed_costs*365
total_annual_fixed_costs_including_gst = total_annual_fixed_costs*1.1
total_daily_fixed_costs = total_retail_component_of_daily_fixed_cost+daily_network_fixed_cost

7.5. Fixed network costs

Key assumptions

- Based on data from QCA determinations, the ratio of fixed to variable costs is calculated and then applied against the TAR so that per dwelling daily fixed charges can be calculated (i.e. the proportion of the TAR allocated to fixed costs divided by numbers of residential dwellings).
- 'proportion of Energex revenue recovered from fixed costs' is a graphical function representing the shifting proportion of costs recovered through fixed element of the tariff. It is based on analysis of QCA data from review of annual determinations. For Powerlink, the proportion of revenue recovered through fixed costs appears to be more constant. As such 'proportion of Powerlink revenue recovered through fixed costs' is assumed to be fixed at 15%.

Representation in Stella



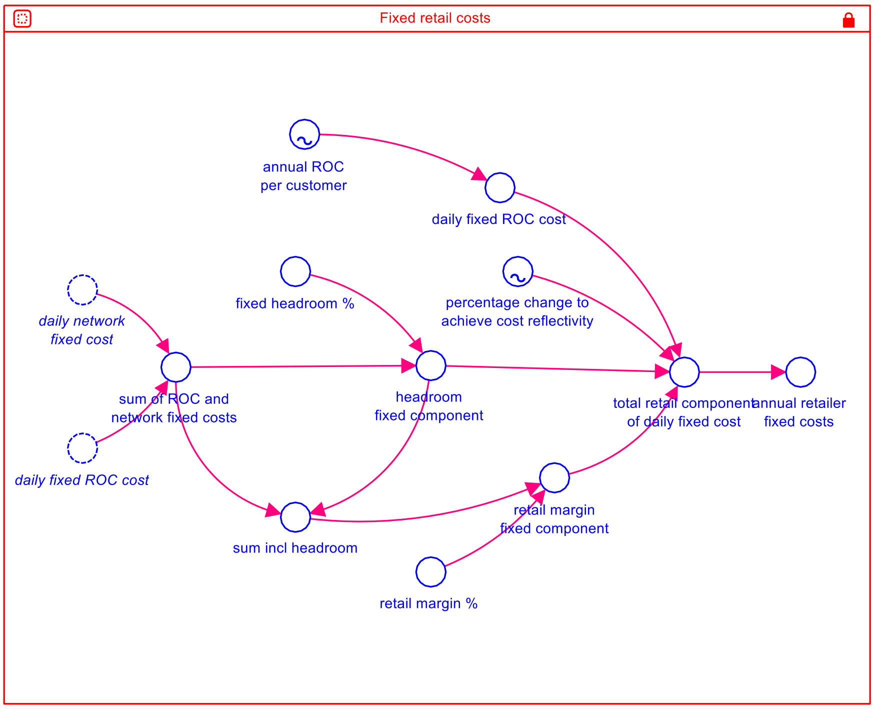
****
Fixed_network_costs:
****
annual_fixed_energex_cost_per_customer = (revenue_recovered_through_fixed_costs/energex_residential_dwellings)*1000000
annual_fixed_powerlink_cost_per_customer = powerlink_revenue_recovered_through_fixed_costs/energex_residential_dwellings*1000000
annual_network_fixed_cost = annual_fixed_energex_cost_per_customer+annual_fixed_powerlink_cost_per_customer
daily_network_fixed_cost = annual_network_fixed_cost/365
energex_residential_dwellings = all_occupied_dwellings*proportion_of_dwellings_in_energex_area
powerlink_revenue_recovered_through_fixed_costs = proportion_of_powerlink_revenue_recovered_through_fixed_costs*actual_transmission_revenue_to_be_recovered
proportion_of_dwellings_in_energex_area = 0.67
proportion_of_energex_revenue_recovered_through_fixed_costs = GRAPH(TIME)
(0.0, 0.130), (6.0, 0.130), (12.0, 0.130), (18.0, 0.130), (24.0, 0.130), (30.0, 0.130), (36.0, 0.130), (42.0, 0.130), (48.0, 0.130), (54.0, 0.130), (60.0, 0.130), (66.0, 0.130), (72.0, 0.130), (78.0, 0.130), (84.0, 0.130), (90.0, 0.130), (96.0, 0.130), (102.0, 0.160), (108.0, 0.160), (114.0, 0.220), (120.0, 0.220), (126.0, 0.180), (132.0, 0.180), (138.0, 0.180), (144.0, 0.180), (150.0, 0.180), (156.0, 0.180), (162.0, 0.180), (168.0, 0.180), (174.0, 0.180), (180.0, 0.180), (186.0, 0.180), (192.0, 0.180), (198.0, 0.180), (204.0, 0.180), (210.0, 0.180), (216.0, 0.180), (222.0, 0.180), (228.0, 0.180), (234.0, 0.180), (240.0, 0.180), (246.0, 0.180), (252.0, 0.180), (258.0, 0.180), (264.0, 0.180), (270.0, 0.180), (276.0, 0.180), (282.0, 0.180), (288.0, 0.180), (294.0, 0.180), (300.0, 0.180), (306.0, 0.180), (312.0, 0.180), (318.0, 0.180), (324.0, 0.180), (330.0, 0.180), (336.0, 0.180), (342.0, 0.180), (348.0, 0.180), (354.0, 0.180), (360.0, 0.180), (366.0, 0.180), (372.0, 0.180)
proportion_of_powerlink_revenue_recovered_through_fixed_costs = 0.15
revenue_recovered_through_fixed_costs = proportion_of_energex_revenue_recovered_through_fixed_costs*actual_distribution_revenue_to_be_recovered

7.6. Fixed retail costs

Key assumptions

- The way in which retailer fixed costs have been calculated for notified prices have changed substantially since 2006 as different elements were introduced. Historical data is based on QCA determinations.
- The ‘annual ROC per customer’ refers to the Retail Operating Costs (ROC) and was included as a fixed cost from 2013
- ‘fixed headroom’ of 5% is applied to all fixed costs
- ‘retail margin’ of 5.7% is applied to sum of all fixed costs including headroom.
- ‘percentage change to achieve cost reflectivity’ is a graphical function that includes the changes to fixed retail costs resulting from the three-year transition process implemented by the QCA from 2013-14 to 2015-16.

Representation in Stella



****
Fixed_retail_costs:
****
annual_retailer_fixed_costs = total_retail_component_of_daily_fixed_cost*365
annual_ROC_per_customer = GRAPH(TIME)
(0.0, 0.0), (6.0, 0.0), (12.0, 0.0), (18.0, 0.0), (24.0, 0.0), (30.0, 0.0), (36.0, 0.0), (42.0, 0.0), (48.0, 0.0), (54.0, 0.0), (60.0, 0.0), (66.0, 0.0), (72.0, 0.0), (78.0, 0.0), (84.0, 0.0), (90.0, 60.0), (96.0, 60.0), (102.0, 150.0), (108.0, 150.0), (114.0, 155.0), (120.0, 155.0), (126.0, 155.0), (132.0, 155.0), (138.0, 155.0), (144.0, 155.0), (150.0, 155.0), (156.0, 155.0), (162.0, 155.0), (168.0, 155.0), (174.0, 155.0), (180.0, 155.0), (186.0, 155.0), (192.0, 154.8), (198.0, 154.8), (204.0, 154.8), (210.0, 154.8), (216.0, 154.8), (222.0, 154.8), (228.0, 154.8), (234.0, 154.8), (240.0, 154.8), (246.0, 154.8), (252.0, 154.8), (258.0, 154.8), (264.0, 154.8), (270.0, 154.8), (276.0, 154.8), (282.0, 154.8), (288.0, 154.8), (294.0, 154.8), (300.0, 154.8), (306.0, 154.8), (312.0, 154.8), (318.0, 154.8), (324.0, 154.8), (330.0, 154.8), (336.0, 154.8), (342.0, 154.8), (348.0, 154.8), (354.0, 154.8), (360.0, 154.8), (366.0, 154.8), (372.0, 154.8)
daily_fixed_ROC_cost = annual_ROC_per_customer/365
fixed_headroom_% = .05
headroom_fixed_component = IF TIME >=90 THEN fixed_headroom_%*sum_of_ROC_and_network_fixed_costs ELSE 0
percentage_change_to_achieve_cost_reflectivity = GRAPH(TIME)
(0.0, 1.000), (6.0, 1.000), (12.0, 1.000), (18.0, 1.000), (24.0, 1.000), (30.0, 1.000), (36.0, 1.000), (42.0, 1.000), (48.0, 1.000), (54.0, 1.000), (60.0, 1.000), (66.0, 1.000), (72.0, 1.000), (78.0, 1.000), (84.0, 1.000), (90.0, 0.750), (96.0, 0.750), (102.0, 0.790), (108.0, 0.790), (114.0, 1.000), (120.0, 1.000), (126.0, 1.000), (132.0, 1.000), (138.0, 1.000), (144.0, 1.000), (150.0, 1.000), (156.0, 1.000), (162.0, 1.000), (168.0, 1.000), (174.0, 1.000), (180.0, 1.000), (186.0, 1.000), (192.0, 1.000), (198.0, 1.000), (204.0, 1.000), (210.0, 1.000), (216.0, 1.000), (222.0, 1.000), (228.0, 1.000), (234.0, 1.000), (240.0, 1.000), (246.0, 1.000), (252.0, 1.000), (258.0, 1.000), (264.0, 1.000), (270.0, 1.000), (276.0, 1.000), (282.0, 1.000), (288.0, 1.000), (294.0, 1.000), (300.0, 1.000), (306.0, 1.000), (312.0, 1.000), (318.0, 1.000), (324.0, 1.000), (330.0, 1.000), (336.0, 1.000), (342.0, 1.000), (348.0, 1.000), (354.0, 1.000), (360.0, 1.000), (366.0, 1.000), (372.0, 1.000)
retail_margin_% = .057
retail_margin_fixed_component = IF TIME >= 90 THEN retail_margin_%*sum_incl_headroom ELSE 0
sum_incl_headroom = headroom_fixed_component+sum_of_ROC_and_network_fixed_costs
sum_of_ROC_and_network_fixed_costs = daily_network_fixed_cost+daily_fixed_ROC_cost
total_retail_component_of_daily_fixed_cost = (daily_fixed_ROC_cost+headroom_fixed_component+retail_margin_fixed_component)*percentage_change_to_achieve_cost_reflectivity

8. <u>Electricity supply sector impacts</u>

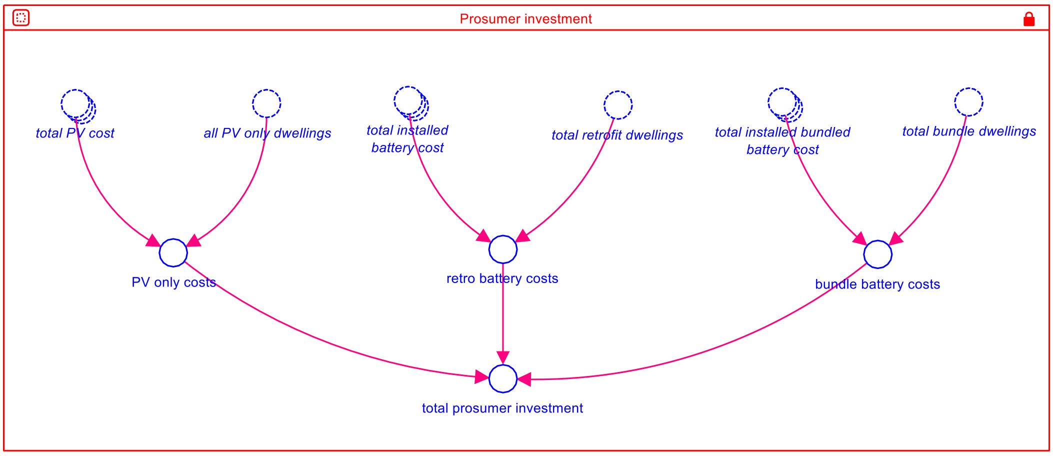
In determining electricity supply sector impacts, the primary method used throughout the following sectors is based on a bottom-up approach. This method is frequently used by electricity supply participants and involves multiplying total customer numbers against the specific metric being considered (Energex 2014).

8.1. Prosumer investment

Key assumptions

- This sector multiplies the cost paid by prosumers for each system type against the number of specific systems installed.

Representation in Stella



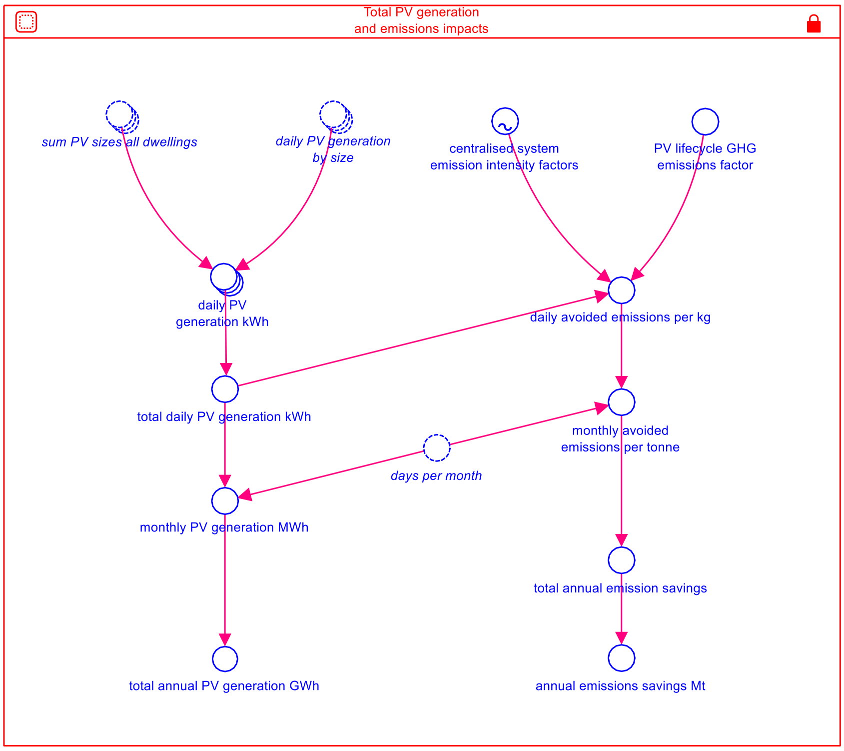
****
Prosumer_investment:
****
bundle_battery_costs = MEAN(total_installed_bundled_battery_cost)*total_bundle_dwellings
PV_only_costs = MEAN(total_PV_cost)*all_PV_only_dwellings
retro_battery_costs = MEAN(total_installed_battery_cost)*total_retrofit_dwellings
total_prosumer_investment = bundle_battery_costs+PV_only_costs+retro_battery_costs

8.2 Total PV generation and emissions impact

Key assumptions

- Total daily PV generation is calculated by multiplying the capacity of each PV system installed by the average generation for that system type.
- This figure is then multiplied by Queensland's centralised electricity emission intensity factor, a graphical function based on data from (DOEE 2016).
- To reflect the emissions created during PV construction a 'PV lifecycle GHG emissions factor' of 0.041 $kgCO_2e\ kWh^{-1}$ based on (Nugent & Sovacool 2014; Louwen et al. 2016). These lifecycle emissions are subtracted to achieve total emissions savings

Representation in Stella



****
Total_PV_generation_and_emissions_impacts:
****
annual_emissions_savings_Mt = total_annual_emission_savings/1000000
centralised_system_emission_intensity_factors = GRAPH(TIME)
(0.0, 0.890), (6.0, 0.890), (12.0, 0.890), (18.0, 0.890), (24.0, 0.880), (30.0, 0.880), (36.0, 0.880), (42.0, 0.870), (48.0, 0.870), (54.0, 0.850), (60.0, 0.850), (66.0, 0.820), (72.0, 0.820), (78.0, 0.800), (84.0, 0.800), (90.0, 0.790), (96.0, 0.790), (102.0, 0.780), (108.0, 0.780), (114.0, 0.780), (120.0, 0.780), (126.0, 0.780), (132.0, 0.780), (138.0, 0.780), (144.0, 0.780), (150.0, 0.780), (156.0, 0.780), (162.0, 0.780), (168.0, 0.780), (174.0, 0.780), (180.0, 0.780), (186.0, 0.780), (192.0, 0.780), (198.0, 0.780), (204.0, 0.780), (210.0, 0.780), (216.0, 0.780), (222.0, 0.780), (228.0, 0.780), (234.0, 0.780), (240.0, 0.780), (246.0, 0.780), (252.0, 0.780), (258.0, 0.780), (264.0, 0.780), (270.0, 0.780), (276.0, 0.780), (282.0, 0.780), (288.0, 0.780), (294.0, 0.780), (300.0, 0.780), (306.0, 0.780), (312.0, 0.780), (318.0, 0.780), (324.0, 0.780), (330.0, 0.780), (336.0, 0.780), (342.0, 0.780), (348.0, 0.780), (354.0, 0.780), (360.0, 0.780), (366.0, 0.780), (372.0, 0.780)

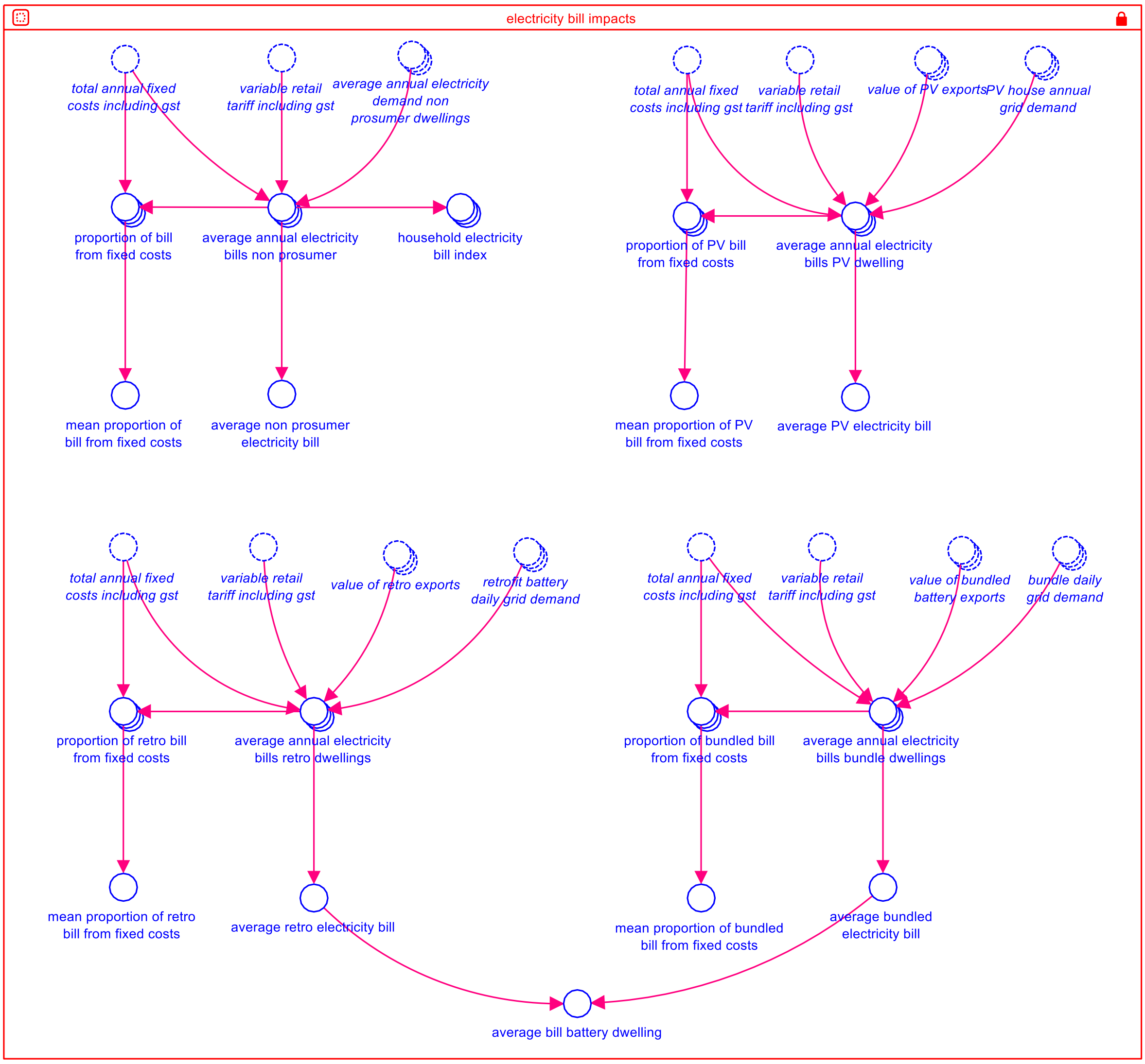
daily_avoided_emissions_per_kg = (centralised_system_emission_intensity_factors*total_daily_PV_generation_kWh)-(total_daily_PV_generation_kWh*PV_lifecycle_GHG_emissions_factor)
daily_PV_generation_kWh[PV_size] = sum_PV_sizes_all_dwellings*daily_PV_generation_by_size
monthly_avoided_emissions_per_tonne = (daily_avoided_emissions_per_kg/1000)*days_per_month
monthly_PV_generation_MWh = (total_daily_PV_generation_kWh*days_per_month)/1000
PV_lifecycle_GHG_emissions_factor = 0.041
total_annual_emission_savings = monthly_avoided_emissions_per_tonne*12
total_annual_PV_generation_GWh = (monthly_PV_generation_MWh*12)/1000
total_daily_PV_generation_kWh = SUM(daily_PV_generation_kWh)

8.3. Electricity bill impacts

Key assumptions

- For each consumer class, average electricity bills are calculated by adding variable costs (a function of individual electricity household demand and PV and battery system type, multiplied by the variable retail tariff) with fixed costs and averaging for each consumer class.

Representation in Stella



****
electricity_bill_impacts:
****
average_annual_electricity_bills_bundle_dwellings[PV_size, Loadprofile, Electricityconsumption, Battery_size] = ((bundle_daily_grid_demand*365*variable_retail_tariff_including_gst) +total_annual_fixed_costs_including_gst) - (value_of_bundled_battery_exports*365)
average_annual_electricity_bills_non_prosumer[Electricityconsumption] = (average_annual_electricity_demand_non_prosumer_dwellings*variable_retail_tariff_including_gst) +total_annual_fixed_costs_including_gst
average_annual_electricity_bills_PV_dwelling[PV_size, Loadprofile, Electricityconsumption] = ((PV_house_annual_grid_demand*variable_retail_tariff_including_gst) +total_annual_fixed_costs_including_gst)-value_of_PV_exports
average_annual_electricity_bills_retro_dwellings[PV_size, Loadprofile, Electricityconsumption, Battery_size] = ((retrofit_battery_daily_grid_demand*365*variable_retail_tariff_including_gst) +total_annual_fixed_costs_including_gst)-value_of_retro_exports
average_bill_battery_dwelling = (average_bundled_electricity_bill+average_retro_electricity_bill)/2
average_bundled_electricity_bill = MEAN(average_annual_electricity_bills_bundle_dwellings)
average_non_prosumer_electricity_bill = MEAN(average_annual_electricity_bills_non_prosumer)
average_PV_electricity_bill = MEAN(average_annual_electricity_bills_PV_dwelling)
average_retro_electricity_bill = MEAN(average_annual_electricity_bills_retro_dwellings)
household_electricity_bill_index[Electricityconsumption] = average_annual_electricity_bills_non_prosumer/ INIT(average_annual_electricity_bills_non_prosumer)
mean_proportion_of_bill_from_fixed_costs = MEAN(proportion_of_bill_from_fixed_costs)
mean_proportion_of_bundled_bill_from_fixed_costs = MEAN(proportion_of_bundled_bill_from_fixed_costs)
mean_proportion_of_PV_bill_from_fixed_costs = MEAN(proportion_of_PV_bill_from_fixed_costs)
mean_proportion_of_retro_bill_from_fixed_costs = MEAN(proportion_of_retro_bill_from_fixed_costs)
proportion_of_bill_from_fixed_costs[Electricityconsumption] = total_annual_fixed_costs_including_gst/average_annual_electricity_bills_non_prosumer
proportion_of_bundled_bill_from_fixed_costs[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF average_annual_electricity_bills_bundle_dwellings>= total_annual_fixed_costs_including_gst THEN total_annual_fixed_costs_including_gst/average_annual_electricity_bills_bundle_dwellings ELSE 1
proportion_of_PV_bill_from_fixed_costs[PV_size, Loadprofile, Electricityconsumption] = IF average_annual_electricity_bills_PV_dwelling>= total_annual_fixed_costs_including_gst THEN total_annual_fixed_costs_including_gst/average_annual_electricity_bills_PV_dwelling ELSE 1
proportion_of_retro_bill_from_fixed_costs[PV_size, Loadprofile, Electricityconsumption, Battery_size] = IF average_annual_electricity_bills_retro_dwellings>= total_annual_fixed_costs_including_gst THEN total_annual_fixed_costs_including_gst/average_annual_electricity_bills_retro_dwellings ELSE 1

8.4. Residential peak demand

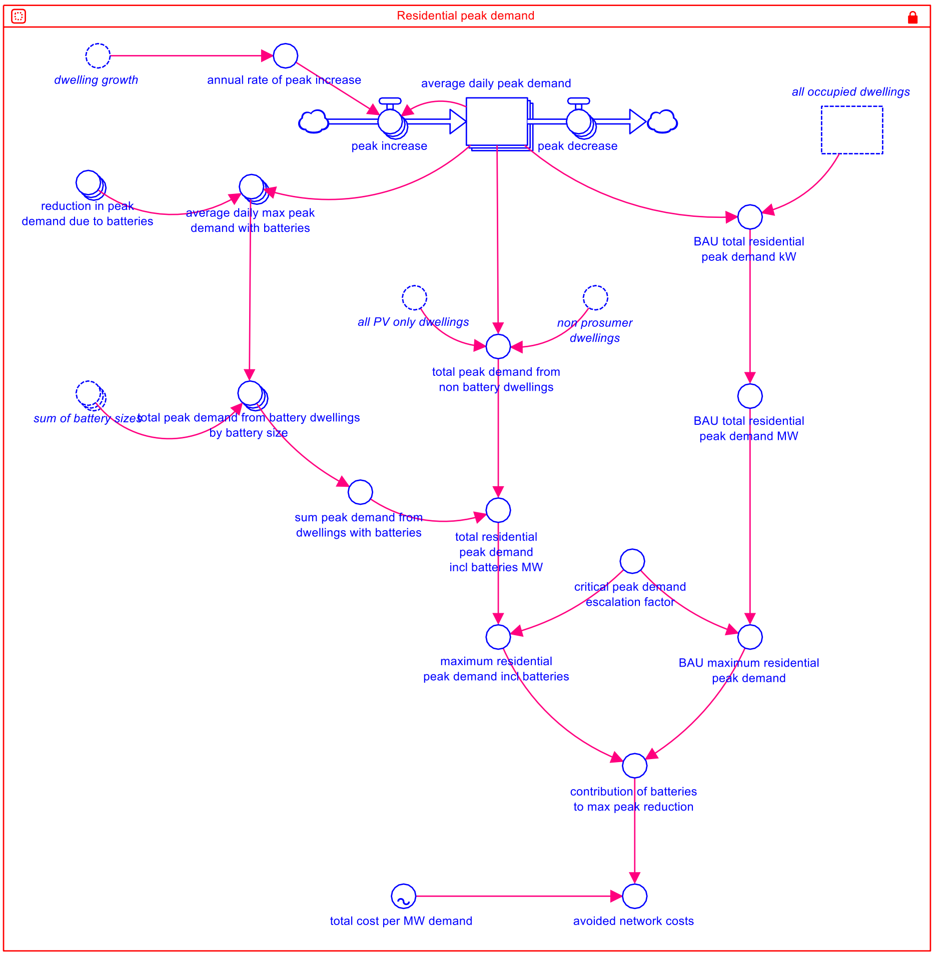
Key assumptions

- 'average daily peak demand' is estimated by calculating the maximum demand for each of the nine different load profiles used in the model and multiplying the average by all occupied dwellings to calculate business-as-usual peak demand (i.e. in the absence of batteries and other demand management activities).
- To determine the impact of battery uptake on peak demand, total household consumption for each load profile is calculated for the peak demand period (between 4pm and 8pm).
- The model assumes that as evening household load increases and PV generation decreases, battery capacity meets the difference in load. Based on the capacity of each of the battery sizes included in the model, the proportionate reduction in peak is calculated i.e. 'reduction in peak

demand due to batteries'. The 'total peak demand from battery dwellings by battery size' is then calculated, which when summed with peak demand from other dwelling types calculates 'total residential peak demand incl batteries MW'

- To determine the effect of batteries on network costs, the model estimates the value of batteries to the network specifically during critical peak periods which can be substantially higher than normal average peak demand. To this end, a 'critical peak demand escalation factor' of 40% is applied to average peak demand.
- The maximum average peak demand of dwellings with batteries can then be subtracted from the business as usual projection described above to determine the contribution of batteries to peak reduction.
- To calculate the financial value of peak demand reductions, historical $/MW values have been used in the model and directly sourced from DNSP benchmarking datasets from AER (2016b). Future projected values are assumed to remain at 2016 prices (AU$286,224/MW) in real terms until the end of the simulation period.

Representation in Stella



****
Residential_peak_demand:
****
annual_rate_of_peak_increase = (dwelling_growth-0.0001)
average_daily_max_peak_demand_with_batteries[Electricityconsumption, Loadprofile, Battery_size] = average_daily_peak_demand[Electricityconsumption, Loadprofile]*reduction_in_peak_demand_due_to_batteries
average_daily_peak_demand[low_consumption, Low_daytime_use](t) = average_daily_peak_demand[low_consumption, Low_daytime_use](t - dt) + (peak_increase[low_consumption, Low_daytime_use] - peak_decrease[low_consumption, Low_daytime_use]) * dt
INIT average_daily_peak_demand[low_consumption, Low_daytime_use] = 1.3
average_daily_peak_demand[low_consumption, Medium_daytime_use](t) = average_daily_peak_demand[low_consumption, Medium_daytime_use](t - dt) + (peak_increase[low_consumption, Medium_daytime_use] - peak_decrease[low_consumption, Medium_daytime_use]) * dt
INIT average_daily_peak_demand[low_consumption, Medium_daytime_use] = 0.9
average_daily_peak_demand[low_consumption, High_daytime_use](t) = average_daily_peak_demand[low_consumption, High_daytime_use](t - dt) + (peak_increase[low_consumption, High_daytime_use] - peak_decrease[low_consumption, High_daytime_use]) * dt
INIT average_daily_peak_demand[low_consumption, High_daytime_use] = 0.9
average_daily_peak_demand[medium_consumption, Low_daytime_use](t) = average_daily_peak_demand[medium_consumption, Low_daytime_use](t - dt) + (peak_increase[medium_consumption, Low_daytime_use] - peak_decrease[medium_consumption, Low_daytime_use]) * dt
INIT average_daily_peak_demand[medium_consumption, Low_daytime_use] = 1.65
average_daily_peak_demand[medium_consumption, Medium_daytime_use](t) = average_daily_peak_demand[medium_consumption, Medium_daytime_use](t - dt) + (peak_increase[medium_consumption, Medium_daytime_use] - peak_decrease[medium_consumption, Medium_daytime_use]) * dt
INIT average_daily_peak_demand[medium_consumption, Medium_daytime_use] = 1.55
average_daily_peak_demand[medium_consumption, High_daytime_use](t) = average_daily_peak_demand[medium_consumption, High_daytime_use](t - dt) + (peak_increase[medium_consumption, High_daytime_use] - peak_decrease[medium_consumption, High_daytime_use]) * dt
INIT average_daily_peak_demand[medium_consumption, High_daytime_use] = 1.50
average_daily_peak_demand[high_consumption, Low_daytime_use](t) = average_daily_peak_demand[high_consumption, Low_daytime_use](t - dt) + (peak_increase[high_consumption, Low_daytime_use] - peak_decrease[high_consumption, Low_daytime_use]) * dt
INIT average_daily_peak_demand[high_consumption, Low_daytime_use] = 2.05
average_daily_peak_demand[high_consumption, Medium_daytime_use](t) = average_daily_peak_demand[high_consumption, Medium_daytime_use](t - dt) + (peak_increase[high_consumption, Medium_daytime_use] - peak_decrease[high_consumption, Medium_daytime_use]) * dt
INIT average_daily_peak_demand[high_consumption, Medium_daytime_use] = 2.1
average_daily_peak_demand[high_consumption, High_daytime_use](t) = average_daily_peak_demand[high_consumption, High_daytime_use](t - dt) + (peak_increase[high_consumption, High_daytime_use] - peak_decrease[high_consumption, High_daytime_use]) * dt
INIT average_daily_peak_demand[high_consumption, High_daytime_use] = 1.85
INFLOWS:
peak_increase[Electricityconsumption, Loadprofile] = average_daily_peak_demand*annual_rate_of_peak_increase
OUTFLOWS:
peak_decrease[Electricityconsumption, Loadprofile] = 0
avoided_network_costs = ((contribution_of_batteries_to_max_peak_reduction*total_cost_per_MW_demand)/1000000)
BAU_maximum_residential_peak_demand = ROUND (BAU_total_residential_peak_demand_MW*critical_peak_demand_escalation_factor)
BAU_total_residential_peak_demand_kW = all_occupied_dwellings*MEAN(average_daily_peak_demand)
BAU_total_residential_peak_demand_MW = BAU_total_residential_peak_demand_kW/1000
contribution_of_batteries_to_max_peak_reduction = (BAU_maximum_residential_peak_demand-maximum_residential_peak_demand_incl_batteries)
critical_peak_demand_escalation_factor = 1.4
maximum_residential_peak_demand_incl_batteries = ROUND(total_residential_peak_demand_incl_batteries_MW*critical_peak_demand_escalation_factor)

reduction_in_peak_demand_due_to_batteries[low_consumption, Low_daytime_use, five_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[low_consumption, Low_daytime_use, fifteen_kWh] = 0
reduction_in_peak_demand_due_to_batteries[low_consumption, Low_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[low_consumption, Medium_daytime_use, five_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[low_consumption, Medium_daytime_use, fifteen_kWh] = 0
reduction_in_peak_demand_due_to_batteries[low_consumption, Medium_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[low_consumption, High_daytime_use, five_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[low_consumption, High_daytime_use, fifteen_kWh] = 0
reduction_in_peak_demand_due_to_batteries[low_consumption, High_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[medium_consumption, Low_daytime_use, five_kWh] = 0.5
reduction_in_peak_demand_due_to_batteries[medium_consumption, Low_daytime_use, fifteen_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[medium_consumption, Low_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[medium_consumption, Medium_daytime_use, five_kWh] = 0.5
reduction_in_peak_demand_due_to_batteries[medium_consumption, Medium_daytime_use, fifteen_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[medium_consumption, Medium_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[medium_consumption, High_daytime_use, five_kWh] = 0.5
reduction_in_peak_demand_due_to_batteries[medium_consumption, High_daytime_use, fifteen_kWh] = 0.2
reduction_in_peak_demand_due_to_batteries[medium_consumption, High_daytime_use, thirty_kWh] = 0
reduction_in_peak_demand_due_to_batteries[high_consumption, Low_daytime_use, five_kWh] = 0.7
reduction_in_peak_demand_due_to_batteries[high_consumption, Low_daytime_use, fifteen_kWh] = 0.3
reduction_in_peak_demand_due_to_batteries[high_consumption, Low_daytime_use, thirty_kWh] = 0.1
reduction_in_peak_demand_due_to_batteries[high_consumption, Medium_daytime_use, five_kWh] = 0.7
reduction_in_peak_demand_due_to_batteries[high_consumption, Medium_daytime_use, fifteen_kWh] = 0.3
reduction_in_peak_demand_due_to_batteries[high_consumption, Medium_daytime_use, thirty_kWh] = 0.1
reduction_in_peak_demand_due_to_batteries[high_consumption, High_daytime_use, five_kWh] = 0.7
reduction_in_peak_demand_due_to_batteries[high_consumption, High_daytime_use, fifteen_kWh] = 0.3
reduction_in_peak_demand_due_to_batteries[high_consumption, High_daytime_use, thirty_kWh] = 0.1
sum_peak_demand_from_dwellings_with_batteries =
SUM(total_peak_demand_from_battery_dwellings_by_battery_size)
total_cost_per_MW_demand = GRAPH(TIME)
(0.0, 229957), (12.0, 227557), (24.0, 225620), (36.0, 223909), (48.0, 220191), (60.0, 253157), (72.0, 274253), (84.0, 275181), (96.0, 287039), (108.0, 286224), (120.0, 286224), (132.0, 286224), (144.0, 286224), (156.0, 286224), (168.0, 286224), (180.0, 286224), (192.0, 286224), (204.0, 286224), (216.0, 286224), (228.0, 286224), (240.0, 286224), (252.0, 286224), (264.0, 286224), (276.0, 286224), (288.0, 286224), (300.0, 286224), (312.0, 286224), (324.0, 286224), (336.0, 286224), (348.0, 286224), (360.0, 286224), (372.0, 286224)
total_peak_demand_from_battery_dwellings_by_battery_size[five_kWh] =
sum_of_battery_sizes[five_kWh]*MEAN(average_daily_max_peak_demand_with_batteries[*, *, five_kWh])
total_peak_demand_from_battery_dwellings_by_battery_size[fifteen_kWh] =
sum_of_battery_sizes[fifteen_kWh]*MEAN(average_daily_max_peak_demand_with_batteries[*, *, fifteen_kWh])
total_peak_demand_from_battery_dwellings_by_battery_size[thirty_kWh] =
sum_of_battery_sizes[thirty_kWh]*MEAN(average_daily_max_peak_demand_with_batteries[*, *, thirty_kWh])
total_peak_demand_from_non_battery_dwellings =
(non_prosumer_dwellings+all_PV_only_dwellings)*MEAN(average_daily_peak_demand)
total_residential_peak_demand_incl_batteries_MW =

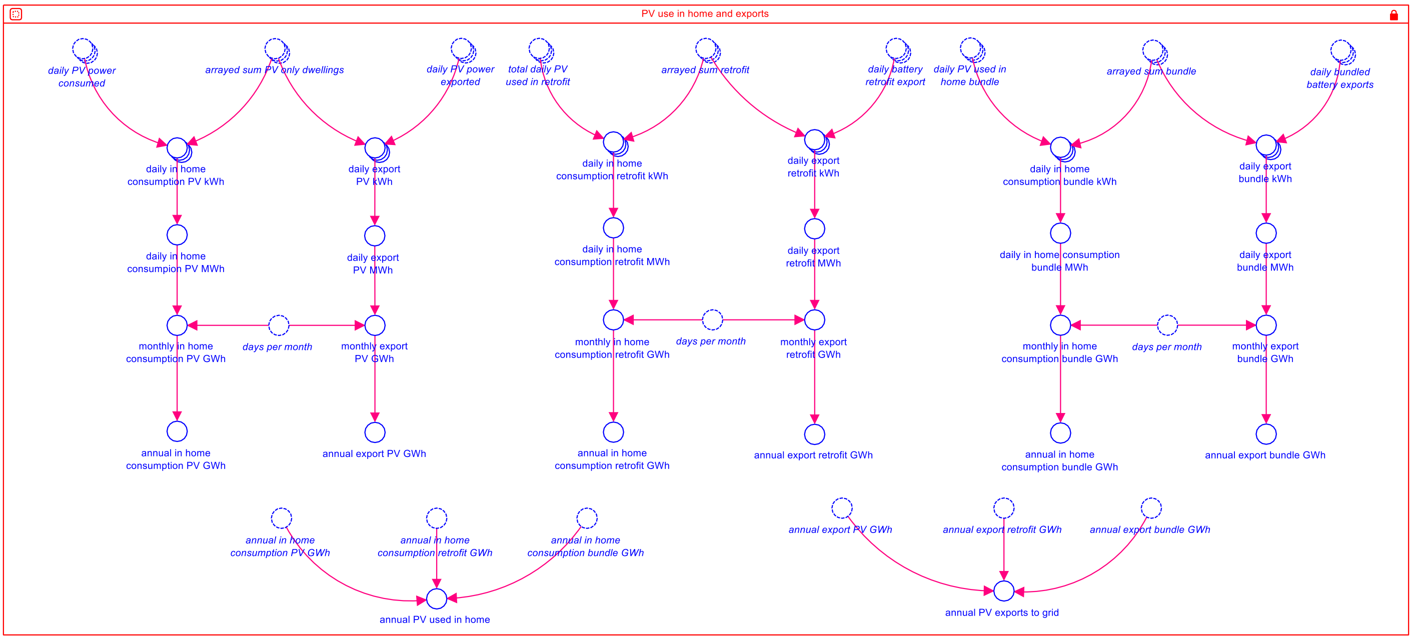
(total_peak_demand_from_non_battery_dwellings+sum_peak_demand_from_dwellings_with_batteries)/1000

8.5. PV used in home and exports

Key assumptions

- This sector calculates the volume of PV used in home and how much is exported. This is a product of the numbers of each dwelling type multiplied by the export/in-home use for each household profile type.

Representation in Stella



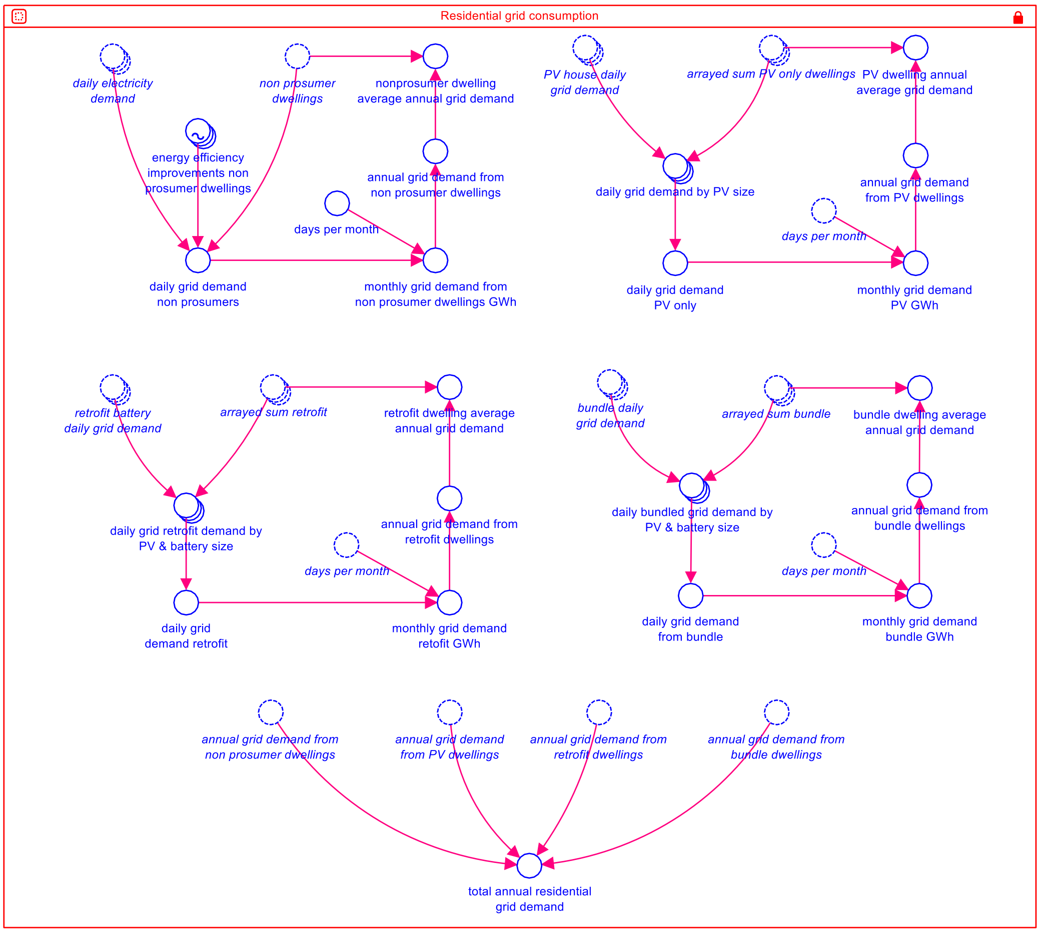
****
PV_use_in_home_and_exports:
****
annual_export_bundle_GWh = monthly_export_bundle_GWh*12
annual_export_PV_GWh = monthly_export_PV_GWh*12
annual_export_retrofit_GWh = monthly_export_retrofit_GWh*12
annual_in_home_consumption_bundle_GWh = monthly_in_home_consumption_bundle_GWh*12
annual_in_home_consumption_PV_GWh = monthly_in_home_consumption_PV_GWh*12
annual_in_home_consumption_retrofit_GWh = monthly_in_home_consumption_retrofit_GWh*12
annual_PV_exports_to_grid = annual_export_PV_GWh+annual_export_retrofit_GWh+annual_export_bundle_GWh
annual_PV_used_in_home = annual_in_home_consumption_PV_GWh+
annual_in_home_consumption_retrofit_GWh+ annual_in_home_consumption_bundle_GWh
daily_export_bundle_kWh[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
daily_bundled_battery_exports* arrayed_sum_bundle
daily_export_bundle_MWh = SUM(daily_export_bundle_kWh)/1000
daily_export_PV_kWh[PV_size, Loadprofile, Electricityconsumption] =
arrayed_sum_PV_only_dwellings*daily_PV_power_exported
daily_export_PV_MWh = SUM(daily_export_PV_kWh)/1000
daily_export_retrofit_kWh[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
arrayed_sum_retrofit*daily_battery_retrofit_export
daily_export_retrofit_MWh = SUM(daily_export_retrofit_kWh)/1000
daily_in_home_consumpion_PV_MWh = SUM(daily_in_home_consumption_PV_kWh)/1000
daily_in_home_consumption_bundle_kWh[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
daily_PV_used_in_home_bundle*arrayed_sum_bundle
daily_in_home_consumption_bundle_MWh = SUM(daily_in_home_consumption_bundle_kWh)/1000
daily_in_home_consumption_PV_kWh[PV_size, Loadprofile, Electricityconsumption] =
arrayed_sum_PV_only_dwellings*daily_PV_power_consumed
daily_in_home_consumption_retrofit_kWh[PV_size, Loadprofile, Electricityconsumption, Battery_size] =
total_daily_PV_used_in_retrofit*arrayed_sum_retrofit
daily_in_home_consumption_retrofit_MWh = SUM(daily_in_home_consumption_retrofit_kWh)/1000
monthly_export_bundle_GWh = (daily_export_bundle_MWh/1000)*days_per_month
monthly_export_PV_GWh = (daily_export_PV_MWh/1000)*days_per_month
monthly_export_retrofit_GWh = (daily_export_retrofit_MWh/1000)*days_per_month
monthly_in_home_consumption_bundle_GWh = (daily_in_home_consumption_bundle_MWh/1000)*days_per_month
monthly_in_home_consumption_PV_GWh = (daily_in_home_consumpion_PV_MWh/1000)*days_per_month
monthly_in_home_consumption_retrofit_GWh = (daily_in_home_consumption_retrofit_MWh/1000)*days_per_month

8.6. Residential grid consumption

Key assumptions

- Residential grid consumption is calculated by summing daily consumption values across each of the four consumer classes based on the specific household profile (i.e. daily consumption and load profile) and the capacity of the PV and/or PV and battery combination.
- Grid consumption for each profile type is calculated and then multiplied by the specific number of households with that description to generate total residential grid consumption.

Representation in Stella



****
Residential_grid_consumption:
****
annual_grid_demand_from_bundle_dwellings = monthly_grid_demand_bundle_GWh*12
annual_grid_demand_from_non_prosumer_dwellings =
monthly_grid_demand_from_non_prosumer_dwellings_GWh*12
annual_grid_demand_from_PV_dwellings = monthly_grid_demand_PV_GWh*12
annual_grid_demand_from_retrofit_dwellings = monthly_grid_demand_retofit_GWh*12

bundle_dwelling_average_annual_grid_demand = IF TIME > 108 THEN SAFEDIV(annual_grid_demand_from_bundle_dwellings*1000, SUM(arrayed_sum_bundle)) ELSE 0
daily_bundled_grid_demand_by_PV_&_battery_size[PV_size, Loadprofile, Electricityconsumption, Battery_size] = arrayed_sum_bundle*bundle_daily_grid_demand
daily_grid_demand_by_PV_size[PV_size, Loadprofile, Electricityconsumption] = arrayed_sum_PV_only_dwellings* PV_house_daily_grid_demand
daily_grid_demand_from_bundle = SUM(daily_bundled_grid_demand_by_PV_&_battery_size)/1000
daily_grid_demand_non_prosumers = (MEAN(daily_electricity_demand)*MEAN(energy_efficiency_improvements_non_prosumer_dwellings) *non_prosumer_dwellings)/1000
daily_grid_demand_PV_only = SUM(daily_grid_demand_by_PV_size)/1000
daily_grid_demand_retrofit = SUM(daily_grid_retrofit_demand_by_PV_&_battery_size)/1000
daily_grid_retrofit_demand_by_PV_&_battery_size[PV_size, Loadprofile, Electricityconsumption, Battery_size] = arrayed_sum_retrofit*retrofit_battery_daily_grid_demand
days_per_month = 365/12
energy_efficiency_improvements_non_prosumer_dwellings[Electricityconsumption] = GRAPH(TIME)
(0.0, 1.000), (12.0, 1.000), (24.0, 1.000), (36.0, 1.000), (48.0, 1.000), (60.0, 1.000), (72.0, 0.990), (84.0, 0.970299), (96.0, 0.96059601), (108.0, 0.95099005), (120.0, 0.941480149), (132.0, 0.932065348), (144.0, 0.922744694), (156.0, 0.913517247), (168.0, 0.904382075), (180.0, 0.895338254), (192.0, 0.886384872), (204.0, 0.877521023), (216.0, 0.868745813), (228.0, 0.860058355), (240.0, 0.851457771), (252.0, 0.842943193), (264.0, 0.834513761), (276.0, 0.826168624), (288.0, 0.817906938), (300.0, 0.809727868), (312.0, 0.80163059), (324.0, 0.793614284), (336.0, 0.785678141), (348.0, 0.777821359), (360.0, 0.770043146), (372.0, 0.760)
monthly_grid_demand_bundle_GWh = (daily_grid_demand_from_bundle/1000)*days_per_month
monthly_grid_demand_from_non_prosumer_dwellings_GWh = (daily_grid_demand_non_prosumers/1000)*days_per_month
monthly_grid_demand_PV_GWh = (daily_grid_demand_PV_only/1000)*days_per_month
monthly_grid_demand_retofit_GWh = (daily_grid_demand_retrofit/1000)*days_per_month
nonprosumer_dwelling_average_annual_grid_demand = annual_grid_demand_from_non_prosumer_dwellings*1000/non_prosumer_dwellings
PV_dwelling_annual_average_grid_demand = annual_grid_demand_from_PV_dwellings*1000/ SUM(arrayed_sum_PV_only_dwellings)
retrofit_dwelling_average_annual_grid_demand = IF TIME > 108 THEN SAFEDIV(annual_grid_demand_from_retrofit_dwellings*1000, SUM(arrayed_sum_retrofit)) ELSE 0
total_annual_residential_grid_demand = (annual_grid_demand_from_non_prosumer_dwellings+annual_grid_demand_from_PV_dwellings+annual_grid_demand_from_retrofit_dwellings +annual_grid_demand_from_bundle_dwellings)

Appendix C Extreme behaviour test – trends over time

Extreme behaviour tests

Each of the below parameters were tested by artificially increasing and decreasing the original value to examine the systems behaviour under extreme conditions. The graphs below show the system behaviour in response for each of three dependent variables. Data inputs were given a low and high value (25% and 175% respectively). The original value for the base-case simulation is included in the graphs for reference.

Battery payback

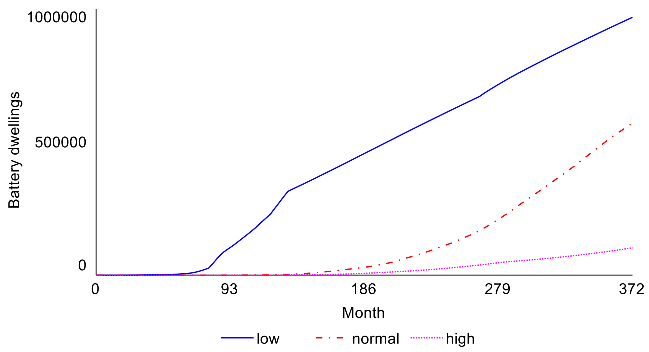


Figure 78 Extreme conditions test on battery payback period – effect on battery dwellings

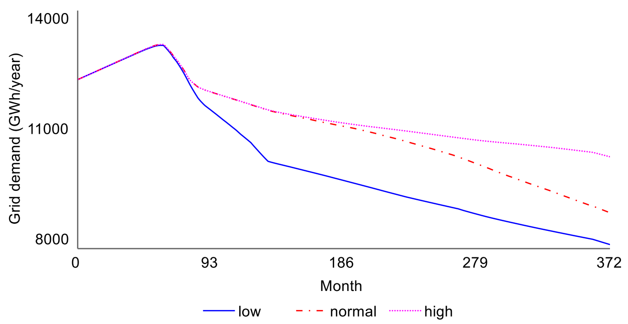


Figure 79 Extreme conditions test on battery payback period – effect on residential grid demand

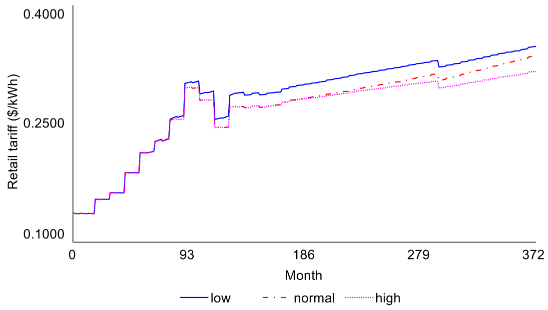


Figure 80 Extreme conditions test on battery payback period – effect on retail electricity tariff

Battery non-financial motivations

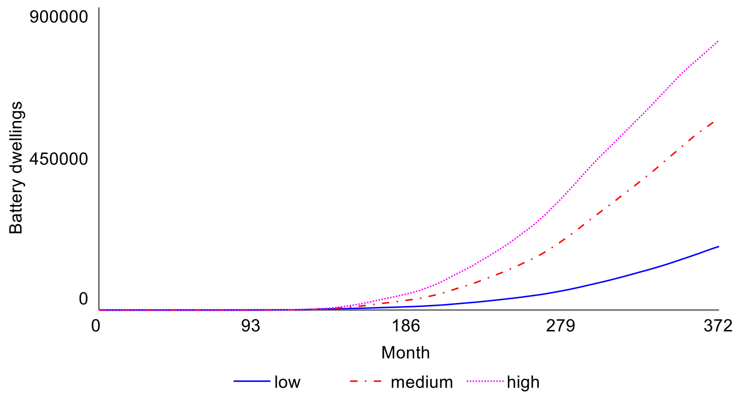


Figure 81 Extreme conditions test on non-financial motivations – effect on battery dwellings

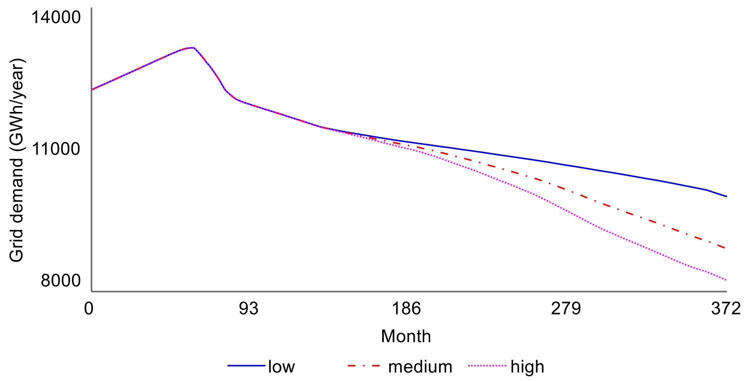


Figure 82 Extreme conditions test on non-financial motivations – effect on residential grid demand

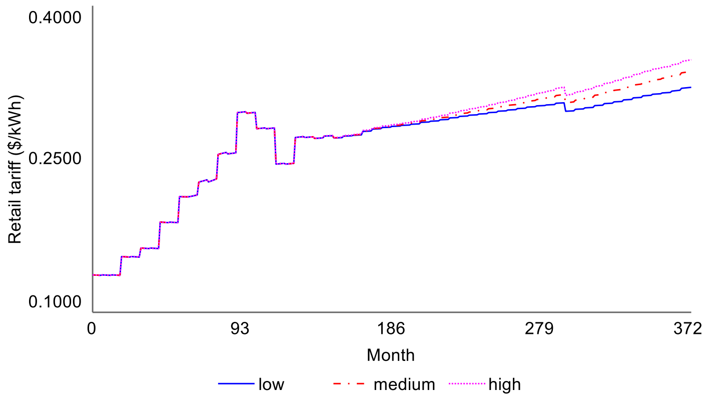


Figure 83 Extreme conditions test on non-financial motivations - effect on retail electricity tariff

Total network recoverable revenue

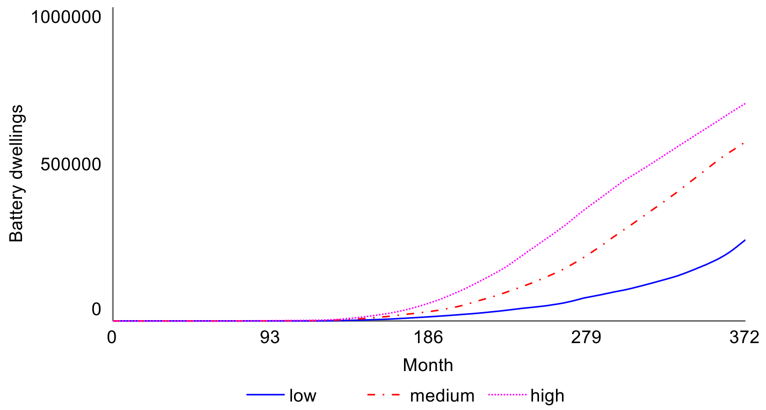


Figure 84 Extreme conditions test on network revenue - effect on battery dwellings

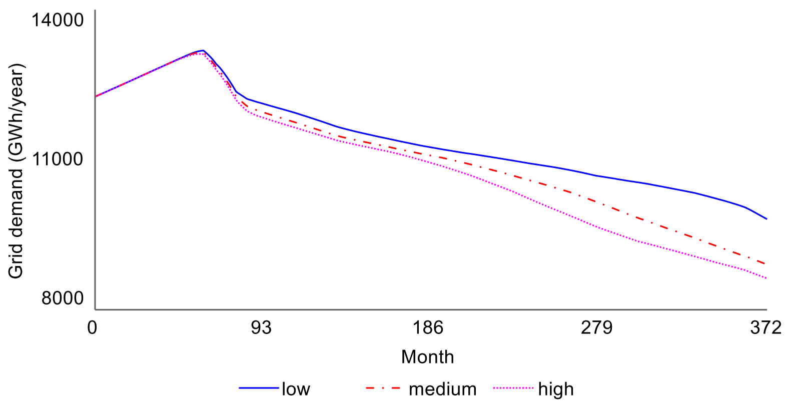


Figure 85 Extreme conditions test on network revenue - effect on residential grid demand

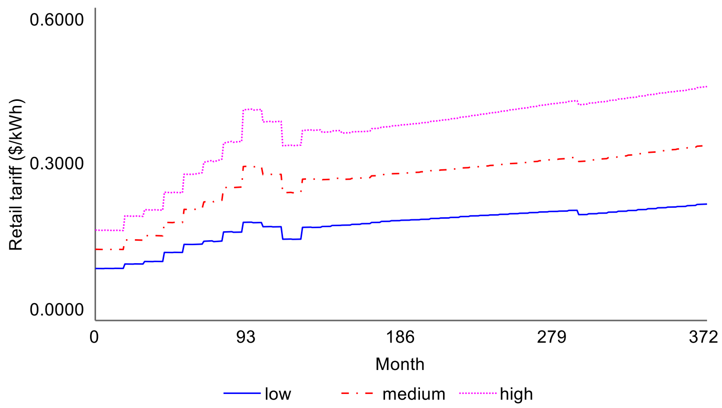


Figure 86 Extreme conditions test on network revenue - effect on retail tariff

Appendix D Discrepancy coefficient calculations

Total PV installs

PV total installs																
					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2006	1116	1116		0	1116	1116		86383	86768	6.E+14	7.E+14	6.E+19	6.E+19		0	385
2007	1591	1269.336		1	-57739	-54483		27527	31169	2.E+13	3.E+13	6.E+17	9.E+17		3257	3642
2008	4678	2075.773		2	-113983	-109428		-28716	-23776	-2.E+13	-1.E+13	7.E+17	3.E+17		4555	4940
2009	22961	4752.942		3	-155030	-162503		-69764	-76851	-3.E+14	-5.E+14	2.E+19	3.E+19		-7473	-7088
2010	71658	39305.94		4	-165663	-183702		-80397	-98050	-5.E+14	-9.E+14	4.E+19	9.E+19		-18038	-17653
2011	166961	157077.8		5	-129691	-121682		-44424	-36030	-9.E+13	-5.E+13	4.E+18	2.E+18		8009	8394
2012	297213	292980.7		6	-58769	-41531		26497	44121	2.E+13	9.E+13	5.E+17	4.E+18		17238	17623
2013	368410	342028		7	-46902	-48235		38364	37416	6.E+13	5.E+13	2.E+18	2.E+18		-1333	-948
2014	426158	384196.9		8	-48485	-61818		36782	23833	5.E+13	1.E+13	2.E+18	3.E+17		-13333	-12948
2015	465070	428142.4		9	-68903	-73625		16363	12027	4.E+12	2.E+12	7.E+16	2.E+16		-4722	-4337
2016	499422	471241.7		10	-93882	-86277		-8615	-626	-6.E+11	-2.E+08	6.E+15	2.E+11		7604	7989
B0	-85266.5	-85651.5		Moments								EBAR	-385			
				M1	-85267	-85652										
B1	59330.35	55751.9		M2	48819.9	52173.85						ESUMS	1.03E+09			
												ESTD	9685.627			
N	11															
		Discrepancy coefficient														
			0.095903													

PV systems by capacity

- Note as there is only historical data from 2010 for specific PV sizes, the discrepancy coefficient is only calculated from 2010.

PV <2kW																
					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2010	49361	33986.56		0	49361	33987		-46477	-47472	-1.E+14	-1.E+14	5.E+18	5.E+18		-15374	-995
2011	130291	115555.5		1	103992	88519		8154	7060	5.E+11	4.E+11	4.E+15	2.E+15		-15473	-1093
2012	183304	174500.9		2	130705	120428		34867	38969	4.E+13	6.E+13	1.E+18	2.E+18		-10277	4102
2013	201286	188841.9		3	122388	107732		26550	26274	2.E+13	2.E+13	5.E+17	5.E+17		-14656	-276
2014	213345	200796.3		4	108147	92650		12309	11191	2.E+12	1.E+12	2.E+16	2.E+16		-15497	-1118
2015	221696	209091.2		5	90199	73908		-5639	-7550	-2.E+11	-4.E+11	1.E+15	3.E+15		-16291	-1911
2016	223872	215206.4		6	66075	52986		-29763	-28472	-3.E+13	-2.E+13	8.E+17	7.E+17		-13089	1291
B0	95837.81	81458.42		Moments								EBAR	-14379			
				M1	95838	81458										
B1	26299.5	27036.66		M2	27298.2	28043.91						ESUMS	25658493			
												ESTD	1914.549			
N	7															
		Discrepancy coefficient														
			0.034595													

PV 2-4kW																
					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2010	7757	3243.493		0	7757	3243		-9983	-14143	-1.E+12	-3.E+12	1.E+16	4.E+16		-4513	-4160
2011	36647	32221.61		1	12999	9632		-4740	-7755	-1.E+11	-5.E+11	5.E+14	4.E+15		-3367	-3015
2012	74272	80266.32		2	26977	35087		9237	17700	8.E+11	6.E+12	7.E+15	1.E+17		8110	8463
2013	97904	100023.4		3	26960	32254		9221	14867	8.E+11	3.E+12	7.E+15	5.E+16		5293	5646
2014	120196	113581.5		4	25605	23222		7866	5835	5.E+11	2.E+11	4.E+15	1.E+15		-2383	-2031
2015	139233	126899.9		5	20995	13951		3255	-3436	3.E+10	-4.E+10	1.E+14	1.E+14		-7044	-6691
2016	144770	139858.5		6	2883	4319		-14856	-13068	-3.E+12	-2.E+12	5.E+16	3.E+16		1436	1788
B0	17739.41	17386.73		Moments								EBAR	-353			
				M1	17739	17387										
B1	23647.79	22589.88		M2	9146.784	12018.45						ESUMS	1.82E+08			
												ESTD	5098.828			
N	7															
		Discrepancy coefficient														
			0.240906													

PV 4-6kW																
					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2010	1569.6	1384.783		0	1570	1385		-94268	-80074	-8.E+14	-5.E+14	8.E+19	4.E+19		-185	14195
2011	8761.95	7765.701		1	-17538	-19271		-113375	-100729	-1.E+15	-1.E+15	2.E+20	1.E+20		-1733	12646
2012	29282.34	31546.24		2	-23317	-22527		-119154	-103986	-2.E+15	-1.E+15	2.E+20	1.E+20		790	15169
2013	50435.01	46005.73		3	-28463	-35104		-124301	-116563	-2.E+15	-2.E+15	2.E+20	2.E+20		-6641	7739
2014	71505.84	62025.73		4	-33692	-46121		-129530	-127579	-2.E+15	-2.E+15	3.E+20	3.E+20		-12429	1951
2015	94131.3	81101.75		5	-37366	-54082		-133204	-135540	-2.E+15	-2.E+15	3.E+20	3.E+20		-16715	-2336
2016	101878.4	101062.8		6	-55919	-61157		-151756	-142616	-3.E+15	-3.E+15	5.E+20	4.E+20		-5239	9141
B0	-3978.86	-3749.5		Moments								EBAR	-6022			
				M1	-27818	-33840										
B1	18353.16	17006.63		M2	16498.13	20316.74						ESUMS	744207941			
												ESTD	10310.937			
	7															
		Discrepancy coefficient														
			0.280075													

PV 8-10kW																
					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2010	711.9	691.1115		0	712	691		-95126	-80767	-9.E+14	-5.E+14	8.E+19	4.E+19		-21	14359
2011	2485.65	1535.016		1	-23814	-25502		-119652	-106960	-2.E+15	-1.E+15	2.E+20	1.E+20		-1688	12692
2012	4241.25	6667.286		2	-48358	-47406		-144196	-128864	-3.E+15	-2.E+15	4.E+20	3.E+20		952	15331
2013	6807.33	7156.99		3	-72091	-73953		-167929	-155411	-5.E+15	-4.E+15	8.E+20	6.E+20		-1862	12518
2014	9229.53	7793.31		4	-95968	-100353		-191806	-181812	-7.E+15	-6.E+15	1.E+21	1.E+21		-4385	9995
2015	12306.45	11049.48		5	-119191	-124134		-215029	-205592	-1.E+16	-9.E+15	2.E+21	2.E+21		-4943	9437
2016	13444.29	15114.12		6	-144353	-147106		-240191	-228564	-1.E+16	-1.E+16	3.E+21	3.E+21		-2753	11626
B0	300.8732	348.4764		Moments								EBAR	-2100			
				M1	-71866	-73966										
B1	2243.823	2265.142		M2	48113.21	49555.8						ESUMS	1.083E+09			
												ESTD	12438.937			
	7															
		Discrepancy coefficient														
			0.127358													

Residential demand

Residential demand					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2006	12655.59	12453.62		0	12656	12454		-588	-576	-2.E+08	-2.E+08	1.E+11	1.E+11		-202	12
2007	12518.99	12648.97		1	12676	12788		-568	-241	-2.E+08	-1.E+07	1.E+11	3.E+09		112	326
2008	13102.59	12845.43		2	13417	13124		173	95	5.E+06	8.E+05	9.E+08	8.E+07		-293	-79
2009	13082.07	13039.41		3	13553	13457		310	428	3.E+07	8.E+07	9.E+09	3.E+10		-96	118
2010	13519.17	13146.31		4	14147	13704		904	674	7.E+08	3.E+08	7.E+11	2.E+11		-444	-230
2011	12826.6	12620.55		5	13612	13317		368	288	5.E+07	2.E+07	2.E+10	7.E+09		-295	-81
2012	12613.42	12075.17		6	13556	12911		312	-118	3.E+07	-2.E+06	9.E+09	2.E+08		-644	-430
2013	12119.58	11914.02		7	13219	12890		-25	-140	-2.E+04	-3.E+06	4.E+05	4.E+08		-329	-115
2014	11666.36	11778.13		8	12923	12893		-321	-137	-3.E+07	-3.E+06	1.E+10	3.E+08		-30	184
2015	11470.54	11639.39		9	12884	12894		-360	-136	-5.E+07	-3.E+06	2.E+10	3.E+08		10	224
2016	11467.1	11500.19		10	13038	12894		-206	-136	-9.E+06	-3.E+06	2.E+09	3.E+08		-144	70
				Moments												
B0	13243.62	13029.62		M1	13244	13030										
				M2	438.8865	331.4529						EBAR	-214			
B1	-157.052	-139.357														
									0			ESUMS	473408.059			
												ESTD	207.453841			
N	11															
		Discrepancy coefficient														
			0.269302													

Electricity price

Electricity price					Detrended					cubed		fourth				
	Historical	Simulated			Historical	Simulated		Hdev	Sdev	H	S	H	S		ERRR(i)	Dev
2006	0.1136	0.118071		0	0.11	0.12		0.02	0.02	1.E-05	8.E-06	3.E-07	2.E-07		0.004	-0.003
2007	0.1136	0.11725		1	0.10	0.10		0.01	0.01	5.E-07	1.E-07	3.E-09	7.E-10		0.005	-0.003
2008	0.1151	0.122354		2	0.08	0.09		-0.01	0.00	-2.E-07	-6.E-08	1.E-09	2.E-10		0.010	0.002
2009	0.124	0.127976		3	0.08	0.09		-0.01	-0.01	-2.E-06	-2.E-06	3.E-08	2.E-08		0.007	0.000
2010	0.1373	0.143487		4	0.08	0.09		-0.01	-0.01	-3.E-06	-1.E-06	5.E-08	2.E-08		0.011	0.003
2011	0.1539	0.156633		5	0.08	0.09		-0.01	-0.01	-2.E-06	-2.E-06	3.E-08	2.E-08		0.009	0.001
2012	0.1641	0.172172		6	0.07	0.09		-0.02	-0.01	-7.E-06	-1.E-06	1.E-07	1.E-08		0.015	0.008
2013	0.1641	0.179864		7	0.06	0.08		-0.03	-0.02	-4.E-05	-5.E-06	1.E-06	9.E-08		0.024	0.017
2014	0.2673	0.236467		8	0.14	0.12		0.05	0.02	2.E-04	2.E-05	8.E-06	4.E-07		-0.022	-0.029
2015	0.28015	0.266091		9	0.14	0.14		0.05	0.04	1.E-04	7.E-05	7.E-06	3.E-06		-0.004	-0.011
2016	0.22238	0.225812		10	0.07	0.08		-0.02	-0.01	-1.E-05	-3.E-06	2.E-07	4.E-08		0.015	0.008
2017	0.2461	0.246753		11	0.08	0.09		-0.01	-0.01	-3.E-06	-4.E-07	3.E-08	3.E-09		0.013	0.006
B0	0.09054	0.097888		M1	0.09	0.10										
				M2	0.0272	0.017825						EBAR	0.01			
B1	0.015381	0.014216														
												ESUMS	0.00141703			
												ESTD	0.01086672			
n	12		Discrepancy coefficient													
				0.241348												