Benchmarking Renewable Energy Sources

Carbon Savings And Economic Effectiveness

Saeed Alokkah

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Everything comes in time to those who can wait.

FRANÇOIS RABELAIS, *Gargantua and Pantagruel*

To my parents, Rashed and Raeesa,
without whom my life's journey would not have been possible.

And to my wife, Mariam,
without whom my life's journey would not have been that colourful and enjoyable.

And to my children, Rahaf, Zainah, Rashed, Hala, Jasser and Saif,
without whom this thesis might have been completed perhaps two years earlier!

"Mom and Dad, I love you so much. I am so sorry that I did not want to add an extra unhappy doctor to a hospital. I hope that adding an extra doctor to a university or a research institute would make up for that."

"Mariam, although you sacrificed a great deal to help me complete this thesis, you never bothered to ask me when this mess was going to be over! I think that was the best thing that ever happened to me during my PhD journey!"

"Hey, kid! If you are reading this, then I want to let you know that it is perfectly fine if you do not read beyond this page. Perhaps you are not the first person nor the last one to do that. But it is worth knowing that throughout my long journey of writing this thesis, I couldn't remember a day that I didn't have to make a choice between being a good father or being a good PhD student. I always chose the former. It would be very nice if you don't give me reasons to regret that. Well, do not worry much. I certainly will not!."

"Oh, forgot to mention something. Although I don't expect you to write a PhD thesis on your own, if you had to write a thesis anyway, then I would certainly expect you to be smarter than me and to avoid the need to make that hard choice!"

Copyright Declaration

Statement Of Originality

I declare that this manuscript and the research referred to therein, are the product of my own work under the guidance of my thesis's supervisor Prof. Richard Green. Any ideas or quotations from the work of others, published or otherwise, are fully acknowledged in accordance with standard referencing practice. I confirm that the material of this thesis has not been accepted for any degree, and has not been concurrently submitted for the award of any other degree.

ABSTRACT

Over the last decade, the levelised cost of energy (LCOE) of many renewable technologies has sharply declined. As a result, direct cost comparisons of LCOE figures have made renewables to be perceived as economically very competitive options to decarbonise energy systems when compared to other low-carbon technologies such as Nuclear and Carbon Capture and Storage. We identify several theoretical shortcomings in relation to using LCOE or similar life-cycle economic metrics to make inferences about the relative economic effectiveness of using renewable technologies to decarbonise energy systems. We outline several circumstances in which the sole reliance on these metrics can lead to suboptimal or misguided investment and policymaking decisions.

The thesis proposes a new theoretical framework to measure and benchmark the cost-effectiveness of decarbonising electric systems using renewables. The new framework is generic, technology-neutral, and enables consolidation of the results of decarbonisation studies that consider various renewable technologies and low carbon technologies. It also enables measuring and tracking the cost-effectiveness of the renewable decarbonisation process at a country or a system level. As a result, it also allows the direct comparison of the economic implications of different decarbonisation scenarios and various policy proposals in a very intuitive graphical way.

In addition, the thesis proposes a new, unit-free metric, tentatively called *Carbon Economic Effectiveness Credit (CEEC)*, to benchmark the relative cost-effectiveness of using different renewable technologies to achieve long-term carbon emission savings. Theoretically, CEEC represents the elasticity of the system total cost with respect to the carbon reduction savings attributable to renewables. In contrast to stand-alone, life-cycle metrics such as the LCOE, the proposed metric considers the economic and technical parameters of the renewable technologies and characteristic of the system under study. It also allows expressing the cost-effectiveness of the renewable decarbonisation process as a function of the system-wide decarbonisation level.

Using historical load profiles, high-resolution solar radiation data and long-term meteorological data for a relatively small Gulf country, we investigate the deep decarbonisation of the electric system through the large-scale deployment of different renewables technologies. In particular, we use two well-established optimisation methodologies that have been used extensively in the literature to study the decarbonisation of power systems, namely: the screening curve (SC) method and the unit commitment (UC) method. In analysing the results of the two methodologies, we find that the choice of the modelling methodology, in some cases, can greatly influence the perceived carbon cost-effectiveness of renewables and subsequently their carbon abatement cost estimates. In particular, our results suggest that under deep decarbonisation scenarios, the estimate of the long-term carbon savings of renewables is strongly influenced by (1) the choice of the modelling method and (2) the technical specifications of the simulation models. Our results suggest that under deep decarbonisation scenarios, using simpler optimisation models may change the perceived economic effectiveness of renewables to decarbonise some electric systems. More importantly, our research sheds light on potential shortcomings in the current modelling practices and help identify patterns of possible inaccuracies or biases in renewable decarbonisation results.

Moreover, our research suggests that the variations in the technical characteristics of renewable technologies can have a large influence on the economics of the decarbonisation process. We show that not all renewable technology types can have a suppressing effect on the variable costs of the systems due to their "zero marginal costs." In particular, we identify certain technologies and circumstances in which an increase in renewable penetration can significantly inflate the variable energy costs of the system. More specifically, we find that under deep decarbonisation scenarios, renewable technologies with a highly volatile production profiles can act as an amplifier for the variable cost of the systems through (1) reducing the effectiveness of thermal generation units due the increased start-up and shutting downing activities, and (2) increasing the energy output levels from more flexible and yet more expensive thermal technologies.

In addition, we identify circumstances in which an increased renewable penetration can materially affect the capacity adequacy of electric systems, leading to an increase in capacity investment in thermal flexibility assets. Perhaps more importantly, we find that these additional flexibility assets will not be commercially viable on an energy-output basis. We believe that this might have specific implications for the energy-only markets.

Finally, we discuss the policy implications of our findings and propose several important recommendations. Altogether, we hope that our work will advance the understanding of the economics of climate change and integrating renewables into energy systems.

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Firstly, I would like to thank my supervisor, Prof. Richard Green, for his invaluable guidance and unlimited support during my PhD journey. It would take me ages and countless pages to justly thank him, and yet I think it will never be enough! Among many other things, he never said “no” to me when I asked for personal help or support. He always listened passionately to my concerns and always tried to do his best to help in all circumstances, he always treated me with unmatched courtesy and respect, he never resented from reading my poor research drafts or from answering my occasionally not very smart questions, he has always been very responsive to my emails, and, most of all, he always tried to make me happier whenever he saw “poor Saeed.” Indeed, I could not have wished for a better supervisor, and I will forever be indebted to him for everything he has done and continues to do for me until now. I can recall only one small con of Prof. Green. Over the years, he lost count of the number of my kids! But frankly, who can blame him?

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2DS	2 Degree Scenario
CAES	Compressed Air Energy Storage
CC	Capacity Credit
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
CRF	Capital Recovery Factor
CSP	Concentrated Solar Power
DNI	Direct Normal Irradiance
DSM	Demand-side management
E2T	Electricity-to-Thermal
GAMS	General Algebraic Modeling System
GEP	Generation Expansion Planning
GHG	Greenhouse gas
GHI	Global Horizontal Irradiance
GRP	Generation Resource Planning
HVDC	High-Voltage, Direct-Current
IEA	International Energy Agency
INDC	Intended Nationally Determined Contribution
IPCC	Intergovernmental Panel for Climate Change
IRENA	International Renewable Energy Agency
LCOE	Levelised Cost of Energy
LDC	Load Duration Curve
MAC	Marginal abatement cost
MILP	Mixed-integer Linear Programming
MRTL	Minimum Running Thermal Load
NREL	National Renewable Energy Laboratory
O&M	Operation and Maintenance
OCGT	Open Cycle Gas Turbine
P2G	Power-to-Gas
P2H	Power-to-H_2
PHES	Pumped Hydroelectric Storage
PV	Photovoltaic
RP	Resource Planning
PT	Parabolic Trough
ROC	Relative Optimality Criterion
RTS	Reference Technology Scenario
SAM	System Advisor Model
SC	Screening Curve
STGS	Short-term Generation Scheduling
STRP	Short-term Resource Scheduling
SMES	Superconducting Magnetic Energy Storage
UNCCC	United Nations Framework Convention on Climate Change
UC	Unit Commitment
V2G	Vehicle-to-Grid
WACC	Weighted Average Cost of Capital

CHAPTER 1

INTRODUCTION

1.1 Motivation

Mitigating the risks of climate change is believed to be one of the most challenging collective tasks of our lifetime. Governments around the world are busy negotiating commitments, setting targets, formulating strategies, and preparing roadmaps to decarbonise their economies and cut their greenhouse gas (GHG) emissions. A common starting point for governments is to set up plans to decarbonise their energy systems, from which significant quantities of GHGs are released into the atmosphere. According to the Intergovernmental Panel for Climate Change (IPCC), GHG emissions associated with energy services are a major cause of climate change (IPCC, 2011). In 2012, the CO_2 emitted by the energy sector accounted for approximately two-thirds of global CO_2 emissions, and the power sector alone was responsible for about 40% of the global primary energy use and CO_2 emissions (IEA, 2015).

At this juncture, there is no shortage of studies predicting a considerable increase in global renewable energy production, albeit that these studies tend to have varying projections about the expected share size of renewables, the technology mix, and the timescale of diffusion and adoption (IEA, 2014a, IEA, 2012, IEA, 2010b, IEA, 2010c, IEA, 2015, IEA, 2016b, IEA, 2017, IRENA, 2021, Equinor, 2021, EIA, 2021, BP, 2020, McKinsey, 2019, ERINDRC, 2015, EC, 2012). The hope is that the projected expanded use of renewables will help stabilise the concentration of GHGs in the atmosphere to a safe level, or at least to the currently perceived lowest acceptable level, technically known as the 2-degree scenario (2DS)[1].

By the end of 2018, the total share of renewable output within the global electricity energy mix was estimated to be about 25%, covering almost 45% of the world's electricity generation growth in 2018 (IEA, 2019). A recent estimate by the International Energy Agency (IEA) suggests that under the 2DS, the share of renewables in the global generation mix might reach as high as 74% in 2060 (IEA, 2017). Besides, by 2050, electricity is expected to be the largest final energy carrier, boosting the role of renewables in reducing global carbon emissions (IEA, 2015).

1 The 2DS is often linked in the literature to "Paris Agreement" which requires the signing nations to collectively limit global warming to well below 2 °C above pre-industrial levels by 2100 (United Nations, 2015).

To date, there has been little agreement in the literature on how to estimate and measure the carbon reduction contributions of renewables. More recently, studies have emerged that offer cautionary insights into overestimating or potentially underestimating the carbon reduction contributions of renewables and their role in achieving the deep decarbonisation of electric systems (Hart and Jacobson, 2012, Strbac et al., 2007, Thomson et al., 2017). In addition to historical estimates, difficulties often arise regarding the projections of the long-term CO_2 saving potential of renewables, especially when an investment or a policy decision must be made based on these estimates or projections. These difficulties include (1) the wide variation in modelling techniques and practises used in the literature for carrying out renewable decarbonisation studies (2) the modeling complexity of existing of energy systems (3) the uncertainty about the characteristics of future electric systems (4) the lack consensus on the way that the renewable emission savings are measured and reported.

One worry is that the possible systematic overestimation of the carbon savings of renewables might jeopardise the ability to meet carbon emission targets. In addition, this might result in misguided investment and policy-design decisions.

Furthermore, uncertainty about the validity, accuracy, and robustness of the carbon saving estimates of renewables might raise further questions about the true economic costs of deeply decarbonising electric systems through expanding the use of renewables. Equally, this would cast doubts on the cost-effectiveness of the envisioned large-scale renewable decarbonisation process of electric power systems worldwide. Importantly, as the carbon saving potential of renewables is frequently cited as one of the primary drivers for expanding their use and justifying their capital-intensive investments and subsidies, there is a real need to ensure that renewables are capable of delivering the hoped-for carbon savings in a technically efficient and cost-effective manner.

1.2 Overall Objective of the Thesis

This thesis explores the economics of decarbonising electric systems, with a special focus on using renewables as a primary option for delivering the deep decarbonisation of electric systems. It seeks to uncover the some of the technical features of the renewable decarbonisation process and shows how these features impact the economics of electric systems in an unconventional way. The ultimate purpose of this dissertation is to fully understand the value of incorporating renewables into electric systems from both climate change mitigation and economic perspectives. To that end, we summarise the key objectives of the thesis in the following points:

1) Proposing a new theoretical framework and gauging metric for measuring and benchmarking the cost-effectiveness of decarbonising electric systems by means of renewables at a country or a system-level.
2) Applying the framework to different analytical contexts including carrying out deep decarbonisation studies using different (a) renewable technologies, (b) modelling methods, and (c) model's specifications to demonstrate the usefulness and versatility of the new developed framework as a powerful analytical tool to understand the different factors that could influence the perceived economic competitiveness of using renewables to decarbonise energy systems.
3) Presenting several original insights about the economics of the renewable decarbonisation process of electric systems and providing multiple, practical policy recommendations related to the topic.

1.3 Thesis Outline

The thesis is organised into seven chapters and two appendices. The specific goals, objectives, and contents of each chapter can be summarised as follows:

- **Chapter 2**
  - Includes a brief review of the challenges of climate change and the anticipated role of renewable energy systems in facilitating the decarbonisation of electric energy systems.
  - Provides a short review of the technical characteristics of intermittent renewables and their implications for the operation and planning of electric energy systems.
  - Presents a concise literature review of the flexibility options that have been suggested in the literature to support the evolution of low-carbon electric systems.

- **Chapter 3**
  - Provides a broad literature review of the current modelling approaches used in the literature to estimate the carbon savings of renewables.

    - Provides a technical literature review of the commonly used optimisation-based modelling methodologies to simulate the operations of electric systems and to make long-term projections about the carbon saving potential of renewables and its economic implications.
    - Presents the study's input data and assumptions and provides a description of the electric system under study.

- **Chapter 4**
    - Provides a critical review of the existing literature on the economics of electric systems' decarbonisation.
    - Discusses the theoretical shortcomings of the existing metrics that are frequently used in the literature to make economic inferences about the competitiveness of renewable technologies to decarbonise electric systems.
    - Discusses the difficulty of making economic judgments about the long-term economic effectiveness of using renewable technologies to decarbonise electric systems in the absence of a theoretical framework that addresses the unique characteristics of the renewable decarbonisation process.
    - Introduces the newly proposed theoretical framework for measuring the economic effectiveness of the renewable decarbonisation process.
    - Introduces a new benchmarking metric for gauging the relative cost-effectiveness of using different renewable technologies or low-carbon technologies to achieve sustained and long-term carbon emission savings.
    - Provides several illustrative examples of the usefulness of the proposed framework and metrics for policy evaluations.
    - Presents a case study comparing the performance of the newly proposed framework and gauging metrics against the performance of the most frequently used metric in the literature.
    - Presents the findings of the research and their policy implications.

- **Chapter 5**
    - Provides a comparative case study featuring two of the well-established optimisation methodologies for studying the decarbonisation of power systems, namely the screening curve (SC) method and the unit commitment (UC) method.
    - Presents a detailed technical study using the UC method. The study features different UC models with different technical specifications. In essence, the study examines the sensitivity of the carbon emission and economic results of decarbonisation studies to variations in the technical specifications of the UC

models. The study features side-by-side comparisons of models with, without, and with varying values of specific technical factors.
  - Reports and discuss the results of the study.
  - Discusses the policy implications of the research findings.

- **Chapter 6**
  - Presents a detailed technical study using different types of renewable technologies with different technical characteristics, namely the photovoltaic (PV) and wind technologies. In essence, the study examines to what extent variations in the technological characteristics across renewable technologies impact the economics of the decarbonisation process.
  - Presents a second detailed technical study using PV and wind technologies; however, it considers comparable cumulative energy output levels for the two technologies rather than comparing them on an equivalent capacity penetration basis as in the previous case study. The new case study helps capture the impact of the variations in the production profiles of the two technologies irrespective of the strength of their underlying renewable resource. In particular, the new case study seeks to uncover the impact of the variations in "production profiles" of renewable technologies on the economics of the decarbonisation process in isolation of the variations in renewable resources' potentials or strengths.
  - Presents a third case study featuring the PV and the concentrated solar power (CSP) technologies. The study cases investigate the effect of the “variability” of the production profile of the renewable technologies on the economics of the decarbonisation process.
  - Reports and discusses the results of the technical studies.
  - Discusses the policy implications of the research findings.

- **Chapter 7**
  - Discusses the overall research findings and conclusions.
  - Discusses the limitations of the research carried out.
  - Discusses the planned future work and open questions.

- **Appendix A**
  - Supplementary results appendix.

- **Appendix B**
  - Modelling notes appendix.

Chapter 2

Literature Review

2.1 Renewable Energy & Climate Change

In December 2015, 196 nations, which are then parties to the United Nations Framework Convention on Climate Change (UNFCCC), signed a historic agreement to combat and mitigate the risks of climate change. This landmark "Paris Agreement" requires nations to collectively limit global warming to well below 2 °C above pre-industrial levels by 2100[2] .Furthermore, in line with recommendations of the Intergovernmental Panel on Climate Change (IPCC), the agreement ambitiously obliges the signed nations to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels (United Nations, 2015).

In November 2016, the Paris Agreement came into effect requiring all nations to prepare and publish their Intended Nationally Determined Contribution (INDC). The INDCs describe the plans of each party state to reduce its greenhouse gas (GHG) emissions and outline its strategies to adapt to or reduce the vulnerabilities expected to be posed by climate change. In principle, the submitted national plans must include a quantifiable carbon reduction target, a reference or a benchmark year, and an implementation timetable. In addition, national plans are expected to include detailed information about the assumptions and methodologies used to estimate and account for GHG emissions. Also, the agreement requires nations to report regularly on their emissions and implementation efforts and to review their plans every five years (United Nations, 2015, IEA, 2016a).

Despite being recognised by the International Energy Agency (IEA) as "an important step forward," the initial collective carbon reduction pledges submitted by the party countries were deemed not sufficient to achieve the objective of the agreement, particularly in relation to limiting the global temperature increase to 2 °C by 2100. According to the IEA analysis, the submitted national carbon reduction pledges,[3] if delivered, would lead to an average increase in global temperature of around 2.7 °C by 2100.[4] Furthermore,

2 There seems to be no consensus in the literature on the temperature increase that would constitute or meet the "well below 2 °C" threshold indicated in the agreement. Furthermore, there is a controversy in the literature about the probability or likelihood of achieving specific temperature targets (IEA, 2016a). Several studies have indicated that the global carbon reduction targets and budgets are very sensitive to this probability or likelihood (IPCC, 2014).

3 Refers to the collective national pledges submitted ahead of the UNFCCC's 21st conference.

4 This figure is based on a 50% likelihood. Other studies suggested different figures. For example, Rogelj et al. (2016) suggested that the INDCs collectively would lead to a median global warming of 2.6-3.1 °C by 2100.

under the same scenario, global temperatures are likely to rise above 3 °C afterwards (IEA, 2016a).

To bridge the gap between the carbon reduction pledges by the different party countries and the objective of the agreement, several governmental bodies, research centres, and thinktanks have engaged in efforts to shed light on the risks of failing to achieve the 2 °C target and to highlight the additional work needed to deliver on the agreement. One notable example is the comprehensive study carried out by the IEA in which they simulated the carbon reduction trajectories of the energy and climate policies announced by the countries as well as their national carbon reduction commitments, technically known as the Reference Technology Scenario (RTS). The study provides a detailed technical analysis of the RTS and compares the carbon emission trajectories of the RTS[5] with the desired two-degree scenario (2DS).

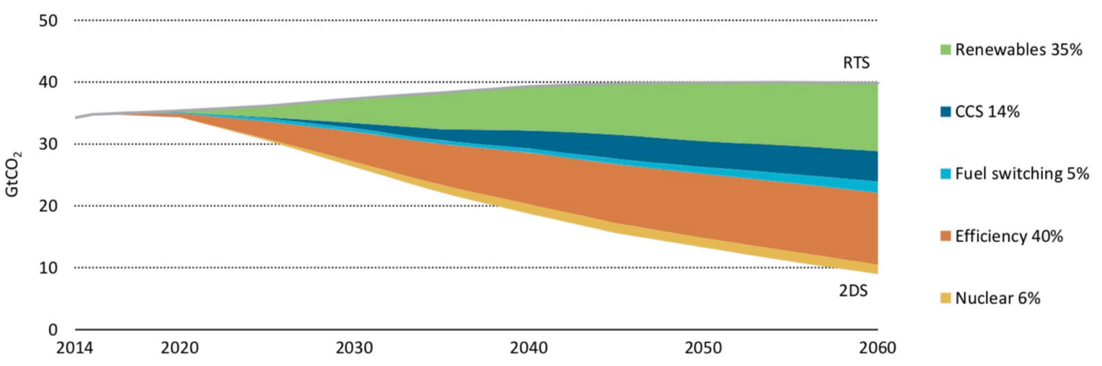

Figure 1: Global CO_2 emission reduction trajectories under the RTS and 2DS. Reproduced from (IEA, 2017).

As Figure 1 indicates, under the RTS, the global CO_2 emission would continue to grow until reaching its peak around 2050. On the other hand, under the 2DS, the global emission would peak around 2020 and continue to fall considerably afterwards, reaching less than 10 $GtCO_2$ by 2060. This implies that the difference in global cumulative carbon budget between the two scenarios would become as high as 760 $GtCO_2$ by 2060.

5 This scenario is assumed as a baseline scenario in the context of the IEA study.

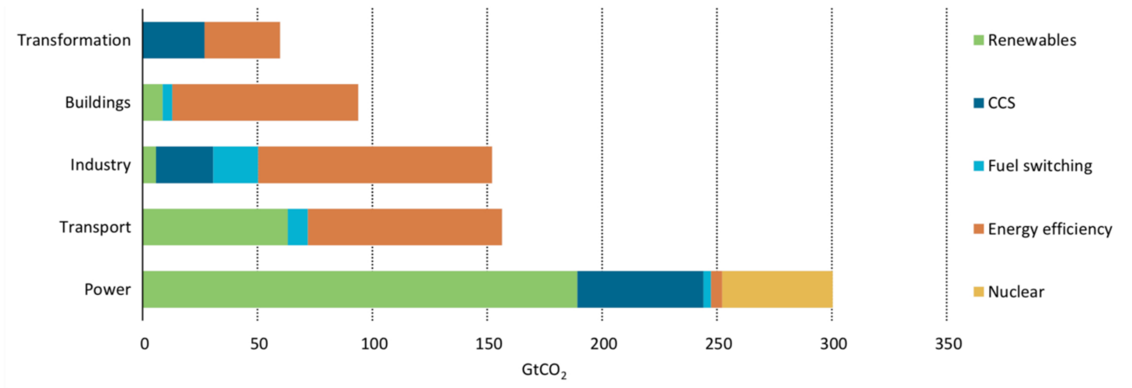

Figure 2: Estimates of the additional cumulative CO2 emission reduction figures needed to meet the 2DS target by 2060 relative to the RTS estimates (by sector and technology). Reproduced from (IEA, 2017).

As Figure 2 indicates, renewables are expected to contribute significantly to delivering the additional carbon reduction needed to achieve the 2DS targets for the power sector. In addition, the enhanced electrification will increase renewables' role in decarbonising the transport and building sectors under the 2DS.

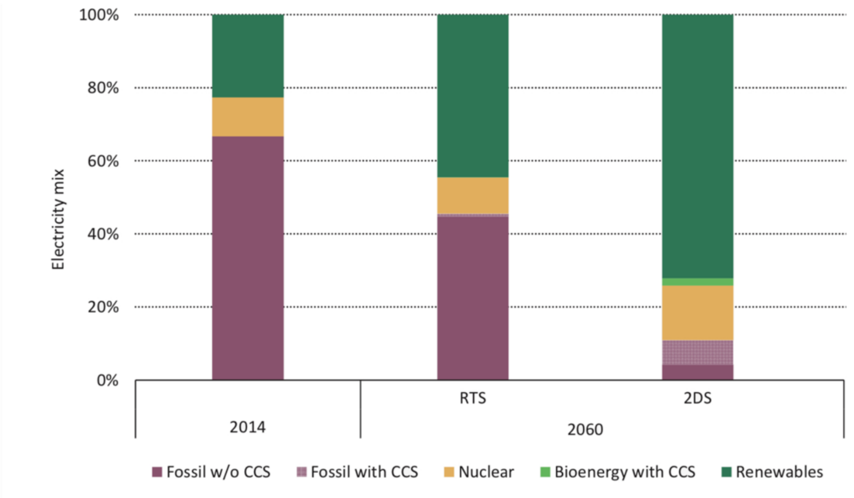

Figure 3: Global generation mix under the RTS and 2DS. Reproduced from (IEA, 2017).

In terms of the technology mix for electric systems, under the 2DS, renewables are expected to deliver around two-thirds of the sector's emission reductions. Furthermore, about 98% of electric energy will come from low-carbon technologies, with the global carbon intensity approaching zero by 2060 (IEA, 2017). This implies a significant transformation of the existing energy systems over the next decades not only at the energy production and consumption levels but also at the planning and operation levels (IRENA, 2017).

2.2 Renewable Energy & Energy Systems

Despite the obvious benefits of renewables, there is a growing recognition that large-scale deployment of variable-output renewable technologies, such as solar and wind, will impose several technical challenges on the operation and planning of current electric systems (Boyle, 2009).

Compared to other energy systems, electric systems are considered to be among the most challenging in terms of planning and operation complexities (Wood et al., 2013). More specifically, the operation of electric systems involves ensuring a continuous equilibrium between the production and consumption of electricity on a second-by-second basis[6] (Pérez-Arriaga, 2013). Furthermore, the multiple planning stages of electric systems involve safeguarding an instantaneous balance between electricity demand and supply for decades to come.

Figure 5 illustrates the traditional planning studies of electric power systems and their respective scope and time horizons and the time resolution of the models used to carry out these studies.

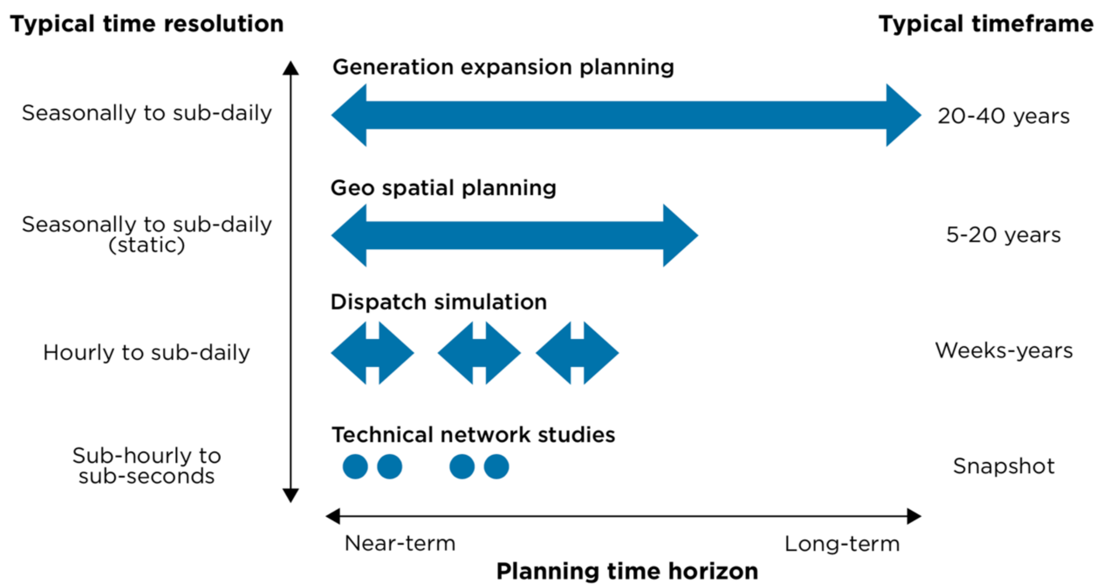

Figure 4: Traditional planning stages of electric power systems and their respective modelling timeframes and models' time resolutions. Reproduced from IRENA (2017).

6 In reality, the timescale can be as small as a few milliseconds for certain grid stability considerations (Kundur, 1994).

Figure 5 illustrates the interdependencies and feedbacks between the different planning stages of electric power systems.

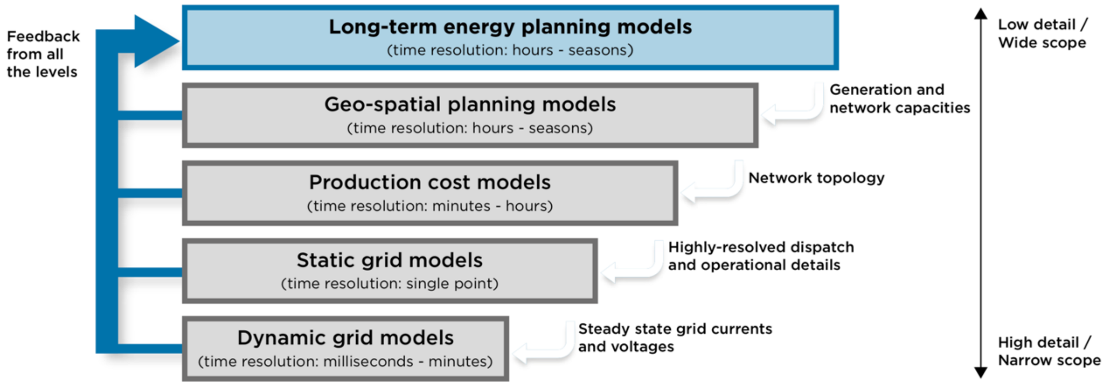

Figure 5: Traditional electric system planning models and their respective modelling scope and timescale. Reproduced from (IRENA, 2017).

The erratic and intermittent nature of variable-output renewables (VRE) makes the already challenging task of long-term planning of electric systems even more difficult (IRENA, 2017). Furthermore, the uncertainty surrounding particular weather characteristics (e.g., cloud cover, dust, wind speed, and wind direction) adds a new layer of complexity to the already sophisticated task (Hart et al., 2012).

Figure 6 illustrates how the unique characteristics of renewable energy sources impact the different stages of electric system planning on various technical levels and timescales.

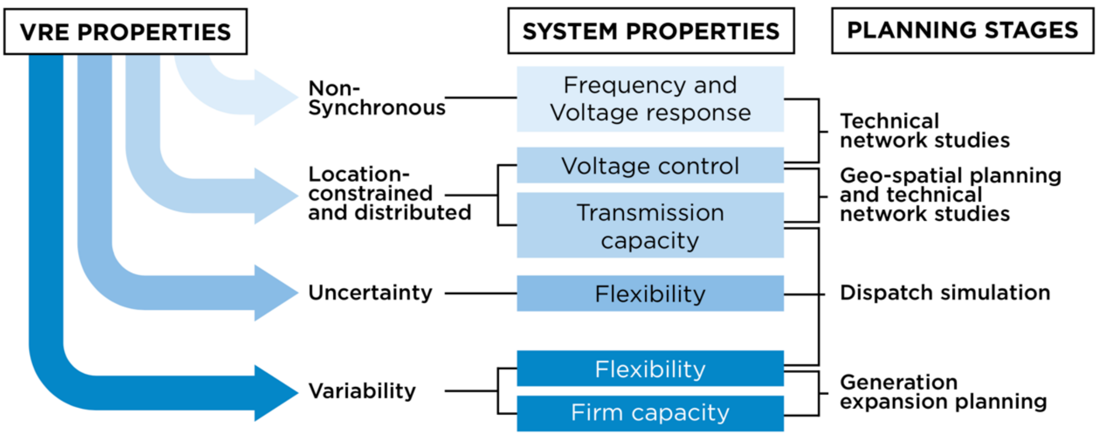

Figure 6: Key relationships between the characteristics of renewable energy sources and power system properties and planning stages. Reproduced from (IRENA, 2017).

2.3 Characteristics of Renewable Energy

Compared to other dispatchable[7] renewable generation technologies (e.g., hydro technology), non-dispatchable generation renewables (e.g., solar, wind, and tidal technologies) have some unique characteristics. Technical reviews of these characteristics are ample in the literature, such as IEA (2014b), Delarue and Morris (2015), and (IRENA, 2017). The following is a brief summary of these characteristics surveyed in the literature.

1- Non-dispatchable output profile

As mentioned earlier, the electricity output of the so-called intermittent[8] generation depends on variations in the underlying natural resources (e.g., wind speed, wind direction, and solar irradiance). Therefore, the energy output of renewable generation can vary widely both on a seasonal and on a diurnal basis. This variability limits the ability to control the output of intermittent generation technologies. Furthermore, it restricts the contribution of renewable generation to the adequacy[9] of the electric system (Strbac et al., 2007). Importantly, this particular characteristic has the potential to affect the operation, economics, and reliability of power systems (Gross et al., 2006).

2- Uncertain output profile

Furthermore, the output of renewables carries a certain level of uncertainty due to its inherent dependence on uncertain weather conditions. However, it is worth noting that the output of conventional generation technologies can also be variable and uncertain.[10] Nevertheless, the output profiles of renewable and convention technologies differ in the frequency and magnitude of their variability and in the degree of uncertainty of their output[11] (Hart et al., 2012). Several studies have indicated that the uncertainty in the output level of variable-output renewables necessitates bigger reserves to run electric

7 Dispatchability in this context refers to the ability of the system operator or the asset owner to actively control the output level of renewable generation in real time (i.e., increasing or decreasing the output levels of the renewable generators).
8 The literature is inconsistent in the terminology describing the exogenous variability of renewable energy sources due to variations in weather conditions. Some studies use the term "variable," while others use the term "intermittent."
9 Generation adequacy refers to having sufficient generation to meet demand at all times (IRENA, 2017).
10 These technologies can be variable due to their changing availability and can be uncertain due to forced outages.
11 The output of wind and solar technologies can fluctuate rapidly over a relatively short timescale, from minutes to hours (Hart et al., 2012).

systems (Doherty and O'Malley, 2005, Ortega-Vazquez and Kirschen, 2009, Madrigal and Porter, 2012). Furthermore, several studies highlighted the importance of advanced computational techniques in improving the forecast of the output of renewable generation and their role in reducing and optimising the allocation of the system's reserve (NERC, 2010, IRENA, 2019, Hodge et al., 2015, Zeng and Qiao, 2011).

3- Location-constrained output profile

Unlike that of conventional generation projects, the technical and financial viability of renewable energy projects hinges to a great extent upon the geographical location of the project. In particular, the availability and the quality of the underlying renewable resource dictate the financials of many renewable projects.

In reality, many optimal locations of intermittent generation can exist in remote areas (e.g., deserts for solar energy and offshore for wind energy). One of the direct implications of this reality is the need for grid infrastructure expansion. This adds to the cost of integrating renewables into electric grids. Several studies have identified the lack or the slow development of grid expansion as a major barrier for integrating renewables into electric systems in many countries around the world, including Europe, the US and China (Green et al., 2016, Lu et al., 2016, Ye et al., 2018). In addition, delays in grid connection have been identified as a driver behind renewables' curtailment in the US and China (Bird et al., 2016, Ye et al., 2018).

4- Modularity and scalability

Solar panels and wind turbines typically come in smaller sizes compared to conventional generation units. The unit size of solar panels ranges from hundreds of watts to several kilowatts, while the size of wind turbines varies from hundreds of kilowatts to several megawatts (IRENA, 2012). The relatively small unit size of renewables makes it possible to connect them at the distribution network instead of at the transmission grid. Although this capability offers several advantages, the interconnection of renewables at the distribution grid raises a number of technical challenges as well, including voltage regulation, congestion management, and system protection and reliability (Walling et al., 2008, Vovos et al., 2007, Harrison and Wallace, 2005, Masters, 2002).

5- Non-synchronous operation

Maintaining the frequency of the system is one of the fundament tasks of system operators (Kundur, 1994, Wood et al., 2013). The frequency of an electric system is directly related to the rotational speed of the electricity generators synchronised with the system. Generators are required to rotate at the same speed (e.g., 3,000 or 3,600 rpm) to be synchronised with the network. As more synchronous generators are connected to the network, the electromechanical inertia of the system increases, thereby enhancing the stability[12] of the system's frequency. Unlike conventional generators, Photovoltaics (PV) cells do not have moving parts; therefore, they do not contribute to the electromechanical inertia of electric systems. On the other hand, wind turbines rotate at variable speeds.[13] However, the kinetic energy stored in the turbines' blades is mechanically decoupled from the grid's electromechanical inertia by power electronic converters (Morren et al., 2006). That is why wind turbines do not have a natural electromechanical inertia contribution[14] to electric systems. However, control strategies can be employed to provide an emulated electromechanical inertia response from the wind turbines, technically known as *synthetic* or *virtual* inertia, during situations in which the electric grid faces disturbances, as illustrated in Figure 7 (Mauricio et al., 2009, Teng and Strbac, 2015, Teng and Strbac, 2016, Van de Vyver et al., 2016, Tamrakar et al., 2017).

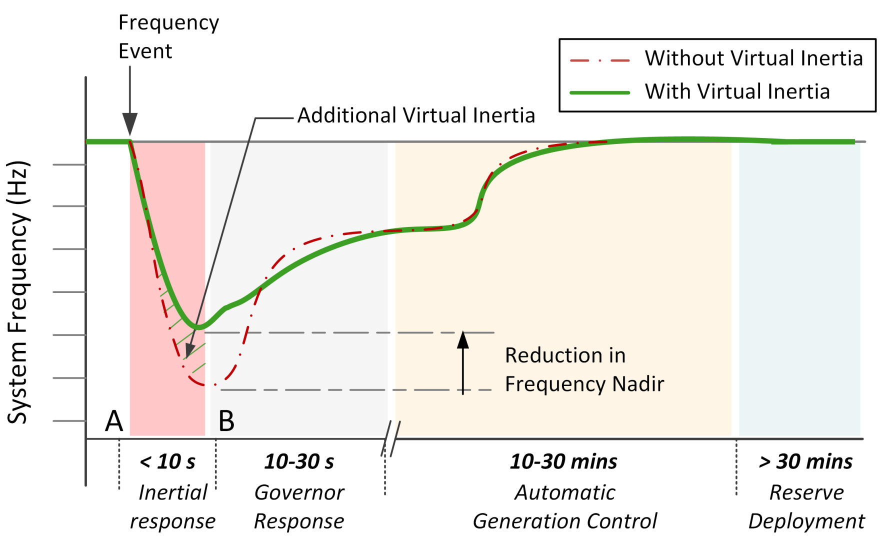

Figure 7: A schematic illustrating the perceived contribution of the so-called virtual inertia of a typical wind turbine to the frequency stability of the electric system. Reproduced from (Tamrakar et al., 2017).

12 The stability of an electric system is a multidimensional concept. Kundur (1994) suggested three main dimensions, or categories, for studying this stability: (1) rotor angle stability, (2) frequency stability, and (3) voltage stability. Further subcategories are also proposed.

13 These are technically known as asynchronous speeds.

14 They do not naturally participate in system-wide frequency control (i.e., primary control response). For example, see Teng and Strbac (2015) and Van de Vyver et al. (2016).

6- Very low marginal costs

Broadly speaking, intermittent renewables tend to have very low marginal costs when compared to other generation technologies. Typically, renewables do not consume fuel and do not incur huge maintenance and variable costs (IEA, 2010a). As a result, their cost structures tend to be dominated by their investment and capital costs, as indicated in Figure 8.

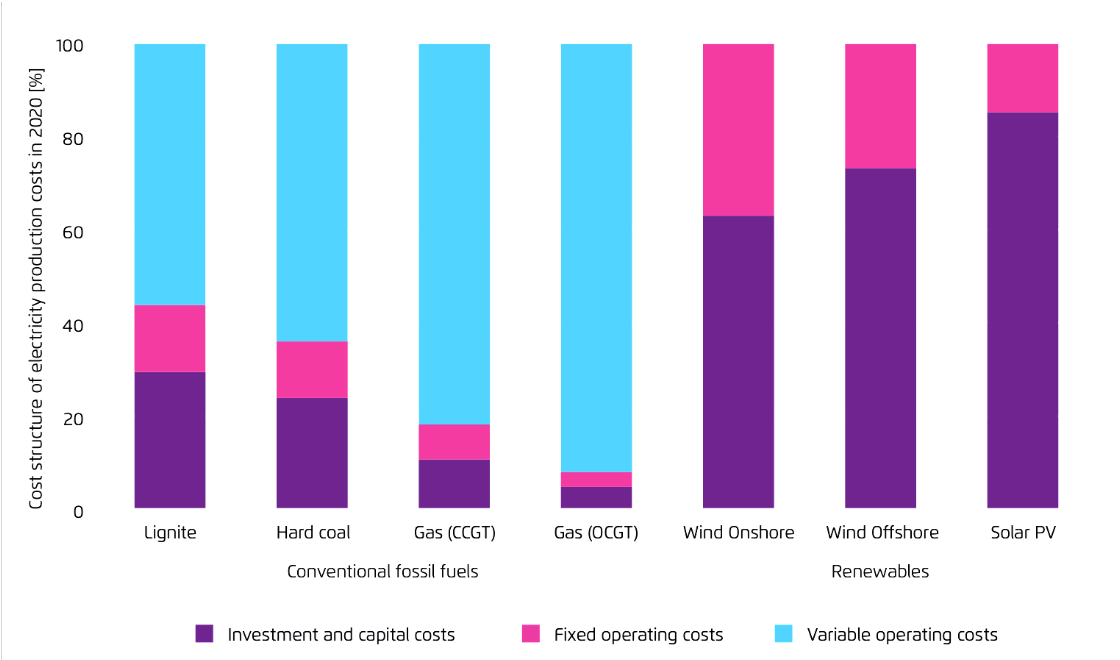

Figure 8: Comparison of the typical cost structures of conventional fossil fuels and renewable technologies. Adapted from (Agora Energiewende, 2018b) and based on data from the International Energy Agency (IEA) and the Nuclear Energy Agency (NEA).

One direct implication of this characteristic is that the increased penetration of "zero marginal costs" renewables can lead to a reduction in the spot market prices. This effect has been reported in many studies covering different electricity markets around the world that have considerable renewable capacity, including the German, Danish, British, and Spanish electricity markets (Baker et al., 2010, Pöyry, 2010, Green and Vasilakos, 2011b). As demonstrated in Figure 9, due to their low marginal costs, renewable energy sources stack at the bottom of the supply curve. The addition of more renewable capacity tends to lower the average prices of the whole electricity market, a phenomenon technically known as "the merit order effect" (Sensfuß et al., 2008, Pöyry, 2010, Cludius et al., 2014, Clò et al., 2015).

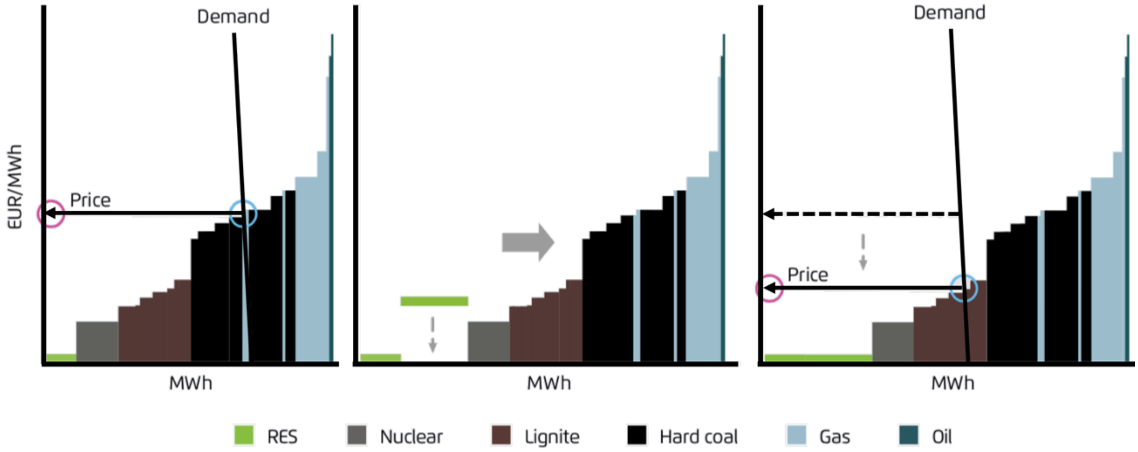

Figure 9: An illustration of the changes in the whole market prices due to the increased penetration of renewables. Adapted from (Agora Energiewende, 2018a).

Figure 10 illustrates the impact of wind power on the December 2005 spot power prices within the western Danish power system.

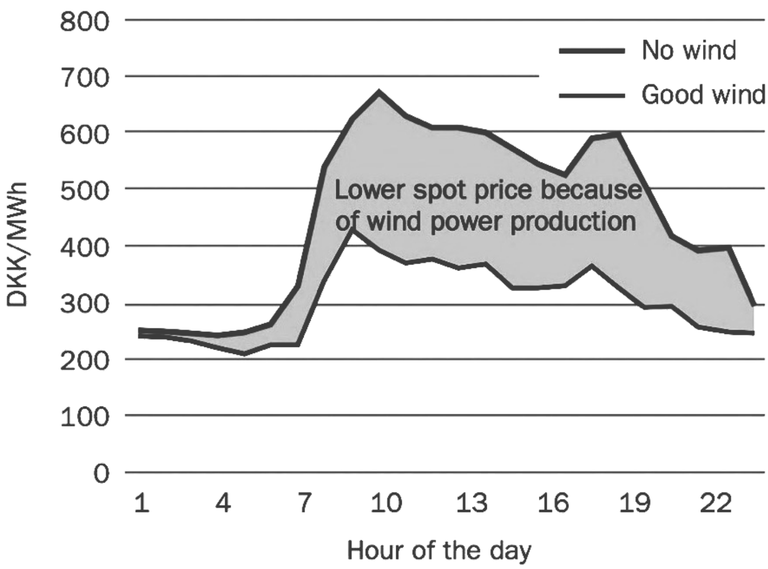

Figure 10: The impact of wind power on the December 2005 spot power price within the western Danish power system. Adapted from (Pöyry, 2010).

Furthermore, it has also been reported that spot market prices might fall to zero or even become negative, particularly when high renewable generation coincides with low-demand periods (Baker et al., 2010). Besides, a 2014 study that investigated the effect of wind generation on spot market prices in Germany reported not only a decrease in spot market prices but also an increase in the prices' volatility due to the increased penetration of wind power (Ketterer, 2014).

2.4 Flexibility Options to Enhance Renewables' Integration

It is widely recognised that accommodating large-scale penetration of intermittent renewables into the system will require additional power system flexibility[15] (Denholm and Hand, 2011, Hart and Jacobson, 2012, Ma et al., 2013a, Brouwer et al., 2015, Strbac et al., 2015, Ulbig and Andersson, 2015). Figure 11 maps some of the technical options that are often discussed in the literature to enhance the flexibility of power systems.

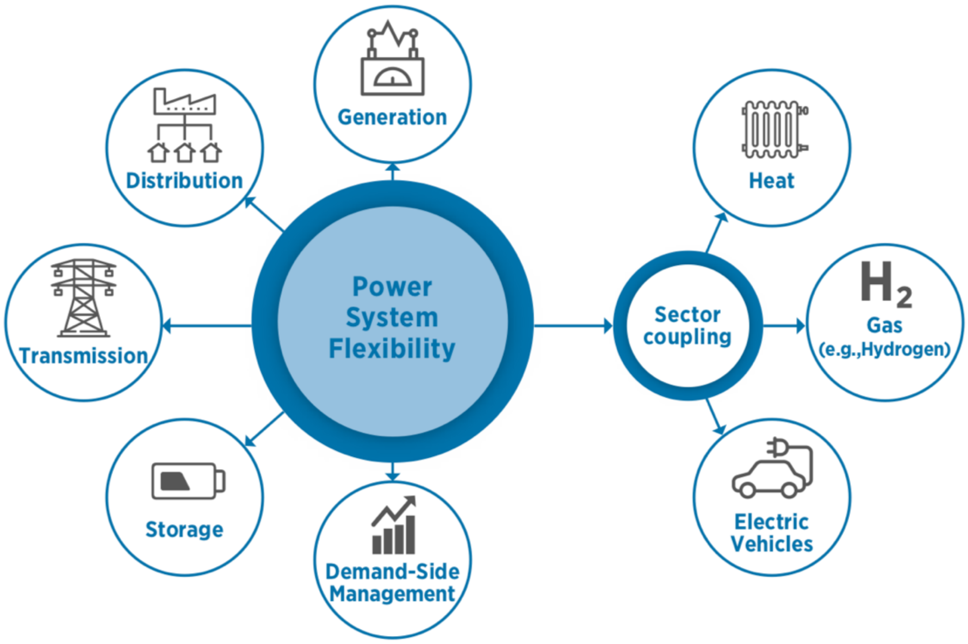

Figure 11: A figure illustrating the different technical options available to enhance the flexibility of power systems. Reproduced from (IRENA, 2018a).

There are many studies that address the flexibility options of power systems. In addition, many reviews have been written on this topic. The following review is based on the taxonomy of flexibility options suggested by Lund et al. (2015).

2.4.1 Supply-side flexibility

2.4.1.1 Generation plants' flexibility

Supply-side flexibility encompasses several operational measures and technologies that can be used to enhance the flexibility of electric systems. One of the major sources of

15 There is no consensus in the literature on a definition for the "flexibility" of electric systems. For example, Ma et al. (2013b) defined flexibility as the ability of a power system to cope with variability and uncertainty in both generation and demand, while maintaining a satisfactory level of reliability at a reasonable cost, over different time horizons.

supply-side flexibility is the operational[16] flexibility offered by the dispatchable plants connected to the system. In essence, the output levels of some plants can be frequently adjusted to cope with possible variations in the system's load, the production levels of renewables, and possible generation or network failures. The flexibility level offered by each generator depends on the technical characteristics of the generators. IRENA (2017) suggested five key technical parameters that determine the flexibility potential of dispatchable power plants:

(1) the ramping rates,[17]
(2) start-up times,[18]
(3) the minimum loading levels,[19]
(4) minimum up- and downtimes,[20] and
(5) the partial load efficiency[21] of the thermal plants.

Figure 12 provides a qualitative illustration of the key flexibility parameters of conventional generation plants.

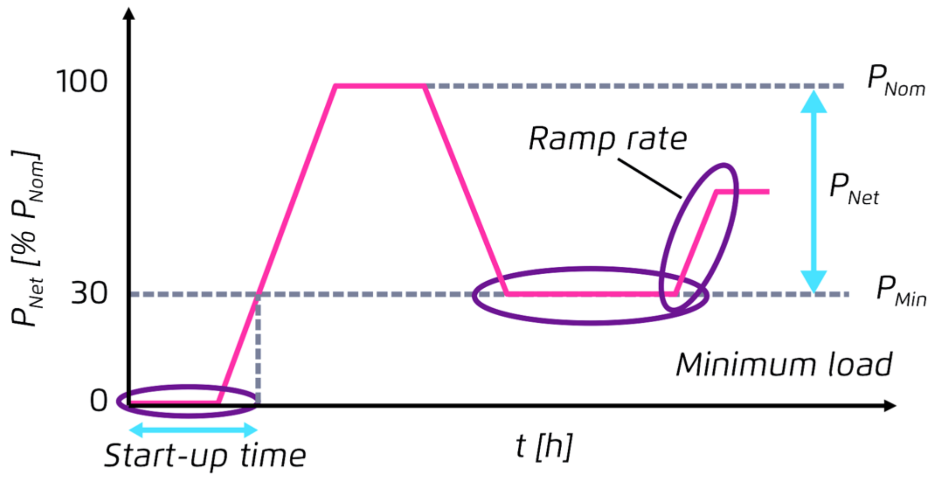

Figure 12: Qualitative illustration of the key flexibility parameters of power plants. Adapted from (Agora Energiewende, 2017).

16 As for electric power flexibility, there is no consensus in the literature on a definition for the "operational flexibility" of electric systems. For example, EPRI (2014) defines the operational flexibility of a power system as the ability to ramp and cycle resources to maintain a balance of supply and demand on timescales of hours and minutes through reliably operating a system at least cost. Other studies suggest less specific definitions. For example, IRENA (2018a) refers to operational flexibility as "how the assets in the power system are operated."
17 A measure for how quickly a power plant connected to the grid can increase or decrease its output (Heptonstall et al., 2017).
18 The time required for a power plant to start up and reach its minimum output level. Technically, plants' start-ups are distinguished depending on how long a power plant has been down (i.e., cold, warm, and hot) (IRENA, 2017).
19 The minimum generation level at which a power plant can be operated stably before it needs to be shut down (IRENA, 2017).
20 The minimum time needed for a plant to be kept online or offline after being synchronised or desynchronised from the grid.
21 The reduced efficiency of a thermal power plant due to its operation under its rated capacity (IRENA, 2017).

As indicated in Figure 13, some conventional generation technologies are better suited and faster than others in terms of responding to variations in the system's conditions.

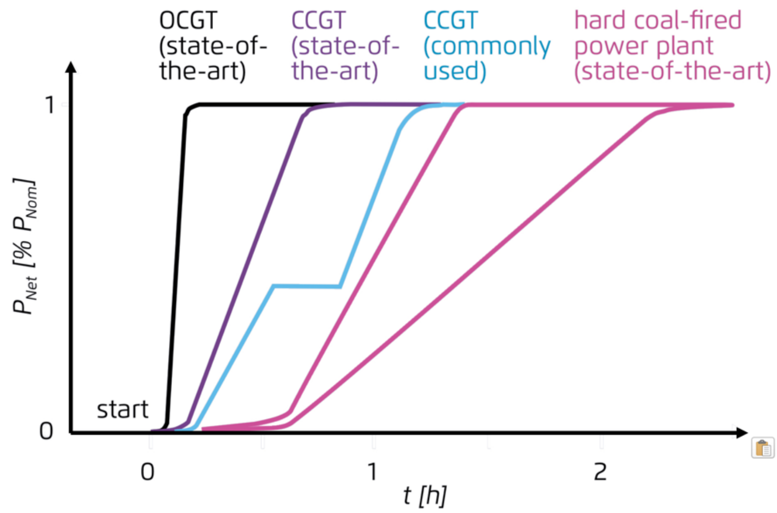

Figure 13: Variations in net power output levels and ramping rates of selected fossil-based generation technologies. Adapted from (Agora Energiewende, 2017).

Table 2 shows indicative figures for the ramping rates, start-up times, and minimum load of different generation technologies.

Technical Property		**OCGT**	**CCGT**	**Hard Coal-fired Plants**	**Lignite-fired Plants**
			Most Commonly Used Power Plants		
Minimum Load[22]	%	40-50	40-50	25-40	50-60
Average Ramp Rate[23]	%/Min	8-12	2-4	1.5-4	1-2
Hot Start-up Time	Min	5-11	60-90	150-180	240-360
Cold Start-up Time	Min	5-11	180-240	300-600	480-600
			State-of-the-art Power Plants		
Minimum Load[22]	%	20-50	20-40	25-40	35-50
Average Ramp Rate[23]	%/Min	10-15	4-8	3-6	2-6
Hot Start-up Time	Min	5-11	30-40	80-150	75-240
Cold Start-up Time	Min	5-11	120-180	180-360	300-480

Table 1: Indicative figures for the minimum load, start-up times, and ramping rates of different technologies. Adapted from (Agora Energiewende, 2017) and based on a survey from various sources.

22 Expressed as a percentage of the nominal load.
23 Expressed as a percentage of the nominal load per min.

2.4.1.2 Curtailment

Limiting renewable energy output, technically referred to as curtailment, is one of the supply-side measures used to control the output of renewables. As the share of renewables considerably increases in the energy mix, this measure can be employed to address several technical issues. These issues include oversupply situations when large and inflexible baseload generation is present during periods of low load demand, when voltage management and system balancing difficulties occur, and when transmission congestion takes place (Fink et al., 2009).

International experience with regard to renewables' curtailment varies widely from country to country, both in scale and in its underlying drivers (Bird et al., 2016). For example, in China, the curtailed wind and solar generation in 2016 amounted to about 17% and 10% of the total renewable power generated, respectively. According to IRENA (2018a), renewables' curtailment in China was driven by several issues, including:

(1) transmission grid constraints,
(2) the existence of contracts that guarantee minimum generation from coal generators,
(3) a lack of market structures that promote investment in flexible plants,
(4) a geographic mismatch between renewable energy resources profiles and the consumption profiles at load centres,
(5) interprovincial transmission restrictions due to bilateral contractual obligations, and
(6) the inflexible operations of the combined heat and power (CHP) plants due to the increase in heat demand.[24]

Several solutions and mitigation options have been proposed to address the curtailment of renewables. These options include storage systems; demand response; integrated planning for the generation, transmission, and distribution networks; investment in additional transmission capacity and interconnections to neighbouring systems; improving renewable generation forecasting accuracy; and providing financial incentives that encourage investment in flexibility assets (Black and Strbac, 2006, Strbac et al., 2015, Ye et al., 2018, Abdilahi et al., 2018, Frew et al., 2021, Zheng et al., 2020). In addition to that, several market and regulatory solutions have been proposed to address the renewable curtailment issue in several countries around the world. These market-based mitigation options include improving spot market and imbalance price signals; reducing

24 CHP coal-fired plants were operated as baseload generation in the northern provinces during winter due to the need to provide constant heat. As a result, their operational flexibility was largely restricted (IRENA, 2018a).

primary frequency regulation requirements allowing for a wider participation in reserve provision and imbalance markets from different market participants including renewable generators; and delivering markets reforms that ensure fairer competition and cost allocation, and greater market liquidity (Sorknæs et al., 2013, Chaves-Ávila and Hakvoort, 2013, Chaves-Ávila et al., 2014, Strbac et al., 2015, Hirth and Ziegenhagen, 2015, Joos and Staffell, 2018, Frew et al., 2021).

2.4.2 Demand-side management

Demand-side management (DSM) or demand response[25] encompasses several demand-side measures and practices that can be used to enhance the flexibility of electric systems. These measures and practices include voluntary adjustments initiated by consumers to their amount or time of energy consumption in response to price signals (Albadi and El-Saadany, 2008). The benefits of DSM are widely reported in the literature. Several studies have highlighted the importance of these benefits, which include reducing the need for generation capacity investments and network infrastructure expansion (Kirschen, 2003, Ma et al., 2013c, O'Connell et al., 2014, Yan et al., 2018). In terms of benefits for electricity markets, DSM could reportedly reduce the prices of peak generation and could potentially shift the market bargaining power from suppliers to consumers (Mathieu et al., 2013).

For a long time, DSM measures were primarily intended to control peak demands and to reduce the need for investment in generation (Kirschen, 2003). Recently, the concept has regained momentum as a way to help accommodate the large-scale penetration of intermittent renewable generation (Aghaei and Alizadeh, 2013). Many studies have indicated that DSM can help reduce the integration costs of renewables (Lamadrid et al., 2011, Jonghe et al., 2012, Papavasiliou and Oren, 2014, Zeng et al., 2014, Gross et al., 2006, Heptonstall et al., 2017, Heptonstall and Gross, 2020, Zheng et al., 2020). For example, in analysing a future UK scenario with 15 GW wind penetration, Roscoe and Ault (2010) reported that demand response can help reduce the requirement for about 8-11 GW of standby generation, potentially saving capital costs of around £2.6 to £3.6 billion.

25 Many definitions of demand response exist in the literature. For example, the Federal Energy Regulatory Commission (FERC) defines demand response as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised (FERC, 2011).

2.4.3 Storage

A large and growing body of literature has investigated the role of storage systems in supporting the evolution of low-carbon systems (Herrmann and Kearney, 2002, Bathurst and Strbac, 2003, Black and Strbac, 2006, McDowall, 2006, Benitez et al., 2008, Denholm and Hand, 2011, Green and Vasilakos, 2012, Green et al., 2011, Foley and Lobera, 2013, Ummels et al., 2008, Kaldellis and Zafirakis, 2007, Strbac et al., 2012).

Storage systems feature a wide range of technologies, including pumped hydroelectric storage (PHES), flywheels, compressed air energy storage (CAES), superconducting magnetic energy storage (SMES), supercapacitors, and different types of batteries.

Examples of notable battery types include lead-acid (L/A) batteries, lithium-ion (Li-ion) batteries, sodium-sulfur (NaS) batteries, vanadium redox batteries (VRBs), and nickel-metal hydride (NiMH) batteries.

Storage systems vary widely in cost, roundtrip efficiency,[26] lifetime,[27] typical power output,[28] standard energy capacity,[29] charging time,[30] discharging time,[31] response time,[32] power density,[33] and other technical characteristics.

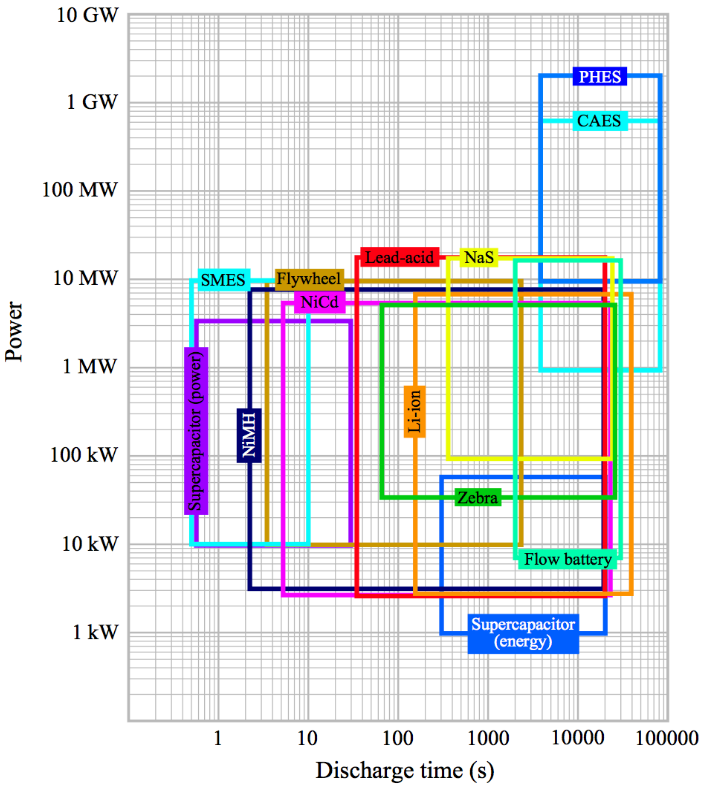

Figure 14: Power output and discharge time for selected storage technologies. Reproduced from (Lund et al., 2015).

26 The ratio of energy discharged by the system to the energy required to charge the system over each cycle, including losses commonly expressed as a percentage.
27 Could be expressed as the number of operating years or the number of cycles depending on the specifics of the technology under consideration.
28 The amount of power that can be discharged from the storage system within the typical discharge duration (measured in MW).
29 The amount of energy that can be stored (measured in MWh).
30 The time needed for the storage system to fully charge.
31 The time needed for the storage system to fully discharge.
32 The time needed for the storage system to start supplying power output.
33 The maximum available power per unit volume (measured in W/L).

The versatility and broad variations in the technical characteristics of storage technologies allow storage systems to provide a wide range of grid services. For example, in their review of storage technologies, Castillo and Gayme (2014) outlined ten grid services that storage technologies can provide: (1) power quality services,[34] (2) transient stability services,[35] (3) frequency regulation services, (4) spinning reserve provision services, (5) load-following services, (6) voltage control services,[36] (7) energy arbitrage services, (8) firm capacity services,[37] (9) congestion relief services, and (10) upgrade deferral services.[38]

Similarly, in their well-cited review, Chen et al. (2009) outlined many grid services that can be provided by storage systems, including peak shaving, area transfer control,[39] and black-start capabilities.[40] They also highlighted the potential role of storage systems in enabling the cost-effective integration of intermittent generation. For example, they highlighted the potential role of storage systems in

1) addressing the intermittency and variability of renewable generation through offsetting the imbalance between demand and supply,
2) reducing the renewable curtailment caused by the lack of expansion of transmission and distribution networks,[41]
3) enhancing the dispatchability of intermittent renewable generation through shifting the time of renewable generation delivery into the grid (i.e., capacity firming),
4) mitigating the risk exposure in the energy markets associated with the forecast errors of renewable generators (i.e., forecast hedge), and
5) suppressing the fluctuation levels in the renewable generation profile through absorbing and reinjecting the renewable generation into the grid over a short time (i.e., profile smoothing).

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34 Refers to services intended to improve the magnitude and the shape of voltage and current waves of the grid's electricity supply. This encompasses many services, such as voltage control, harmonics suppression, and power factor corrections. Some studies suggested that the large-scale deployment of renewables can cause many power quality issues, including voltage fluctuations, increasing harmonics, and flicker levels (Liang, 2017, Tareen et al., 2017).

35 This includes providing support to maintain the synchronous operation of the grid when the grid is subject to a sudden or a large disturbance.

36 For example, this might include injecting or absorbing reactive power from the grid to keep the voltage within acceptable operational limits. Other references suggested that storage systems might provide unbalanced load compensation services, which include injecting and absorbing power from the individual phases of the multiphase grid supply as a result of supplying unbalanced load (Ibrahim and Ilinca, 2013).

37 Refers to providing energy capacity to meet peak power demand (Castillo and Gayme, 2014).

38 Refers to deferring either generation or transmission asset upgrades as a result of using energy storage to reduce the loading on the system (Castillo and Gayme, 2014).

39 Refers to preventing unplanned transfer of power between one utility and another.

40 Refers to units with the capability to start up on their own in order to energise the transmission system and assist other generation facilities to start up and synchronise to the grid after a full or a partial blackout (Ibrahim and Ilinca, 2013).

41 Other studies indicated that storage can also help reduce the curtailment caused by network congestion. For example, see Eyer et al. (2004).

	L/A battery	Li-ion battery	NaS battery	VRB flow battery	Super capacitors	SMES	High-powered flywheels	Pumped hydro	CAES
Energy storage capacity (kW h)	⩽100	⩽10	⩽100	20–50	⩽10	⩽10	1–25	⩾150	⩾10
Typical power output (MW)	1–100	0.1–5	5	0.01–10	0.1–10	0.1–10	0.01–10	250–1000	100–300
Energy density (W h/L)	50–80	200–500	150–250	16–33	2–10	0.2–2.5	20–80	0.5–1.5	3–6
Power density (W/L)	10–400	0	0	0	100,000	1000–4000	1000–2000	0	0.5–2
Discharge duration	Hours	Minutes–hours	Hours	2–8 h	Seconds	Hours	Seconds–minutes	Several hours	Hours
Charge duration	Hours	Minutes–hours	Hours	2–8 h	Seconds	<Seconds	15 min	Several hours	Hours
Response time	<Seconds	Seconds	Milliseconds	<Seconds	Seconds	<Milliseconds	Seconds	Seconds–minutes	Minutes
Lifetime (years)	3–10	10–15	15	5–20+	5–20	5–20	20	25+	20+
Lifetime (cycles)	500–800	2000–3000	4000–40,000	1500–15,000	50,000	>50,000	>100,000	>50,000	>10,000
Roundtrip efficiency (%)	70–90%	85–95%	80–90%	70–85%	90%	>90%	85–95%	75–85%	45–60%
Capital cost per discharge ($/kW)	$300–$800	$400–$1000	$1000–$2000	$l200–$2000	$1500–$2500	$2000–$13,000	$2000–$4000	$1000–$4000	$800–$ 1000
Capital cost per capacity ($/kW h)	$150–$500	$500–$1500	$125–$250	$350–$800	$300–$2000	$1000–$10,000	$1500–$3000	$100–$250	$50–$150
Power quality			√	√	√	√	√	√	
Transient stability	√				√	√	√		
Ancillary services									
Regulation		√	√	√	√	√	√		
Spinning reserves	√	√	√	√				√	√
Voltage control		√	√	√	√		√		
Energy services									
Arbitrage			√	√				√	√
Load following	√	√	√	√		√	√	√	√
Firm capacity							√	√	
Congestion relief	√	√	√	√				√	√
Upgrade deferral	√	√	√	√	√	√	√	√	√
Advantages	Low cost, high recycled content	High efficiency, high energy density,	High energy density, quick response, efficient cycles	Higher depth of discharge, high cycling tolerance	Rapid response time, high power density	High efficiency	Rapid response time, low maintenance, high cycles	Rapid response time, large capacity	Rapid response time
Disadvantages	Low energy density, large footprint, limited discharge depth	Cost prohibitive, overheats, limited discharge depth	Safety issues	Low energy density, low efficiency	Cost prohibitive	Cost prohibitive, low energy density	Cost prohibitive, tensile strength limitations	Geographically constrained	Low efficiency, geographically constrained

Figure 15: Technical comparison of selected types of storage systems and technologies. Reproduced from (Castillo and Gayme, 2014).

2.4.4 Infrastructure

A considerable amount of literature has been published on the role of infrastructure development in enabling the effective and economic grid integration of renewables. These studies address a wide range of topics, including infrastructure development, the challenges of technical implementation, and the policies and market designs that facilitate the transition towards low-carbon systems (Kohler et al., 2010, Torbaghan et al., 2014, Xydis, 2013, Blarke and Jenkins, 2013, Coll-Mayor et al., 2007). Additionally, these studies often vary widely in their context, scope, and infrastructure elements under consideration. Moreover, terms such as supergrids, smart grids, and microgrids s are increasingly used in regard to renewables within infrastructure development research.

Supergrids are made up of a network of high-voltage, direct-current (HVDC) lines connecting different remote sources of renewables (Torbaghan et al., 2014). One important driver for developing such grids is to smooth out the output fluctuations of renewables through connecting sources with different spatial characteristics and load profiles (Brinkerink et al., 2019, Chatzivasileiadis et al., 2013, Ardelean and Minnebo, 2017). Several projects have been proposed as supergrid concepts, such as DESERTEC projects (Samus et al., 2013).

Smart grid is an umbrella term that encompasses several concepts. In its simplest form, a smart grid is a grid in which all the market participants are connected through advanced communication networks with some level of automation to the network assets, which may involve distributed generation, storage systems, and remote metering (Farhangi, 2010, Mohsenian-Rad et al., 2010, Gungor et al., 2011). Microgrids, on the other hand, can be defined as distributed generation technologies that can be used to supply energy services to local areas. These technologies include generation technologies (e.g., micro-CHP), local distribution networks, storage systems, and controllable loads (Lund et al., 2015).

2.4.5 Advanced technologies

In addition to the flexibility options discussed earlier, in recent years, an increasing amount of literature has become available on several advanced technologies that could provide further grid flexibility to support the accommodation of renewables. These technologies include electricity-to-thermal (E2T), power-to-gas (P2G), power-to-H_2 (P2H), and vehicle-to-grid (V2G) technologies.

2.5 Renewables' Grid Integration Impacts

In recent years, several attempts have been made to quantify the economic and environmental implications of renewables' grid integration (Dale et al., 2004, Doherty and O'Malley, 2005, Strbac et al., 2007, Leite da Silva et al., 2010, George and Banerjee, 2011, Perez-Arriaga and Batlle, 2012, Ueckerdt et al., 2013, Brouwer et al., 2014, Huber et al., 2014, Paraschiv et al., 2014, Hirth et al., 2015b, Degeilh and Gross, 2015). However, these attempts vary widely in their scope, timescale, category of impact, technology under consideration, generation mix, and the market condition of the electric system under study. In addition, several review studies have been published on the topic. Good examples of these studies include Gross et al. (2006), Skea et al. (2008), Madrigal and Porter (2012), Heptonstall et al. (2017), and Heptonstall and Gross (2020).

The integration of renewable generation into electricity grids has several technical and economic impacts. Different taxonomies have been proposed to classify these impacts. For example, Holttinen (2004) classified the technical impacts of renewables' grid integration on power systems into (1) an increase in the size of generation reserve, (2) less efficient operation of thermal generation, (3) replacement of thermal capacity by renewable capacity, (4) limiting excess renewable generation (curtailment), and (5) transmission losses and voltage fluctuations.

In assessing the economic implications of these technical impacts, various studies have taken different approaches to evaluating the grid integration costs of renewables. One stream of literature has focused on quantifying the costs of certain technical impacts in great detail. For example, some studies investigated the effects of increased cycling and start-up activities of thermal generators on the economics of the power system (Van den Bergh and Delarue, 2015, Göransson et al., 2017).

Other studies have emphasised evaluating the increase in the unit cost of generation, or the levelised cost of energy (LCOE), due to renewables' penetration in power systems. Good examples of this stream of studies include Dale et al. (2004), Strbac et al. (2007), Ueckerdt et al. (2013), and Hirth et al. (2015b).

An extensive literature review on the costs of renewables' grid integration reveals a lack of consensus on reporting these costs. For example, in their review, Gross et al. (2006)

proposed two categories to report the costs of renewables' grid integration. The first category relates to the short-term adjustments needed to manage the fluctuations in renewables' output, the so-called costs of intermittency or system balancing costs. The second category relates to the long-term contribution of renewables to the reliability of supply, the so-called reliability impacts. On the other hand, Strbac et al. (2007) reported the costs of wind integration into the UK system using three cost categories: (1) costs of wind generation, (2) balancing costs, and (3) network costs. Furthermore, Hirth et al. (2015) took a market perspective to report the costs of renewables' grid integration. They proposed three categories to reflect the market value of renewables' generation. The first category relates to the reduction in market value due to deviations from day-ahead generation schedules, the so-called balancing costs. This cost category is largely driven by forecast errors of renewables' generation. The second category relates to a reduction in market value due to the location of renewables' generation within the grid. This category is driven by transmission costs. The third category relates to the market value of renewables' generation due to the profile of renewables' generation, the so-called profile costs. This category reflects the time value of generation in the market.

In addition, a literature review on the factors driving the grid integration costs of renewables reveals a wide range of factors, which vary widely with the scope of the study and the technical impact under consideration. Skea et al. (2008) identified several broad factors affecting the grid integration costs of renewables. These factors include (1) the nature of the environmental resource, (2) the level of penetration of renewables and their spatial diversity, (3) the condition of the electricity transmission and distribution infrastructure, and (4) the operating and regulatory practices related to the system operation. Based on these drivers, they suggested that the costs of renewables' grid integration are context specific and that they can change over time.

Likewise, a large and growing body of literature has looked at the environmental contributions of renewables. Broadly speaking, these studies vary widely in scope, timescale, and level of depth and details. Furthermore, they also tend to vary widely in their analytical approaches and technical and economic perspectives. A detailed review of the scholarly works covering the environmental contributions of renewables is a particularly lengthy topic. Therefore, in the interest of avoiding repetition and keeping this chapter as concise as possible, a more specific review on the topic will be included in the later chapters of this thesis.

CHAPTER 3

METHODOLOGY & DATA

3.1 Introduction

Building on the literature review presented in Chapter 2, in this chapter, we briefly review the methodologies used in the literature to study and quantify the expected carbon savings of renewables. Then, we focus on discussing the methodologies we used in our study. In particular, we discuss their origins, merits, and present their mathematical formulations.

In addition, we present and discuss the study's input data and assumptions and we provide a description of the electric system under study. Furthermore, we briefly present our modelling approach and discuss the modelling assumptions we used in our study.

3.2 Overview of Renewable Energy Carbon Saving Estimation Methods

Broadly speaking, there are two dominant types of modelling approaches or two "families of models" that have been used in the literature to quantify the carbon savings of renewables. The first family encompasses different variations of statistical models, and the second family includes different variations of optimisation-based models.

3.2.1 Statistical Models

In the statistical approach, researchers often use historical data and different regression methods and models to estimate the carbon savings of renewables. Owing to its simplicity and light technical data requirements, this approach has become particularly popular for studying the historical trends of carbon emission in the power sector in different regions of the world.

In one study, for example, Cullen (2013) used two statistical models to estimate the emissions offset by wind power for a large electricity grid in Texas between 2005 and 2007. In contrast to similar statistical studies such as Kaffine et al. (2013), Cullen controlled in his analysis for some of the dynamic aspects of power system operations, such as the operation status of the units prior to dispatch, the congestion of the transmission lines, and the operating temperature of the generation units. He reported that not controlling for these dynamic impacts would overestimate the wind emission savings by approximately 31%. He attributed this to a significant shift in the composition of the displaced generation from carbon-intense technologies (i.e., coal) in his first "static" model to relatively cleaner technologies (i.e., gas-fired) in his second "dynamic" model. His results highlight the significant difference between the two approaches in estimating the carbon savings of renewable technologies.

In another study, Katzenstein and Apt (2009) compared the carbon emission estimates of a statistical model with an emission displacement analysis using average carbon displacement values. Using 1-minute resolution data capturing the interactions between the variable wind profile and solar resources in different parts of the United States and different types of regulating gas turbine units, Katzenstein and Apt simulated the CO_2 emissions of the regulating gas units as a function of the units' power level and ramp rate. They concluded that the conventional emission displacement analysis would overestimate the emission reductions by approximately 23% for CO_2 emissions and between 55% and 80% for the NO_x emissions of the simulated gas turbine units considered in the study. It is worth noting that their emission reduction analysis and simulations were carried out at the level of the gas generating units rather than at a system-wide level. Their analysis also suggests that the CO_2 emission factors would decrease linearly with renewable penetration, albeit slower than expected under the conventional offset assumption. By contrast, the NO_X emission factors were found to stay roughly constant at relatively high renewable penetration rates, limiting the effectiveness of the renewables in reducing the NO_X emissions of the gas turbines under consideration.

Despite the popularity of using this method to quantify the emission savings of renewables, this approach is believed to have several disadvantages. Cullen (2013) outlined several limitations of the statistical models in analysing the carbon saving trends of renewables. For example, Cullen pointed out that statistical models require a significant portion of renewable production to estimate its effects on reducing carbon emissions. This restricts studying the impact of shallow and modest penetration levels of renewables. Furthermore, it restricts the analysis beyond the observed levels. In addition, Cullen noted that statistical models cannot deal with grid technical issues such as reliability and congestions issues that engineering models can handle. Perhaps the most serious shortcoming is that it does not incorporate the mathematical and engineering relationships capturing the physical behaviour of the power systems and the economic and environmental implications of this behaviour. This serious drawback limits its power to analyse future scenarios and restricts the validity of its results beyond the historical data available. *This explains why we did not use this method for carrying out our study as it focuses on projecting the long-term renewable carbon savings under deep decarbonisation scenarios. This also explains why we choose to build techno-economic models for the purpose of our study.*

3.2.2 Optimisation-based Models

In the optimisation approach, researchers typically build bottom-up, techno-economic models for the power systems under study. There are significant variations among these models in terms of their temporal resolutions, the amount of technical detail included, and, in some cases, mathematical formulations. In the forthcoming sections, we will review the most common models' types used in the literature to study the integration of renewables into electric systems and to quantify their emission savings. In particular, we will review two of the most extensively used variations in the literature: the Screening Curve (SC) models and the Unit Commitment (UC) models. This explains our focus on these particular optimisation-based methods' variations for carrying out our research.

3.2.2.1 Screening curve method

The SC method is one of the earliest and most used methods for optimising the generation capacity mix of electric power systems. Owing to its simplicity and light computational and data requirements, the SC method continues to be extensively used in scholarly works. Notable early works that contributed to the development of the SC method include Kirchmayer et al. (1955), Massé and Gibrat (1957), Hicks (1959), Galloway et al. (1960) and Phillips et al. (1969).

The SC method aims to find the optimal generation mix that minimises the investment and operation costs of generation assets in a given power system. The original formulation considers two cost components for each generation asset class or type namely: *fixed* and *variable* costs. The *fixed cost* is typically associated with the investment and the fixed Operation & Maintenance (O&M) costs[42]. The *variable cost* is typically broken down into fuel and variable (O&M) costs[43]. The total cost of each generator's type is often expressed as a function of the number of operating hours over the desired planning horizon[44]. Then, a cost screening curve is plotted for each generator type over the optimisation period considered[45]. This allows for identifying the optimum number of operating hours for each generator's type during which a particular type would be the least-cost option for meeting the system demand. This can be graphically identified by tracking the number of hours associated with the points of intersections for the

42 Typically expressed as annualized cost figure (i.e., $/MW-y).
43 Typically expressed as hourly cost figure (i.e., $/MWh).
44 For example, 8760 hours.
45 Each screening curve has a slope equal to the sum of the generator's variable costs and an intercept equal to the annualised fixed cost.

different screening curves considered. Then, these hours are typically matched with the Load Duration Curve[46] (LDC) graph of the system to work out the corresponding size of each generator type required to meet the system demand. Traditionally in SC analysis, expensive to build and cheap to operate generators are called “baseload” or sometimes “must-run” plants. Cheaper to build but more expensive to operate are typically called “intermediate” plants. Cheap to build and expensive to operate are called “peakers” as they tend to operate in high or peak demand hours.

Interestingly, the economic intuition of having “peakers” units in electric systems can be traced back to the early works of Kirchmayer et al. (1955) who explained the economic value of having a new class of units with low capital and high operating costs to co-optimise the investment and operation of electric systems having expensive to build and cheap to operate units. In 1960, using a heuristic computer model and LDC analysis, Galloway et al argued for having a third class of units “intermediate plants” to further optimise the investment in thermal power plants.

In addition to early graphical solution approaches, the screening curve problem has been mathematically formulated and solved as a linear programming (LP) problem with the objective of minimising the total system cost of meeting the system demand (Anderson, 1972)[47]. The objective function of the LP program can be expressed using the following mathematical formulation for all generators sets over the planning horizon :

$$C^{Total} = min \sum_{g \in G} \left(\sum_{t \in T} P_{g,t} \, C_{g,t}^{Var} + I_g \, C_g^{fix} \right) \tag{1}$$

Where C^{Total} represents the total system cost, $P_{g,t}$ represents the power output of generator g at time t, $C_{g,t}^{Var}$ represents the total variable costs of generator g, C_g^{fix} represents the total fixed costs of generator g, and I_g represents the installed capacity[48] of generator g. Subject to:

$$\sum_{g \in G} P_{g,t} = L_t \qquad \forall \quad t \in T \tag{2}$$

Where L_t represents the total system load at time t

46 LDCs are non-chronological load curves in which demand data is ordered in descending order of magnitude against the duration of the demand level over the time horizon considered (i.e., one week or one year).

47 It is suggested that Massé and Gibrat (1957) introduced perhaps the first representation of the capacity planning investment model as an LP optimisation problem.

48 Typically, implemented as a non-negative value decision variable.

Despite the dominance of the original formulation, incremental improvements to the basic method continue to emerge in the literature. These improvements tend to address the dynamic aspects of power system operations that the original method did not capture. These aspects include the start-up costs of generation units, the indivisibility of the generating plants, the minimum stable output levels, the partial loading efficiency penalty, the reserve margins and participation levels, and other system-level security constraints and requirements (De Sisternes, 2013). Examples of these studies include Batlle and Rodilla (2013), Zhang and Baldick (2015), Staffell and Green (2016), and Zhang and Baldick (2017).

In one study, for example, Staffell and Green (2016) propose a new heuristic for incorporating the generators' start-up costs into the traditional SC model. Staffell and Green gauged the performance of their new heuristic against the performance of a traditional SC model and a more technically detailed mixed-integer linear programming (MILP) model for the British system. The heuristic yields a better representation of the hourly pattern of electricity prices and reduces the errors in capacity investment by a factor of two while preserving the model's simplicity and light data requirement.

Scholarly works using the SC modelling approach to study renewable grid integration are common in the literature. Examples of these studies include Martin and Diesendorf (1983), Grubb (1991), Lamont (2008), Green and Vasilakos (2011a), Ueckerdt et al. (2015), Belderbos and Delarue (2015), Palmintier and Webster (2016), and Poncelet et al. (2016).

3.4.2.2 Unit commitment models

As the name suggests, UC models seek to find the optimal commitment status (on, off) of the system's generating units over a given period of time. In its simplest form, it seeks to minimise the operation costs of meeting the demand of an electric system subject to an array of operational, environmental, and reliability constraints (Wood and Wollenberg, 1996). Extended formulations of the basic UC models also allow for optimising the investment costs in building or retiring power plants[49]. Notable early works that led to the development and

[49] Literature review revealed inconsistency among researchers in using the technical terms to refer to this class of models. For example, some researchers use the term Resource Planning (RP) or Generation Resource Planning (GRP) models. Readers may refer to Marwali and Shahidehpour (2000) and Shahidehpour et al. (2005) as examples. Other researchers use the term Generation Expansion Planning (GEP) models. Examples of researchers using this term include Meza et al. (2009) and Dehghan et al. (2014).

popularity of the UC method for optimising the operation and investment in power systems include Baldwin et al. (1959), Kerr et al. (1966), Guy (1971), Anderson (1972), Pang and Chen (1976), and Cohen and Wan (1987). It might be worth noting that some of the literature surveyed tend to use the term, Short-term Resource Scheduling (STRP) to refer to the UC problem such as Ferreira et al. (1989) and Svoboda et al. (1997). Other studies refer to it as Short-term Generation Scheduling (STGS) such as Marwali and Shahidehpour (2000).

In contrast to SC models, UC models allow for the representation of the operational characteristics of the generating units. These include the units' sizes, start-up emissions and costs, the minimum stable output levels, ramping rates, heat curves, and reserve margins. It also allows for imposing system-level constraints, such as must-run technologies, transmission congestion restrictions[50], interconnection transfer limits[51], and reliability constraints[52]. While contributing to improving the quality of power system modelling, this increased modelling sophistication translates into a significant increase in the computational complexity of solving these models, especially for larger ones. In the literature, this increased complexity is often referred to as the "curse of dimensionality[53]" (Farhat and El-Hawary, 2009).

Literature survey reveals multiple variations in the mathematical formulations of the UC models. One key variation among UC models is related to how uncertainty in the models' inputs[54] is treated. Traditional UC models take a deterministic approach in representing the models' inputs while UC models that consider data uncertainty uses a stochastic approach to formulating and solving the UC problem. Examples of scholarly works that adopt the stochastic approach include Carpentier et al. (1996), Takriti et al. (1996), Ozturk et al. (2004), Wu et al. (2007), Wu et al. (2008) and Tuohy et al. (2009).

It is worth noting that a hybrid stochastic-deterministic approach to solving the UC problem does exist in the literature. Readers may refer to Restrepo and Galiana (2011) and Tan and Shaaban (2015) as examples of this class of hybrid UC models.

50 See Batut and Renaud (1992), Shaw (1995), and Wang et al. (1995).
51 See Yuan-Yin et al. (1991), (Lee and Feng, 1992), and Yong et al. (2005).
52 See Guy (1971), Wu et al. (2008), and Hedman et al. (2010)
53 The term can be traced back to the increased difficulty associated with solving dynamic programming models. In particular, it is believed that the term was first coined and popularised by Bellman (1957).
54 This might include uncertainty in renewable generators' production levels, demand forecast, and failure of power systems components (Zheng et al., 2015).

Solution methods for the UC problem have attracted the attention of many researchers across multiple fields. These methods include heuristic methods (e.g., priority lists[55]), mathematical methods (e.g., dynamic programming[56], Lagrangian relaxation[57], quadratic programming[58], mixed-integer linear programming, branch-and-bound[59]), and computational intelligence methods (e.g., artificial neural network[60], simulated annealing[61], genetic algorithms[62], tabu search[63], ant colony[64], particle swarm optimisation[65], firefly algorithm[66], and fuzzy logic[67]).

More recently, however, in contrast to other UC solution methods, the mixed-integer linear programming (MILP) method has become a popular method for solving large-scale UC models. Despite its early existence in the literature, high computational power requirements and long computational times have made MILP models an unattractive method for solving large UC problems in the early days[68] (Dillon et al., 1978). Yet, continued advances in computing technologies and computational power capabilities, improved solving techniques, formulations, and algorithms have significantly contributed to its current popularity (Bixby and Rothberg, 2007, Morales-España et al., 2013a).

New research tends to focus on improving the mathematical representation of some technical characteristics of the generating units and their operational constraints, introducing tighter formulations, and improving the computational performance of MILP UC models. Examples of these studies include Carrion and Arroyo (2006), Ostrowski et al. (2012), Morales-España et al. (2013a), Morales-España et al. (2013b), Palmintier and Webster (2014), and Morales-España et al. (2016). In addition, many studies compare the performance of MILP with other solving techniques, such as Lagrangian relaxation. This stream of studies includes Hobbs et al. (2001),

55 See Baldwin et al. (1959), Tong et al. (1991), and (Senjyu et al., 2003)
56 See Pang and Chen (1976) and Wang and Shahidehpour (1993).
57 See Cohen and Wan (1987), Ruzic and Rajakovic (1991), (Shaw, 1995), and Ongsakul and Petcharaks (2004).
58 See Finardi and Silva (2006).
59 See Cohen and Yoshimura (1983) and Chen and Wang (1993).
60 See Sasaki et al. (1992) and Ouyang and Shahidehpour (1992).
61 See Zhuang and Galiana (1990), Mantawy et al. (1998b), Simopoulos et al. (2006) and Purushothama and Jenkins (2003).
62 See Chuan-Ping et al. (2000), Dasgupta and McGregor (1994) and Swarup and Yamashiro (2002).
63 See In-Keun et al. (1998), Mantawy et al. (1998a), Shi et al. (2004), and Victoire and Jeyakumar (2005).
64 See Sisworahardjo and El-Keib (2002) and Simon et al. (2006).
65 See Saber et al. (2007), Zwe-Lee (2003) and Zhao et al. (2006).
66 See Rampriya et al. (2010) and Chandrasekaran and Simon (2012).
67 See Saneifard et al. (1997) and Kadam et al. (2009).
68 It is believed that the first MILP power scheduling model was introduced by Garver (1962). Other early works include Hara et al. (1966). Interestingly, it is widely recognised that the application of mathematical models to the optimisation of industrial processes, including power scheduling, was largely influenced by the development of economic planning models (Dantzig, 1955, Charnes and Cooper, 1957).

Tao and Shahidehpour (2005), and Frangioni et al. (2011). A full review of all solution techniques of UC models is understandably beyond the scope of this chapter; however, excellent reviews were provided by Sen and Kothari (1998), Padhy (2004), Yamin (2004), Saravanan et al. (2013), Zheng et al. (2015), and Abujarad et al. (2017).

Table 2 summarises the advantages and disadvantages of the surveyed techniques for solving the UC models based on the review provided by Abujarad et al. (2017). In addition, Table 3 compares the structure, solution algorithms, advantages, and disadvantages of the common stochastic UC models based on the literature survey done by Zheng et al. (2015).

Studies using the UC modelling approach to study the impact of renewables integration into power systems and their carbon savings are ample in the literature. Examples include Denny and O'Malley (2006), Tuohy et al. (2009), Ma et al. (2013a), Belderbos and Delarue (2015), and Cebulla and Fichter (2017).

In one study, for instance, Hart and Jacobson (2011) used UC models to investigate the potential of decarbonising the Californian electricity system using both a deterministic and a stochastic treatment of the output of renewables. Hart and Jacobson investigated the carbon abatement potential of multiple renewable technology portfolios, including wind turbines, photovoltaics (PV), concentrated solar power (CSP), and geothermal power in California. The results showed that the deterministic treatment of the output of renewables in integration studies might overestimate the achievable carbon emission reductions of the Californian system by approximately 33% when compared with the stochastic treatment using Monte Carlo simulations. Their study thus demonstrated the impact of the choice of modelling approach of the renewable output on carbon estimates of decarbonisation studies.

In another study, Palmintier and Webster (2016) used SC and UC models to investigate the carbon emission savings for a hypothetical renewable target (i.e., 20% Renewable Portfolio Standard and carbon tax (i.e., \$90/ton CO_2), for Texas-like system data. they reported that the difference in CO_2 emission results between the two models can be as high as 35% for the scenario reported. Their results thus highlighted the impact of incorporating flexible generator parameters on the accuracy of CO_2 predictions.

Method		Advantages	Weakness/disadvantages
Heuristic	Priority List	Simplest and easiest UC method and converge very fast.	The solution is usually far from optimal and the quality is not very high.
Classical/ Mathematical	Dynamic Programming	Relatively easy to add constraints that affect operation at any hour	Require to limit the commitments considered at any hour.
		Ability to maintain the solution feasibility.	Suboptimal treatment of minimum up and downtime constraints and time-dependent start-up cost.
		Ability to solve problems of a variety of sizes and to be easily modified to model characteristics of different utilities.	Curse of dimensionality, which may result in unacceptable solution time. These disadvantages lead to suboptimal schedules.
	Lagrangian Relaxation	Easily modified to model characteristics of specific utility.	Require to limit the commitments considered at any hour.
		Flexibility in dealing with different types of constraints.	Suboptimal treatment of minimum up and downtime constraints and time-dependent start-up cost.
			Curse of dimensionality, which may result in unacceptable solution time. These disadvantages lead to suboptimal schedules.
	Stochastic Programming	The optimal decision ensures the minimum total cost in an expected value sense.	The computational costs increase significantly compared to deterministic formulation
	Quadratic Programming	Simultaneously solves UC and economic load dispatch.	
	Mixed Integer Linear Programming	Flexible and accurate modelling capabilities.	Computational complexity
		Ability to reach a globally optimal solution.	Takes a long time compared to fast methods like priority list.
	Branch-and-Bound	Finds an optimal solution (if the problem is of limited size and enumeration can be done in a reasonable time).	Exponential growth in the execution time with the size of the UC problem.
		Expresses power generation characteristics more accurately.	Augments the problem dimension and the complexity.
Hybrid Meta-Heuristic	Different Hybrid Techniques	Obtain better solutions through a strategy for escaping from a local solution.	Fine-tuning is one of the main drawbacks faced by almost all heuristic-based approaches.
		To handle indifferentiable cost functions and constraints.	
		High speed and accurate solution.	
		Improving the computational efficiency and accuracy of the model.	
Computational intelligence	Artificial Neural Network	Capable of dealing with a stochastic variation of the scheduled operation point with increasing data.	The computation time increases exponentially with the increase of the size of the problem.
		Flexibility with noisy data.	
		Implicit nonlinear modelling and filtering of system data.	
		Ability to handle large and complex systems with many interrelated parameters.	
	Simulated Annealing	It does not need a complicated mathematical model of the problem.	It takes a great deal of CPU time to find the near-optimal solution.
		The starting point can be any given solution and the algorithm will attempt to improve the solution.	
		The final solution does not strongly depend on the initial solution.	
		Does not need large computer memory.	
		It has been theoretically proved to converge to the optimum solution.	

Table 2: Advantages and disadvantages of different solving techniques of the UC models. Reproduced from Abujarad et al. (2017) based on several sources.

Method		Advantages	Weakness/disadvantages
Computational intelligence	Genetic Algorithm	it provides flexibility in modelling both time-dependent and coupling constraints.	It cannot guarantee the optimally of the provided solution
		It can be very easily converted to work in a parallel converter.	GA has a high execution time.
	Tabu search	It is one of the general optimization techniques; the cost function has no limitations.	It can be trapped in a local optimum, without the possibility of exploring other regions of the solution space
		It is based on heuristics, but the computational efficiency is better than other optimization ones.	
		It does not make use of random numbers. The obtained solutions are not influenced by the quality of the random number.	
		Simplicity	
	Ant Colony	Inherent parallelism	Theoretical analysis is difficult.
		Positive Feedback accounts for the rapid discovery of good solutions	Sequences of random decisions (not independent).
		Efficient for Traveling Salesman Problem and similar problems	Probability distribution changes by iteration.
		Can be used in dynamic applications	Research is experimental rather than theoretical.
			Time to convergence uncertain (but convergence is guaranteed!)
	Particle swarm optimization	Robust to solve problems featuring nonlinearity and non-differentiability	The candidate solutions in PSO are coded as a set of real numbers. But, most of the control variables such as load changes and generation capacities change discretely.
		Multiple optima and high dimensionality through adaptation.	Real coding of these variables represents a limitation of PSO methods as simple round-off calculations may lead to significant errors.
		Easy implementation, simple concept, and potential to achieve a high-quality solution with stable convergence characteristics.	Slow convergence in refined search stage (weak local search ability).
		Fast convergence speed.	
		Less parameter to tune.	
		Easily deal with non-convex objective functions.	
		Flexibility to control the balance between the global and local exploration of the research space.	
		Easy search in large scale problems like UC problem.	
	Fire Fly	Easy to understand and code.	Slow convergence.
		It is more effective in optimization of environmental and economic dispatch problem	
	Fuzzy Logic	The crisp output can be further used in developing a qualitative interpretation.	Cannot handle large scale systems.
		Ability to handle any type of unit characteristics data	

Table 3: Advantages and disadvantages of different solving techniques of the UC models. Reproduced from Abujarad et al. (2017) based on several sources - Cont'd.

Stochastic Optimisation UC methods	Structures	Algorithm	Advantage	Disadvantage
Stochastic Programming	Two-stage models	• Benders Decomposition (BD) • Accelerated BD • Lagrangian Relaxation (LR) • Stabilized LR (using Bundle methods) • Sample Average Approximation	• Minimize total expected; easier to understand (and compute) than minimizing regret or minimizing the worst-case cost. • Various decomposition and sampling-based algorithms already existed with convergence and performing guarantees. • Can address robustness issues using risk measures. • Can provide an expected value of perfect information (EVPI) and value of the stochastic solution (VSS).	• Need to assign probabilities for scenarios. • Computationally demanding for large numbers of scenarios. • Difficulties in dealing with integer variables in the second stage (e.g., unit rescheduling in real-time). • Static Assumption of the uncertainties.
	Multi-stage models	• Lagrangian Relaxation (LR) • Augmented LR • Column Generation (CG) • Progressive Hedging • Stabilized LR or CG (using Bundle methods) • Nested CG	• Truly a decision-making model (as opposed to "what-if" analysis) over multiple time periods under uncertainty. • Ability to model the dynamic process of uncertainties and decisions. • Useful for systems with generators that can reschedule quickly. • Can provide EVPI and VSS.	• Curse of dimensionality, and hence computationally very expensive. • Need explicit scenario trees and random paths' probabilities. • Even more difficult with integer variables present in all stages.
Robust Optimization	Bi-level and tri-level models	• Benders Cutting Plane methods (dual) • Column-Constraint Generation methods (primal)	• Do not need probability distribution. • Solutions can provide decision-makers guarantee towards the worst-case. • Computationally not as demanding as stochastic programming models with large numbers scenarios.	• May yield over-conservative solutions. • Need expertise and rationale in uncertainty set construction. • Need to use different algorithms for different types of uncertainty sets. • Difficult to incorporate the uncertainty dynamics (e.g, multi-level/stage models).
(Approx.) Stochastic Dynamics Programming	Multi-stage, discrete-time models	• Value-function approximation • Policy iteration/Model predictive control • State-space approximation	• ADP can handle multi-stage stochastic problems with a relatively low computational burden. • Can model closed-loop systems (such as real-time pricing).	• For ADP, convergence to optimal solutions may be difficult to establish. • Integer variables may present difficulties in general.

Table 4: Comparison of the structure, solution algorithms, advantages, and disadvantages of the common stochastic UC models. Reproduced from the review of Zheng et al. (2015) based on several sources.

3.3 Mathematical Formulations of Unit Commitment Models

In this section, we present the mathematical formulations of the common unit commitment models due to their popularity in carrying out renewables grid integration studies (Abujarad et al., 2017). We also make references to the core UC model we used in our study and the additional extensions and constraints that might appear in some renewable integration studies based on the literature surveyed. It is worth noting that the mathematical formulations outlined in the following sections are largely based on the formulations presented in Palmintier (2013) and Palmintier and Webster (2014).

For the remainder of the thesis, the following indices, parameters, and decision variables are defined as follows:

Index	Description
g, G	Generation units
$\hat{g}$, $\widehat{G}$	Generation cluster or group
t, τ	Time period (hour)
ρ	Reserve category ∈ [1, 2, 3]
dir	Reserve direction ∈ [up, down]

Variables	Description	Unit
C^{total}	Total system cost	[M$]
$C^{var}_{g,t}$	Variable costs	[M$]
$C^{start}_{g,t}$	Startup costs	[M$]
n_g	Total units in cluster g	Integer [69]
$P_{g,t}$	Power output	[GWh]
$U_{g,t}$	Commitment state	[0, 1]
$S_{g,t}$	Startup indicator	[0, 1]
$D_{g,t}$	Shutdown indicator	[0, 1]
$R^{1,up}_{g,t}$	Regulation up reserves	
$R^{1,down}_{g,t}$	Regulation down reserves	
$R^{2,up}_{g,t}$	Load follow up & contingent reserves	
$R^{2,down}_{g,t}$	Load follow down reserves	
$R^{3}_{g,t}$	Replacement reserves	

69 Usually implemented in optimisation environments as a positive integer

Parameters	Description	Unit
a_g^{size}	Size of units in cluster g	[MW]
a_g^{CRF}	Capital recovery factor	Fraction
a_g^{life}	Lifetime of unit type g	[yrs]
$c_g^{Capital}$	Annualised capital cost	[$/MW/y]
$c_g^{FixO\&M}$	Annualised fixed O&M cost	[$/MW/y]
$c_g^{VarO\&M}$	Variable O&M cost	[$/MWh]
C_g^{nl}	No load cost of generator g	[$/h]
C_g^{m}	Marginal cost of generator g	[$/MWh]
L_t	Total system load at time t	[MW]
$c_{g,t}^{fuel}$	Fuel cost	[$/mmbtu]
$f_{g,t}\,(P_g\ )$	Affine fuel use function	[mmbtu/MWh]
f_g^{start}	Fuel usage at startup	[mmbtu]
$c_g^{fixstart}$	Fixed cost per startup	[M$]
P_g^{Max}	Maximum power output of g	[MW]
P_g^{Min}	Minimum power output of g	[MW]
Δp_g^{down}	Maximum downramp rate	[MW/h]
Δp_g^{up}	Maximum upramp rate	[MW/h]
$r^{1,up}$	Regulating up reserve load fraction	Fraction
$r^{1,down}$	Regulating down reserve load fraction	Fraction
$r^{2,up}$	Load follow up reserve load fraction	Fraction
$r^{2,down}$	Load follow down reserve load fraction	Fraction
r^{outage}	Spinning contingency reserve load fraction	Fraction
$r^{replace}$	Replacement reserve load fraction	Fraction
x^{nosync}	Load follow & contingency offline fraction	Fraction
$a_g^{quickstart}$	Quick start ability	[0, 1]
m_g^{Up}	Minimum up time of g	[h]
m_g^{Down}	Minimum downtime of g	[h]

3.3.1 Core Model

The generic UC problem formulation aims to minimise the total operation cost of meeting the system demand. In this section, however, we present one of the most common UC extended formulations to allow for optimising the investment costs in building power plants. The objective function of minimising the total system investment and operation costs can be expressed by the following equation:

$$C^{Total} = min\left(\sum_{g \in G} \left(\sum_{t \in T} P_{g,t}\, C_{g,t}^{Var} + I_g\, C_g^{fix} \right) + \sum_{t \in T} S_{g,t}\, C_{g,t}^{start} \right) \quad \textbf{(3)}$$

Where $P_{g,t}$ is the power output of generator g at time t,

$C_{g,t}^{Var}$ is variable system costs,

I_g is the installed capacity of each generator type [70],

C_g^{fix} is total fixed costs

Variable Cost

Variable costs are typically expressed as a function power output $P_{g,t}$, fuel consumption $f_{g,t}$ fuel cost c_g^{fuel}, and variable O&M costs $c_{g,t}^{varO\&M}$ as follows:

$$C_{g,t}^{var} = f_{g,t}(P_{g,t})\ c_g^{fuel} + P_{g,t}\ c_{g,t}^{varO\&M} \qquad \forall \quad g \in \boldsymbol{G},\ t \in \boldsymbol{T} \quad \textbf{(4)}^{71}$$

$$P_{g,t} \geq 0,\ f_{g,t} \geq 0 \qquad \forall \quad g \in \boldsymbol{G},\ t \in \boldsymbol{T} \quad \textbf{(5)}$$

Fuel Use Function

Fuel usage is usually expressed as a function of the power output of the generators. In essence, this function captures the typical, non-linear relationship between fuel usage and power output of thermal plants. For many thermal plants, this relationship tends to be quadratic in nature (Padhy, 2004). This particular relationship is a major source of non-linearity of the UC problem (Abujarad et al., 2017). In UC literature, one common formulation for approximating the fuel usage function is to express it as a convex, piecewise, linear function constraint with segment X_g such as:

70 Typically, expressed as a non-negative variable.
71 It is a common practice to include the carbon cost as part of the variable costs of the system in other variations of UC models that consider the carbon cost of the system.

$$F_{g,t}(P_{g,t}) \geq h_{g,x} P_{g,t} + U_{g,t} f_{g,x}^{P=0} \qquad \forall \; x \in \boldsymbol{X_g} \qquad (6)$$

Where for each piecewise linear segment, x:

$h_{g,x}$ represents the incremental heat rate amount for each plant type (slope)

$f_{g,x}^{P=0}$ represents the fuel use amount if it was allowed to hypothetically run at zero power (intercept)

Enforcing this constraint will account for the fuel usage of each plant under different dispatch statuses. Mathematically, when the plant is running, the optimiser will always minimise the fuel usage as the fuel cost parameter has a positive value forcing the inequality to equality for the highest piecewise segments. On the other hand, the commitment variable, $U_{g,t}$, ensures that the fuel use goes to zero when the plant is not running.

Fixed Cost

Due to the capital-intensive nature of many generation projects, the investment costs are typically annualised using a Capital Recovery Factor (CRF) that covers both the capital costs and the interest payments over the economic lifetime a_g^{life} of the project. In addition, the annualised, Capital Recovery Factor, a_g^{CRF} is commonly expressed as a function of the Weighted Average Cost of Capital (WACC)[72] as shown in Equation *(7)*:

$$a_g^{CRF} = \frac{WACC}{1 - \left(\frac{1}{1+WACC}\right)^{a_g^{life}}} \qquad (7)$$

Furthermore, the total fixed cost C_g^{fix} is commonly computed as a function of capital cost and fixed O&M costs as follows:

$$C_g^{fix} = c_g^{CRF} \; c_g^{capital} + c_g^{fixO\&M} \qquad (8)$$

72 It is the effective percentage interest rate adjusted for the debt and equity ratios of the project.

Startup Cost

The startup cost covers the fuel cost of starting up the thermal plant in addition to the maintenance and personnel costs[73]. Variations in expressing the startup costs do exist in the literature. Some studies use exponential formulations to express the startup costs such as (Padhy, 2004). Other studies tend to present a discrete, stairwise cost formulation expressed as a function of the unit's downtime or alternatively its operational startup status (i.e., hot, warm, and cold startup) such as Morales-España et al. (2013b). Other studies present a linear model to calculate the startup cost such as Palmintier and Webster (2014). A common linear formulation assumes a constant fuel use per startup and a fixed cost component, c_g^{fix} , to cover the maintenance and personnel costs as follows:

$$C_{g,t}^{start} = S_{g,t} * \left(f_g^{start}\ c_g^{fuel} + c_g^{fix} \right) \qquad \forall\ g \in \boldsymbol{G},\ t \in \boldsymbol{T} \tag{9}$$

Where $S_{g,t}$, represents the startup status of the unit.

Startup and Shutdown Events

The commitment $U_{g,t}$, startup $S_{g,t}$, and shutdown $D_{g,t}$, variables of the units are commonly expressed by the following state equation:

$$U_{g,t} = U_{g,t-1} + S_{g,t} - D_{g,t} \qquad \forall\ g \in \boldsymbol{G},\ t \in \boldsymbol{T} \tag{10}$$

$$\textit{where}\ \ U_{g,t}\ ,\ S_{g,t},\ D_{g,t}\ \in\ [0,1]$$

Under this formulation, the startup and shutdown state variables are set to 1 only in dispatch periods during which startup or shutdown events take place. It is worth noting that some researchers suggested alternative formulations for the startup and shut down variables. For example, Carrion and Arroyo (2006) suggested an alternative formulation to relax the binary constraints for both variables in the interest of reducing the computational complexity and runtime of the UC problem. Yet, Ostrowski et al. (2012) showed that enforcing the binary constraint for the startup and shut down variables can

73 Some studies presented formulations that allow for accounting for the startup carbon emissions such as Deng et al. (2015) and Göransson et al. (2017).

have a considerable computational advantage with modern solvers[74]. Likewise, Palmintier (2013) reported almost five times faster runtimes for the 3-discrete variable formulation as part of the numeric testing he did for his PhD thesis work[75].

System Energy Balance

The energy balance constraint ensures that the demand-supply balance is maintained at all times. Mathematically, this implies that the sum of the instantaneous power output of all generators equals the total system demand L_t, at all time[76,77].

$$\sum_{g \in G} U_{g,t} \quad P_{g,t} = L_t \qquad \forall \; t \in \mathbf{T} \tag{11}$$

In addition, Equation (12) limits the production of the real power of generators to be less than the installed capacity.

$$0 \le P_{g,t} \le I_g \qquad \forall \; t \in \boldsymbol{T}, \; g \in \boldsymbol{G} \tag{12}$$

Unit Minimum and Maximum Output Limits

The below equation guarantees the power output of individual generators is falling between the generators' minimum and maximum output levels, at all times.

$$U_{g,t} \; P_g^{Min} \le P_{g,t} \le U_{g,t} \; P_g^{Max} \qquad \forall \; t \in \boldsymbol{T}, \; g \in \boldsymbol{G} \tag{13}$$

74 The work of Carrion and Arroyo (2006) was carried out using CPLEX solver version 9.0 while the study done by Ostrowski et al. (2012) was performed using CPLEX 12.1. A notable improvement between the two reported CPEX versions is the implementation of the "feasibility pump" approach developed by Fischetti et al. (2005). Feasibility pump is a computationally-efficient heuristic used to find feasible solutions to general mixed-integer problems and it is reportedly showing better performance for solving problems with binary variables than for general integer variables (Boland et al., 2012).

75 His PhD work was implemented on GAMS using CPLEX 12.2. This might explain the consistency of his results with the findings reported by Ostrowski et al. (2012).

76 As our model has a 1-h time resolution, the generators' power output and system demand are expressed in MWh while MW or GW are commonly used to express the instantaneous demand-supply balance for similar UC models.

77 Other UC formulations add the network losses term to the right-hand side of the equation.

Spinning Reserve Margin

The constraint below guarantees that committed plants have enough spinning reserve SR_t capacity to deal with the potential deviation or uncertainty in demand forecasts or any unexpected loss of generation.

$$\sum_{g \in G} U_{g,t} \; P_g^{Max} \geq L_t + SR_t \qquad \forall \; t \in \boldsymbol{T} \tag{14}$$

Minimum Up and Down Times

This constraint ensures enforcing the minimum time needed for a unit to be kept online or offline after being synchronised or desynchronised from the grid. This particular constraint tends to affect the effective dispatchability of the units after the start and stop activities of the units.

The formulation below is based on the compact formulation suggested by Rajan and Takriti (2005), Hedman et al. (2009) and Ostrowski et al. (2012).

$$U_{g,t} \geq \sum_{T=t-m_g^{up}}^{t} S_{g,T} \qquad \forall \; t \in \boldsymbol{T}, \; g \in \boldsymbol{G} \tag{15}$$

$$1 - U_{g,t} \geq \sum_{T=t-m_g^{down}}^{t} D_{g,t} \qquad \forall \; t \in \boldsymbol{T}, \; g \in \boldsymbol{G} \tag{16}$$

Where m_g^{up} and m_g^{down} are the minimum up and downtimes respectively.

3.3.2 Additional Constraints

In addition to the core model presented in the previous section, here we make brief references to additional constraints that can be found in UC literature that have been used in surveyed renewable integration studies, albeit they tend to appear less frequently compared to the constraints presented in the core model.

Units Ramping Limits

These constraints restrict how fast committed plants can adjust their power output.

$$P_{g,t-1} - P_{g,t} \leq U_{g,t}\, \Delta P_g^{downmax} + max\left(p_g^{min}, \Delta P_g^{downmax}\right) D_{g,t} \qquad \textbf{(17)}$$

$$P_{g,t} - P_{g,t-1} \leq U_{g,t}\, \Delta P_g^{upmax} + max\left(p_g^{min}, \Delta P_g^{upmax}\right) S_{g,t} \qquad \textbf{(18)}$$

$$\forall\ g \in \boldsymbol{G},\ t \in \boldsymbol{T}$$

Where $\Delta P_g^{downmax}$ and ΔP_g^{upmax} are the down and up ramp limits of individual plants respectively. This formulation enforces the standard units' ramp rates under the normal dispatch operating conditions while it allows for higher ramps during start-up and shutdown events if the standard up and down ramp rates are deemed low.

Operating Reserves[78]

Some UC formulations allow for modelling different classes of operating reserve such as the primary[79], secondary[80] and tertiary reserves[81]. The following equations and constraints show how these reserve types have been formulated in several UC models.

1) Primary Reserve

The following two constraints ensure that the sum of the up or down frequency regulating reserve contribution provided by the system's generators $R_{g,t}^{1,up}$ and $R_{g,t}^{1,down}$ are in excess of the mandatory, pre-defined system-level, frequency reserve requirement $r^{1,up}$ expressed as a fraction of the system load l_t .

---

[78] Literature review reveals variations in defining and classifying the different classes of operating reserve. Readers may refer to Ela et al. (2011) for a comprehensive discussion about the subject. In this section, however, we follow and adopt the definitions and formulation offered by Palmintier (2013) and Palmintier and Webster (2014) for all reserve classes presented here.

[79] Refers to the reserve needed to compensate for the frequency deviation of the grid. This reserve type is responsive to rapid changes to the system frequency (i.e., operates within a few seconds timescale).

[80] Refers to the reserve needed to compensate for the system contingencies and load following tasks (i.e., operates within a few minutes timescale).

[81] Refers to the offline reserve units that can be synchronised quickly to the grid when needed. This category might also include quick-start small units.

$$\sum_{g \in G} R_{g,t}^{1,up} \geq r^{1,up} \, l_t \quad \forall \, t \in \boldsymbol{T} \tag{19}$$

$$\sum_{g \in G} R_{g,t}^{1,down} \geq r^{1,down} \, l_t \quad \forall \, t \in \boldsymbol{T} \tag{20}$$

2) Secondary Reserve

Similarly, Equations (21) and (22) ensure that the sum of the up or down secondary reserve contribution provided by the system's generators $R_{g,t}^{2,up}$ and $R_{g,t}^{2,down}$ are greater than the mandatory, system-wide load following requirements expressed as a fraction of the system demand l_t . For the secondary up reserve contributions, the formulation allows for expressing the load following requirement as a function of the additional reserve required for the system contingency r^{outage} which typically matches the size of the largest plant or the transmission capacity of the main interconnector of the system. In addition, the formulation allows for supplying a portion of the secondary up reserve by non-synchronised resources x^{nosync} such as quick starting units.

$$\sum_{g \in G} R_{g,t}^{2,up} \geq \left(r^{2,up} l_t + r^{outage} \right) \left(1 - x^{nosync} \right) \; \forall \, t \in \boldsymbol{T} \tag{21}$$

$$\sum_{g \in G} R_{g,t}^{2,down} \geq r^{2,down} l_t \quad \forall \; t \in \boldsymbol{T} \tag{22}$$

3) Tertiary Reserve

The following constraints ensure that both the tertiary $R_{g,t}^{3}$, and secondary up reserve $R_{g,t}^{2,up}$, resources can jointly contribute to tertiary reserve requirements of the system $r^{replace}$ as allowed by Equation (21) from the proportion provided by non-synchronised units while enabling the tertiary reserve to be met by committed units when appropriate.

$$\sum_{g \in G} \left(R^{3}_{g,t} + R^{2,up}_{g,t} \right) \geq r^{2,up} l_t + r^{outage} + r^{replace} \quad \forall \quad g \in \boldsymbol{G}, \; t \in \boldsymbol{T} \tag{23}$$

In addition, the following constraint ensures that the quick start units can only be chosen from the non-synchronised units pool.

$$R^{3}_{g,t} \leq \left(1 - U_{g,t} \right) a^{quickstart}_{g} \; p^{max}_{g} \quad \forall \; g \in \boldsymbol{G}, \; t \in \boldsymbol{T} \tag{24}$$

Where $a^{quickstart}_{g}$ represents the fraction of units' capacity that can be deployed fast enough as a dispatchable fast start capacity.

Unit Reserve Capabilities

The constraints below guarantee that units can only provide (1) the type and (2) amount of reserve that are deemed to be capable of depending on the units' technical and flexibility characteristics[82] or their mode of operation[83].

$$R^{\rho,dir}_{g,t} \leq \; a^{\rho,dir}_{g} \; p^{max}_{g} \quad \forall, \rho, dir, g \in \boldsymbol{G}, t \in \boldsymbol{T} \tag{25}$$

Where Reserve category, $\rho \in [1, 2, 3]$

Reserve direction, $dir \in [up, down]$

3.3.3 Clustered Formulation

As indicated earlier, variations in mathematical formulations of the UC problem do exist in the literature. A notable variation among UC models is related to the way in which the status of the generating units with identical or similar characteristics is mathematically represented in optimisation models.

[82] Several technical characteristics affect the operational flexibility of thermal units including their ramping rates, start-up times, the minimum loading levels, minimum up and downtimes, and their partial load efficiency (IRENA, 2017).

[83] The operational flexibility and reserve contributions of thermal units can be sometimes restricted due to being part of combined heat and power (CHP) operation scheme (IRENA, 2018a).

The traditional approach treats the status of each plant separately. In other words, each plant would have an "on or off" status in each optimisation interval (e.g., each hour or half-hour). The main advantage of using this approach is that it allows for a "plant-by-plant" analysis. However, it is computationally expensive. Other formulations assign a binary or an integer variable to a group or a cluster of units sharing the same or similar characteristics.

For example, Sen and Kothari (2001) grouped similar thermal units using a binary variable for a UC model. A key drawback of using a binary variable to model the status of a group of units (i.e., 0 or 1) is that it switches the whole group or cluster on or off, which might not represent the actual behaviour of the cluster in real circumstances.

In comparison to the typical UC binary formulations of generation units, grouping identical units drastically reduces the computational dimensionality, the number of equations, and the number of variables of the optimisation problem. It also speeds up the search for the optimum solution by eliminating the identical or very similar permutations of binary commitment decisions (Sherali and Smith, 2001, Palmintier and Webster, 2016).

For example, Palmintier and Webster (2014) compared the results and running speed of several models using both binary and aggregated units for a Texas-based system with 205 generating units. They reported that models that grouped units had estimation errors of 0.05%–0.9% across several metrics while providing several orders of magnitude faster solution times (about 400 times) compared to the traditional binary formulations. They also reported that further aggregation of units increases the error metrics slightly (about two times) while running 2000 times faster than the traditional binary formulation.

Similarly, a more recent study by Meus et al. (2018) compared the total system costs of UC models with different formulations of the Central Western European (CWE) system, which encompasses the power systems of 5 countries, with 806 power plants and 4 pumped storage units. They found that the error in approximating the total system cost of a traditional UC model with a binary formulation and another UC model with a clustering formulation does not exceed 0.06%.

This approach of grouping identical or similar units ("heterogeneous clustering") has been adopted by many researchers studying different aspects of power systems, including long-term expansion planning, operation and maintenance planning, price estimation, and carbon emissions. Examples of such studies include Hara et al. (1966), Langrene et al. (2011), Gollmer et al. (2000), Staffell and Green (2016), and Palmintier and Webster (2016).

Mathematical Formulation

Conceptually, clustering formulation relies on the discretisation and grouping of all generation units that have very similar or identical economic and technical characteristics. Unlike the traditional formulation of UC expansion planning models, this modelling approach allows the optimiser to make plants' investment decisions in discrete steps - typically equal to the units' sizes - rather than in a continuous fashion. Mathematically, this can be expressed as follows:

$$I_g \in [\,0\,,\, a_g^{\text{size}},\; 2\,a_g^{\text{size}}\,,\; \ldots\ldots\ldots\,,\; n_g^{\max}\, a_g^{\text{size}}\,] \tag{26}$$

Where I_g is the total installed capacity of each generator type

a_g^{size} is the unit size of each unit

In common cluster formulations, however, in the interest of ease and increased tractability, the same concept is being implemented through replacing the individual units index, g, with a newly defined index representing the whole cluster or group of units sharing similar characteristics $\hat{g}$ such that

$$n_{\hat{g}} = \frac{I_{\hat{g}}}{P_{\hat{g}}^{Plantsize}} \tag{27}$$

Where $n_{\hat{g}}$ is an integer variable representing the number of units in the cluster.

This allows the system modellers to neatly expand the range of the commitment, startup and shutdown variables of the units as follows:

$$\widehat{U_{\hat{g}}}\;,\; \widehat{S_{\hat{g}}}\; - \widehat{D_{\hat{g}}}\; \in [0,1,\,\ldots\ldots\ldots,\, n_{\hat{g}}\;] \quad \forall\, \hat{g} \tag{28}$$

In addition, the common cluster formulation attracts minimal changes to the common UC formulation presented in sections *3.3.1 Core Model* and *3.3.2 Additional Constraints*. In fact, after applying the substitutions suggested above, no changes are needed for the equations related to the objective function, variable costs, commitment state, startup costs, piecewise linear fuel use, system balance, unit output constraints, minimum up time, system reserve requirements, and the non-tertiary reserve capabilities. However, some changes are required for the below relationships and equations as follows:

Ramping limits

Equations (29) and (30) replace Equations (17) and (18) respectively.

$$P_{\hat{g},t-1} - P_{\hat{g},t} \leq (\widehat{U_{\hat{g},t}} - \widehat{S_{\hat{g},t}})\, \Delta P_{\hat{g}}^{downmax} - p_{\hat{g}}^{min}\, \widehat{S_{\hat{g},t}} + min\left(p_{\hat{g}}^{max}(t),\, max\left(p_{\hat{g}}^{min},\, \Delta P_{\hat{g}}^{downmax}\right) \widehat{D_{\hat{g},t}}\right) \quad \textbf{(29)}$$

$$P_{\hat{g},t-1} - P_{\hat{g},t} \leq (\widehat{U_{\hat{g},t}} - \widehat{S_{\hat{g},t}})\, \Delta P_{\hat{g}}^{upnmax} - p_{\hat{g}}^{min}\, \widehat{D_{\hat{g},t}} + min\left(p_{\hat{g}}^{max}(t),\, max\left(p_{\hat{g}}^{min},\, \Delta P_{\hat{g}}^{upmax}, p_{\hat{g}}^{quickstart}\right) \widehat{D_{\hat{g},t}}\right) \quad \textbf{(30)}$$

$$Where\ p_{\hat{g}}^{quickstart} \equiv a_{g}^{quickstart}\, p_{g}^{max}$$

Minimum Down Times

Similarly, Equations (31) replaces Equation (16).

$$n_{\hat{g}} - \widehat{U_{\hat{g},t}} \geq \sum_{T=t-m_{\hat{g}}^{mindownn}}^{t} \widehat{D_{\hat{g},t}} \quad \forall\ t \in \boldsymbol{T},\ g \in \boldsymbol{G} \quad \textbf{(31)}$$

Tertiary reserve capabilities

Likewise, Equations (32) replaces Equation (24).

$$R_{\hat{g},t}^{3} \leq \left(n_{\hat{g}} - \widehat{U_{\hat{g},t}}\right) a_{\hat{g}}^{quickstart}\, p_{\hat{g}}^{max} \quad \forall\ g \in \boldsymbol{G},\ t \in \boldsymbol{T} \quad \textbf{(32)}$$

3.4 Implementation of Optimisation Models

3.4.1 Mathematical Formulation

In our work, we used both SC and UC models for our simulations. For the SC model, we used the standard formulation presented in section *3.2.2.1 Screening curve method*. In addition, for the UC work, we adopt a linearised version of the core UC model presented in section *3.3.1 Core Model* based on the formulations presented by Baldick (1995) and Gollmer et al. (2000) for thermal-only systems. In addition, we adopted the clustered formulation presented in section *3.3.3 Clustered Formulation* for building our MILP UC model based on the MILP model presented in Palmintier (2013) and Palmintier and Webster (2014). *We specifically adopted the MILP modelling approach due to its demonstrated computational advantages and its wide prevalence in the literature for carrying out renewable decarbonisation studies (Abujarad et al., 2017)*.

3.4.2 Software Environment

We implemented the SC and UC models using the General Algebraic Modeling System (GAMS) software (Brooke et al., 1998). We run both models using CPLEX 12.6.3 LP/MILP solvers (IBM, 2015).

We used Microsoft Excel to manage and store the input data. However, we developed several GAMS routines to automate the process of recalling and pre-processing data from the Excel environment. We also developed additional GAMS routines to manipulate the input data to make it compatible with the standard units used in SC and UC models. Furthermore, we developed several GAMS routines to post-process the simulation results and to export them back to the Excel environment for graphing and analysis purposes. We include more details about the program codes, and other technical details in the modelling notes appendix. It might be relevant to mention that the core GAMS code was designed in a highly modular way in terms of data management, separation of functional utilities and configurability. Among other things, this proves useful for code-debugging activities and for automating the process of running multi-dimensional sensitivity analysis for specific data inputs or even running similar models using different types of solvers[84].

84 The relative Optimality Criterion (ROC) of all solvers used was set to zero for all simulations done.

4.4.3 Simulation Assumptions & Implementation notes

As indicated earlier, our modelling is based on a linearised version of the core UC model presented in *3.3.1 Core Model.* However, we made several assumptions and simplifications that we summarise as follow:

Constant incremental heat rate with an offset

- We assumed a *single-segment* piecewise heat curve with a constant incremental heat rate and offset for each plant type. This replaces the *multiple-segment* piecewise linear fuel usage constraints expressed in Equation (6). This assumption implies using a single incremental fuel usage rate with a fixed no-load fuel usage offset for each generator type. Palmintier (2013) showed that this assumption reduces the size of the UC problem by reducing the number of constraint equations while having a mild effect on the results. We also assumed that units in each generation cluster are in fact identical having the same heat-rate characteristics.
- In terms of implementation, we derived the linearised no-load cost coefficients and a marginal cost coefficient for each generator type using both the heat-rate curves and the corresponding fuel costs. This was done by using a linear regression analysis for deriving the linearised no-load and marginal heat-rate usage coefficients from the quadratic heat-rate plants' data provided by Brouwer et al. (2015). Then, the cost coefficients were calculated by multiplying the derived linearised heat-rate usage coefficients by the corresponding fuel costs. The linear regression analysis was performed using the Microsoft Excel regression analysis toolbox for all thermal plants considered in this study.

Constant Startup Cost

- In our simulation, for simplicity, we assumed a constant total cost per startup for each type of generator. The assumed total cost covers the fuel cost per startup, and the additional fixed cost per startup to cover the maintenance and personnel costs. This replaces the startup cost equation (9). This simplification has been commonly used in the literature for similar long-term UC capacity planning studies that involve studying renewable integration. Examples of these studies include EnerNex (2010) and Kirschen et al. (2011).

Combined Reserves

- For simplicity, we did not model the primary, secondary and tertiary reserve types discussed earlier. However, we assumed a combined reserve margin to deal with the potential grid frequency deviation, uncertainty in demand forecasts or any unexpected loss of generation for all UC model simulations considered.
- We assumed this to be a 20% reserve margin (i.e., spinning reserve) relative to the system's load demand to all UC model simulations considered.

Must Run Generation Technology Choice

- We also did not actively select or enforce a specific thermal generation technology to meet the minimum running generation constraints of the system. However, we let the optimiser choose the most cost-effective technology given the system conditions and renewable penetration levels.
- In reality, energy system modellers might prefer a specific technology for a specific system. However, for the sake of exploring the natural investing tendency of the capacity optimiser, we gave the optimiser more flexibility in choosing the base and must-run generation.
- We did not consider nuclear power as an option for providing a base or must-run generation. Owing to its relatively low contribution to meeting the global electricity demand (IEA, 2019), we focused more on coal and gas plants in these simulations. However, further research can study systems dominated by nuclear power plants.

Renewable Curtailment

- We only allowed renewable curtailment when the renewable production cannot be absorbed by the system due to the minimum running thermal generation constraints.
- This was done for the sake of maximising the penetration levels of renewable generation in the energy mix to the greatest practical level possible. In particular, this assumption enables us to capture the effect of the envisioned deep renewable decarbonisation of the system which is one of the main focus points of our research.
- In essence, we treated the renewable generation as a negative load for calculating the net residual load[85] of the system. As a result, all renewable generation was given a top priority to meet the demand of the system. As such, the renewable production was

85 Net residual load is defined in this context as the total system load minus the total renewable production.

only curtailed when the net residual load drops below the pre-defined minimum running thermal generation level.

- Crucially, however, this assumption also allows us to implicitly integrate the minimum kinetic inertia requirement of the system as *a lower-bound static limit*[86] into the dispatch model. Fundamentally, this assumption is intended to avoid a sustained low-inertia situation for the system under consideration as it is assumed to be not interconnected with other systems (Milano et al., 2018).
- In reality, this assumption implies curtailing, wholly or partially, specific renewable generators or feeders under oversupply conditions. In practice, this is typically implemented through (1) automatic signaling or (2) order of curtailment (Bird et al., 2014).
- Under the automatic signaling scheme, control signals are sent in real-time to renewable generation facilities through the Supervisory Control and Data Acquisition (SCADA) systems[87]. These signals include pro-rata curtailment directives when certain power management conditions are met (i.e., oversupply conditions). These signals are initiated in the Automatic Control Generation (ACG) module of the SCADA system enabling precise sizing of the amount of power to be curtailed from different generators to maintain the nominal frequency of the system in real-time. These signals typically require a confirmation from the renewable facility for implementation. In some markets, regular market signals are used to send curtailment signals. Operators can send automatic *flag* signals to renewable generators that are needed to be dispatched below their full dispatchable level. These signals include their required base-points production levels as opposed to the curtailment amount. It is common practice for system operators to follow-up with a phone call to ensure that renewable generators will be curtailed as required (Bird et al., 2014).
- Under the order of curtailment scheme, however, system operators use their technical judgments to order renewable generators to curtail their production levels. These orders are often issued under balancing-related challenges such as transmission congestion or oversupply conditions. The amount of the curtailed power required is influenced by several factors including the market design, contractual obligation, generators economics and the effectiveness of the renewable generators in mitigating the system challenge (Bird et al., 2014).

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86 It is important to note that, the system inertia is typically modelled as a time-dependent variable for stability studies (Kundur, 1994). However, modelling system stability aspects in great detail is understandably beyond the scope of our study.

87 The standard software application used by system operators for managing and controlling networks assets remotely.

Residual Load Calculation

- In terms of implementation, this was done at the pre-processing stage and before running the UC model by running a GAMS routine that calculates the hour-by-hour amount of renewable energy that cannot be absorbed by the system due to the minimum running thermal generation constraints, if applicable[88].
- Then, the routine is programmed to adjust the net hourly residual load of the system that must be met by the thermal plants accordingly, preventing the net residual load to drop below the minimum running thermal generation level. After that, the newly adjusted, effective hourly net residual load of the system gets passed to the UC program for running the thermal mix optimisation.

Renewable Curtailment Cost

- For all scenarios considered, the cost of renewable capacities was passed to the optimiser as an exogenous input. This cost includes the total investment costs[89] for each renewable penetration scenario. Therefore, to avoid double-counting, we did not assume any additional curtailment cost in our simulations as the cost of spilled renewable generation is inherently included in the total renewable investment costs. This implies that occasionally renewable generators are not producing at their full potential as a result of being curtailed by the system operators.
- In reality, this assumption might imply that all renewable generators are guaranteed to sell their full production to the network irrespective of the amount that can be absorbed by the system (i.e., they will be compensated otherwise for the unsold quantity on a pro-rata cost basis if curtailed by the system operator). Alternatively, this might imply a mutual agreement in which renewable generators can be curtailed at no cost while they are still compensated for their investment and fixed O&M costs.

Other Considerations

- **Simulation Perspective:** We take the perspective of a monopolistic system planner.
- **Demand:** We assumed an inelastic, nonresponse electric demand profile with a 1-hour temporal resolution. We also assumed that the load shape will stay the same during the hypothetical optimisation period considered.

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88 The program creates a separate time-series of the renewable generation that cannot be absorbed by the system due to the pre-defined minimum running thermal generation level. This series can be used later for calculation purposes such as calculating the total amount of power curtailed.

89 This includes both the CAPEX and fixed O&M costs.

- **Transmission & Interconnections:** We did not consider the impact of having access to interconnection capacity or having transmission- or reliability-related constraints. We also did not consider the cost associated with transmission losses or wheeling charges of power and we assumed that all generation units are connected to a single node.
- **Carbon Price:** We assumed a zero carbon price.
- **Storage:** We also did not consider the existence of storage systems.
- **Life Cycle Emissions:** We did not take the life cycle emission considerations in our analysis or simulations

3.5 Test System Details

The study cases presented in this thesis are loosely based on the Qatari electric system. However, due to commercial data confidentiality issues, we were unfortunately not able to simulate the existing generation assets of the system. Therefore, for consistency and demonstration purposes, we used a greenfield approach for the simulations.

3.5.1 Demand data

We used historical hourly demand data for the Qatari system for the year 2011 (Kahramaa, 2012). Each data point of the 8760 data points used represented the average demand for the recorded hour. Figure 16 shows the load shape and the daily demand curves of the test system. In addition, Table 5 provides a summary of the key descriptive statistics of the system's load.

Peak Demand	(MW)	5349
Minimum Demand	(MW)	1752
Minimum Thermal Running Load[90]	(MW)	500
Total Annual Demand	(TWh)	29.3

Table 5: Selected descriptive statistics for the test system under consideration based on datasets from (Kahramaa, 2012).

It is worth noting that contrary to the widespread expectation for a hot country like Qatar, the load profile of the country is much flatter than someone would normally expect. This is due to the extended use of air-conditioning systems during night hours which makes up

90 Assumed value for simulation purposes only for the baseline scenario.

the majority of the domestic load as the temperature tends to stay hot during night hours in the summer season. That also explains why during low demand period (i.e., wintertime) the system load drops by almost 60%, yet the load shape stays almost the same (Bayram et al., 2018).

Estimated normalised average daily demand curves for the test system (by month).

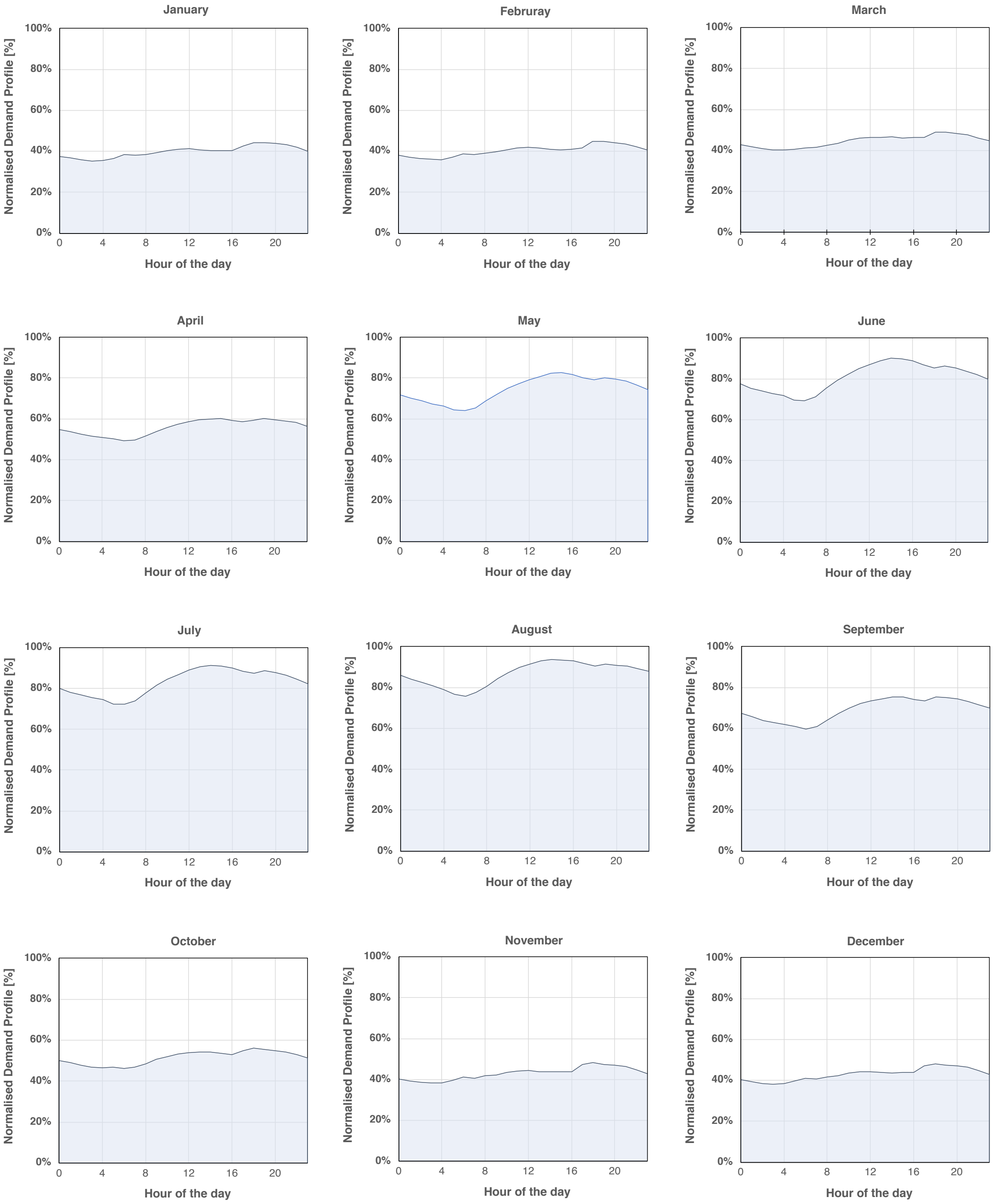

Figure 16: Normalised average daily profiles for the system under consideration based on historical data (Kahramaa, 2012). Graphs were produced using the SAM viewer software based on 1h resolution data for the whole year (8760 data points for the whole year).

3.5.2 Generation plants' data

We collected and compiled the cost and technical data of the conventional and renewable technologies from multiple sources.

For PV, CSP and wind power technologies, the capital cost values are sourced from a comprehensive cost review report prepared by the International Renewable Energy Agency (IRENA). The cost values used are the calculated, global weighted average values for renewable projects in 2015. It is worth noting that the cost values used for wind power are the values related to onshore wind power projects only.

Similarly, the main cost and technical data of the conventional plants were sourced from a comprehensive review report prepared by the U.S. Energy Information Administration (EIA). The values used represent the technical data and cost estimates for generic utility-scale electricity generating projects (EIA, 2013b).

For the fuel and plants flexibility data, we compiled them from multiple sources, including EIA (2013b), EPA (2015), Brouwer et al. (2015), Van den Bergh and Delarue (2015), and Göransson et al. (2017). Similar to other governmental publications and peer-reviewed studies, the data presented in these studies were collected from a large number of sources. However, we can neither guarantee their full completeness nor their total accuracy.

In addition, as indicated in the previous section, we derived the linearised no-load cost coefficients and a marginal cost coefficient for each generator type using the quadratic heat-rate plants' data provided by Brouwer et al. (2015). We present the original data and the respective derived coefficients in Table 9 and Table 10. Moreover, Table 6 - Table 8 summarise the key input cost and technical data with their respective sources.

Technology	Capex	Fixed O&M	Discount Rate	Lifetime
	[USD/kW]	[USD/kW-yr]	[%]	[Yr]
CSP	5550	67.26	5%	30
PV	1810	24.67	5%	30
Wind	1560	39.55	5%	30
Data Sources	(IRENA, 2016)	(EIA, 2013b)	Assumed	Assumed

Table 6: Key cost data for CSP, PV, and wind technologies

Technology	Full Load Efficiency	Capex	Fixed O&M	Variable O&M	Discount Rate	Lifetime
	[%]	[USD/kW]	[USD/kW-yr]	[USD/MWh]	[%]	[Yr]
OCGT	35%	676	7.04	10.37	5%	30
CCGT	48%	917	13.17	3.60	5%	30
Steam Coal	39%	3246	37.80	4.47	5%	30
CCS Coal	28%	5227	80.53	9.51	5%	30
Data Sources	(EIA, 2013b)	(EIA, 2013b)	(EIA, 2013b)	(EIA, 2013b)	Assumed	Assumed

Table 7: Key cost and technical data for conventional generation technologies.

Technology	Minimum Load Level	Start-up Cost	Minimum Up Time	Minimum Downtime	Unit Size
	[%]	[USD/MW]	[h]	[h]	[MW]
GT	50%	39.86	1.00	1.00	150
CCGT	20%	53.15	6.00	6.00	300
Steam Coal	35%	303.18	10.00	10.00	300
Data Sources	(Göransson et al., 2017)		(Van den Bergh and Delarue, 2015)		Assumed

Table 8: Selected flexibility parameters for conventional generation technologies.

Technology	a[91]	b	c
	[p.u]	[p.u]	[p.u]
GT	0.41	1.16	-0.57
CCGT	0.72	0.48	-0.19
Steam Coal	0.82	0.35	-0.17
Data Sources	(Brouwer et al., 2015)		

Table 9: Quadratic part-loading efficiency coefficients for conventional generation types.

Technology	No-Load[92]	Incremental
	[p.u]	[p.u]
GT	0.183	0.815
CCGT	0.088	0.914
Steam Coal	0.047	0.952
Data Sources	(Brouwer et al., 2015)	

Table 10: No-load and incremental cost estimates for conventional generation technologies.

91. Relative part-load efficiency of power plants as a percentage of full-load efficiency expressed as $y = a + bx + cx^2$, where x is the load of the power plant as a percentage of max load based on (Brouwer et al., 2015)
92. The relative (linearised) no-load and incremental fuel cost coefficients are based on data from Brouwer et al. (2015), following Staffell and Green (2016) approach. See Table 9 for the relative fuel cost curves for each technology against the relative plant output (based on generic quadratic curves for each technology).

Technology	Fuel Price	Specific CO_2 Emission
	[USD/MMBtu]	[Kg/MMBTu]
Natural Gas	10	53.02
Coal	2.19	95.52
Data Sources	Assumed	(EPA, 2015)

Table 11: Cost and emission data for the fossil fuel types considered.

3.5.3 Renewable resource data and capacity factors

In the following study cases, depending on the focus and purpose of the study, we consider the PV, CSP, and wind technologies for the large-scale deployment for the system under study.

3.5.3.1 CSP capacity factors

We initially built a bottom-up technical model to simulate the operation of a generic CSP plant based on the long-term weather and solar radiation data obtained from Meteonorm[93]. The solar radiation dataset included hourly P90 and P50 solar datasets calculated based on recorded measurements covering the years from 1991 to 2010 (Meteonorm, 2017). It is worth noting that the P90 and P50 values are exceedance probability measures representing the amount of renewable resources expected to be available at a certain site. For example, P90 resource figures mean that there is a 90% chance that in any given year, the renewable resource at the site will exceed the specified amount. Likewise, this implies that there is only a 10% chance that that renewable resource will be lower than the stated amount. The P90, P70, and P50 figures are the most commonly used measures in the context of presenting statistical data on renewable resources. They are typically derived by employing probability and statistical analyses using many years of historical weather data. Both P50 and P90 values of renewable projects are often required by banks and investment firms for project finance assessments. These figures are often used as measures of the economic risks associated with the inter-annual variability of renewable resources (Dobos et al., 2012). However, in the interest of getting more accurate estimates, we did not use the loading profiles generated by the developed model as it is widely reported that the direct normal irradiance (DNI) data is site-specific and very sensitive to local meteorological and environmental factors (IRENA,

93. We would like to thank Meteonorm for providing us with high-quality, commercial-grade solar data for free.

2013). Therefore, we did not use the DNI long-term average solar radiation data for the CSP simulations. Rather, we adopted the hourly loading factors from Martín-Pomares et al. (2017)[94] of a 50 MW parabolic through (PT) plant, which was simulated based on measured solar radiation data in Qatar. Simulations were carried out using a technically detailed SAM[95] model (Blair et al., 2014).

3.5.3.2 PV capacity factors

For the solar PV scenarios, we used P90 solar data to simulate the hourly loading factors of the PV technology[96] (Meteonorm, 2017). We used a generic PV system model to generate the hourly output profiles of the PV panels simulated using the System Advisor Model (SAM) software (Blair et al., 2014). We assumed 10% total PV system losses

3.5.3.3 Wind capacity factors

In addition, for the wind technology simulations, we obtained the hourly loading factors using the Renewables Ninja online simulation platform with a standard Vestas V90 2000 frame (Staffell and Pfenninger, 2016).Table 12 presents a summary of the capacity factors for CSP, PV, and wind technologies and their respective sources..

Technology	Capacity Factor [%]	Data Source
CSP	26.4%	Martín-Pomares et al. (2017)
PV	22.8%	Meteonorm (2017)
Wind	29.0%	Staffell and Pfenninger (2016)

Table 12: Capacity factors for CSP, PV, and wind technologies and their respective sources.

Figure 17 shows the normalised average daily production profiles for the CSP technology. Furthermore, Figure 18 present a reproduced solar map from Martín-Pomares et al. (2017) showing the DNI and GHI yearly average estimates in Qatar based on data for the period from 2003 to 2013. Likewise, Figure 19: compares the normalised average daily production profiles for the PV and wind technologies.

94. We are grateful to Luis Martín-Pomares for sharing his quite sophisticated CSP simulation model and results with us.
95 The System Advisor Model (SAM) is a free techno-economic modelling software of renewable energy technologies. The software was developed by the National Renewable Energy Laboratory (NREL) to assist and facilitate decision-making for professionals in the renewable energy industry:
96 We would like again to thank Meteonorm for providing us with high-quality, commercial-grade solar data for free.

Normalised daily production profiles for the CSP technologies (by month)

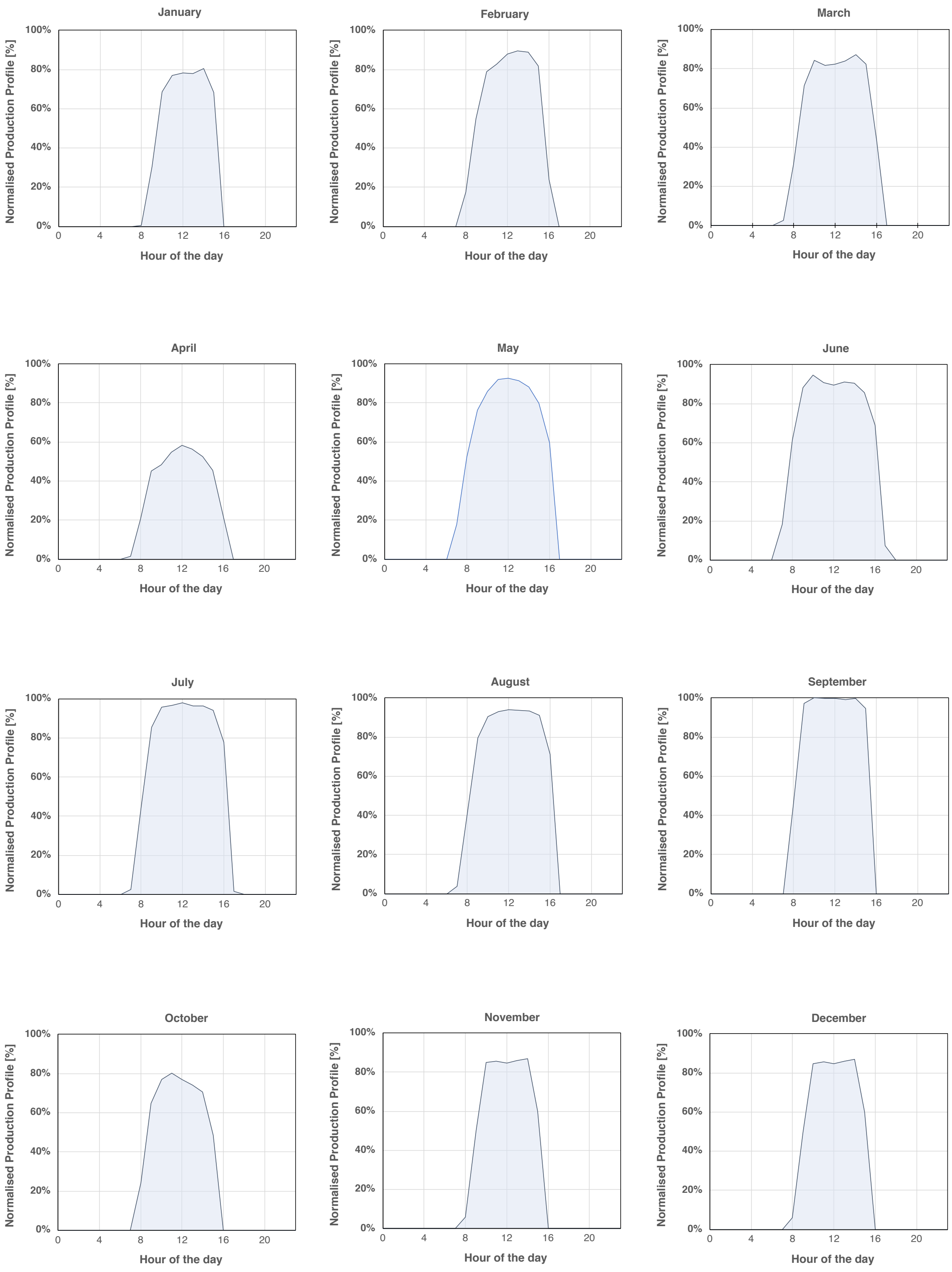

Figure 20: Normalised average daily production profiles for the CSP technologies based on the simulation results of Martín-Pomares et al. (2017). Graphs were produced using the SAM viewer software based on 1h resolution data for the whole year (8760 data points for the whole year).

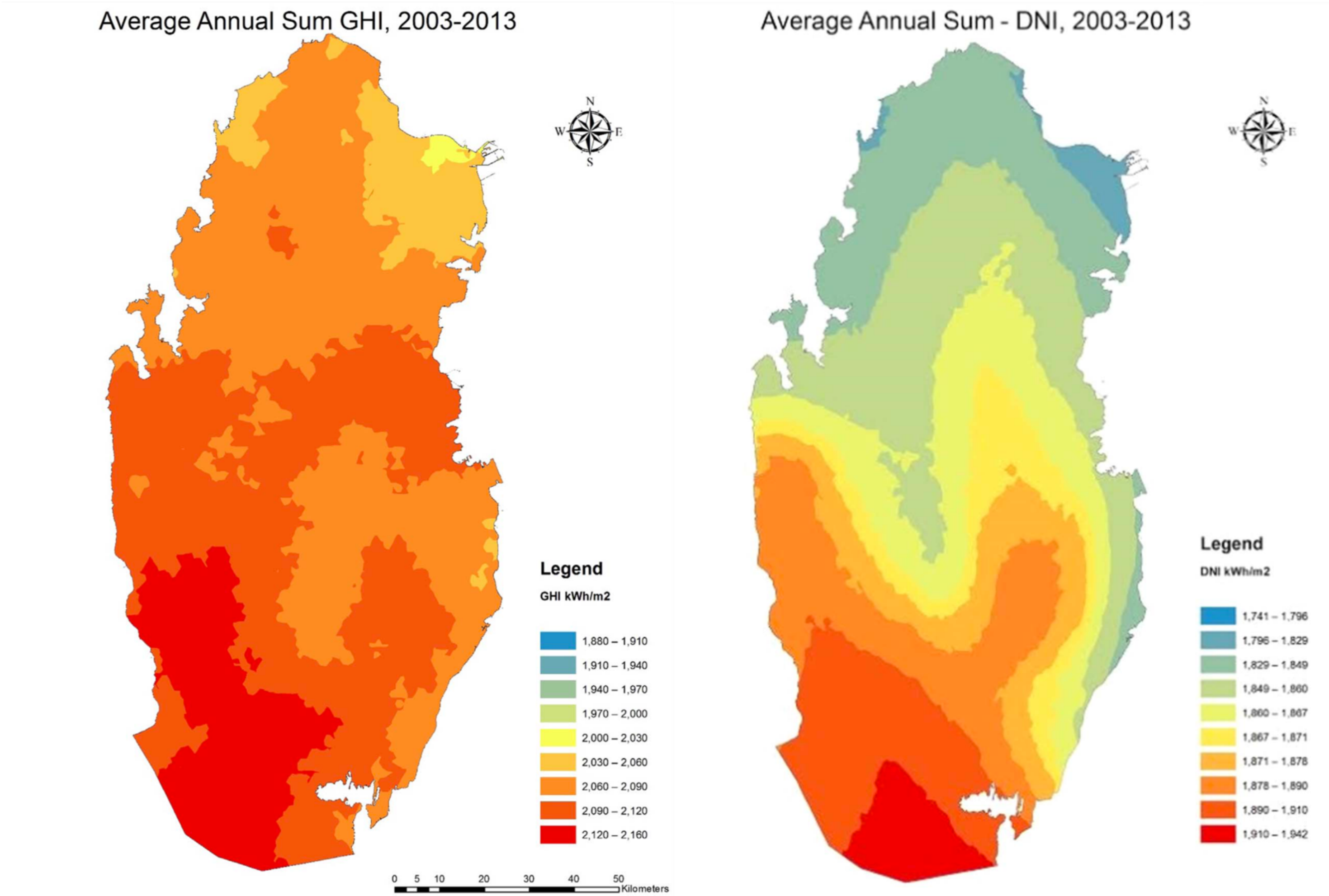

Figure 21: DNI and GHI yearly average estimates (2003–2013) in Qatar (kWh/m²/year). Reproduced from Martín-Pomares et al. (2017)

Normalised daily production profiles for the PV and wind technologies (by month)

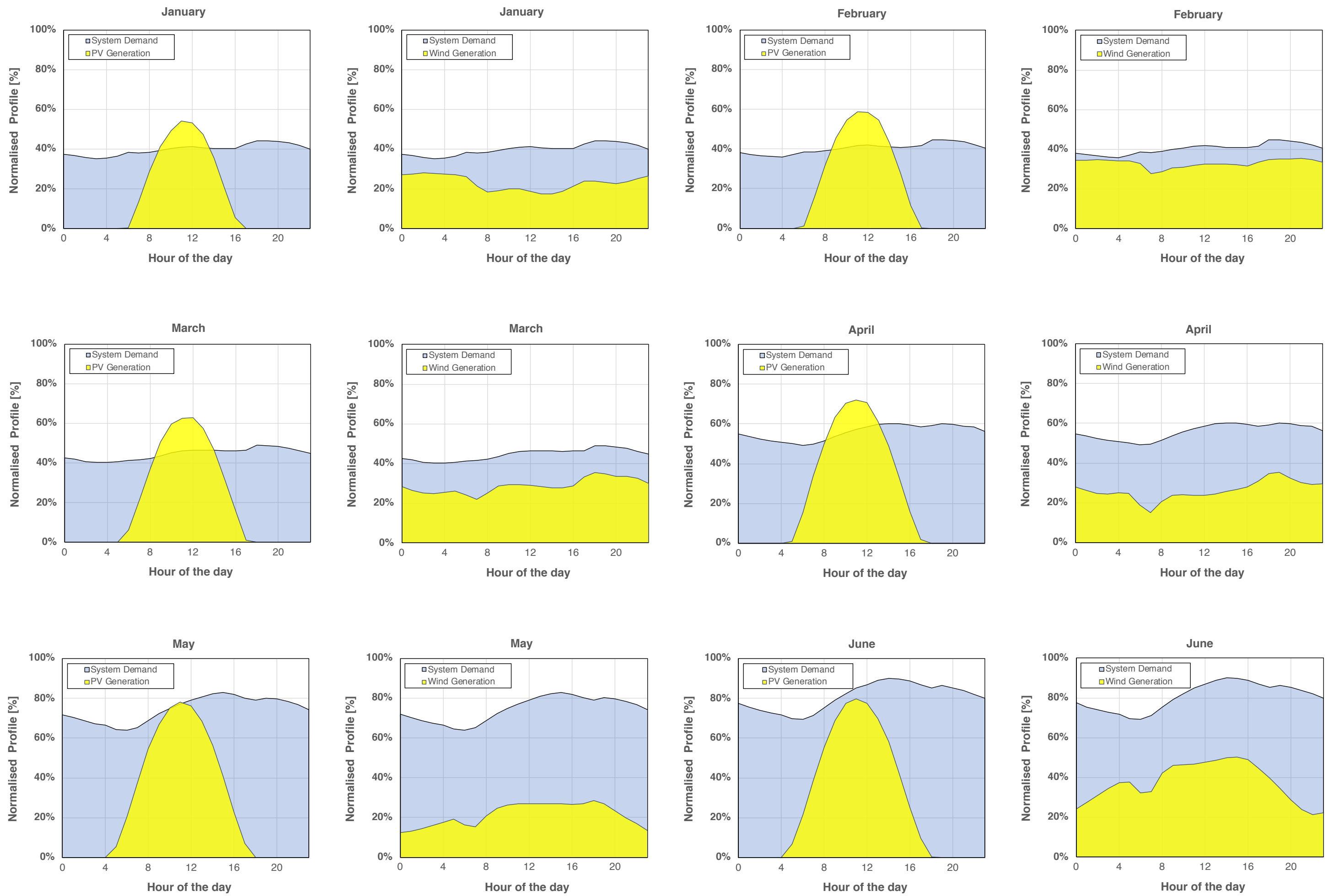

Figure 22: Normalised average daily production profiles (January to June) for the PV and wind technologies based on data from (Meteonorm, 2017) and Staffell and Pfenninger (2016) respectively. Graphs were produced using the SAM viewer software based on 1h resolution data for the w whole year (8760 data points for the whole year).

Normalised daily production profiles for the PV and wind technologies (by month)

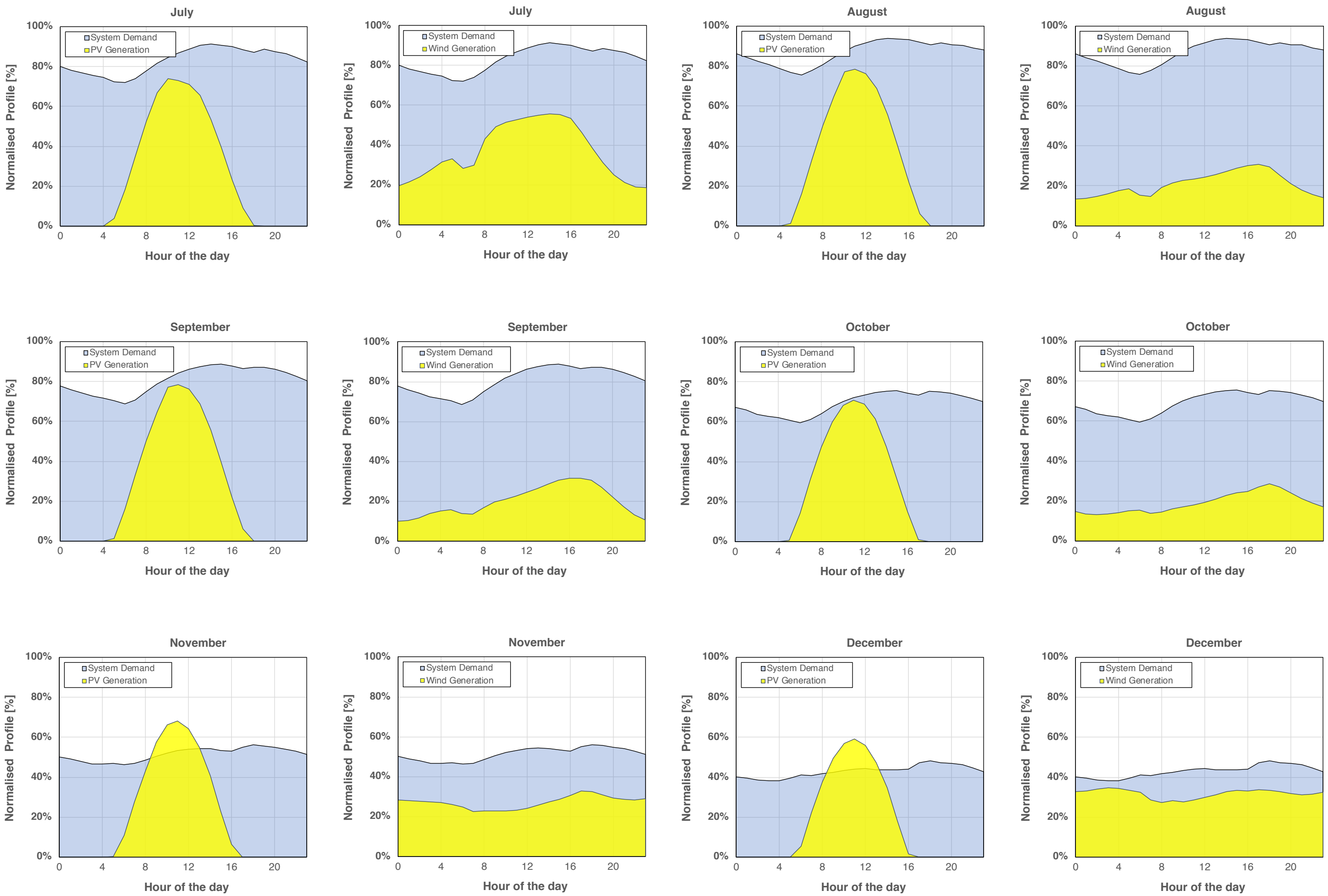

Figure 23: Normalised average daily production profiles (July to December) for the PV and wind technologies based on data from (Meteonorm, 2017) and Staffell and Pfenninger (2016) respectively. Graphs were produced using the SAM viewer software based on 1h resolution data for the whole year (8760 data points for the whole

CHAPTER 4
BENCHMARKING THE CARBON SAVINGS & ECONOMIC EFFECTIVENESS OF RENEWABLE ENERGY SOURCES: A NEW THEORETICAL FRAMEWORK[97]

97 Significant portion of this chapter was presented as a paper at the 7th Bergen Economics of Energy and Environment Research (BEEER) conference which was organised by the Norwegian Association for Energy Economics (NAEE) and the Energy and Environment Group at the Norwegian School of Economics (NHH). I would like to thank the participants of the conference for their insightful comments and very valuable feedback. I am very grateful to the Qatar Foundation for their generous support to attend the conference and funding my scholarship.

4.1 Introduction

Building on the technical and economic literature review presented earlier, in this chapter, we critically review the existing literature on the economics of electric systems decarbonisation. In particular, we explore the existing metrics frequently used in the literature to make inferences about the economic effectiveness of using renewable technologies to decarbonise electric systems. We identify several theoretical shortcomings of the existing metrics and outline several circumstances in which the sole reliance on these metrics can lead to suboptimal or misguided investment and policymaking decisions. Recognising this gap in the literature, we aim to make a theoretical contribution by proposing a new theoretical framework and a new gauging metric for measuring and benchmarking the cost-effectiveness of decarbonising electric systems by means of renewables. Drawing on the research results and findings, we also present several original insights related to the economics of the renewable decarbonisation process, as well as providing several practical policy recommendations related to the evaluation of climate change economic policies.

In the first section of this chapter, we review the existing technical literature related to measuring and quantifying the emission savings attributable to renewable energy sources. We also provide a review of the economic studies related to the subject. In the following section, we identify some of the gaps that exist in the current literature and explain the need for the proposed framework and metric. We also discuss the theoretical and practical shortcomings of existing metrics. In the third section, we introduce the proposed framework and present some explanatory examples to demonstrate its usefulness. Thereafter, we summarise our research findings and discuss some policy implications of our results.

4.2 Summary of Literature Review

There are many recent studies that examine the emission savings attributable to renewable energy sources. These studies tend to differ significantly in terms of their scope, methodological approaches, and technical and economic emphasis. In this work, we identify four related streams of literature that address the environmental benefits of renewables and the economics of integrating them into electric systems.

The first stream of the literature identified investigates the emission savings of renewables using detailed engineering models. These studies tend to underscore the technical aspects of efficiently reducing the carbon emissions of electric systems. Examples of this stream of literature include Denny and O'Malley (2006), Hart and Jacobson (2012), Gutiérrez-Martín et al. (2013), Clancy et al. (2015) and Pereira et al. (2016).

The second strand of literature uses a statistical approach to estimate and quantify the emission savings attributable to renewables in certain regions or systems. Representatives of this stream of literature include Hawkes (2010), Cullen (2013), Kaffine et al. (2013), Wheatley (2013), Novan (2015), Thomson et al. (2017), Staffell (2017), O'Mahoney et al. (2017) and Liddle and Sadorsky (2017). In one study, for example, Staffell (2017) investigated the carbon savings of renewable technologies for the British System between 2013 and 2016. Following Hawkes (2010) approach, Staffell estimated and compared the displaced emissions by wind and solar power. Like Cullen (2013), Staffell reported different carbon displacement proportions for several conventional technologies. In addition, while he reported comparable carbon displacement figures per MWh generated for both solar and wind during the study period, Staffell further reported notable variations in their corresponding carbon displacement trends over time.

The third stream of the literature identified takes a more economic perspective on the emission savings and environmental benefits delivered by renewable energy technologies. Examples of this stream of literature include Sims et al. (2003), Denny and O'Malley (2007), Fell and Linn (2013), Marcantonini and Ellerman (2015), Marcantonini and Valero (2017) and Cullen and Mansur (2017). For instance, in their well-cited review summary prepared for the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), Sims et al. (2003) examined the comparative costs of reducing the global carbon emissions from the power sector using a range of conventional and renewable energy technologies. They estimated the cost of CO_2 abatement based on the anticipated long-term effects of displacing carbon-intense generation technologies with low carbon and renewable technologies. Their analysis was largely based on various assumptions and projections about diffusion scenarios of the low carbon and renewable technologies and the anticipated carbon intensity figures of the expected displaced carbon-intense technologies. Their analysis indicated that the abatement cost of CO_2 using PV and solar power was then predicted to be by far the most expensive option compared with the alternative options, including coal- and gas-fired plants fitted with carbon capture and storage technologies. The conclusions of the study recognised that the cost savings and carbon emission reduction benefits are location-specific and are likely to vary from case to case. However, it did not include engineering modelling and simulations for the electric systems under consideration in the study.

On the other hand, Denny and O'Malley (2007) used an hourly engineering dispatch power model to carry out an economic cost-benefit analysis of integrating wind for the Irish system. Their analysis concluded that the net benefits of wind are not particularly sensitive to the pricing regimes of SO_2 and NO_X emissions due to the relatively large difference in magnitudes between the saved CO_2 emissions and the released SO_2 and NO_X emissions. They also presented similar findings in their previous work Denny and O'Malley (2006). Likewise, Cullen (2013) reported that the justification of wind subsidy will be predominantly driven by the CO_2 emission savings rather than the SO_2 and NO_X emission saving benefits for the Texas System while using a statistical approach in his analysis. Denny and O'Malley (2007) also reported that under a high pricing scenario of CO_2, the benefits of the altered merit order effect can be limited by the increased cycling costs given the fleet composition and technical emission data assumed for the Irish generation fleet for their study.

Fell and Linn (2013) compared the cost-effectiveness for a range of renewable energy promoting policies in reducing the CO_2 emissions for the Electric Reliability Council of Texas (ERCOT) market using long-term investment models. They compared the cost-effectiveness of setting a carbon price, production subsidy, feed-in tariffs and other existing policies such as the clean electricity standard (CES) and the Renewable Portfolio Standard (RPS) for reducing the system's carbon emission. In their analysis, Fell and Linn gauged the cost-effectiveness of these policies using the change in the value of the producer and consumer welfare divided by the change in value for the system's emissions compared with a no-policy setting. Their results indicate the feed-in tariff policy promotes investment in technologies with the lowest cost irrespective of their environmental value, whereas the RPS policy and production subsidies were found to promote investment in technologies with the greatest market value. In comparison, the CES policy was found to promote investment in technologies with both the highest market and environmental value. Nevertheless, setting a CO_2 price was found to be more cost-effective in reducing the system's carbon emissions than the CES policy. In another study, Marcantonini and Ellerman (2015) calculated the implicit carbon price of decarbonising the German system using solar and wind power. Using the cost and remuneration data covering the period between 2006 and 2010 and carbon emission saving estimates of Weigt et al. (2013), Marcantonini and Ellerman estimated that under a range of different scenarios, the implicit carbon price would always remain in the range of few tens €/tCO_2 for wind energy and in the order of hundreds of €/tCO_2 for solar energy.

The fourth strand of literature examines the added costs and the economic and policy implications of integrating renewables into the electric energy system but not primarily from the emission saving or climate change perspective. Examples of this stream of literature include Denholm and Margolis (2007), Lamont (2008), Sáenz de Miera et al. (2008), Weigt (2009), Troy et al. (2010), MacCormack et al. (2010), Green and Vasilakos (2011a) , Mills and Wiser (2013), Hirth et al. (2015a) and Hirth (2015). For example, Green and Vasilakos (2011a) analysed the long-term impact of integrating wind power on electricity prices and generating capacity for the British system. They also investigated the impact of integrating wind power on the revenues and profitability of the conventional thermal generation. In addition, Hirth et al. (2015a) developed a framework to quantify and report the integration costs of renewables from the market perspective. Their framework proposed splitting the cost of integrating renewables into three categories. The three categories relate to the reduction in the market value of renewables due to deviations from day-ahead generation schedules, location, and profile of renewable generation. The cost categories reflect the cost of forecast error, transmission costs and the time value of renewable generation. In comparison, Gross et al. (2006) proposed two categories to report the cost of the grid integration of renewables: (1) costs of intermittency or system balancing costs, which relate to the short-term adjustments needed to manage the fluctuations of renewables output, and (2) reliability impacts, which relate to the long-term contribution of renewables to the reliability of supply.

4.3 Issues with Existing Literature & Economic Effectiveness Metrics

Following and building on our literature review section, we would like to note the following points. Firstly, our literature survey reveals that a large and growing body of literature has examined the emission savings attributable to renewables. We note that many studies tend to focus on estimating, quantifying or monitoring the renewable carbon savings in a particular system or country. Although we recognise that these scholarly works make valuable contributions to estimating the expected environmental benefits of expanding the use of renewables, they nevertheless give little insight into the cost-effectiveness of the renewable decarbonisation process at a system or a country level. In addition, we were unable to identify a theoretical framework tailored to the power sector for measuring or reporting the cost-effectiveness of the renewable decarbonisation process. For example, we note that the least-cost marginal abatement cost (MAC) curves presented by Jackson (1991) which is widely known as "McKinsey Curves", despite their significant value and usefulness, cannot easily present the complexity and the dynamics of the renewable decarbonisation process of the power sector. A typical MAC curve consists of a set of rectangles showing the amount of emissions that can be saved by different technologies or abatement options at a given constant cost per ton of CO_2 as shown Figure 24. This presentation does not easily allow reflecting the increasing difficulty of maintaining marginal carbon saving with increased renewable penetration. Likewise, it cannot easily represent the changes in the marginal abatement cost of renewables as the power system decarbonises. Although the MAC method is intuitive and appealing in representing the abatement costs of different technologies at a certain point or scenario, it cannot track the economic changes under different scenarios or assumptions as the system decarbonises.

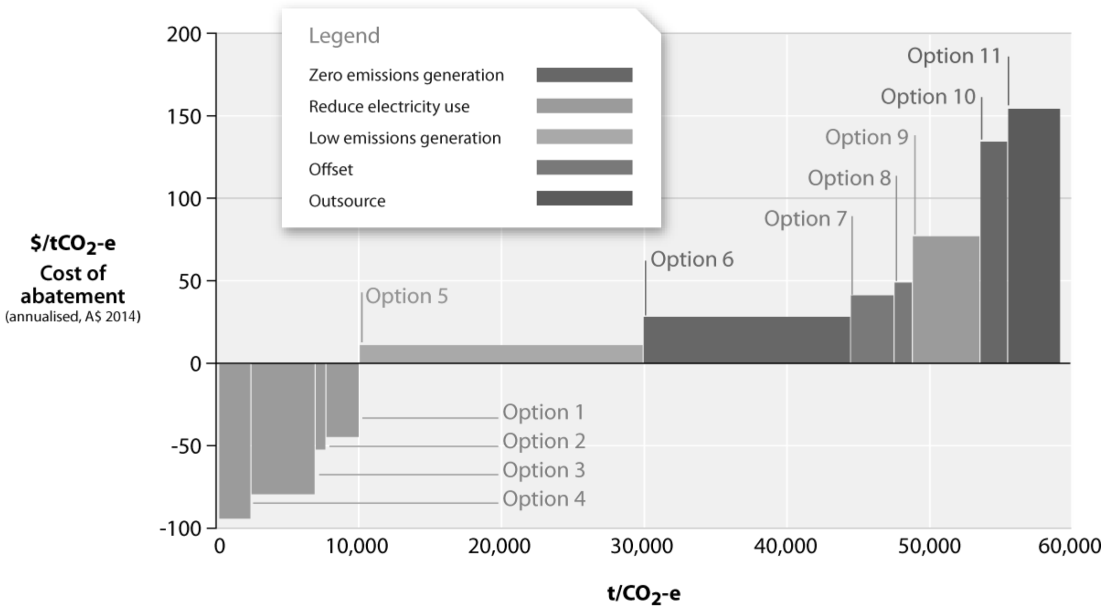

Figure 24: Illustrative graph showing typical MAC curves for different CO_2 abatement options. Adapted from (CitySwitch, 2019)

Secondly, our literature survey reveals that renewable decarbonisation studies that have economic focus and emphasis vary widely in terms of their modelling methodology, level of analysis, amount of technical detail, characteristics of the system under study, and the renewable technologies under consideration. As a result of these variations, and in the absence of a universal theoretical framework for reporting the results, we find it increasingly difficult to compile and disseminate the results of these valuable studies in a comparative fashion.

Thirdly, our review discloses a lack of consensus between researchers and practitioners with regard to the metrics they use to express the competitiveness of renewable technologies for decarbonising energy systems. We believe that this hinders the efforts of many researchers to compare, synthesise and draw meaningful insights from these valuable studies. For example, some studies tend to express their results in USD/ton of avoided CO_2 emissions metric, along with its currency variations, to measure and compare the relative economic effectiveness of decarbonising electric systems using different renewable technologies. In our work, we argue that although the USD/ton of avoided CO_2 provides a reasonable "snapshot" of the economic effectiveness of the renewable decarbonisation process at a given time, such a static metric falls short of encompassing its highly dynamic nature, especially for long-term studies. As we shall demonstrate in detail later in the chapter, the carbon savings delivered by renewables tend to change over time. In other words, the ability of renewable generation technologies to save carbon emissions changes as the share of renewables expands and grows. This variation in the long-term environmental value of renewable generation over time alters the economics of the decarbonisation process at the system level. In addition, the cost of integrating renewables changes with increased penetration too (Hirth et al., 2015a). This necessitates a more rigorous and robust economic treatment.

Moreover, countless studies, professional reports, and governmental publications have used the levelised cost of energy for a wide range of renewable technologies as benchmarking metric to report their relative economic competitiveness. More recently, LCOE of many renewable technologies has sharply declined (IRENA, 2018). As a result, direct cost comparisons of LCOE figures have made renewables to be perceived as economically competitive options for decarbonising energy systems when compared to other low-carbon technologies such as nuclear power and carbon capture and storage (CCS). In his well-cited work, Joskow (2011) argued that the levelised cost of energy is a flawed metric for gauging the relative economic competitiveness of renewable technologies when compared to other conventional generation technologies. Among other reasons, Joskow justified his conclusion based on the fact that the levelised cost of energy does not reflect the time-varying market value of renewable generation. In our work, we further argue that this metric should not be used to benchmark the relative economic competitiveness of renewable technologies for decarbonising electric systems as it does not reflect or internalise the varying carbon savings delivered by different renewable technologies. For example, there might be a situation in which a renewable technology is cheaper than another on a levelised cost basis. Nevertheless, this does not necessarily guarantee that the former will outperform the latter in terms of its cost-effectiveness in reducing the carbon emission of a given system because of the different technical characteristics and varying expected carbon saving potentials of different technologies. In addition, we further argue that such a life-cycle metric does not take into account the changes in the long-term environmental value of renewables over time as the system decarbonises. Nor does it take into account the characteristics of the system under study. Therefore, we argue that these metrics, despite their usefulness, must be used with caution when evaluating the relative economic competitiveness of renewable technologies for decarbonising electric systems, especially for long-term studies.

In this chapter, we intend to make the following contributions.

Firstly, we want to make a theoretical contribution by proposing a new mathematical framework for measuring the cost-effectiveness of the system-wide decarbonisation process of electric systems. To the best of our knowledge, this is the first framework capable of measuring and tracking the cost-effectiveness of the decarbonisation process from a system-level perspective. The new framework is generic, technology neutral, and enables the consolidation of the economic results of decarbonisation studies that consider various renewable technologies as well as low-carbon technologies such as nuclear power and CCS. Furthermore, it allows the compilation of results from studies that use different modelling methodologies, assumptions, and data sets. Notably, the new framework enables measuring and tracking the cost-effectiveness of the renewable decarbonisation process at a country or a system level by directly linking the changes in the system's total cost to the carbon reduction savings attributable to renewables. As a result, it allows the direct comparison of the economic implications of different decarbonisation scenarios and various policy proposals in a very intuitive graphical way. By doing so, we hope to fill this gap in the literature, and we believe this will be of particular relevance and importance in informing the policy decision-making process and providing a useful tool for climate change policy evaluation.

Secondly, we propose a new benchmarking metric for gauging the relative cost-effectiveness of using different renewable technologies or low-carbon technologies to achieve sustained and long-term carbon emission savings. Unlike the existing cost-effectiveness metrics, the proposed metric takes into account the dynamic nature of the decarbonisation process. In addition, it includes the technical and economic parameters of the renewable technologies and their interaction with the characteristics of the system under study. Moreover, the new metric allows expressing the cost-effectiveness of the decarbonisation process as a percentage of the system-wide decarbonisation level. By doing so, we aim to overcome the shortcomings of the existing metrics used in the literature.

Thirdly, drawing on the multiple findings and results of the research carried out, we propose and provide several original, country-level policy recommendations and insights related to the economics of renewable decarbonisation. We hope that this will help researchers, policymakers and practitioners alike with regard to climate change economic policy evaluation. Altogether, we hope that our work will advance our understanding of the economics of climate change and contribute to the literature addressing the environmental economics of energy systems.

4.4 Nature of the Decarbonisation Process

Previous studies, such as Hart and Jacobson (2012) and Katzenstein and Apt (2009), reported that the system-wide carbon emission intensity tends to fall with increased renewable generation. Nevertheless, it tends to decline at different rates with increased penetration. For demonstration purposes, a typical system-wide decarbonisation graph using Photovoltaic (PV) technology or the so-called "carbon curve" can be depicted in Figure 25. As shown in Figure 25, the typical carbon curve tends to initially decline in a linear fashion with increased renewable penetration and then to gradually flatten as the incidence of curtailment becomes more pronounced. This explains the diminishing marginal carbon saving potential of renewables at relatively high penetration rates as the added renewable generation does not get readily absorbed by the system. Despite its usefulness, the carbon curve gives little insight into the economics of the decarbonisation process.

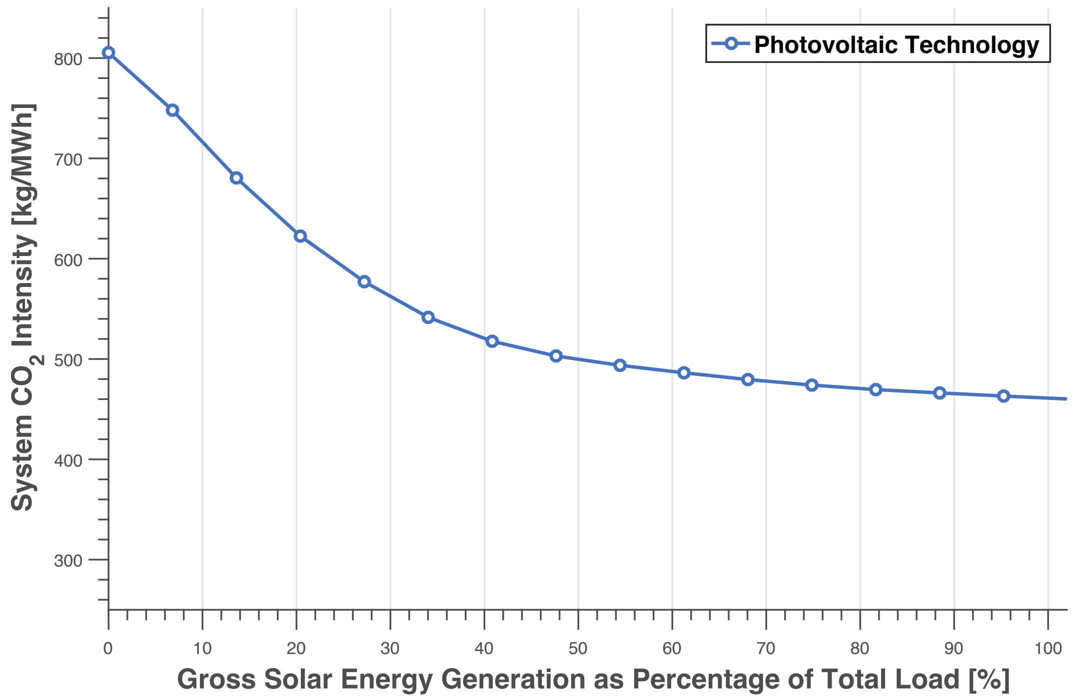

Figure 25: The system's carbon curve illustrating the fall of the system's average carbon intensity as the renewable generation share grows. The steepness of the curve tends to flatten as more solar energy is spilled with increased penetration.

One way of examining the economic changes of increased penetration at the system level would be through tracking the changes in the system's total production cost or the average unit production cost, which includes both the fixed (i.e. investment and fixed maintenance costs) and variable system costs (i.e. fuel and variable maintenance costs).

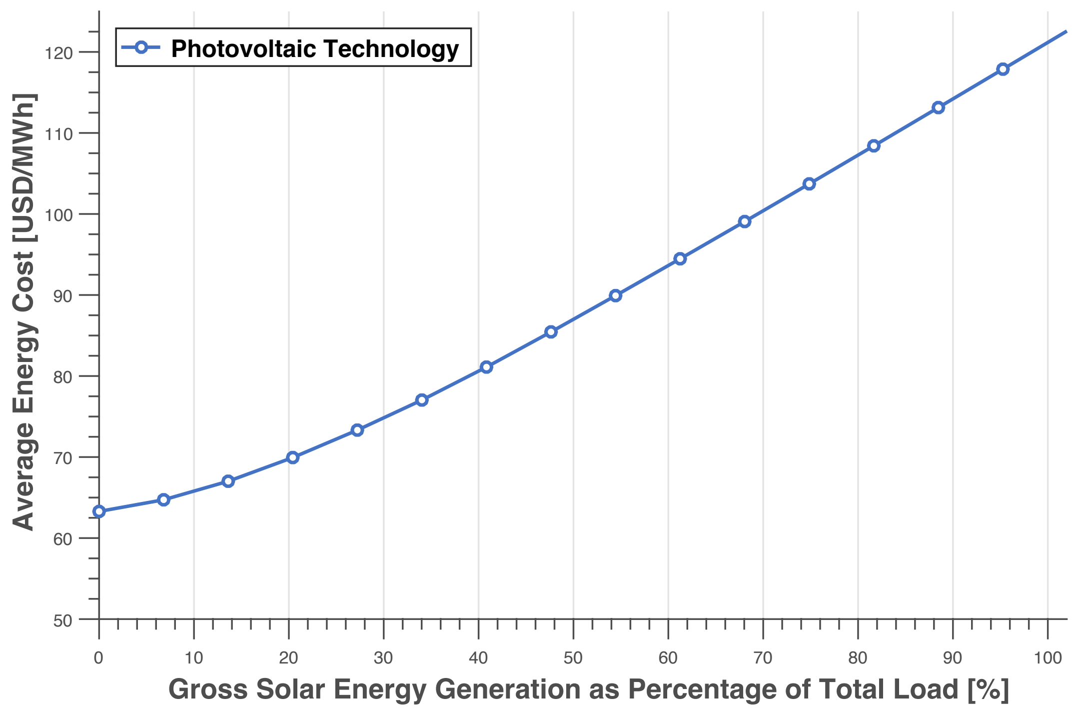

Figure 26: The system's average unit projection with increased renewable penetration

As shown in Figure 26, in this example, the increased renewable penetration leads to a gradual increase in the average unit production cost. One might anticipate that the production cost changes at potentially different rates and magnitudes depending on the characteristics of the renewable energy considered and the system under consideration. Nevertheless, in many cases, this trend tends to be broadly linear. A major drawback of exclusively using this relationship to make inferences about the economics of the decarbonisation process at a system level is its failure to take into account the potentially diminishing carbon savings with increased renewable penetration. In particular, the marginal carbon savings tend to decline as the system decarbonises. This makes it more likely for the production cost of energy and the underlying decarbonisation process to go at increasingly different speeds with increased renewable penetration. This, in turn, makes it particularly challenging to make informed inferences about the economics of the decarbonisation process by solely tracking the renewable penetration rates with the expected corresponding changes in the average unit production cost or the total system cost. We argue that a more useful approach would be to directly link the anticipated carbon emission savings with the corresponding economic changes taking place at the system level. A graph showing the anticipated saved volumes of CO_2 with the expected changes in the system's cost is depicted in Figure 27.

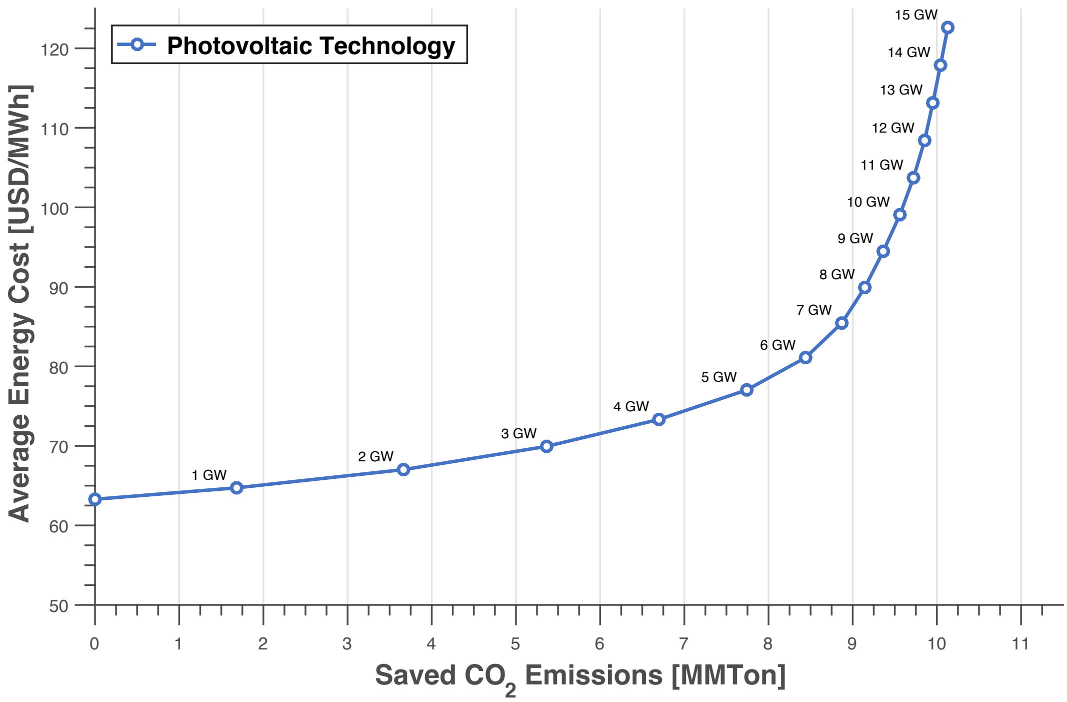

Figure 27: Relationship between the saved CO_2 emissions and the change in the system's average energy production cost

Looking closely at this relationship, we can make the following initial observations. Firstly, the total production cost or the average unit production cost exhibits a nonlinear relationship with the additional carbon emission savings, even though the total production cost scales linearly with increased renewable penetration under the same penetration scenarios. We argue that this particular economic relationship is at the heart of studying the economics of decarbonising electric systems through the use of renewable energy sources, because it directly links the system-wide environmental benefits of renewables to the expected changes in the system's production cost.Secondly, from the emission saving perspective, the graph clearly demonstrates the increasing difficulty of maintaining marginal carbon savings with increased penetration. The pace of saving carbon emissions tends to be highest at relatively low renewable penetration rates, and it tends to fall considerably afterwards. At relatively high penetration rates, the marginal carbon savings tend to decline sharply. This explains the exponential pace of production cost escalation at higher penetration rates. The sharp decline in the carbon savings might be attributed to the increased incidence of curtailment and the inability of renewable generation to achieve more capacity savings at the system level.

4.5 Introducing the New Framework

We further argue that a better way to examine and present the relationship between the saved carbon emissions and the system's economics would be to examine their inter-relationship in relative rather than absolute terms, as shown in Figure 28. This new presentation has many advantages.

Firstly, it provides an intuitive representation of the renewable decarbonisation process at the system level. For example, as shown in Figure 28, the new framework provides a convenient and powerful tool for graphically estimating the economic implications of decarbonising electric systems using different renewable energy sources. For instance, for Technology 1 in Figure 28, it can be estimated that a 40% system-wide carbon reduction would result in an approximately 50% increase in the total system's cost. On the other hand, achieving an additional 10% carbon reduction (50% system decarbonisation) would result in an approximately 100% increase in the total system's cost.

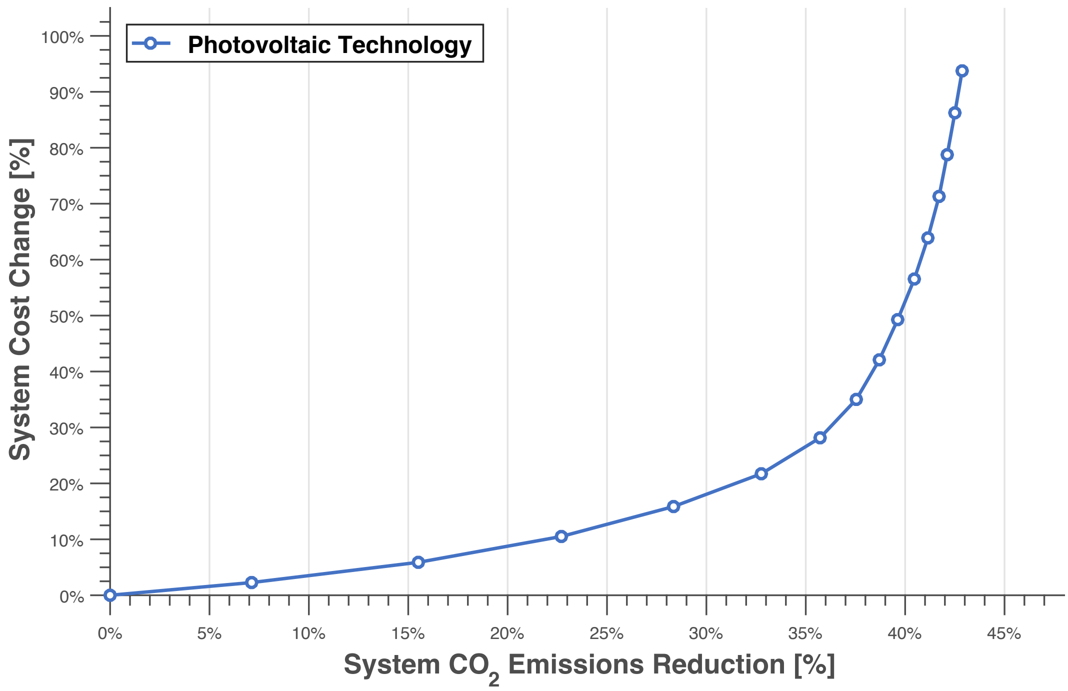

Figure 28: Proposed representation of the relationship between the relative saved CO_2 emissions and the relative change in the system's average energy production cost

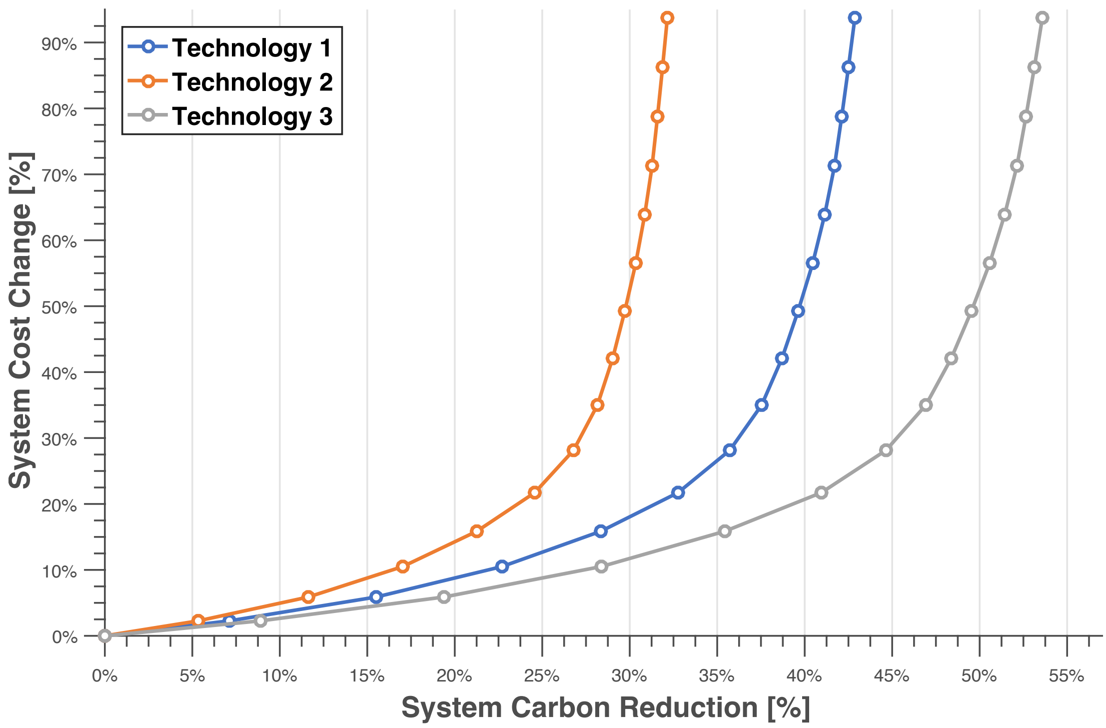

Figure 29: An example of the graphical benefits of the proposed framework

Another advantage of using this framework is its intuitive representation of the maximum theoretical decarbonisation limits that various renewable technologies can achieve along with its corresponding economic implications. For example, it could be estimated that

Technology 3 in Figure 29 has the edge compared to the other technologies in terms of its deep decarbonisation potential, which could reach as high as 53%. On the other hand, it could be estimated that with a 50% increase in the system's total cost, Technology 1, Technology 2, and Technology 3 can deliver about 30%, 40%, and 50% system decarbonisation, respectively.

Thirdly, as we shall argue in the following section, presenting this relationship in relative terms has a significant theoretical and practical value in that it provides a new mathematical framework for measuring the cost-effectiveness of the renewable decarbonisation process. In addition, it has many practical advantages for practitioners and policymakers.

4.6 Proposed Carbon Cost-effectiveness Metric

Building on the previous sections, we can now introduce some useful formulas and definitions. In this work, we refer to each individual curve shown in the framework as the "carbon economic effectiveness curve". Mathematically, each point on the curve represents the elasticity of the system's total cost with respect to the corresponding system's decarbonisation level or the level of the renewable carbon emission savings.

The shape of the carbon economic effectiveness curve varies significantly across different technologies and systems. These variations in the curve's shape reflect differences in the technical and economic parameters of the renewable technologies considered and their interaction with the characteristics of the system under study. In certain cases, the carbon economic effectiveness curve might take negative numbers. This implies that the penetration of renewable energy contributes to lowering the total systems cost. More generally, the relationship between the relative increase in total system cost and the corresponding carbon emission reduction or savings can be expressed in the following mathematical form:

$$C_{\%,\,Tech} = f\left(E_{\%,\,Tech}\right) \tag{33}$$

Where

$\boldsymbol{C_{\%,\,Tech}}$ The change in the system's total cost (in %) as a result of a given technology penetration

$\boldsymbol{E_{\%,Tech}}$ The system-wide decarbonisation level (in %) attributable to the technology under study

In practice, researchers and policymakers might need to compile several data points that ideally cover a wide range of decarbonisation scenarios to construct this mathematical relationship. In the absence of a large number of data points, researchers also might consider using curve fitting techniques to construct a function that best represents their results' data points. the significance of this relationship is that it encompasses how the carbon cost- effectiveness of a system changes under a wide range of different decarbonisation scenarios or desired study outcomes considered by system planners, policymaker or researchers alike. In other words, it embodies the inherently dynamic nature of the renewable decarbonisation process and its corresponding expected economic implications over an extended period of time. Therefore, it will be very helpful to policymakers and system planners to examine this relationship carefully when taking a long-term policy or investment decision. In essence, the framework can be used as a tool to facilitate transparency with regard to proposed environmental and economic policies at the country level. We shall discuss this in more detail in the following section. Likewise, it can be used by project developers and investors to provide evidence about the economic and environmental soundness of their renewable investment portfolios in a given country. Among other possible usages, it could also be used by international donors as a tool for identifying renewable technologies with the highest environmental value at given host countries.

Illustrative Example

In evaluating the economic implications of a potential policy decision to decarbonise the electric system by 30% relative to the current level, a policymaker might refer to the relevant carbon economic effectiveness curves in his or her analysis. For instance, the policymaker will note that using Technology 1, 2 or 3 will result in an increase in the system's total cost of about 10%, 20%, and 50%, respectively. We refer to each value of those numbers as the carbon economic effectiveness factors (CEEFs) for each technology; in other words, $CEEF_{30\%,\ Tech1} = 10\%$, $CEEF_{30\%,\ Tech2} = 20\%$ and $CEEF_{30\%,\ Tech3} = 50\%$. Choosing to take Technology 2 as a reference technology, the policymaker could further express the relative economic effectiveness ratios as 2, 1, and 0.4, respectively. In other words, Technology 1 is twice as cost-effective in delivering the same carbon emission savings as the reference technology. Similarly, Technology 3 is about four-tenths as cost-effective, and so on. We refer to these relative cost elasticity ratios or the relative

CEEF as the carbon economic effectiveness credit (CEEC) for each technology. Mathematically, we can represent it using the following formula:

$$CEEC_{\%,\ Tech1} = \frac{CEEF_{\%,Ref}}{CEEF_{\%,Tech1}} \tag{34}$$

	CEEF $_{30\%,\ Tech}$	**CEEC $_{30\%,\ Tech}$**
Technology 1	10%	2.0
Technology 2 (Ref)	20%	1.0
Technology 3	50%	0.4

Table 13: Summary of CEEF and CEEC factors for Technology 1, 2 and 3 for a 30% decarbonisation scenario

The significance of expressing these factors in relative form is that they could be used as a weighting or multiplication factor for policy design purposes. For example, in considering the renewable subsidy level for different types of renewable technologies, a policymaker might allocate subsidy levels that are proportional to the expected CCEC values for each technology type.

In addition, this gives the policymaker great flexibility in choosing the reference technology that suits the analysis's needs. For example, a policymaker might consider benchmarking cost-effectiveness of renewable savings with respect to the savings delivered by a low-carbon technology like nuclear power. As the framework is generic and technology-neutral, it could be used to measure the cost-effectiveness of the decarbonisation process using different technologies, including non-renewable technologies. In the following sections, we discuss some policy implications of our work in more detail.

4.7 Comparison to Existing Metrics

In this section, we present an example to show how the sole reliance on the existing economic competitiveness metrics might lead to suboptimal or misguided long-term investment and policy-making decisions with regard to the economics of the decarbonisation process. In particular, we compare the levelised cost estimates for PV and CCS technologies with carbon cost effectiveness estimates using the framework developed for a wide-range of decarbonisation scenarios of a relatively small electric system.

Case Study Details Summary

The study case presented is loosely based on the Qatari electric system. We used historic hourly demand data for the Qatari system presented in *3.5.1 Demand data*. However, as indicated earlier, due to commercial data confidentiality issues, unfortunately, we were not able to simulate the existing generation assets of the system. Nevertheless, for consistency and demonstration purposes, we used a greenfield approach to help illustrate the cost-effectiveness of using the PV and CCS technologies for decarbonising the small electric system considered. Furthermore, for simplicity, we used a basic screening curve (SC) optimisation model to explore the different least-cost decarbonisation scenarios of the system. The SC model is based on the mathematical formulation presented in *3.2.2.1 Screening curve method*. We implemented the SC models for both technologies using the General Algebraic Modeling System (GAMS) software (Brooke et al., 1998, Bussieck and Meeraus, 2004). For more details on GAMS implementation, data processing and other modelling assumptions, the reader is encouraged to refer to *3.4 Implementation of Optimisation Models* .In addition, section *3.5 Test System Details* show selected graphs and summary tables about the characteristics of the system under consideration as well as details of the renewable energy resources of the test system.

We consider four types of thermal generation technologies: open cycle gas turbine (OCGT), combined cycle gas turbine (CCGT), coal-fired steam plants (Steam Coal), and coal-fired steam coal fitted with carbon capture and storage technology[98] (Steam Coal with CCS). The cost and technical data of conventional and renewable technologies are based on the compiled data presented in section *3.5.2 Generation plants' data.*

Levelised Cost Estimation

Levelised cost of energy is one of the most commonly used methods of comparing the relative competitiveness of different renewable and non-renewable generation technologies (IRENA, 2018b). Owing to its simplicity and its ease of applicability to a wide range of technologies, the LCOE continues to be used by many governmental entities and professional bodies to make inferences about the economics of renewable

98 Based on amine scrubbing system, utilizing monoethanolamine as a solvent to capture CO_2 from the flue gas

energy technologies (REN21, 2016, Fraunhofer ISE, 2018, EIA, 2019). In essence, the measure indicates the average fixed revenue per unit of electricity generated that would be needed to recover the costs of building, operating, and sometimes the decommissioning of a generating plant over its economic lifetime. Full derivation of the LCOE is included in Appendix A. As pointed earlier, Section *3.5.2 Generation plants' data* includes the key cost and technical data considered in this brief study for the PV and CCS technologies. Additional details about LCOE calculations and sensitivity analyses of key technical and economic inputs are enclosed separately at the supplementary results Appendix A.

Study Cases Results

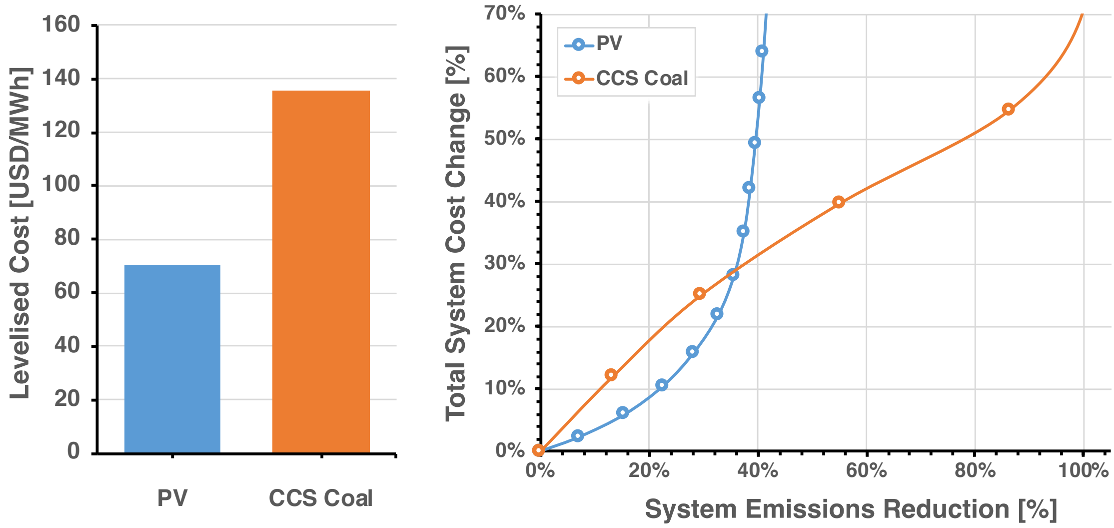

Figure 30: A comparison between the LCOE metric and the proposed metric for gauging the cost-effectiveness of the decarbonisation process

We simulated the deep decarbonisation of the system for a wide range of penetration scenarios for both the PV and CCS technologies. In addition, we develop the levelised cost estimates of the PV and CCS technologies respectively. As shown in Figure 30, although the cost of PV technology is almost half the cost of CCS technology on a levelised cost basis, this did not necessarily guarantee the cost-effectiveness of the PV technology to achieve sustained and deep decarbonisation of the electric system. In addition, the case study also highlights the wide variation among renewable and low-carbon technologies in terms of their potential to decarbonise electric systems and their cost-effectiveness in delivering that. For example, at shallow decarbonisation levels, PV tended to have the edge over CCS as a more cost-effective option to decarbonise the system. However, at deeper decarbonisation levels, CCS technology emerged as a superior option, although it is twice as expensive on a levelised cost basis.

It is important to note that the economic findings of this small case study do not necessarily hold true for all systems or to the same extent given the different natures of the systems and the studies' underlying assumptions. Nevertheless, these findings highlight the shortcomings of the existing technology-level economic metrics such as LCOE to capture the complexity of the decarbonisation economic effectiveness at the system level. In addition, the findings highlight the usefulness of the proposed framework in understanding the economics of the decarbonisation process at a system level.

4.8 Policy Implications and Insights

Building on the research conducted, in this section, we briefly discuss and summarise some of the main findings of this part of the research.

Our research establishes that the long-term environmental value of renewable generation changes over time. We find that the nature and scale of this change hinge upon the technical and economic characteristics of the renewable technology considered, the nature of the system under study, and the stage and level of the decarbonisation process.

Furthermore, our results suggest that the environmental value of many renewable technologies is likely to depreciate over time. In particular, the carbon savings per GW of renewable capacity tend to decline as the system decarbonises. In other words, renewable carbon saving productivity is expected to slow down with increased renewable capacity growth.

One relevant insight is the importance of making a distinction between the renewable decarbonisation process and the process of adding more renewable capacity to electric systems. Although our research suggests that these two processes tend to go hand-in-hand at the beginning of the decarbonisation process, they are likely to decouple at higher decarbonisation and renewable penetration rates. Another relevant insight is that renewable carbon saving productivity is expected to be highest at low renewable penetration rates. This would suggest that renewables would have much better chances to compete with low-carbon technologies for "shallow decarbonisation" levels rather than the envisioned "deep decarbonisation" levels of power systems, especially in the absence of cheap storage options. At the policy level, this would suggest the following recommendations:

- Policymakers might need to revisit the environmental rationale of expanding certain renewable technologies as the system decarbonises, especially the ones with the fastest environmental depreciation rates.
- In addition, policymakers might need to consider scaling down their renewable incentive programs as the system decarbonises in line with the expected decline in carbon savings of renewables.
- Furthermore, investors who expect that certain premiums on their renewable assets are proportional to the environmental value delivered should be aware that such premiums might decrease over time.

Moreover, our research shows that the diminishing environmental benefits of renewables affect the economics of the decarbonisation process in a very fundamental way, especially at higher decarbonisation levels. In particular, as the systems decarbonise, the capital costs of renewables grow at a much faster pace compared to fuel and operation savings of thermal generation at the system level. In addition, the energy value of renewables tends to depreciate as a result of the increased incidence of curtailment (Mills and Wiser, 2013). At the same time, the renewable capacity value of many renewable technologies tends to fall sharply with increased penetration (Castro and Ferreira, 2001, Ueckerdt et al., 2015). As a result, the marginal cost of saving carbon emission at the system-level of some renewable technologies tends to escalate with increased decarbonisation. This observation been reported in several previous studies such as Heuberger et al. (2016).

This result has several policy implications. One fundamental policy implication is that the abatement carbon cost of renewables is, in fact, neither static nor flat. It tends to be highly dynamic, and it changes as more renewable capacity is added to the system. Although the typical marginal abatement cost curve suggests a flat abatement carbon cost for different renewable technology types, we argue that for each renewable technology type, the implied cost of saving carbon will change as the electric system decarbonises. Therefore, we believe that using a constant carbon abatement cost of renewables in policy evaluation processes might lead to inaccurate estimates about the true cost of decarbonisation. Furthermore, it might lead to suboptimal investment and policy design decisions. Therefore, for policy evaluation purposes, we recommend that policymakers

- consider setting a dynamic or progressive carbon abatement cost figures in their analysis as the system decarbonises and
- frequently revise their implied carbon cost' estimates for renewables over time, especially for systems with fast and impressive renewable adoption rates.

Our additional research results demonstrate that renewable technologies vary widely in terms of their long-term environmental contributions. Although renewables are perceived by many to be equally green, renewable technologies vary significantly in terms of their ability to save carbon at the system level. Importantly, our results corroborate similar findings of previous works such as Novan (2015) and Callaway et al. (2018).
At the policy design level, a particular worry is the existence of policy or incentive programs that allocate equal economic incentives to renewable technologies that deliver unequal long-term environmental benefits. One relevant policy insight is that the economic effectiveness of such programs will hinge upon identifying and allocating investments to technologies that have the least-cost carbon abatement potential in the long run.

Another relevant worry is the existence of policies that promote investment in technologies with the lowest production or levelised cost irrespective of their environmental value and cost-effectiveness. Our research shows that for renewable and low-carbon technologies, the economic competitiveness at the technology level (i.e. on a levelised cost basis) does not necessarily guarantee the cost-effectiveness of decarbonising an electric system. One important policy insight is that the failure to internalise the environmental value of renewable generation in investment and incentive programs is likely to lead to misguided or suboptimal long-term policy decisions.

Based on that, we recommend policymakers to better align their renewable energy investment and subsidy programs with the environmental value delivered by renewable technologies and their relative economic effectiveness. As the carbon saving potential of renewables is frequently cited as one of the primary drivers to expand their use and justify their capital-intensive investments and subsidies, there is a real need to ensure that renewables are capable of delivering the hoped-for carbon savings in a cost-effective manner. As previously noted, we believe that using the ECCE values of renewable technology sources will greatly help in informing the policymaking process in this regard.

CHAPTER 5

BENCHMARKING THE CARBON SAVINGS & ECONOMIC EFFECTIVENESS OF RENEWABLE ENERGY SOURCES: A METHODOLOGICAL COMPARATIVE STUDY[99]

99 Part of this chapter was presented at the 16th IAEE European Conference which was organized by School of Economics and Business, University of Ljubljana and the Slovenian Association for Energy Economics (SAEE). I would like to thank the participants of the conference for their insightful comments and very valuable feedback particularly at the poster presentation session. I am very grateful for the Management Department of Imperial College Business School for their generous funding to support my participation at the conference.

5.1 Introduction

Building on the theoretical framework presented in Chapter 4, in this chapter, we investigate several important factors that are often absent from the current debate about the carbon saving cost-effectiveness of renewables. In particular, we look at how the choice of modelling methodology of renewable decarbonisation studies can alter their economic results and hence change the perceived competitiveness of renewables to decarbonise electric systems. The chapter provides a methodological comparative study featuring two of the most used power systems modelling methodologies to investigate this effect. The guiding research question of the chapter is, how does the methodological variation across decarbonisation studies affect the perceived economic competitiveness of renewable technologies in decarbonising energy systems?

In the following sections, we present three study cases to explore to what extent the modelling methodology or approach can influence the perceived carbon cost-effectiveness of renewables to decarbonise electric systems. In the first case, we compare the decarbonisation results of an SC model and a UC model. In the second case, within the UC approach, we compare two models with different technical model specifications to understand to what extent variations in the model's specifications can alter the perceived carbon cost-effectiveness. In particular, we consider the variation in a system-level technical constraint, namely the minimum running thermal load (MRTL) level of the system. In contrast, in the third case, we consider omitting a unit-level technical detail to study the effect of omitting unit-level constraints on the accuracy of the decarbonisation results.

Similar to the previous study cases, the study case presented is loosely based on the Qatari electric system. Reader may refer to section *3.5 Test System Details* for details of the characteristics of the system under consideration as well as details of the renewable energy resources of the test system.

In additional, readers are encouraged to refer to the *Methods and Data Chapter* for a full review of the data used, mathematical formulations of SC and UC models, and the implementation assumptions made for carrying out this study.

5.2 Effect of Choice of Modelling Methodology

5.2.1 Baseline scenario results

5.2.1.1 Optimum capacity mix and energy output results

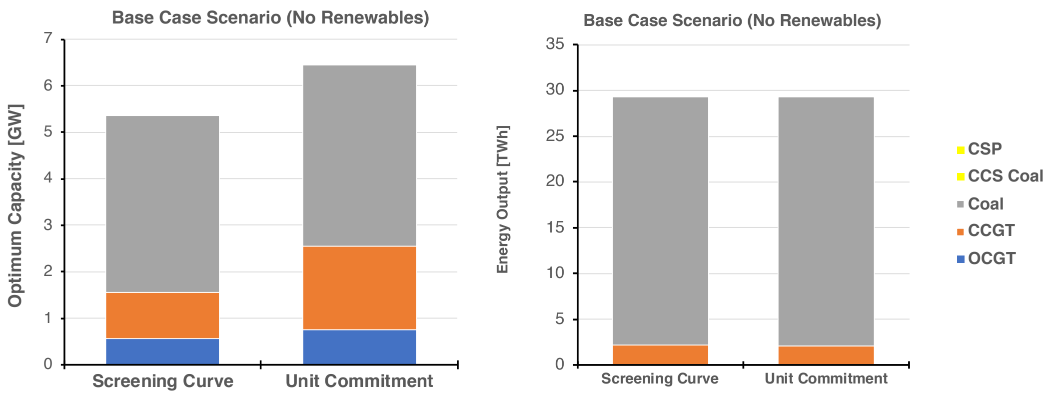

Figure 31: Capacity mix and energy output results for the baseline scenario for the SC and UC models under no renewable generation penetration.

Figure 31 shows the baseline capacity mix and energy output results for the SC and UC models in the absence of renewable penetration. It is worth noting that, for the rest of the thesis, CCS technology appears in the legend of the results' graphs to remind the reader that it was an option for the optimiser to choose from in the simulations carried out.

Predictably, the UC model shows higher capacity requirements and a relatively more flexible mix compared to the SC model. The differential in the total capacity mix results of the two models amounts to about 1.1 GW in favour of the UC model. This reflects the additional capacity needed to (1) meet the reserve requirement of the system, (2) support the system's flexibility needs, and (3) account for the specific characteristics of thermal generating units, such as the indivisibility of the generating units, their minimum running levels, up and downtimes, and other dynamic considerations that are not captured by the SC model. Interestingly, although the capacity mixes of the SC and UC models are materially different, the cumulative energy outputs of the two models are still comparable. The SC model underestimates the energy output of the OCGT technology by about 12.5% but overestimates the energy output of the CCGT technology by about 8.5% compared to the UC model results. The difference in energy output with the carbon-intense coal technology is almost negligible, being in the region of 0.6%. This explains the convergence of the carbon emissions results of the two models, as shown in Figure 32.

5.2.1.2 Emissions results

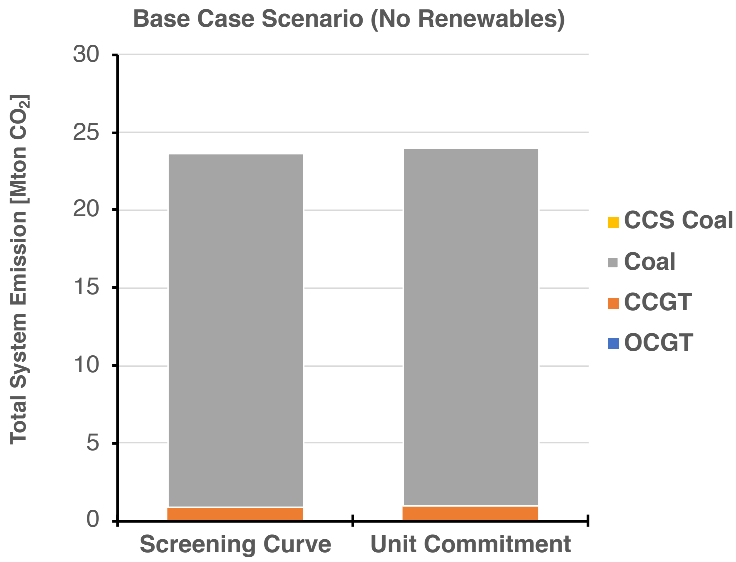

Figure 32: CO_2 emission results for the baseline scenario for the SC and UC models, showing comparative emissions levels under no renewable generation penetration.

Figure 32 shows the emissions results of the SC and UC models in the absence of renewable penetration. Referring to the figure, we can make several observations.

First, in line with the energy output variations trends, at the aggregate level, the SC model slightly underestimates the carbon emissions relative to the UC model. The estimated error appears to be insignificant, being in the region of 1.5%.

Second, at the technology level, the SC model underestimates the carbon emission by 25.9%, 7.6%, and 1.2% for OCGT, CCGT, and Coal, respectively, when compared to the UC model results. The increased emissions of the UC model appear to reflect the added fuel consumption of the units due to the partial loading efficiency penalty that the SC model is unable to capture. For example, while the energy output deviation between the two models for the OCGT technology is in the region of 13%, the carbon emission deviation for the same technology is about 26%. This reflects the fact that OCGT plants tend to consume more fuel and consequently emit more CO_2 per MWh generated when partly loaded. However, due to its relatively low generation volumes at the system level, the additional emissions of partly loaded OCGT plants tend to have a limited effect on the overall system's emission deviation.

5.2.1.3 System cost results

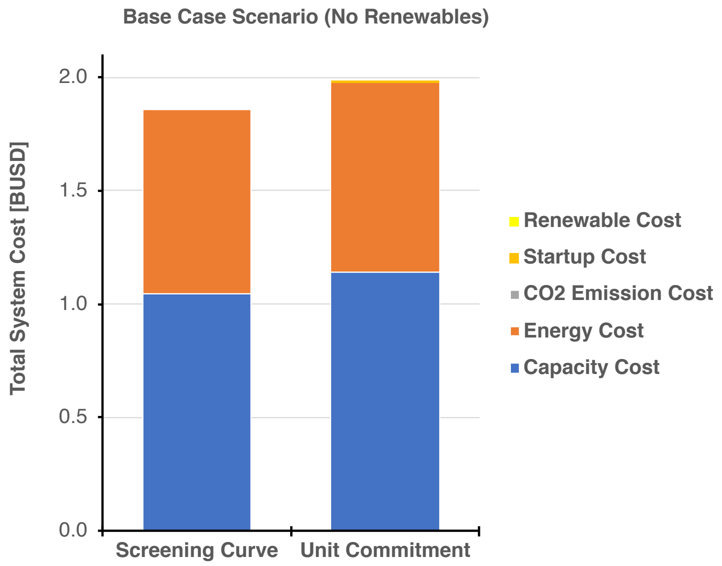

Figure 33: Total system cost for the baseline scenario for the SC and UC models under no renewable generation penetration.

Figure 33 compares the system cost results of the SC and UC models in the absence of renewable penetration. It is important to note that, for the rest of the thesis, the cost results will be reported into four[100] categories: (1) renewable cost[101], (2) capacity cost[102], (3) energy cost[103], (4) startup costs[104]. In addition, in some cases, we will use term *variable system cost* to refer to the total energy and startup costs.

As the figure indicates, at the aggregate level, the SC model underestimates the total system cost by almost 6% compared to the UC model. Overall, the cost differences reflect (1) the additional cost of a more flexible generation mix, (2) the cost of reserves, (3) the cost of generation start-ups, and (4) the implied part-load operation costs that are not captured by the SC methodology.

The cost difference is mainly driven by the capacity cost, which is off by about 8.4%. The energy cost deviation is modest, being less than 2.8%.

100 Although CO_2 emission cost category shows in the legend of many graphs, we do not use it in the presented study cases. It appears, however, to remind the reader about the ability of the models used to take into account the emissions costs in case carbon price is considered.
101 This is driven by CAPEX and fixed O&M costs of renewable technologies.
102 This is driven by the CAPEX and fixed O&M costs of conventional generators (i.e., fossil fuel based).
103 This is driven by the fuel and variable O&M costs of conventional generators.
104 This is driven by the startup costs of conventional generators.

5.2.2 Shallow and deep renewable penetration scenarios

Building on the baseline scenario, in this subsection, we compare the results of the SC and UC models under shallow and deep renewable penetration scenarios of CSP technologies. Figure 34 - Figure 51 summarise the key result of this section.

5.2.2.1 Optimum capacity mix results

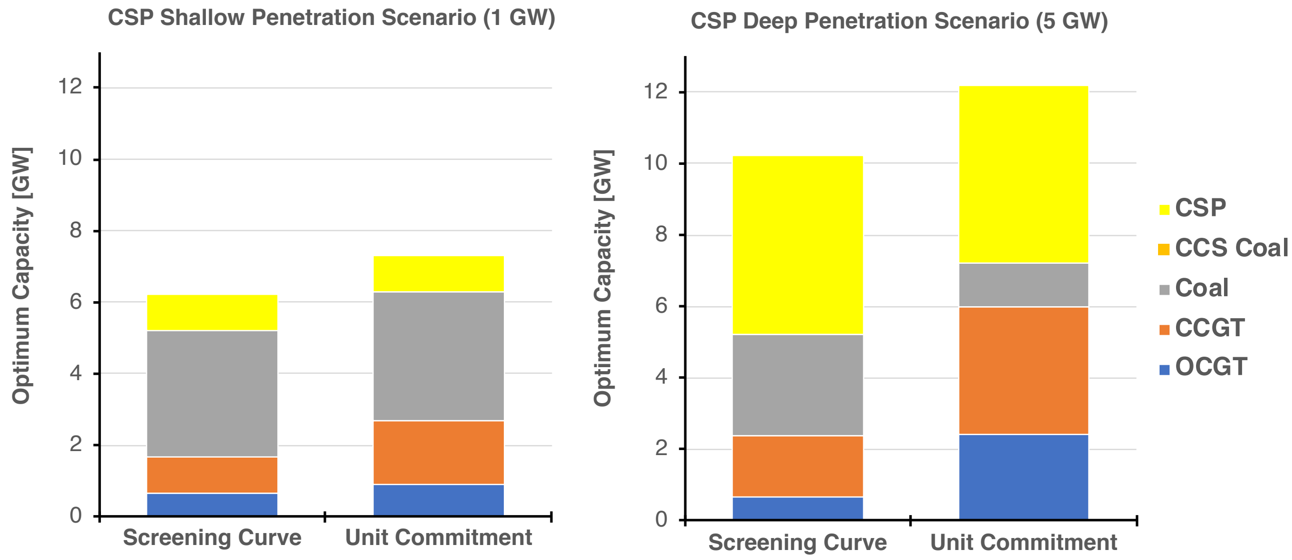

Figure 34: Comparison of the optimum technology mix results for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 34 compares the optimum technology mix results for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Referring to the figures, we can make several observations:

1. Under shallow and deep scenarios, SC model produces in both cases a less flexible technology mix compared to the UC model results.

2. Under the low-penetration scenario, the SC model underinvests in all thermal technologies, but by uneven proportions. In particular, the SC model underinvests in OCGT, CCGT and Coal by about 28%, 43% and 2% respectively. Notably, in line with capacity mix results under no renewable scenario, the deviation of investment in

Coal generation assets seems to be insignificant, being in the region of 2% under the low-penetration scenario.

3. By contrast, under deep renewable penetration, the SC model underinvests in OCGT and CCGT by about 74% and 52%, respectively. However, it overinvests in Coal assets by a significant margin of about 134%. This can be explained by the inherent inability of the SC model to capture the dynamic aspects of power system operations imposed by the deep renewable penetration and the additional flexibility required to run the system with high shares of renewables. As a result, SC models tend to overinvest into cheap, inflexible, and more carbon-intensive generation capacities when compared to the results of the UC models for the system under study. This particular fact has significant implications on the ability of SC models to accurately predict the system-wide carbon emissions under deep renewable penetration scenarios. We will discuss this in more detail in the following sections.

5.2.2.2 Energy output results

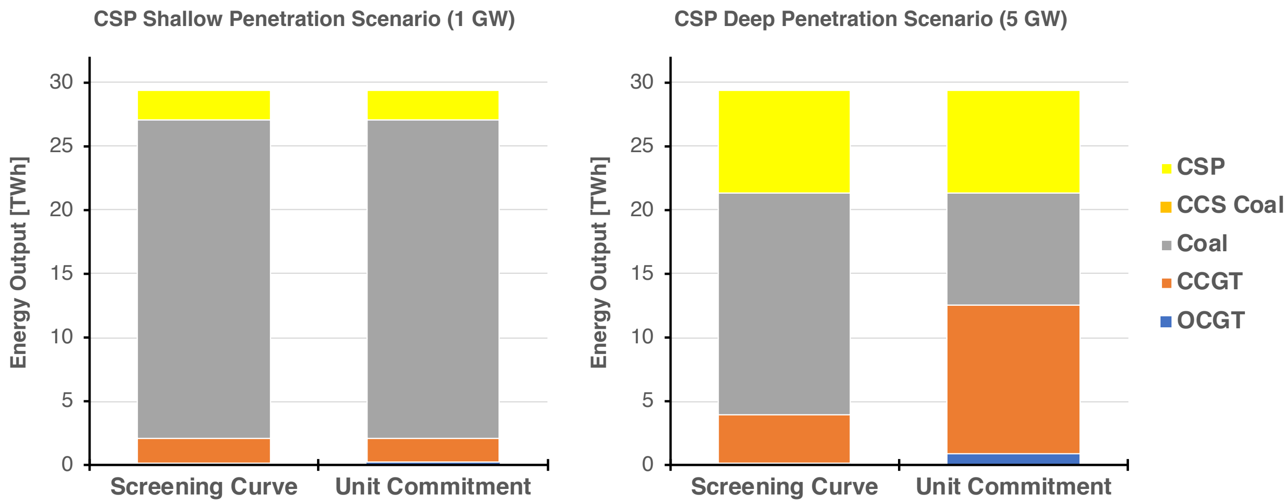

Figure 35: Energy output comparison for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 35 compares the energy output for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

As shown in the figure, the deviation amounts of the two models under shallow and deep decarbonisation scenarios are substantially different.

For example, under a low renewable penetration scenario, the SC model underestimates the cumulative energy output of the OCGT technology by about 8.5% but overestimates the output of the CCGT technology by about 1.3%. However, the energy output of the Coal technology is almost the same.

In contrast, under deep renewable penetration, the SC model underestimates the cumulative energy output of the OCGT and CCGT technologies by about 76% and 68%, respectively, relative to the results of the UC model. At the same time, it overestimates the energy output of the Coal technology by a significant margin of about 97%.

5.2.2.3 Emissions results

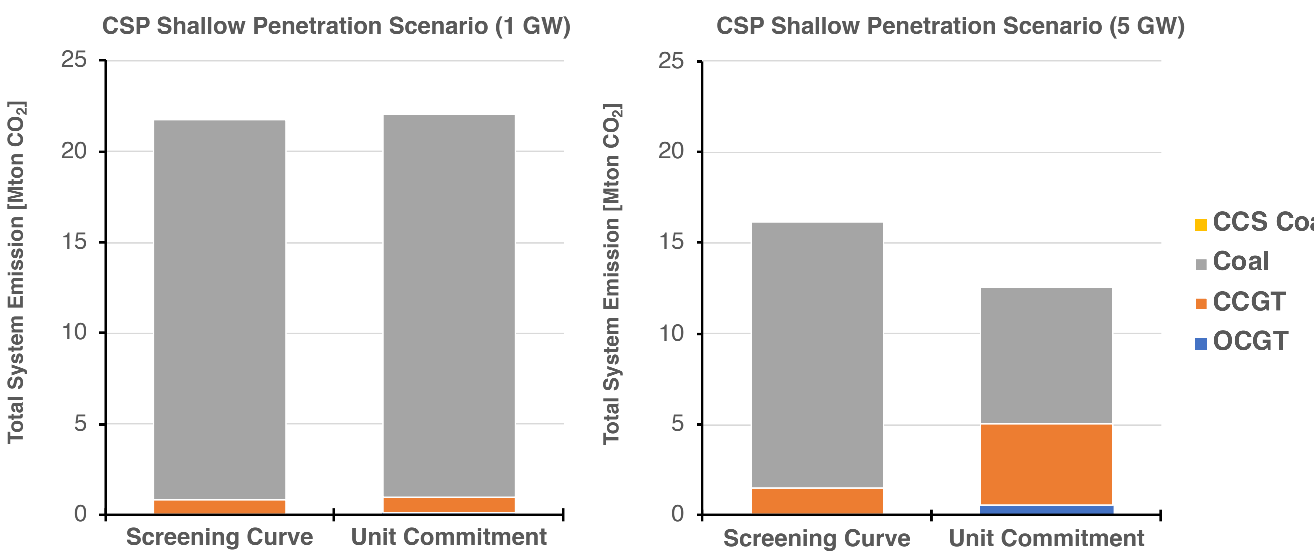

Figure 36: Comparison of carbon emission results for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 36 compares system-wide carbon emissions of the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Referring to the figure, we can make several observations.

Firstly, in line with the energy deviation trends, the deviation figures of the carbon emission results are significantly different under the two renewable penetration scenarios. As Figure 36 shows, on the one hand, at the aggregate level, under the shallow renewable penetration scenario, the SC model slightly underestimates the system-wide carbon emissions relative to the UC model's results by less than 2%. On the other hand, it significantly overestimates the total system emission results under the deep decarbonisation scenario by about 29%. This can in part be explained by the scale of the error in estimating the energy output of the carbon-intense Coal technology in both cases.

Under shallow renewable penetration levels, the energy output difference with the carbon-intense Coal technology for the SC and UC models is negligible. Nevertheless, under the deep renewable penetration scenario, the energy output deviation of the Coal technology is almost double the output energy of the UC model by volume. This observation explains the convergence of the carbon emissions results of the two models under the shallow renewable penetration scenarios and their significant divergence under the deep decarbonisation scenario.

Second, at the technology level, the SC model underestimates the emissions from the OCGT and CCGT technologies under both the shallow and the deep decarbonisation scenario. However, the scale of the deviation appears to vary with the renewable penetration level. Under the shallow penetration scenario, the carbon results deviations were in the regions of 23% and 13% for the OCGT and CCGT technologies, respectively. In contrast, under the deep penetration scenario, the carbon results deviations were in the regions of 80% and 70% for the same technologies.

5.2.2.4 System cost results

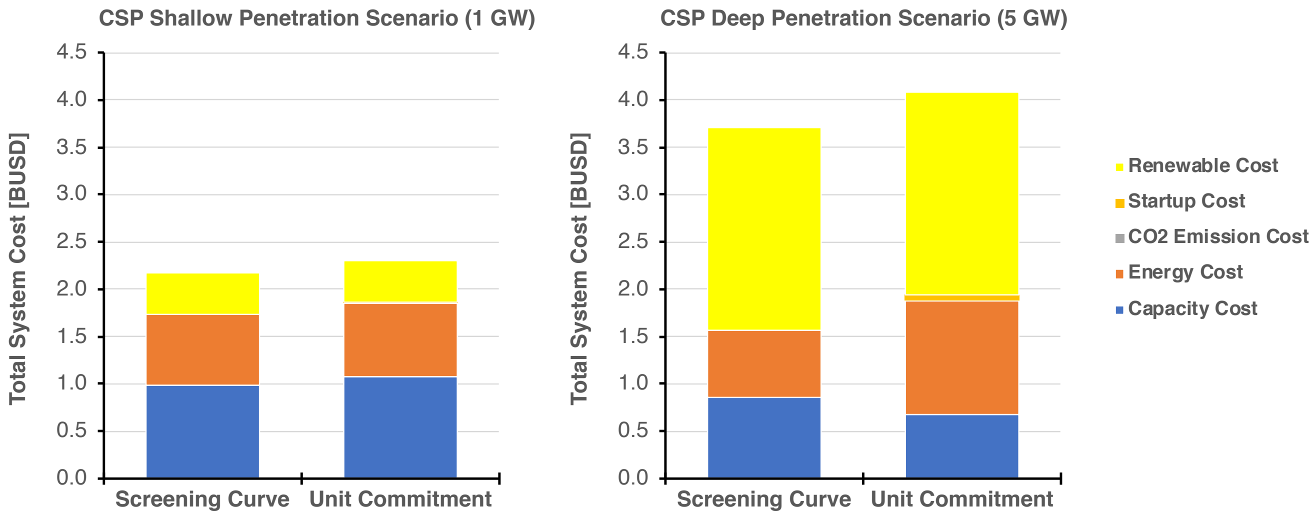

Figure 37: Comparison of the system total costs for the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 37 compares total system costs of the SC and UC models under shallow and deep renewable penetration scenarios of the CSP technology. As shown in Figure 37, the SC model underestimates in both cases the costs of the system compared to the cost estimates of the UC model.

Under the shallow renewable penetration scenario, the SC model underestimates the total system cost by about 6%. In contrast, it underestimates the cost by 9% under the deep decarbonisation scenario.

It is worth noting that under the shallow renewable penetration scenario, the system cost deviation is dominated by the differences in the capacity cost estimates across the two models. Conversely, the differences in the energy cost estimates tend to dominate the cost deviation figures under the renewable penetration scenario.

5.2.3 Effect on the perceived carbon cost-effectiveness

Building on the scenarios presented earlier, we run additional decarbonisation scenarios using the CSP technology. We summarise the findings in Figure 38 - Figure 40.

5.2.3.1 System-wide carbon emission estimates

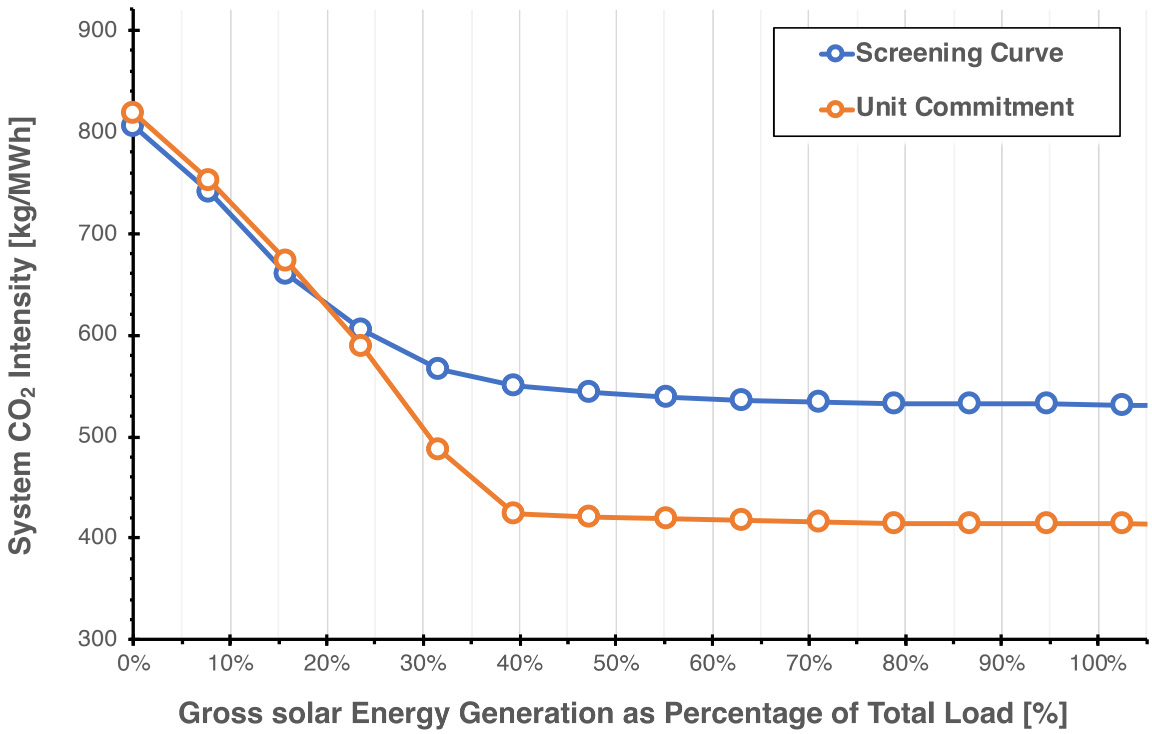

Figure 38: Projected system-wide carbon intensity trends using SC and UC modelling methodologies.

Figure 38 shows the predicted system-wide CO_2 carbon intensity based on the SC and UC models under different solar penetration scenarios.

As indicated in the previous sections, in the absence of renewables, at the aggregate level, the SC model slightly underestimates the carbon emissions relative to the UC model. This trend of underestimating the emissions continues under shallow solar penetration levels. However, this trend is likely to change with increased renewable generation. The inflection point occurs under deeper penetration rates when the UC model gravitates towards investing more into flexible yet cleaner units to deal with the increased residual demand volatility and the flexibility requirement of the system with increased variable generation (i.e., mostly from coal-fired to gas-fired generation). The inability of the SC model to capture this leads to systematically overinvesting into cheaper but more polluting units, leading to overestimating the expected carbon emission intensity of the system under deep decarbonisation levels. This also gives rise to systemically underestimating the system's decarbonisation potential of the solar technology under consideration.

5.2.3.2 System-wide cost estimates

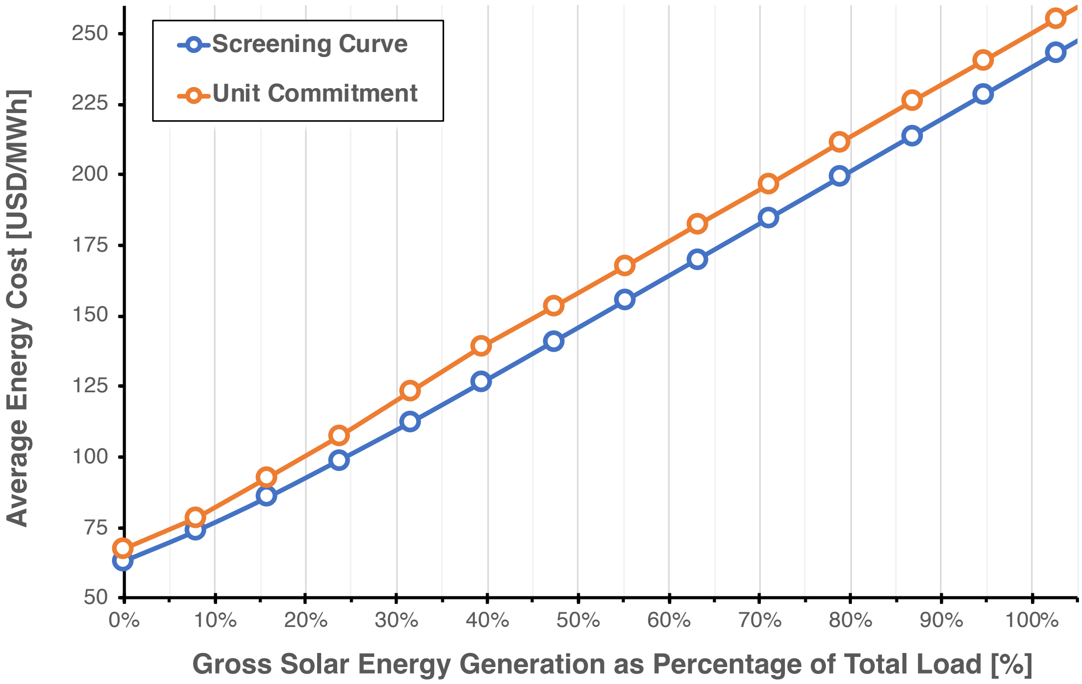

Figure 39: Projected average energy cost trends using SC and UC modelling methodologies.

Figure 39 shows the predicted average production energy cost of the system based on the SC and UC models under different solar penetration scenarios.

We find that the SC methodology tends to systemically underestimate the system's total cost when compared with the cost estimates obtained by the UC method. Simulation results show that the estimation errors range from about 6% to 9% under different penetration scenarios. Overall, the cost differences reflect (1) the additional cost of a more flexible generation mix, (2) the cost of reserves, (3) the cost of generation start-ups, and (4) the implied part-load operation costs that are not captured by the SC methodology.

It is worth noting that the relative importance of these factors tends to change for different renewable penetration levels. For example, in the low-penetration scenarios, the largest cost differences tend to stem from the difference in the capacity costs of the two models. However, at higher penetration rates, the differences in operating costs dominate, as a result of higher operating costs (i.e., fuel cost and increased switching activities). Additional results are available in the results appendix.

5.2.3.3 Effect of the perceived carbon cost-effectiveness

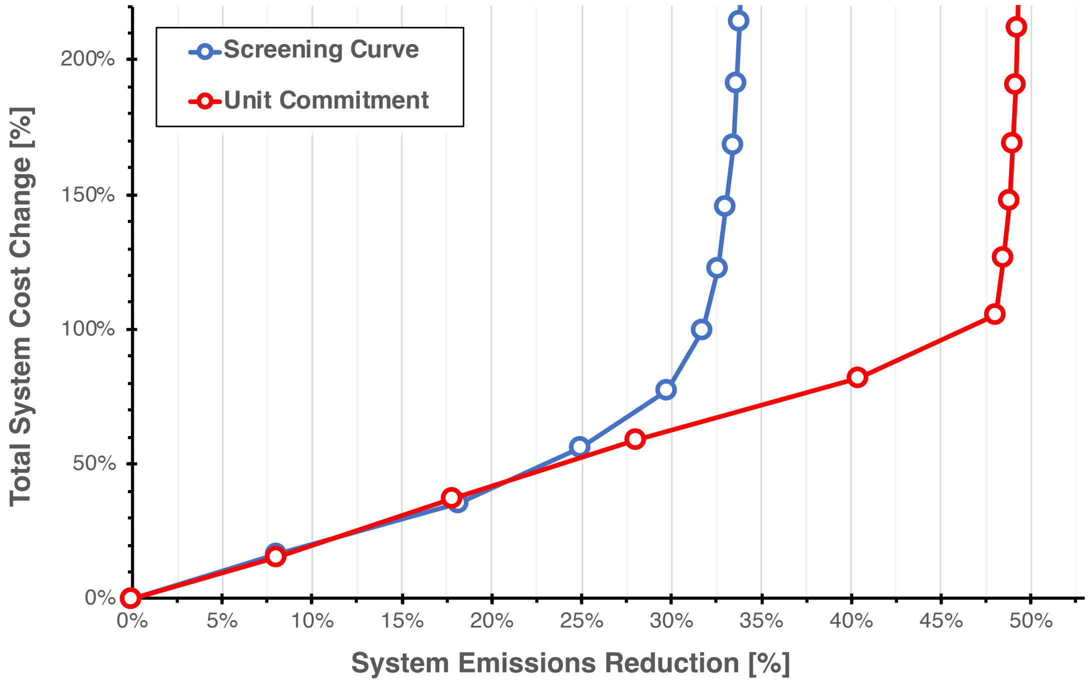

Figure 40: Projected carbon cost-effectiveness trends using SC and UC modelling methodologies.

Figure 40 shows the projected carbon cost-effectiveness trends of the system based on the SC and UC models under different system decarbonisations levels.

The results suggest that under deep decarbonisation scenarios, the SC method might *in some cases*, perhaps counterintuitively, overestimate the carbon abatement costs of renewables. This is mainly driven by the tendency of the SC method to underestimate the carbon savings of renewables under deep decarbonisation scenarios *due to its inability to identify the coal-gas switch for the study case considered*. This would suggest that the precision of estimating the system's total carbon emission, *in some cases*, has the greatest influence on accurately estimating the economic effectiveness of the renewable decarbonisation process."

More generally, our results suggests that the choice of modelling methodology can in some cases, considerably influence the perceived economic effectiveness of the renewables to decarbonise electric systems and subsequently their carbon abatement costs estimates.

5.3 Effect of Minimum Running Thermal Generation

In the earlier sections, we look at how the choice of modelling methodology of renewable decarbonisation studies can systematically alter their economic and carbon emission results and hence change the perceived competitiveness of renewables to decarbonise electric systems. We explored this question with a comparative case study featuring two of the well-established optimisation methodologies that have been used extensively in the literature to study the decarbonisation of power systems.

In the following two sections, we look at how the optimisation model's specification and the amount of technical detail included in decarbonisation studies affect the perceived economic competitiveness of renewable technologies to decarbonise energy systems. We identify and investigate several underexplored technical factors that have a great influence on the economic results of decarbonisation studies. Our study features side-by-side comparisons of UC optimisation models with, without, and with varying values of the identified technical factors. The results of the study strikingly show to what extent ignoring these factors can impact the economic results of decarbonisation studies. In the following section, we focus on the system-level technical factors and in the next section we address the unit-level technical factors that can largely affect the results of renewable decarbonisation studies.

In considering different system-level technical factors, we identify the minimum running thermal load (MRTL) of the system or the system's total rotating load as a key factor that is likely to have a large influence on the perceived economic competitiveness of renewables to decarbonise electric systems. We were unable to find a study that examined or quantified this effect before.

The minimum thermal system's load or the "inflexible generation" level exists in the system for many technical and commercial reasons. For example, some thermal-based generation technologies are typically kept online to increase the system's mechanical inertia and hence to enhance the system's stability. Other fossil-fuel-based technologies become a must-run generation in the system as a result of being part of a cogeneration scheme. The need to produce a constant stream of steam for other industrial processes, such as water desalination, necessitates the plants to be on at all times, restricting their flexibility.

In this section, we assumed two levels of the minimum running thermal load constraint of the system. In the baseline scenario, we assumed an MRTL constraint of 0.5 GW, which represents about 9% of the system's peak load. In the second scenario, we assumed an MRTL constraint of 1 GW, as shown in Figure 41.

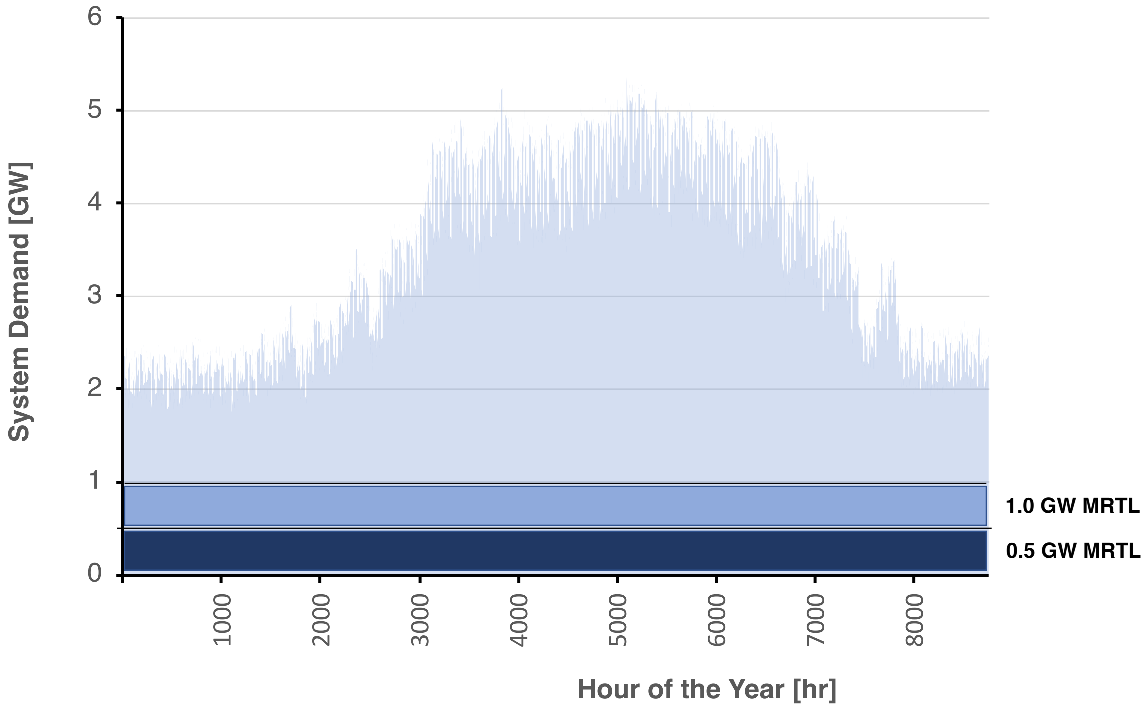

Figure 41: Assumed minimum thermal running load levels for the scenarios considered in this section.

5.3.1 Shallow and deep renewable penetration scenarios

In this section, we compare the results of two UC models with different MRTL constraints under shallow and deep renewable penetration scenarios of CSP technologies. We seek to understand to what extent variations in the model's specifications can alter the results of the models under different renewable penetration scenarios. Figure 42 - Figure 51 summarise the key result of this section. However, we include the full results in the supplementary results appendix.

5.3.1.1 Optimum capacity mix results

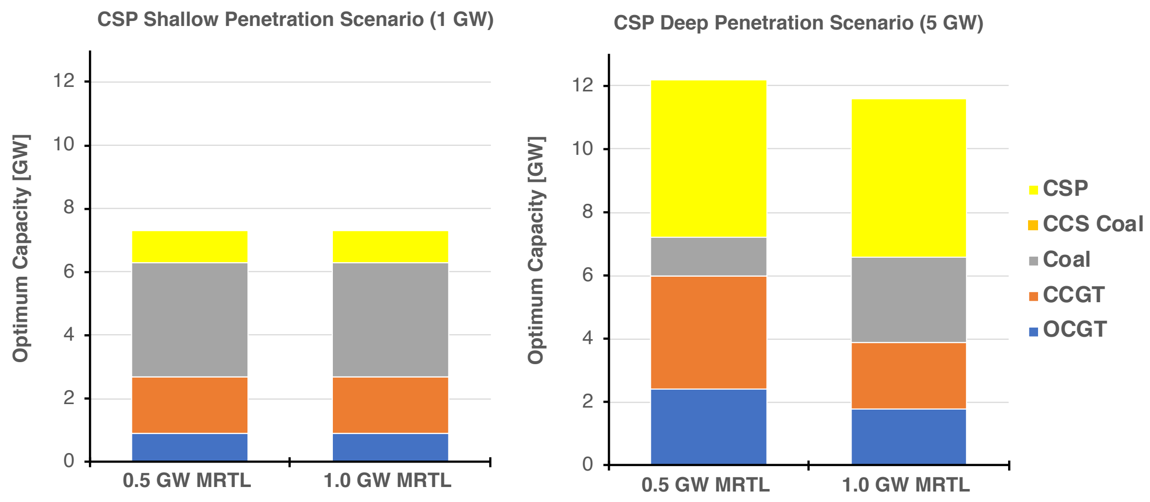

Figure 42: Comparison of the optimum technology mix results for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 42 compares of the optimum technology mix results for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology.

As indicated above, the capacity mix deviation of the two models under shallow and deep decarbonisation scenarios are substantially different. Under the shallow renewable penetration scenario, the MRTL constraints have no effect on the optimum technology mix of the system

On the other hand, under the deep renewable penetration scenario, the MRTL constraints have a significant effect on the optimum technology mix as the system's dynamics becomes more pronounced. In particular, the UC model with a high MRTL constraint underinvests in OCGT and CCGT by about 29% and 33%, respectively. However, it doubles the capacity investment in the Coal technology relative to the investment level of the UC model with a lower MRTL constraint. This can be attributed to the reduced flexibility needs imposed by the higher MTRL level as a result of the reduced volatility of the residual demand and the increased incidence of curtailment.

5.3.1.2 Energy output results

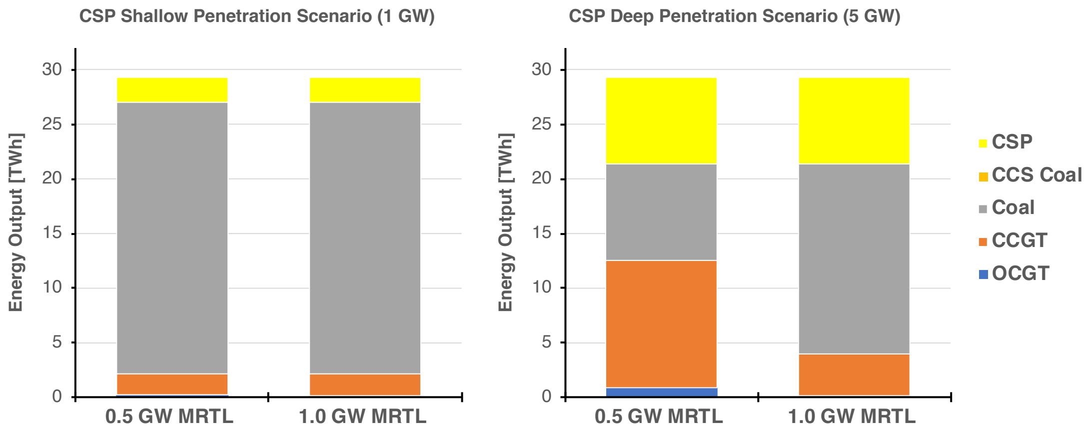

Figure 43: Energy output comparison for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology.

Figure 43 compares of the energy output for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology. As shown in the figure, under the shallow renewable penetration scenario, the MRTL constraint has no effect on the energy output of the system. By contrast, under the deep renewable penetration scenario, the MRTL constraint has a significant impact on the energy out of the system's generating units. In particular, the UC model with a high MRTL constraint underestimates the cumulative energy output of the OCGT and CCGT technologies by about 4% and 67%, respectively. However, the energy output of the Coal technology is more than doubled.

5.3.1.3 Carbon emissions results

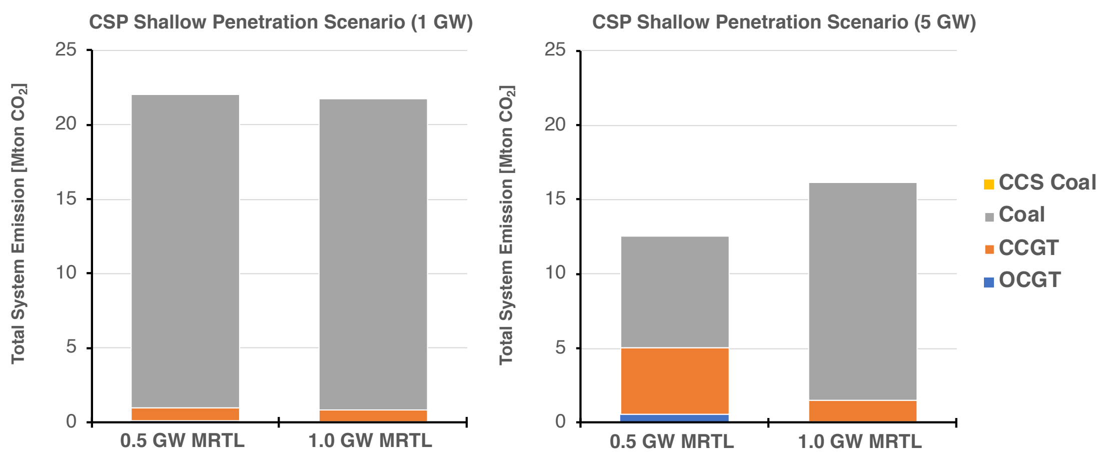

Figure 44: Carbon emission results comparison for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology.

In line with energy output results, under the shallow renewable penetration scenario, the MRTL constraint does not affect the carbon emission estimates of the system, as shown in Figure 44.

However, under the deep renewable penetration scenario, the MRTL constraint has a significant impact on the system's emissions. At the aggregate level, the UC model with a high MRTL constraint overestimates the carbon emissions of the system by about 39% relative to the results of the UC model with a lower MRTL constraint. This can be attributed to increased investment in and more utilisation of less flexible and yet more polluting generation technology (i.e., coal) at the expense of more flexible and relatively cleaner technologies (i.e., OCGT and CCGT) when a higher MRTL constraint is enforced. In terms of specifics, the UC model with high MRTL constraints underestimates the carbon emissions of the OCGT and CCGT technologies by about 4% and 66%, respectively. At the same time, the energy output of the Coal technology is more than doubled.

5.3.1.4 System cost results

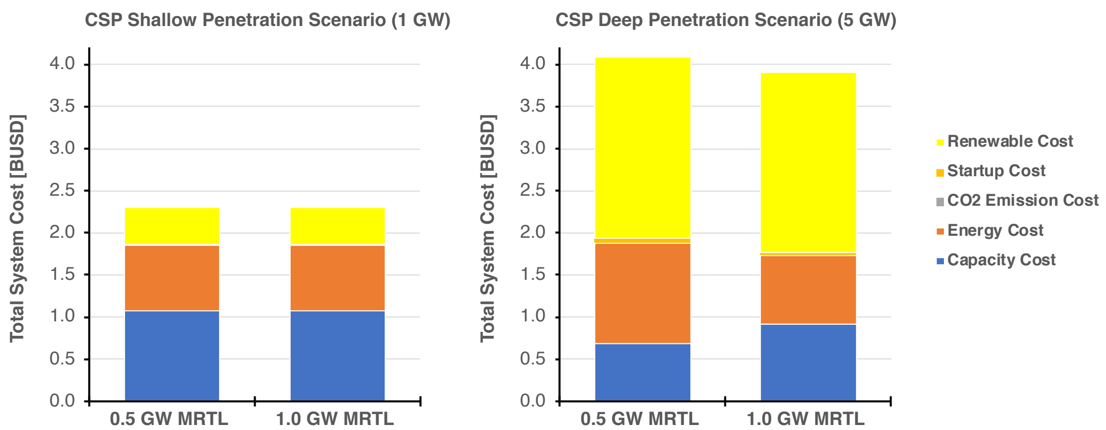

Figure 45: System total cost comparison for UC models with different minimum thermal running load levels (MRTL) under a shallow and deep renewable penetration scenario of the CSP technology.

Figure 45 compares the system cost results for UC models with different minimum thermal running load levels under shallow and deep renewable penetration scenarios of the CSP technology. As shown, under the shallow renewable penetration scenario, the MRTL constraint does not affect the total system cost estimates. Furthermore, under the deep renewable penetration scenario, the higher MRTL constraint has a marginal effect on carbon emissions of the system at the aggregate level. However, estimates of the capacity and energy costs have sizable deviation percentages.

5.3.2 Effect on the perceived carbon cost-effectiveness

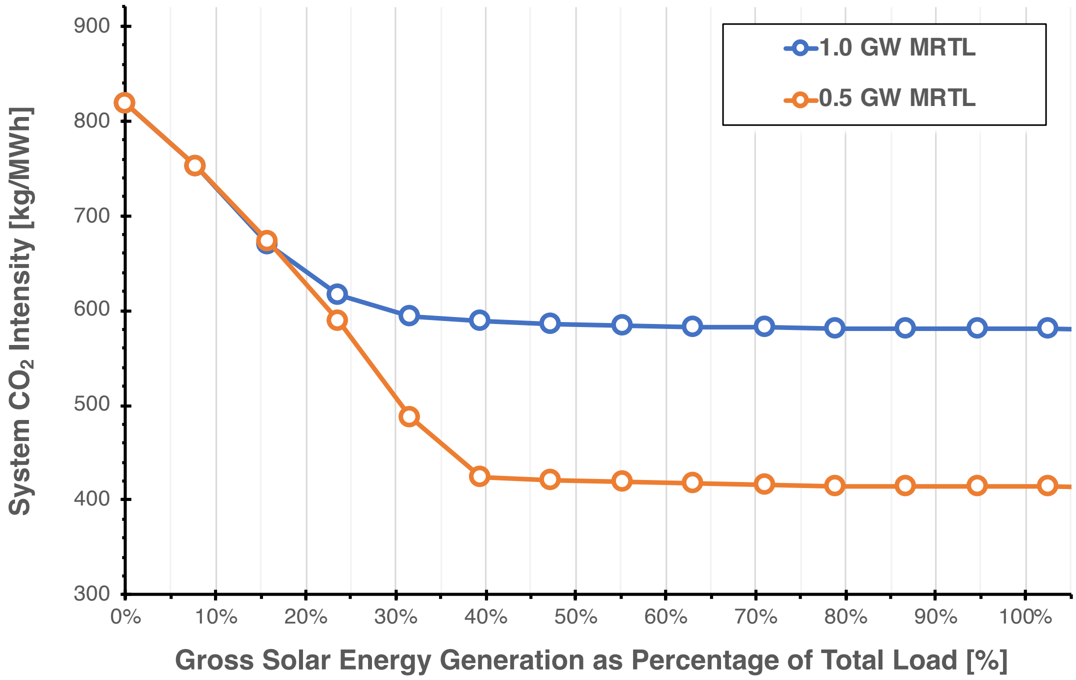

Figure 46: Projected system-wide carbon intensity under different MRTL levels.

Figure 46 shows the projected system-wide carbon intensity under different MRTL levels. As shown in Figure 46, we find that changing the system's minimum thermal running generation from 500 MW (about 9% of the system's peak load) to 1000 MW has limited impacts on the decarbonisation results under low-penetration scenarios. However, under deep decarbonisation scenarios, the effect of the minimum thermal running generation constraint of the model on estimating the system-wide carbon emission becomes more pronounced.

For example, at a 5 GW penetration rate, this results in about a 39% deviation in estimating the total system carbon emission. This substantial difference in total carbon emission could be attributed to (1) the reduced decarbonisation potential and increased incidence of curtailment due to the increased thermal generation base and (2) a disproportionate increase in capacity investment and energy output from carbon-intensive units (i.e., coal), which apparently becomes the more cost-effective option when a higher thermal generation base is enforced.

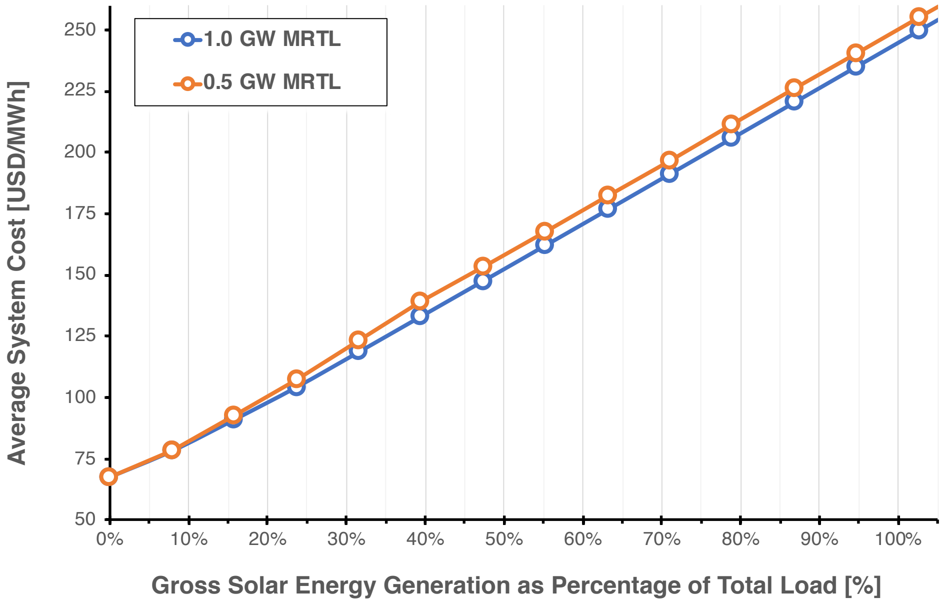

Figure 47: Projected average production cost of the system under different minimum running thermal load (MRTL) levels and renewable penetration scenarios.

In addition, we find that the difference in total system cost is about 4% between the two aforementioned scenarios, as Figure 47 indicates. However, under low-penetration scenarios, the cost estimates are the same. Figure 48 shows how relatively small variations in the system's minimum running load can greatly influence the perceived economic competitiveness of renewables to decarbonise electric systems and hence the projected abatement costs of renewables.

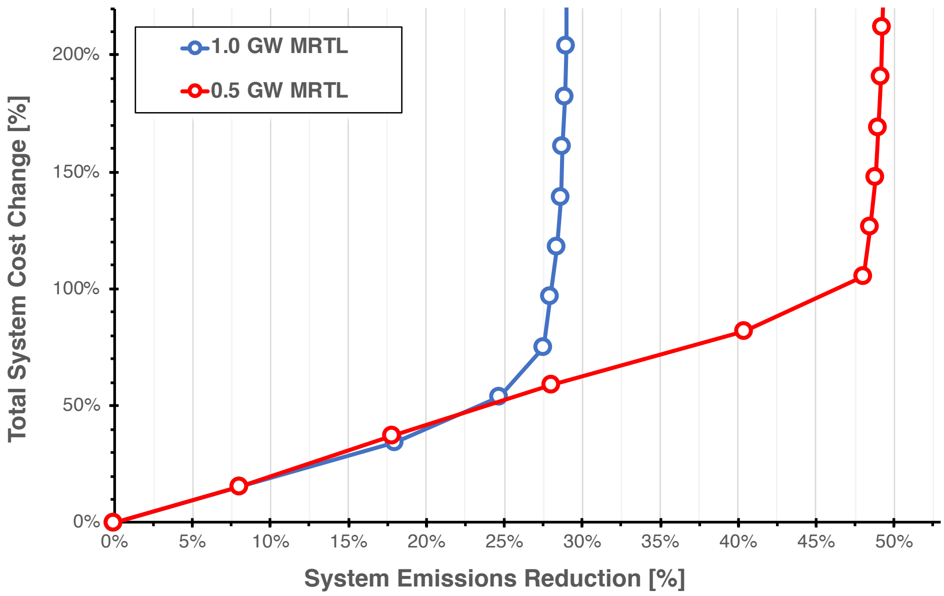

Figure 48: Projected carbon cost-effectiveness trends using two UC models with different levels of MRTL constraints.

5.4 Effect of the Units' Dynamic Constraints

In the previous section, we examined the impact of a system-level technical factor, the MRTL, on the results of renewable decarbonisation studies. In this section, we investigate a unit-level technical factor that can largely affect the results of renewable decarbonisation studies. In particular, we considered the impact of including and excluding the minimum up- and downtimes of the generating units on the perceived economic competitiveness of renewables to decarbonise electric systems. We were unable to find a study that examined or quantified this effect before. In the interest of brevity, we will briefly summarise the results of the case in Figure 49, Figure 50 and Figure 51. However, we include the full results in the supplementary results appendix.

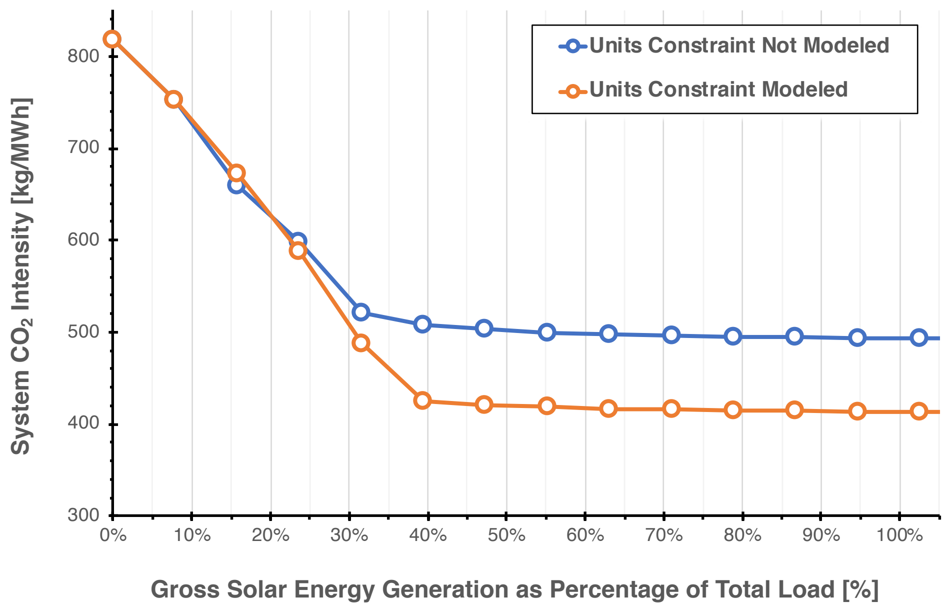

Figure 49: Projected carbon cost-effectiveness trends with and without enforcing the minimum up- and downtimes of generating plants.

Interestingly, we find that imposing the minimum up- and downtime constraints results in a relatively large difference in the projected carbon emission savings under deep decarbonisation scenarios. For example, running the previous baseline scenario without imposing the units' minimum up- and downtime constraints results in about a 19% increase in the total system emissions. This carbon emission increase reflects the natural tendency of the optimiser to invest in a more polluting, less flexible, and cheaper generation mix in the absence of the dynamic constraint. Yet this also demonstrates how the exclusion of merely one dynamic constraint can impact the accuracy of the carbon projections of decarbonisation studies.

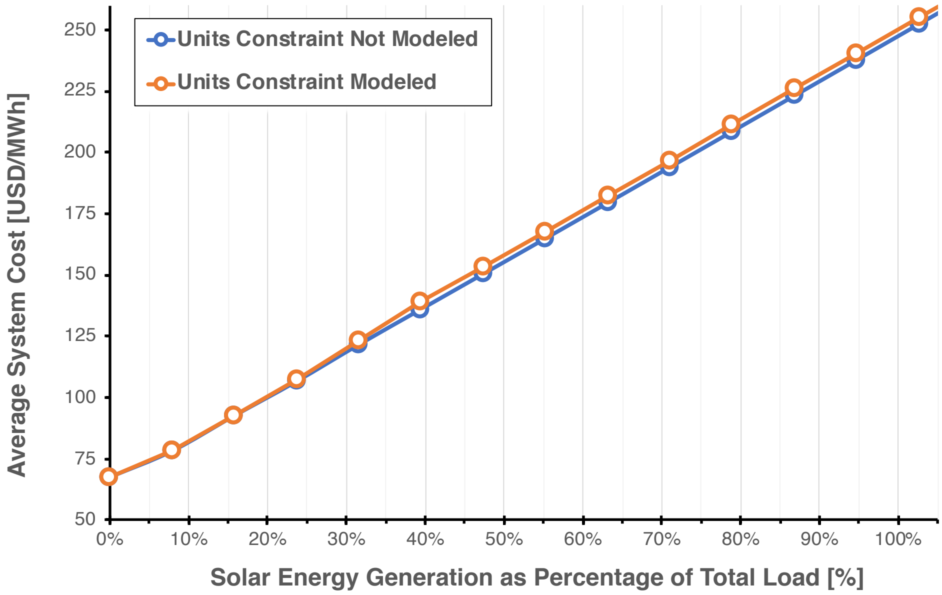

Figure 50: Projected average energy production cost of the system with and without enforcing the minimum up- and downtimes of generating plants.

We find that the difference in cost estimates is very modest in the region of about 4% under a deep renewable penetration scenario, as indicated in Figure 50. Furthermore, Figure 51 shows how excluding one of the unit's dynamic constraints can greatly influence the perceived economic competitiveness of renewables to decarbonise electric systems and hence the projected abatement costs of renewables.

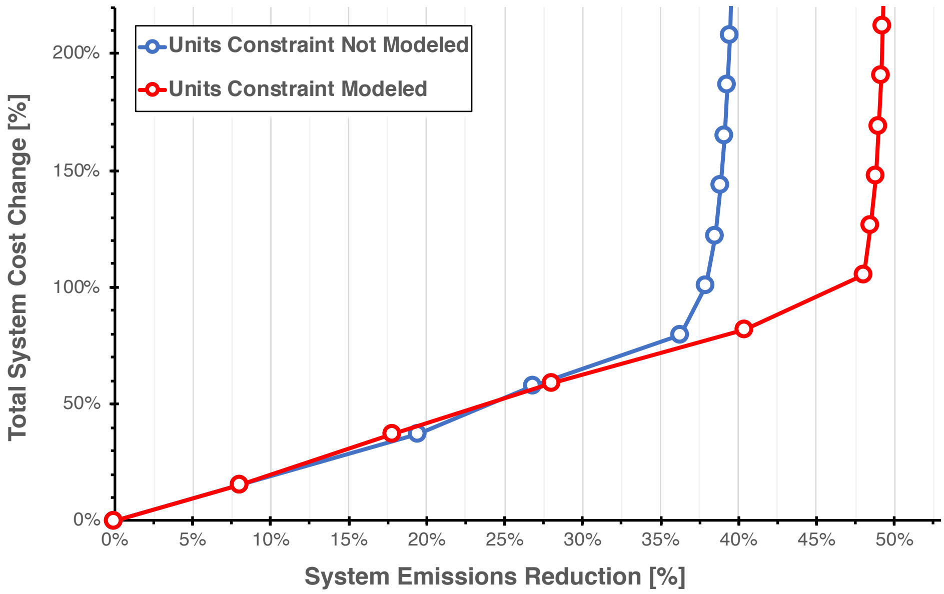

Figure 51: Projected carbon cost-effectiveness trends with and without enforcing the minimum up- and downtimes of the generating plants.

5.5 Research Findings and Policy Implications

The scenarios presented in this study *are not meant to predict the renewable carbon emissions savings from a particular system or to be generalisable to all systems in the same way or to the same extent*. Instead, they serve as a diagnostic tool to understand a range of possible shortcomings in the current modelling practices. In essence, they are meant to identify patterns of possible systematic inaccuracies or biases in renewable decarbonisation results. In addition, these scenarios help evaluate to what extent methodological bias can alter the perceived cost-effectiveness of renewable technologies to decarbonise electric systems. Although further research will be required to confirm and refine these findings for different electric systems, these findings already highlight some important trends and insights. We can summarise them as follows.

We find that the tendency of the SC method to overestimate or underestimate the long-term carbon savings of renewables depends largely on the renewable penetration rates and the decarbonisation level of the system under study. We find that under low and moderate renewable penetration rates and decarbonisation levels, at the aggregate system level, the SC method tends to slightly underestimate or even overestimate the carbon offsets of renewables. We find that the carbon projection error is too small to markedly affect the perceived cost-effectiveness of renewables to decarbonise electric systems.

However, under deeper decarbonisation scenarios and renewable penetration rates, we find that the SC method can systemically underestimate the long-term carbon emission offsets. As a result, this leads to a systematic alteration of the projected estimates of the carbon abatement costs of renewables and the system-wide decarbonisation costs. We find that for coal-dominated systems, the scale of the errors is large enough to question the robustness and the quality of the carbon saving projections and subsequently the carbon abatement costs of renewables. Further research is needed to quantify the scale of the errors for systems with no or little coal generation assets. We also find that the SC method tends to systematically underestimate the total system costs. However, our results suggest that for deep decarbonisation studies, the perceived cost-effectiveness of renewables to decarbonise electric systems hinges predominantly on the accuracy of the long-term carbon projections or estimates of the system.

One relevant policy insight is that policymakers and researchers should pay special attention when evaluating the carbon emission projections of renewable deep decarbonisation studies carried out using the SC method. While it provides an excellent first approximation for carbon projections at shallow decarbonisation levels, there is convincing evidence to question the validity of its projections at deeper decarbonisation levels. Our results suggest that in some cases, the "accuracy penalty" might outweigh the speed and light data requirement benefits of SC models. The accuracy penalty appears to vary with the renewable penetration level[105]. Researchers should be aware of the limits of this trade-off and the acceptable "operating bandwidth" of SC models, especially when doing long-term carbon emissions projections.

In addition, while we find that SC models can underestimate the theoretical carbon saving potential of renewables, we also find that SC models can underestimate the role of renewables in the decarbonisation process. More generally, one important insight is that renewables might have an underappreciated but nonetheless important role in accelerating the deep decarbonisation process of energy systems that goes beyond their conventional role as "carbon-free energy producers". Our research finds that some renewables act as "decarbonisation accelerators" by unnoticeably facilitating the fuel switching from high-carbon-intensity fuels to low-carbon-intensity fuels, particularly from coal to gas. Our research suggests that the increased flexibility requirements for running a system with a higher share of weather-dependent renewables are expected to attract more investment in technologies with high-flexibility characteristics (e.g., gas-fired OCGT). In addition, our results suggest that even in the absence of a carbon price, more flexible technologies with mid-Capex, high-Opex technologies (e.g., gas-fired CCGT) will be more economically viable to meet the baseload demand at the expense of the less flexible high-Capex, low-Opex technologies (e.g., coal-fired steam technology).

It is worth noting, given the system size and the specific technologies mix considered in this study, this finding cannot be extrapolated to all electric systems. Neither it can be transferable to many systems in the same scale. Electric systems differ significantly in terms

105 The error margin becomes materially significant after the coal-gas switch for the system under study and as it tends to increase with increased renewable penetration under the deep penetration scenarios considered. However, this might not be the case for other systems..

of their fleet technology composition and their relative sizes. For example, the large-scale deployment of weather-dependent renewables to some systems with a high share of nuclear power might not necessarily lead to the same effect reported. Similarly, for systems dominated by gas technologies, the deep penetration of renewables might lead to an increase in the production from inefficient but flexible gas units at the expense of the production from more efficient, less polluting and yet less flexible units due to the increased flexibility requirements of the system. However, given that the global energy system is still dominated by coal generation, such finding should not be discounted from the current debate about the role of renewables as a potential accelerator to the transition towards a low carbon energy system

One relevant policy implication is that renewables might accelerate the retirement of existing coal generation assets much sooner than expected. This might increase the risk of “stranded assets” of the existing generation plants. Furthermore, it implies that in the future, coal generation plants must compete with other thermal plants with respect to both production cost and flexibility provision basis. We believe that the technical improvement of coal plant flexibility capabilities will be critical in this regard.

In addition, our research suggests that in the long run, and even in the absence of a carbon pricing scheme, the projected carbon saving gains from the indirect fuel switching effect induced by adding more renewables might in some cases outweigh the carbon saving benefits of the direct capacity displacement effect. This occurs because the capacity and energy value of renewables tend to fall sharply under deep decarbonisation scenarios. Although this might not be observable in all systems, it is expected to be strongest in coal-dominated systems, especially under deep decarbonisation scenarios. Yet, given that the global electricity mix is still dominated by coal-fired stations (IEA, 2019), our research suggests that this less obvious and often-forgotten role of renewables as decarbonisation accelerators should not be discounted from the current debate about the value of renewables in decarbonising electric systems. For some, this might count as a rather positive, unintended consequence of adding renewables to electric systems. For others, it might add another layer of complexity in analysing the long-term environmental and capacity value of renewables.

In terms of UC models, our results showed that using UC models does not automatically make the carbon predictions error free. Our results indicate that the technical specification of UC models has a significant impact on the accuracy of the long-term carbon projections and subsequently on evaluating the costs of the renewable decarbonisation process. We identify several technical factors that, if omitted, would have a large influence on the accuracy of the results. In particular, we find that considering the minimum running thermal generation of the system has a great influence on the accuracy of the decarbonisation results of UC models for a small system like that of Qatar. More generally, we find that the relative importance of these factors changes over time as the system decarbonises. For example, we find that the carbon savings of renewables will initially be dominated by the static factors of renewable integration, such as the capacity and energy values of renewable generation. This explains the convergence of different variations in the results of UC models at low-penetration scenarios. However, as the system decarbonises, the accuracy of the UC results will hinge upon the representation of the dynamic aspects of power systems. This explains the divergence between the different UC model variants at particularly deep decarbonisation levels as the interplay between these factors becomes more pronounced. In other words, our work suggests that the influence of variations in the specifications of UC models is more apparent under deep decarbonisation scenarios.

CHAPTER 6

BENCHMARKING THE CARBON SAVINGS & ECONOMIC EFFECTIVENESS OF RENEWABLE ENERGY SOURCES: A TECHNICAL COMPARATIVE STUDY

6.1 Introduction

Building on the methodological work presented in Chapter 5, in this chapter, we look in depth at the relative importance of various technical factors that affect the renewables' ability to make sustained and cost-effective carbon reductions. We study the underlying drivers and mechanisms in which these factors affect the economics of the decarbonisation process. The guiding questions of this chapter are, how, why and to what extent can the technical variations across renewable technologies affect the cost-effectiveness of the decarbonisation process? We investigate these questions using several comparative case studies featuring different types of renewable technologies.

We use the same input data and simulation assumptions given in *CHAPTER 3: METHODOLOGY & DATA*. In following sections, we will briefly present and comment on some of the simulation results of this case study. In particular, we will focus on the deep decarbonisation scenarios as the effects of the variations in the production profiles of renewable technologies become more pronounced. We include additional simulation results in the supplementary results appendix.

Finally, we present several original insights related to the subject and discuss important policy implications.

6.2 Case 1: Impacts of Renewable Technology Characteristics on the Economics of Decarbonisation

In this section, we investigate to what extent variations in the technological characteristics across renewable technologies can affect the economics of the decarbonisation process. In particular, we provide comparative case studies featuring two renewable technologies with different technological characteristics: PV and wind technologies.

Table 14 summarises the key technical and economic data of the two technologies. The reader is encouraged to refer to section
3.5.3 Renewable resource data and capacity factors to compare the two technologies' production profiles and to review the full details of their full technical and cost data.

Technology		PV	Wind
Capacity Factor	%	22.8%	29.0%
Overnight Capital Cost	USD/kW	1810	1560
Opex (Fix)	USD/kW-yr	24.67	39.55
Project Lifetime	Yr	30	30
Discount Rate	%	5.0%	5.0%

Table 14: Key technical and economic assumptions summary for the PV and wind technologies

In the following sections, for brevity, we compare the decarbonisation results of the PV and wind models developed under deep renewable penetration scenarios.

6.2.1 Deep renewable penetration scenarios results

In this subsection, we present and compare the results of the PV and wind models under the deep renewable penetration scenarios. In the following section, we discuss the findings of our case studies.

6.2.2.1 Capacity mix results

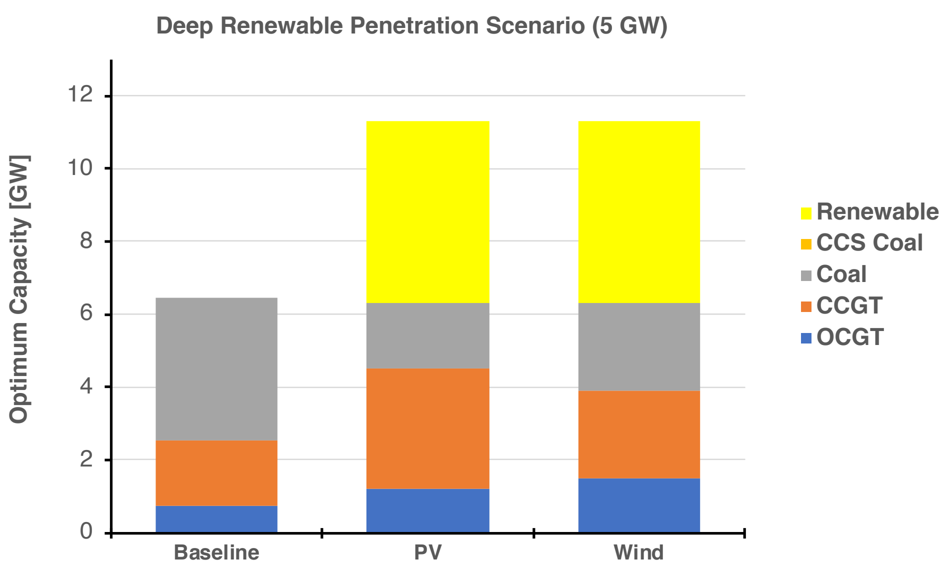

Figure 52: Optimum capacity mix results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

Figure 52 compares the optimum capacity mix results of the PV and wind technology models under a 5 GW penetration scenario. In comparison to the shallow scenario, both PV and wind technologies fail to make additional thermal capacity savings under the deep penetration scenarios. Furthermore, the deep penetration of the two technologies results in material changes to the structure of their respective capacity mixes. We can summarise some of the changes in the capacity mix in the following points.

First, the PV technology mix has greater CCGT and fewer coal assets compared to the wind technology mix. In particular, the PV capacity mix has an additional 0.9 GW of CCGT assets and is short of 0.6 GW of coal assets relative to the wind technology's capacity mix figures. This represents an increase of about 33% for the CCGT technology and a reduction of about 27% relative to the wind capacity levels.

The considerable increase in the system flexibility requirements needed to run the system due to the higher volatility of the residual demand under the deep PV penetration rates can explain this difference. As Figure 53 indicates, the penetration of PV technology leads to a substantial increase in the thermal start-up activities. This explains the reduced effectiveness and competitiveness of coal generators to follow the system's load under these demand conditions due to their less flexible characteristics and substantially more expensive start-up costs. Conversely, perhaps counterintuitively, the wind mix has slightly more OCGT generators. This can be explained by the variations in the scale of the flexibility requirements needed to run the system and the subsequent relative cost-effectiveness of the different thermal technologies to meet them.

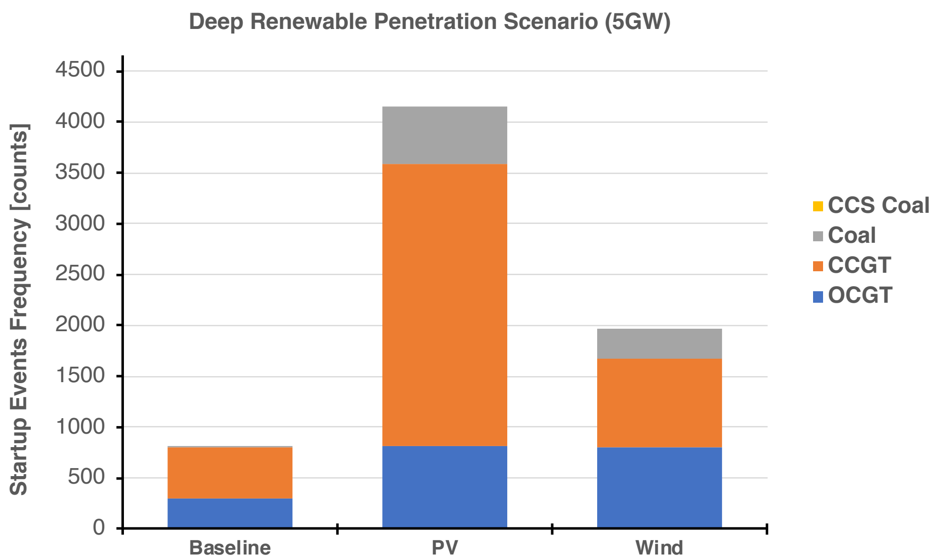

Figure 53: Thermal generation start-up activities results comparison between the baseline model and the PV technology model under a deep penetration scenario (5 GW)

In particular, we find that although the volatility of the solar residual demand is greater than the volatility of the wind residual demand at the aggregate level, wind penetration can nevertheless cause a few erratic incidents of residual demand throughout that year. These few events tend to max out the flexibility characteristics of the incumbent thermal fleet requiring more investment in flexible assets with great load-following capability, which can be switched on and off in a short time frame. That explains the optimiser's decision to invest in additional OCGT assets, which becomes the most cost-effective option to cover the system's flexibility requirement for a few hours during the year due to its low investment costs. On the one hand, this underscores the role of demand response in saving thermal capacity with increased renewable penetration. On the other hand, this highlights the importance of keeping extra flexibility assets to deal with the possible erratic variations in residual load given the inherent variable and uncertain nature of the renewable generation.

Figure 54 shows the reduced 'utilisation effect' of the OCGT assets under the deep penetration scenarios. As the figure indicates, the commitment incidents of the additional OCGT units needed for flexibility provision are substantially lower than the fleet's average. We argue this effect can have many significant implications. One particular issue is that the investment in these flexibility assets might not be financially viable on an energy output basis given their very low utilisation figures. We will discuss this in more detail later in the chapter.

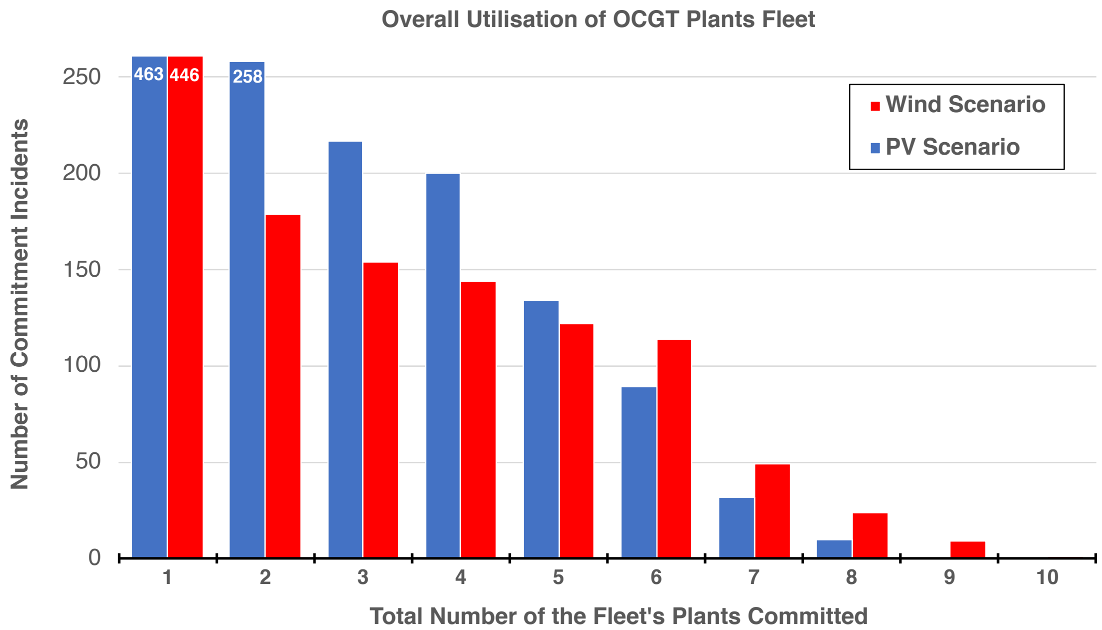

Figure 54: Statistical summary about the commitment incidents of the OCGT fleet under the PV and wind scenarios

6.2.2.2 Energy output results

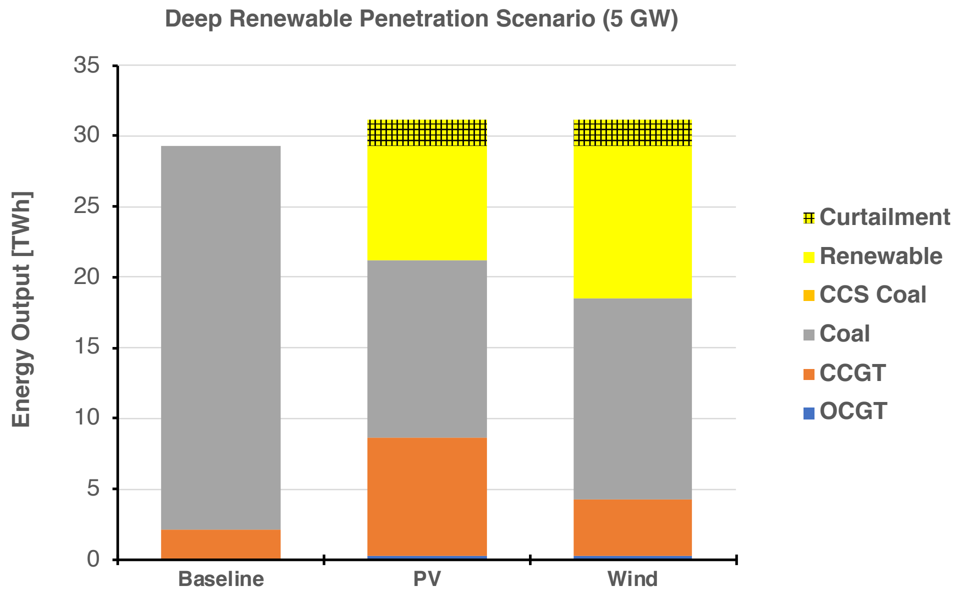

Figure 55: Energy output results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

Figure 55 reveals significant changes to the energy output mix of the PV and wind technology models under 5 GW penetration scenarios. As Figure 55 indicates, wind power achieves deeper energy penetration rates. In particular, the differential in the cumulative energy output of the two technologies amounts to 2.66 TWh. This represents about a 33% increase in the energy output relative to the PV energy production levels. At the system level, however, this represents about 13% of the total system energy demand.

This can be explained by the higher capacity factor of wind power compared to PV technology and the lower curtailment rates of wind relative to its production levels. For example, the total curtailed PV energy amounts to about 18% of the total. By contrast, for wind energy, despite having a higher capacity factor, the total curtailed wind energy amounts to about 15% of the total generated energy due to the higher variance of the shape of its load profile because the output is less concentrated at particular times. In line with the capacity mix changes, PV outperforms wind in terms of offsetting the energy generated from coal. More specifically, PV technology displaces an additional 1.74 TWh from coal as a result of having fewer coal generators; this represents a 14% reduction in energy output levels from coal relative to the wind scenario. By contrast, wind technology outperforms PV in offsetting the energy generated from OCGT and CCGT technologies. In particular, wind technology displaces an additional 0.01 TWh and 4.40 TWh from

OCGT and CCGT technologies, respectively, relative to the PV displacement figures. This translates to reducing the energy output levels by 4% from OCGT and 53% from CCGT relative to their respective production levels under the PV technology penetration scenario.

6.2.2.3 Carbon emissions results

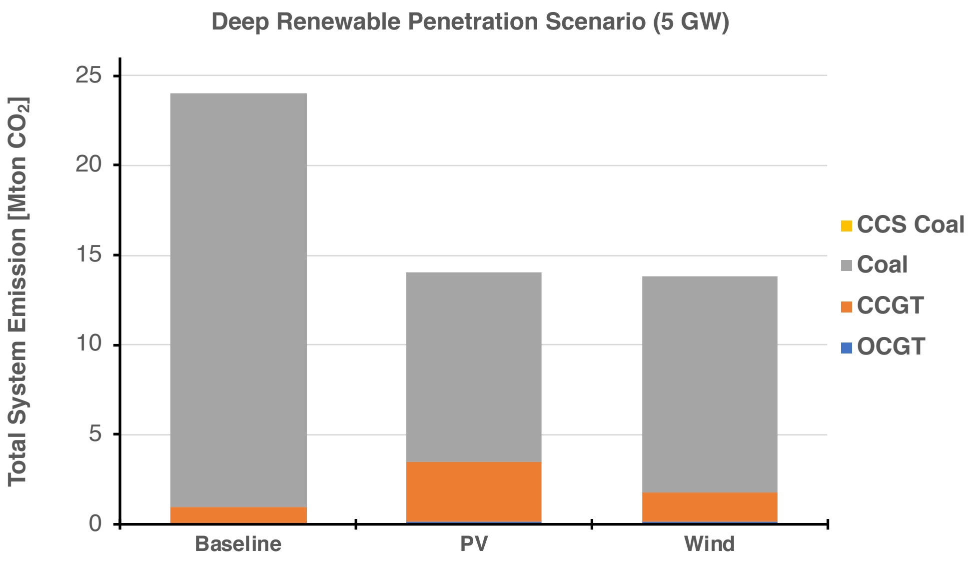

Figure 56: Carbon emissions results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

As Figure 56 indicates, the two technologies result in comparable CO_2 emission savings. The differential in CO_2 emission levels between the two technologies amounts to 0.18 Mton in favour of wind technology. This represents about a 1% reduction in CO_2 emission levels relative to the emissions levels of the PV model. This can be explained by the higher capacity factor of the wind model relative to the PV model and the ability to achieve deeper energy penetration levels.

In line with the energy mix displacement trends, PV outperforms wind in terms of offsetting the CO_2 emission generated from coal. Conversely, it underperforms wind technology in terms of offsetting CO_2 emission generated from OCGT and CCGT technologies. This explains the comparable level of CO_2 emission between the two scenarios despite the higher capacity factor and deeper energy penetration levels of wind technology because PV tends to displace more carbon-intensive energy.

6.2.2.4 System costs results

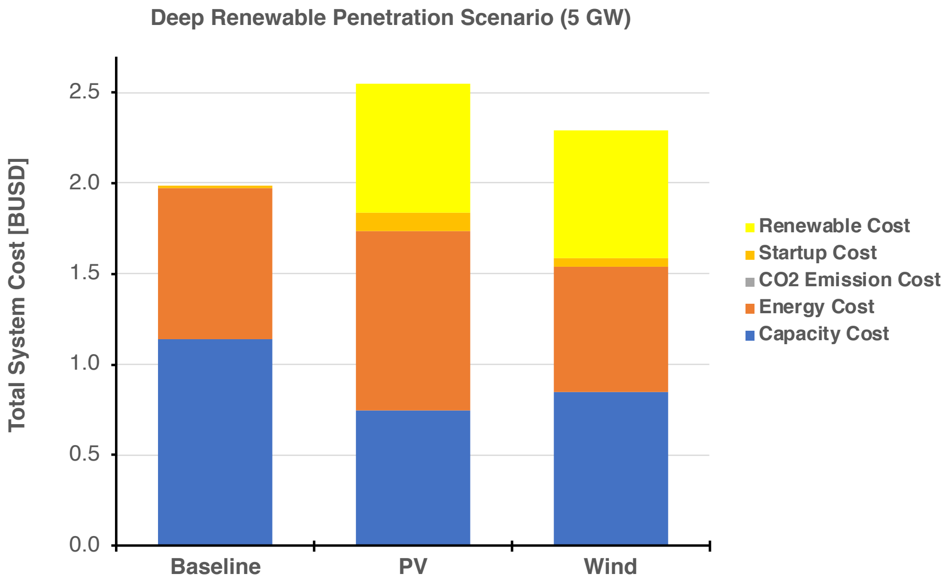

Figure 57: System costs results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

Figure 57 and Table 15 reveal significant changes in the total cost trends under deep renewable penetration scenarios. Due to their importance, we will summarise them in the following points:

	Baseline Cost [MUSD]	PV Cost [MUSD]	Wind Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	749.7	848.8	99.1	13%
Energy Cost	835.2	984.9	691.8	-293.0	-30%
Start-up Cost	10.9	100.9	46.1	-54.8	-54%
Renewable Cost	0.0	712.1	705.2	-6.9	-1%
Total Cost	1986.4	2547.4	2291.9	-255.5	-10%

Table 15: System costs results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

1) Overall cost trend

As Table 15 indicates, wind technology penetration results in much cheaper total system costs when compared to the total costs of the PV system under the deep penetration scenario. The differential in the cost is about 256 MUSD, which represents about 10% of the total system cost relative to the PV model results. Notably, the differential in the annualised capacity costs of the two renewable technologies is negligible and amounts to about 0.3% of the total system cost. In other words, although the two technologies have almost the same capacity investment costs, due to their different technical characteristics, they tend to have very diverse impact on the system's costs structure. In turn, this has significant impact on their relative cost-effectiveness in saving carbon emissions. We will discuss this in more detail in a later section of this chapter.

2) Capacity cost

In line with the capacity mix figures presented earlier, PV results in a cheaper capacity mix as a result of having fewer coal generation assets compared to the wind mix; this explains the cheaper conventional capacity costs of the PV system. As Table 15 indicates, the differential in capacity costs amounted to 99.1 MUSD, which represents about a 13% reduction in capacity cost compared to the wind cost levels.

3) Variable cost of conventional plants[106]

Similar to the results of shallow penetration scenarios enclosed in the results appendix, changes in the cost of producing energy from conventional generators are the main driver of the system cost differential between the two technologies. However, under the deep penetration level, we notice a *major* shift in both the *scale*[107] and the *direction*[108] of this trend's underlying driver. Due to the significance of these issues, we will separately summarise them in the following points:

Variable costs escalation pace

For example, under the shallow renewable penetration scenario (1 GW), the differential in energy costs of the two technologies was about 22 MUSD in favour of wind. By contrast, under the deep renewable penetration scenario (5 GW), the differential in energy costs amounted to 293 MUSD. This implies that increasing the PV capacity penetration by five times results in an increase in the cost differential of more than thirteen times. Similarly, under the PV 1 GW scenario, the start-up costs were about 11 MUSD. By

106 We would like to remind the readers that variable costs of conventional plants are driven by the fuel, variable O&M, and startup costs of conventional generators.

107 Refers to the pace at which the energy system costs decrease or escalate as a result of additional renewable penetration. For example, the increase of 10% generation from certain renewable technology may lead to a 5% increase in the energy cost of the system. However, a 20% increase in renewable generation may inflate the energy cost by 25% resulting in an unequal impact on the system cost for an equal increase in renewable generation penetration level.

108 Refers to the way in which the renewable generation impacts the system's energy cost structure (i.e. reducing or increasing the energy cost of the system). The system energy cost is primarily driven by the fuel and operation costs of conventional plants. In many cases, the introduction of renewable generation leads to a reduction in the total energy costs as a result of fuel and operation costs savings from conventional plants that otherwise will be dispatched to meet demand. However, in some cases, the large-scale introduction of renewable generation might raise the energy cost of the system as the work of this thesis shows.

contrast, under the 5 GW scenario, the start-up costs exceeded 100 MUSD. In other words, under deep penetration scenarios, PV technology tends to raise the system's variable cost. In addition, our simulations indicate that under the shallow and intermediate penetration scenarios, the penetration of the two technologies consistently results in an overall reduction in the energy cost relative to the base scenario. However, under the deep penetration scenario, this consistent trend is broken because PV technology leads to an increase in the total energy cost of the system relative to the baseline scenario.

Drivers of variable costs escalation

Under the shallow renewable penetration scenario, the differential in energy costs of the two technologies was largely driven by the variation of their respective capacity factors. In particular, the higher capacity factor of wind is the major driver underlying the energy cost differentials. However, under the deep penetration scenarios, we notice that the increase in the system's energy cost is mainly driven by the *substantial increase in the baseload generation costs of the system*. This can be explained by the significant shift in the capacity mix and the subsequent substantial increase in the energy output towards more flexible, yet more expensive, technologies (mostly from coal to CCGT) under the deep PV scenarios. More specifically, the substantial increase in the flexibility requirements imposed by the deep penetration of PV makes flexible mid-Capex, high-Opex technologies (i.e. CCGT) more economically viable to meet the residual demand at the expense of the less flexible high-Capex, low-Opex technologies (i.e. coal-fired steam technology).

In addition, the increased incidence of curtailment tends to limit the effectiveness of PV generation to make a deeper energy penetration, subsequently continuing to contribute to lowering the total energy system cost. This explains the increase in the energy system cost of the system compared to the baseline scenario. These factors combined tend to increase the 'baseline' of the energy costs at the system level[109]. We argue this often-overlooked and largely unnoticed effect can have many significant implications. One

109 It is worth noting that the minimum thermal generation running generation was assumed to be 500 MW, which represents 9% of the system's peak load and about 28% of the system's minimum load. Increasing this level might further increase the incidence of curtailment, preventing PV from further contributing to lowering the system costs. Conversely, this might reduce the residual demand volatility of the system and contribute to increasing the output levels from the cheap coal assets. It is particularly interesting to examine the sensitivity of this effect to changes in the minimum thermal generation running generation levels of the system.

particular implication is that in some cases the *indirect* increase in the baseload generation costs can outweigh the energy savings gained from the penetration of the 'zero marginal cost' renewable generation. Equally, this would suggest that renewable technologies vary significantly in terms of not only the *scale* of their influence on the energy market but also the *direction* of their influence. For example, we find that wind penetration consistently leads to a decrease in the energy cost on the system in the scenarios considered. By contrast, we find that under deep penetration scenario, PV penetration might lead to an increase in the energy costs of the system. This is particularly important in the context of energy-only markets. We will discuss this in more detail in this chapter's findings sections.

6.2.2 Effect on the perceived carbon cost-effectiveness

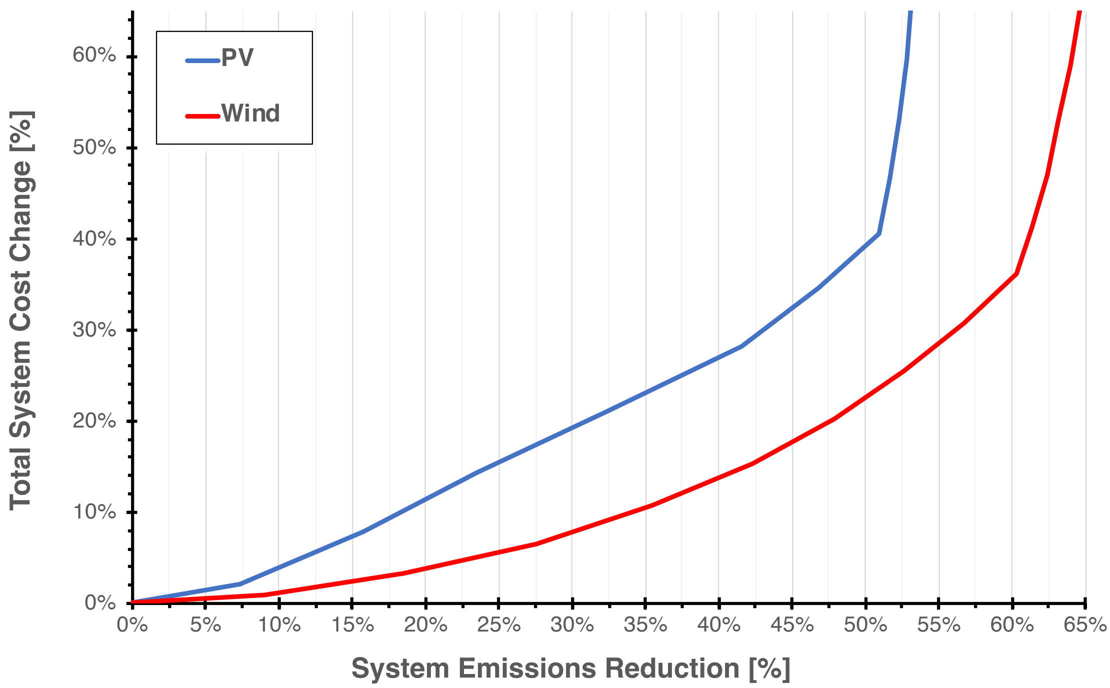

Figure 58: Projected carbon cost-effectiveness trends of the PV and wind technologies models under different decarbonisation levels

Figure 58 shows how the carbon reduction cost-effectiveness of the system changes across a range of different penetration and decarbonisation scenarios for both the PV and wind technologies.

Notably, the carbon saving differentials between wind and solar technologies were modest under both the shallow and deep decarbonisation scenarios for the system under study.

In particular, the carbon saving differentials between the two technologies were in the range of 1% to 2% relative to the total system emissions under the different scenarios considered in favour of wind; however, wind technology has a clear edge in terms of its cost-effectiveness to reduce carbon emission.

This can be explained by wind technology's ability to deliver higher costs savings at the system level relative to the system's costs incurred under the PV penetration scenarios. In particular, the penetration of wind results in a cheaper total system cost due to its higher capacity factors, its less volatile residual load and its ability to achieve higher maximum energy penetration rates compared to PV technology. These factors combined allowed wind to deliver more OPEX savings relative to the PV models' OPEX costs. Of note, the differentials in the investment costs in both technologies were negligible. Nevertheless, the differentials in their respective system-level costs amounted to about 10% of the total system cost in favour of wind.

Building on this, our results suggest that the variations in the technical characteristics of renewable technologies can have a marked influence on the economics of the decarbonisation process. For example, decarbonising the system by 50% will lead to an almost 20% increase in the system cost using wind technology, whereas doing so would increase the system cost by almost double percentage points (nearly 39%) using PV technology.

6.3 Case Study 2: Impacts of Renewable Production Profiles on the Economics of Decarbonisation

6.3.1 Scenario assumptions

As indicated in our first case study, each GW of wind technology produces about 27% of usable energy than GW of solar[110]. As discussed earlier, the deeper energy penetration

110 The total DC-to-AC conversion losses were about 10% of the generated energy. This is a conservative estimate. Recent research reports much lower losses figures that might further increase the PV output levels of the baseline scenario (Baumgartner, 2017).

levels of wind generation influenced its ability to (1) save carbon and (2) deliver cheaper total system costs, thereby levelling up its relative cost-effectiveness against PV technology.

In this case study, we control for the variations in the cumulative energy output levels of the two technologies reported in our first case study by considering comparable cumulative energy output levels for the two technologies rather than comparing them on an equivalent capacity penetration basis . The new comparison is meant to allow us to capture the impact of the variations in the production profiles of the two technologies, irrespective of their underlying renewable resource's strength. In particular, we seek to uncover the impact of the variations in 'production profiles' of renewable technologies on the economics of the decarbonisation process without factoring in the renewable resources' variations in strength and potential."

In reality, this implies building additional PV capacity relative to the PV baseline scenario to allow the PV units to achieve energy penetration levels comparable to that of wind technology. In the interest of consistency and ease of comparison, we assumed comparable cost production levels of the PV and wind technologies. In the context of the previous case, this implies a sufficient drop of the per KW_e cost of PV technology that would give an equal cost per MWh generated relative to wind technology's production costs.

For brevity, in this section, we will present and comment on some of the simulation results of this case study. In particular, we focus on the deep decarbonisation scenarios because the impact of the variations in the production profiles of the two technologies is more pronounced. However, we include additional simulation results in the supplementary results appendix.

6.3.2 Simulation results

6.3.2.1 Capacity mix results

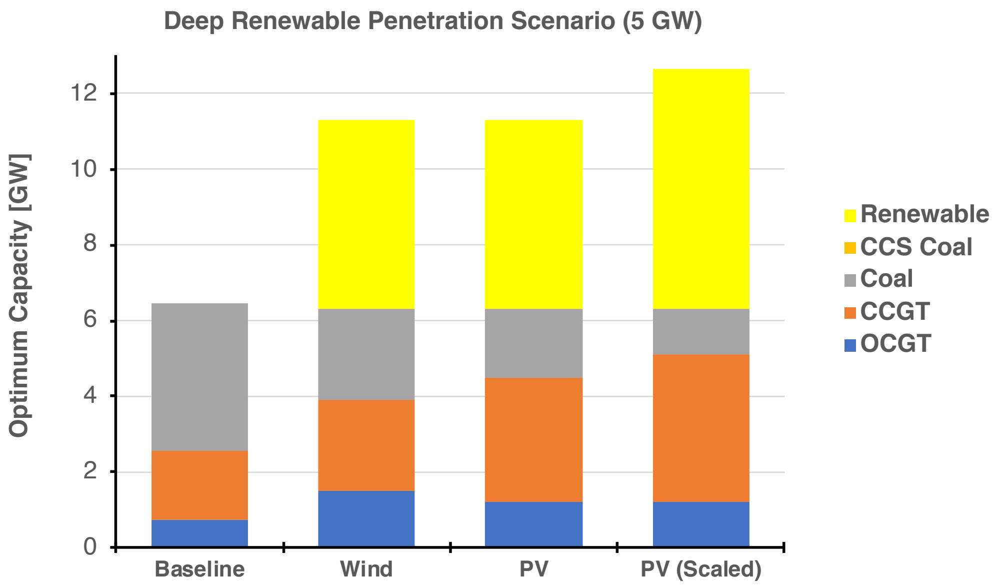

Figure 59: Optimum capacity mix results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

As Figure 59 indicates, the capacity mixes of the two PV scenarios are materially different under the deep penetration scenario. In particular, the PV scenario with the higher capacity (PV Scaled) results in an additional 0.6 GW of CCGT capacity at the expense of 0.6 GW coal capacity, relative to the baseline PV scenario. This represents an increase of about 18% in CCGT generation assets and a reduction of about 33% in coal assets relative to the baseline PV scenario. The shift in capacity mix is mainly driven by the increased volatility of residual demand due to the deeper penetration levels of the PV generation. This tends to reduce the effectiveness of the coal assets and attracts more flexible generation.

6.3.2.2 Energy output results

Figure 60 shows the changes in the energy mix under the deep decarbonisation scenarios. Referring to the figure, we can make several observations.

First, by comparing the PV (scaled) and wind scenarios, we can note the following:

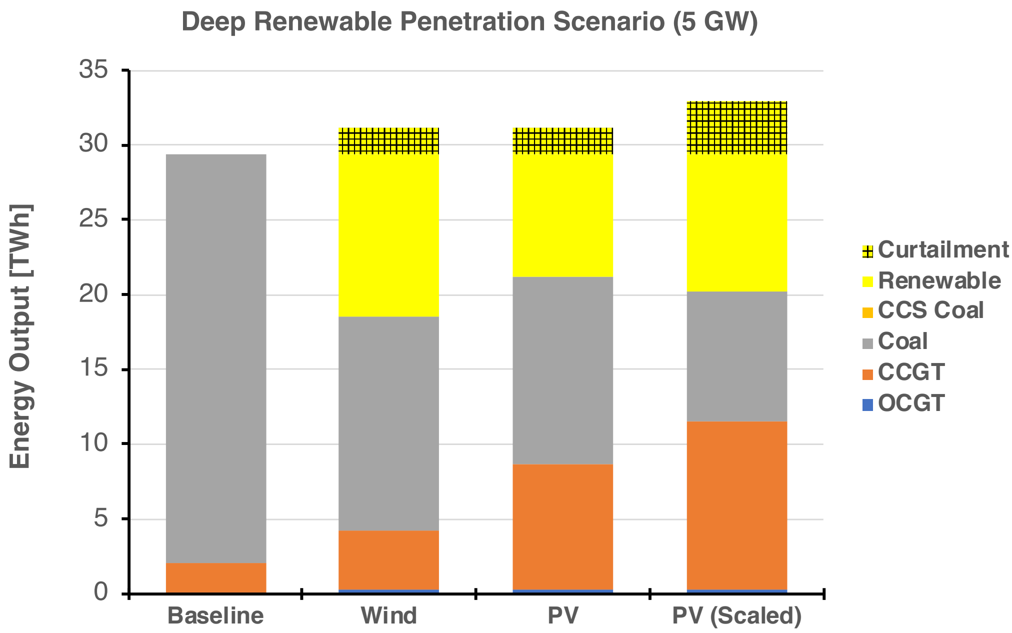

Figure 60: Energy output results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

1) As Figure 60 indicates, despite having the same energy generation levels, wind power still outperforms PV technology in terms of its deeper energy penetration ability. At the aggregate level, wind displaces an additional 1.73 TWh of thermal energy compared with the scaled PV penetration scenario; this represents about 19% of the total PV energy consumed by the system.
2) The variations in the energy curtailment levels of the two technologies can explain the differential in the energy penetration levels. This is driven by the underlying significant variation in the shape of their respective production profiles and the subsequent correlation with the system's demand profile.
3) At the technology level, the total curtailed wind energy amounted to about 15% of the total generated power. By contrast, the total curtailed PV power amounted to about 28% of the total generated power.

Second, by comparing the two PV scenarios, we can note the following:

1) Under the scaled PV scenario, the generated PV energy increased by 2.71 TWh compared to the baseline scenario. Nevertheless, the system consumed only an additional 0.94 TWh overall. The curtailed power amounted to 1.77 TWh, which

represents a 98% increase in power curtailment levels compared to the baseline PV scenario despite the fact that the energy output levels increased by only 27% relative to the baseline scenario.

2) Regarding the changes in displacement trends, as indicated in Figure 60, the energy mixes of the two scenarios are substantively different. In line with the changes in the capacity mix, the scaled PV model outperforms the baseline PV model in offsetting the energy generated from OCGT and coal technologies. In particular, the scaled PV model displaces an additional 0.01 TWh and 3.76 TWh from OCGT and coal technologies, respectively, relative to the baseline PV displacement figures. This translates to reducing the energy output levels by 3% from OCGT and 30% from coal relative to their respective production levels under the baseline PV penetration scenario. Conversely, this leads to an increase in the output levels from the CCGT technology. The differential represents a 34% increase in the energy output level relative to the PV baseline scenario.

6.3.2.3 Carbon emissions results

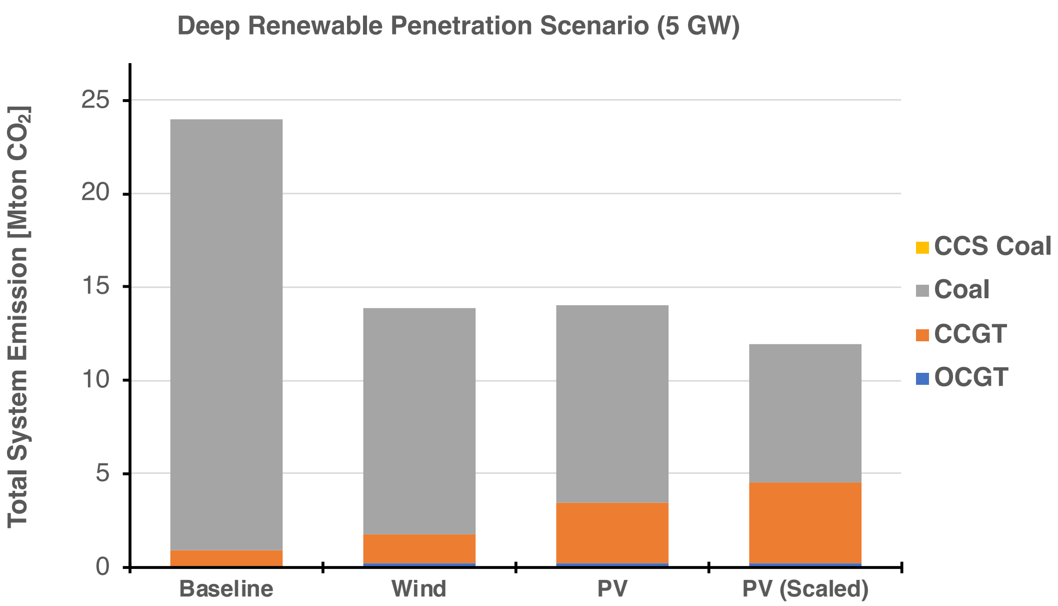

Figure 61: Carbon emissions results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

Figure 61 shows the changes in carbon emission trends under the deep decarbonisation scenarios. Referring to the figure, we can make several observations.

First, by comparing the PV (scaled) and wind scenarios, we can note the following:

1) Despite its lower energy penetration levels compared to wind technology (as indicated earlier), PV technology is able to deliver more emission savings compared to wind at the aggregate level. Variations in their respective capacity and energy mix mainly drive this difference. The differential in the carbon emissions levels amounts to 1.92 Mton, which represents about 16% of the total PV emissions level.

2) More importantly, this implies that the impact of the underlying shifts in the capacity and energy mixes caused by the PV and wind technologies penetration can outweigh their direct energy displacement effect in terms of their potential to save carbon emissions at the system level, especially under deep penetration scenarios. This would equally suggest that the variations in the renewable technologies' production profiles have a critical impact on the renewables' ability to save carbon emissions that goes beyond their direct energy displacement effect. We will discuss this in further detail later in the chapter.

Second, by comparing the two PV scenarios, we can note the following:

1) Under the scaled PV scenario, the generated CO_2 emissions dropped by 2.1 Mton compared to the baseline scenario. This represents a reduction of 15% relative to the baseline PV scenario.

2) Regarding the changes in displacement trends, the differential in the CO_2 emission levels of the two PV models is dominated by the reduction in the coal emission levels. In particular, the scaled PV model outperforms the baseline PV model in offsetting the CO_2 emissions generated from coal by 3.15 Mton; this represents a reduction of about 30% relative to the baseline PV model. Conversely, the CO_2 emissions displacement from the OCGT technology amounted to only 0.01 Mton, which represents about a 3% change relative to the levels of the PV baseline scenario. Furthermore, emissions levels from CCGT technology are up by 1.06 Mton; this represents about a 32% increase relative to the baseline PV scenario.

6.3.2.4 System costs results

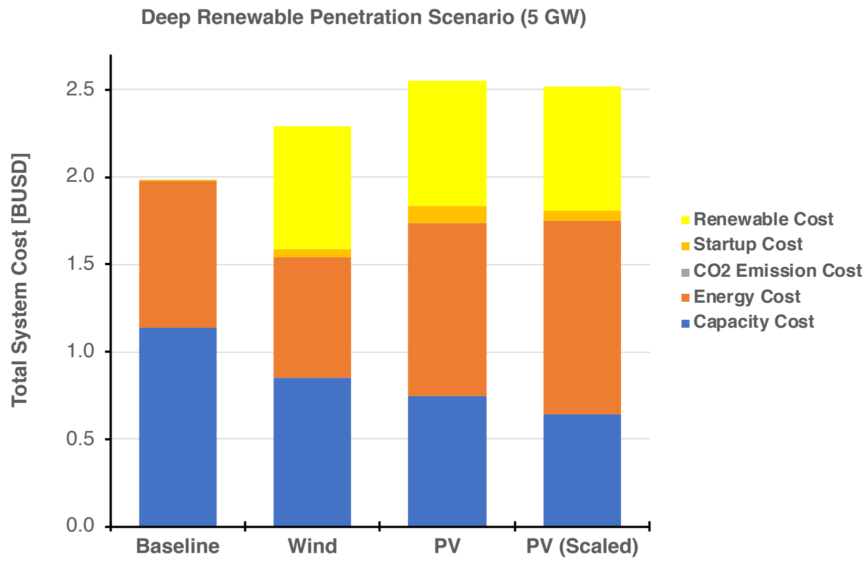

Figure 62: System costs results comparison between the PV technology and wind technology models under deep renewable penetration scenarios (5 GW)

Figure 62 shows the changes in the carbon emission trends under the deep decarbonisation scenarios. Referring to the figure, we can make several observations.

First, by comparing the PV (scaled) and wind scenarios, we can note the following:

1) Overall, the increase in the PV technology's energy penetration levels leads to a slight reduction in the total system costs. Nevertheless, the changes in the two systems' cost structure have become more pronounced under the scaled PV scenario.
2) In particular, the differentials in the capacity and energy costs of the two systems have further expanded. For example, the differential in the capacity costs under the previous scenario amounted to 99.1 MUSD in favour of the wind scenario. Under the PV scaled scenario, the differential amounted to about 204 MUSD. Similarly, the energy cost differential amounted to 293 MUSD under the previous scenario; however, the differential amounted to 412 MUSD under the PV scaled scenario.

Second, by comparing the two PV scenarios, we can note the following:

1) As indicated in Figure 61, at the aggregate level, the increase in PV technology's energy output levels leads to a slight reduction to the overall cost by about 26 MUSD. This represents about 1% of the total system costs. Nevertheless, the cost structures of the two scenarios are materially different.

2) In particular, under the scaled PV scenario, the capacity cost is down by about 106 MUSD; this represents about a 14% reduction in the capacity costs relative to the baseline PV scenario. The retirement of the high CAPEX coal plants can explain this change.
3) By contrast, the energy cost of the system increased by about 119 MUSD under the scaled PV scenario; this represents a 12% increase in the energy cost relative to the baseline PV scenario. Crucially, although the PV energy penetration further increases under the scaled scenario, this does not contribute to reducing the system's total energy costs. This further confirms and validates our earlier findings concerning the amplification effect that the volatile PV generation has on the energy costs of the system, especially under the deep penetration scenario. This further underscores the significance of the production profile's role in dictating the *nature* and *scale* of the economic impact that renewables would have on the energy market.
4) Interestingly, although the number of start-ups increased under the scaled PV scenario, the system's start-up costs dropped by about 40 MUSD nevertheless. This represents about a 39% reduction in the start-up costs relative to the baseline PV scenario; this occurrence can be explained by the retirement of the coal assets, whose start-up costs are particularly high when compared to the other thermal technologies' start-up costs.
5) As Figure 63 indicates, CCGT technologies are taking a leading role in providing the flexibility requirement needed under the deep PV renewable scenarios. We will discuss this point in more detail when we discuss our research findings.

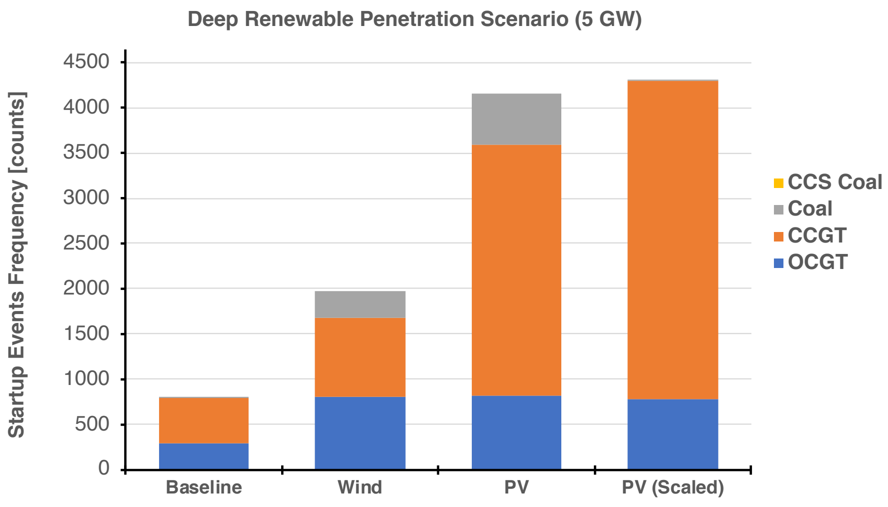

Figure 63: Thermal generation start-up activities results comparison between the baseline model and the PV technology model under a deep penetration scenario (5 GW)

6.3.3 Effect on the perceived carbon cost-effectiveness

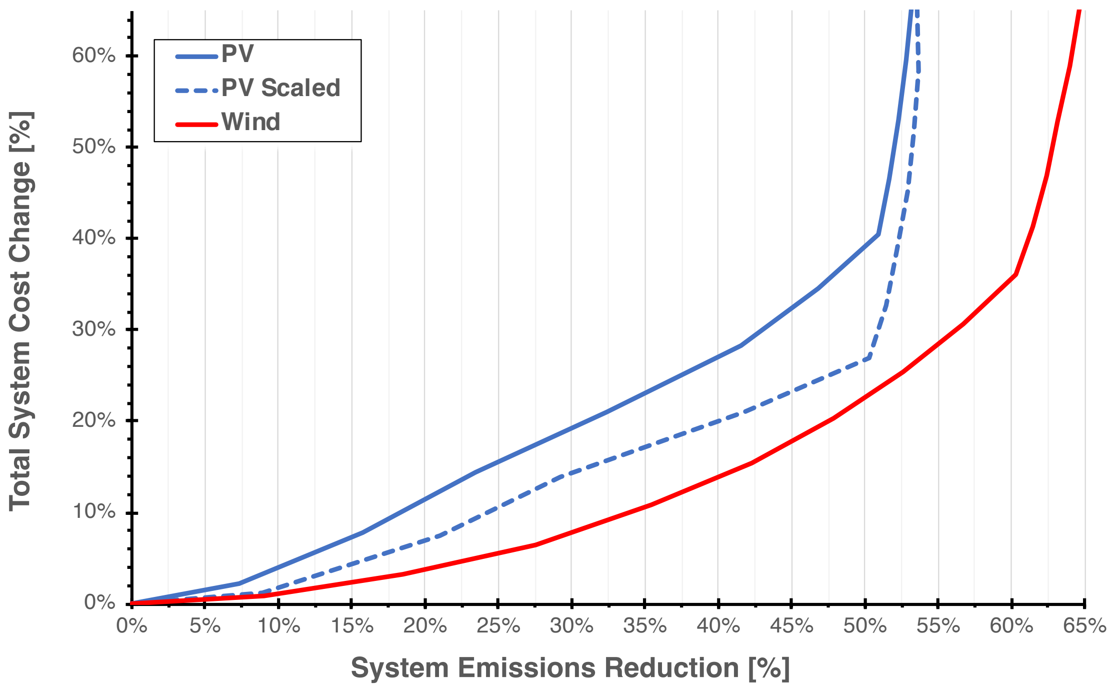

Figure 64: Projected carbon cost-effectiveness trends of the PV and wind technologies models under different decarbonisation levels

Overall, the scaled PV scenario outperforms the baseline PV scenario in terms of its cost-effectiveness in decarbonising the electric system under consideration. This can be explained by the lower system costs and the greater carbon reductions delivered per GW of the higher, load-factor scaled PV scenario.

In addition, Figure 64 shows that the cost of achieving a given percentage reduction in emissions is lower with the scaled PV scenario than in the original PV case, but higher than with wind energy. The amount of PV output required for a given reduction in emissions tends to be identical between the two PV scenarios (since the pattern of PV output over time, and the fossil fuels that are displaced, are matching), but in the scaled PV scenario, this PV output comes at a lower unit cost.

6.4 Case Study 3: Impacts of Renewable Production Profile Variability on the Capacity and Flexibility Requirements of an Electric System

In previous case studies, we explored the effect of variations in the production profile of technologies with different underlying renewable resource characteristics. In particular, we were interested in capturing the effect of the 'shape' of the production profile on influencing the economics of the decarbonisation process. In this case study, however, we focus on the effect of the 'variability' of the production profile on the economics of the decarbonisation process. We investigate this effect using a case study that features two technologies that share the same underlying renewable resource but have different variability levels in their respective output levels. In particular, we present a case study comparing the deep decarbonisation of the electric system using PV and CSP technologies.

Figure 65 shows the variation in the standard deviation of the residual profiles of the two technologies under different renewable penetration scenarios. As the figure suggests, the variability of the CSP is greater than the variability of the PV profile.

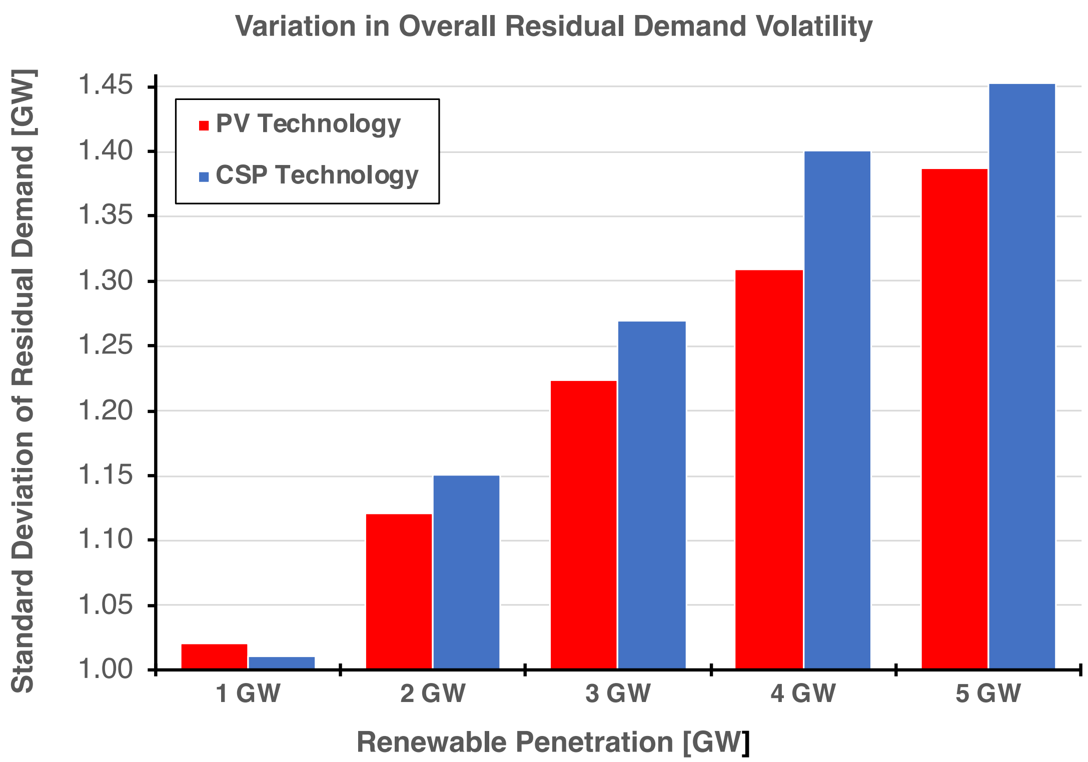

Figure 65: Variation in the standard deviation of the residual profiles of the two technologies under different renewable penetration scenarios

The increased variability of the CSP profile is driven by the following:

1) The high sensitivity of CSP solar resources to variations in weather conditions. This is due to the fact that unlike solar PV, which utilises both the direct and indirect components of sunlight known technically as the Global Horizontal Irradiance, CSP technologies use only the direct component of sunlight, known technically as the Direct Normal Irradiance. For example, the direct component of sunlight represents up to 90% of the total sunlight during sunny days; however, it is negligible on cloudy days (Taylor et al., 2013). Equally, dust conditions can prevent direct sunlight from reaching the CSP mirrors, thereby largely affecting negatively its production levels even during extremely sunny days.

2) The nonlinear relationship between the underling solar resources and CSP plant output. Unlike PV power, which converts sunlight directly to electricity, CSP plants concentrate the sun's rays to heat fluids, which in turn are used to run a thermodynamic cycle that converts heat to electricity. This explains the nonlinearity of the relationship between the underlying solar resources and CSP energy output.

It is worth noting that we actively did not consider a CSP system with a thermal storage (1) due to our limited knowledge in terms of jointly optimising the operation of a CSP plant and the operation of the power system at the same time (2) and more importantly because the existence of thermal storage might have a large smoothing effect on the production profile of the CSP plant, which would defeat the purpose of this case study because it focuses on the 'variability' effect of the renewable profile on the economics of decarbonisation studies.

Similar to the previous, we use the same input data and assume the same simulation assumptions in *CHAPTER 3: METHODOLOGY & DATA*. In following sections, we will briefly present and comment on some of the simulation results of this case study. Similar to the previous case study, we will also focus on the deep decarbonisation scenarios as the effects of the variations in the production profile become more pronounced. We also include additional simulation results in the supplementary results appendix.

6.4.1 Simulation results

6.4.1.1 Capacity mix results

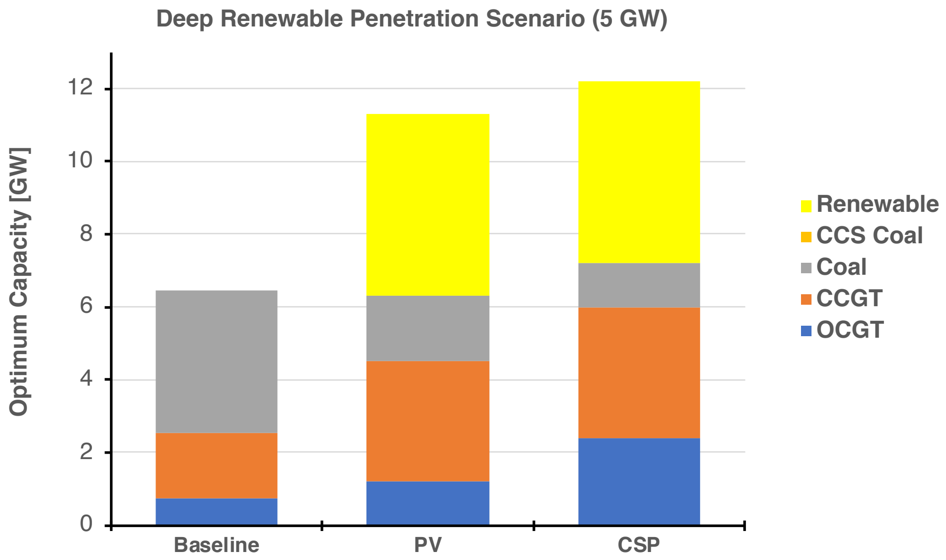

Figure 66: Optimum capacity mix results comparison between the PV and CSP technology models under deep renewable penetration scenarios (5 GW)

Figure 66 compares the optimum generation technology mix results of the PV and CSP models under the deep (5 GW) penetration scenarios. As Figure 66 indicates, the capacity mixes of the PV and CSP models are materially different under the deep penetration scenario. Referring to the figure, we can make the following observation:

Compared to the PV model, the CSP model is characterised by the following

(1) a more flexible technology mix

(2) and perhaps more importantly, an increase in the total thermal capacity requirements for running the system compared to the PV model

At the aggregate level, the increase in thermal capacity requirement amounts to 0.9 GW. This represents about a 14% increase in the thermal generation assets compared to the levels of the PV scenario.

This can be explained by a reduction in the operational availability of the incumbent thermal plants and subsequently their dispatchability potential due to the substantial increase in the number of starts and stops under the deep renewable penetration scenario. In particular, the significant increase in the thermal plants' shutdown frequency reduces their effective operational availability to be re-dispatched again due to the minimum downtime constraints of the units. Equally, the significant increase in the number of starts reduces the number of units available to respond to the sharp reduction in the system's demand as a result of the minimum uptimes of the units. This, in turn, attracts additional investments in thermal capacity to compensate for the reduced dispatchability of the incumbent thermal plants to maintain the system's ability to respond to rapid upward or downward changes in demand under high renewable penetration scenarios.

For example, when a CCGT plant is stopped, it can be unavailable to be dispatched again for six hours. In other words, although the unit is counted as 'installed capacity' for statistical purposes, nevertheless it would not be contributing to the system adequacy from an operational perspective during its 'minimum downtime' period. Equally, when the same unit is started, due to certain technical considerations and the high startup costs of the unit, it should be kept online for up to six hours before it can be stopped again. This restricts the number of units that can be stopped during this period and subsequently affects the operational flexibility options available to the system operator to respond to a steep downward change in the system's demand. Moreover, the minimum stable generation level of each individual unit further restricts the number of units that can be partially loaded, forcing the system operator to de-commit more units under steep downward load changes — thereby affecting the dispatchability potential of more thermal units.

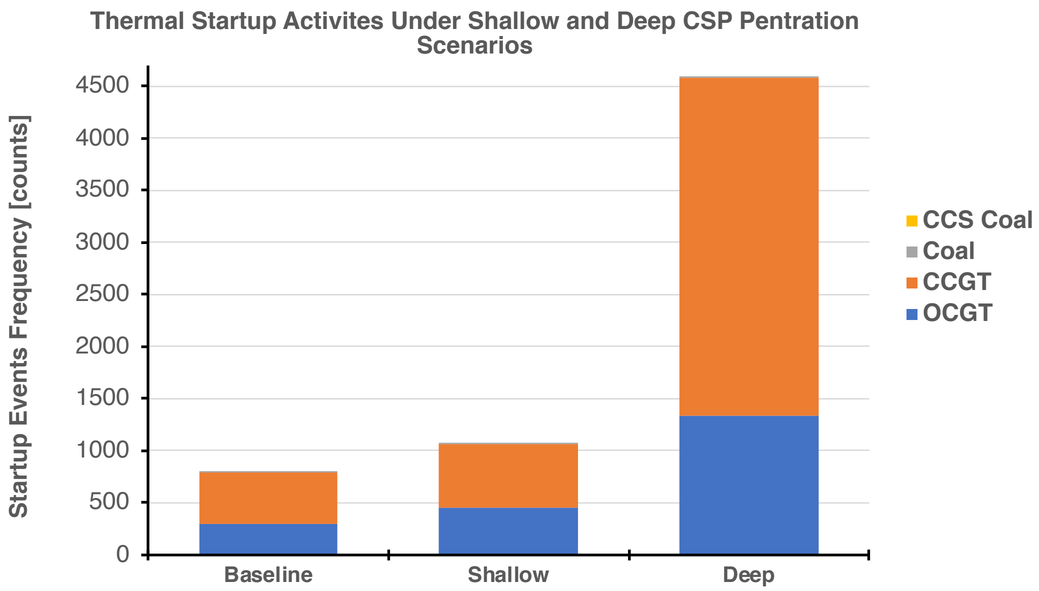

Figure 67: Thermal generation startup activities results comparison between the baseline, shallow, and deep penetration scenarios for the CSP technology

It is worth noting that under normal circumstances of relatively gradual changes in the system demand, the effective dispatchability of the power plants is also affected by the start and stop activities of thermal units. However, the scale of this effect tends to be more pronounced with the increased frequency in the rapid changes in the system demand. This explains the increase in the capacity investment in thermal generation under the deep penetration scenario compared to the capacity investment levels under the baseline and shallow decarbonisation scenario.

The below figures compare the variations in residual demand as a result of deep penetration of PV and CSP technologies under heavy load conditions for a selected number of hours.

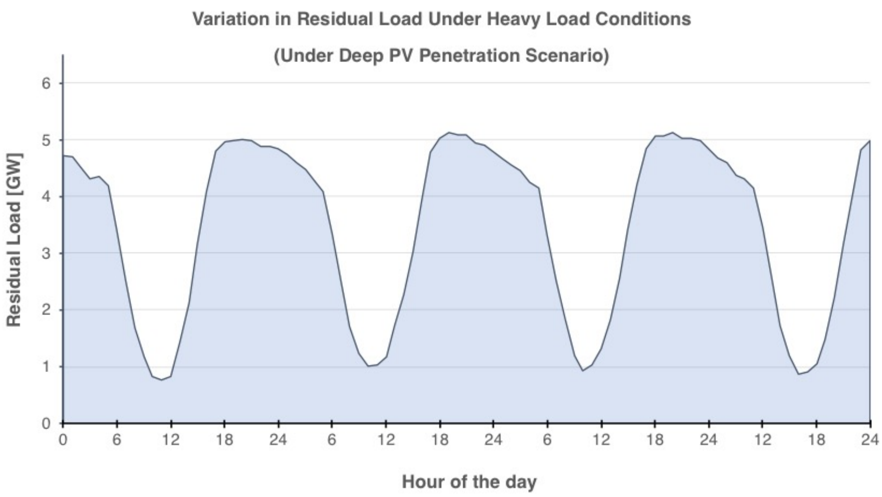

Figure 68: Variations in residual demand under heavy load conditions and deep penetration scenario for the PV technology for selected hours of the year

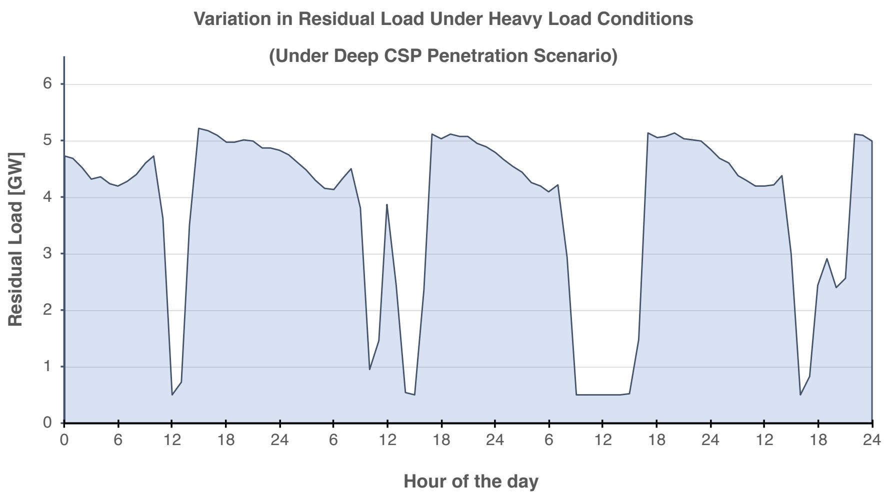

Figure 69: Variations in residual demand under heavy load conditions and deep penetration scenario for the CSP technology for selected hours of the year

CSP technology penetration tends to increase the level of volatility and the frequency of rapid changes in residual demand. This explains the additional investment in the OCGT assets, which have great load-following capability and can be started and stopped in a relatively short period of time compared to other types of thermal plants.

To illustrate this point further, we ran the same CSP technology scenarios without enforcing the minimum up and downtime limits of the thermal units.

Table 16 presents the optimum capacity mix results for a deep decarbonisation scenario with and without enforcing the minimum up and minimum downtimes constraints the thermal generating units.

		Units Constraints Not Modelled	**Units Constraints Modelled**		
	Baseline	5 GW CSP	5GW CSP	Diff	Diff
	[GW]	[GW]	[GW]	[GW]	[%]
OCGT	0.75	0.90	2.40	1.50	167
CCGT	1.80	3.30	3.60	0.30	9%
Coal	3.90	2.10	1.20	-0.90	-
CCS Coal	0.00	0.00	0.00	0.00	-
Total	6.45	6.30	7.20	0.90	14%

Table 16: Optimum capacity mix with and without enforcing the minimum up and minimum downtime constraints of the thermal generating units under deep CSP technology penetration scenarios

As Table 16 indicates, without enforcing the minimum up and downtime constraints, increasing renewable penetration does not lead to an increase in the thermal capacity requirement to run the system under the deep renewable penetration scenarios considered. This is because despite not enforcing the constraints, the effective availability and dispatchability of the thermal plants were not affected by the start and stop activities of the units. Not enforcing the constraints implies that, in practice, the system operator can sequentially switch the thermal plants on and off at the beginning of each dispatch period regardless of their respective operation statuses prior to that. In reality, however, this does not reflect the actual operations of power systems, which are largely dictated by the physical and thermodynamic characteristics of the generating units.

To illustrate this point further, we compare variations in the maximum committed capacity and the total installed capacity over the overall simulation period with and without enforcing the unit's dynamic constraints, under the simulated deep CSP penetration scenario (5 GW).

	Units Constraints Not Modelled	**Units Constraints Modelled**
	[GW]	[GW]
Peak System Load	5.35	5.35
Peak Residual Load[111]	5.17	5.17
Maximum Committed Capacity	6.30	6.30
System Installed Capacity	6.30	7.20

Table 17: Variations in maximum committed capacity and maximum installed capacity with and without enforcing the unit's dynamic constraints under deep CSP penetration scenarios (5GW)

As Table 17 indicates, without enforcing the units' constraints, the maximum committed capacity amounts to 6.3 GW, which satisfies the optimisation conditions of meeting the maximum residual demand, in addition to the system reserve margin[111] totalling about 6.2 GW.

Furthermore, the simulation results indicate there is no difference between the total maximum capacity committed during the overall simulation period and the total capacity installed to run the system when the units minimum up and downtimes are not enforced. This implies that, without enforcing the constraints, the investment decision regarding the total capacity requirements for running the system is dictated by the need to meet the system's peak demand plus the respective reserve margin at the highest periods of system demand.

In contrast, when the units' constraints were enforced, as Table 17 indicates, the total maximum capacity committed during the simulations period did not change. Nevertheless, the total system capacity did. This implies that, with increased renewable penetrations, the investment decision in the total capacity is not only dictated by the ability of the system to meet the demand and reserve requirement under peak hours but also depends on meeting the flexibility requirement at the system level. In particular, the

111. Reserve margin amounted to 1.03 GW at the peak demand.

optimiser tends to invest in more thermal assets to compensate for the reduced dispatchability of the incumbents' thermal units that were affected by the increased start and stop activities due to the renewable penetration.

Furthermore, to understand the value of flexibility of the thermal fleet in saving additional investment in thermal capacity, we ran the same CSP scenario again while considering half the minimum up and minimum downtimes of the units considered in the previous scenario. Table 18 summarises the results of our simulation.

		Full Min Up/Downtime	**Half Min Up/Downtimes**		
	Baseline	Deep Penetration	Deep Penetration	Diff	Diff
	[GW]	[GW]	[GW]	[GW]	[%]
OCGT	0.75	2.40	1.20	-1.20	-50%
CCGT	1.80	3.60	3.30	-0.30	-8%
Coal	3.90	1.20	1.80	0.60	50%
CCS Coal	0.00	0.00	0.00	0.00	-
CSP	0.00	5.00	5.00	0.00	-
Thermal	6.45	7.20	6.30	-0.90	-13%

Table 18: Optimum capacity mix with enforcing (1) full and (2) half the minimum up and minimum downtime constraints of the thermal generating units' deep penetration scenario of the CSP technology

As Table 18 indicates, halving the minimum up and downtimes of the thermal fleet has a considerable impact on saving investments in thermal capacity. Referring to the table, we can make the following observations:

1. At the aggregate level, more flexible thermal fleets result in a reduction of 0.9 GW in thermal capacity requirement compared to the baseline scenario. This represents about a 13% reduction in thermal generation assets compared to the levels of the less flexible generation fleet.

2. The savings in the thermal capacity are dominated by savings in the flexible OCGT assets. In particular, the more flexible thermal fleet results in 1.2 GW savings in investment in OCGT assets. This represents a 50% reduction in the OCGT assets relative to the less flexible fleet. Equally, this represents 19% of the total thermal installed capacity of the system.

3. This would suggest the flexibility characteristics of the thermal fleets play an important role not only in terms of enabling the integration of renewable generation but also in terms of determining the extent to which renewable generation can affect the effectiveness and adequacy of the incumbent generation fleet and subsequently the ability of renewables to save thermal capacity.

6.4.1.2 Energy mix results

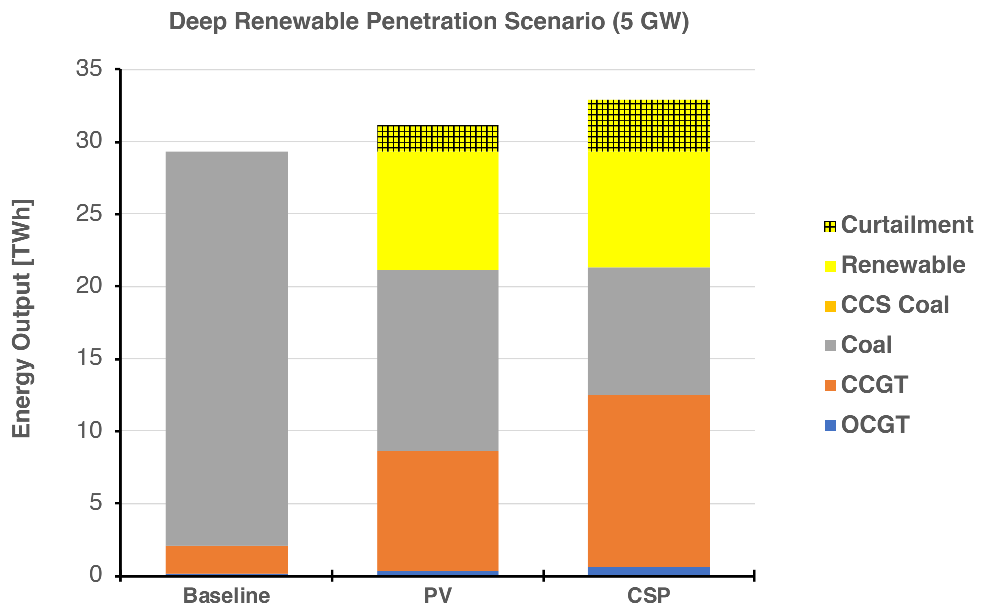

Figure 70: Energy output results comparison between the PV and CSP technology models under deep renewable penetration scenarios (5 GW)

Figure 70 reveals significant changes to the energy output mix of the PV and CSP technology models under the 5 GW penetration scenarios. Figure 70 indicates that, although CSP has a higher capacity factor, both technologies tend to achieve comparable energy penetration rates. This can be explained by the higher curtailment incidences for CSP.

In terms of energy displacement trends, in line with the changes in the capacity mix, the CSP outperforms PV in offsetting the energy generated from coal technologies as a result of needing a more flexible generation mix to deal with the increased residual demand volatility.

6.4.1.3 Carbon emission results

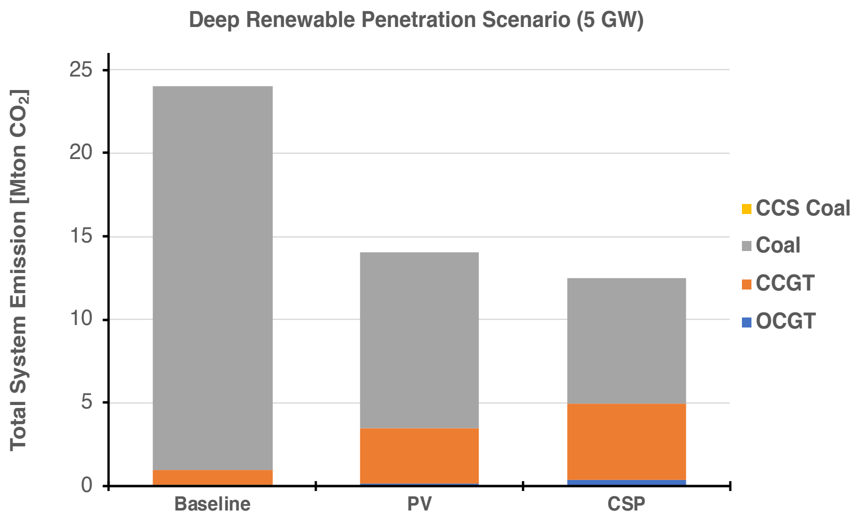

Figure 71: Carbon emissions results comparison between the PV and CSP technology models under deep renewable penetration scenarios (5 GW)

Figure 71 illustrates the changes to the CO_2 emission results of the PV and CSP technology models under the 5 GW penetration scenarios.

Figure 71 shows that CSP outperforms PV in terms of delivering greater CO_2 emission reductions due to its ability to displace more coal energy than PV. At the aggregate level, the differential between the two models amounts to 1.57 Mton. This figure represents about an 11% reduction in CO_2 emission at the system level.

6.4.1.4 System costs results

Figure 72 shows the changes in the carbon emission trends under the deep decarbonisation scenarios. Referring to the figure above, we can briefly make several observations:

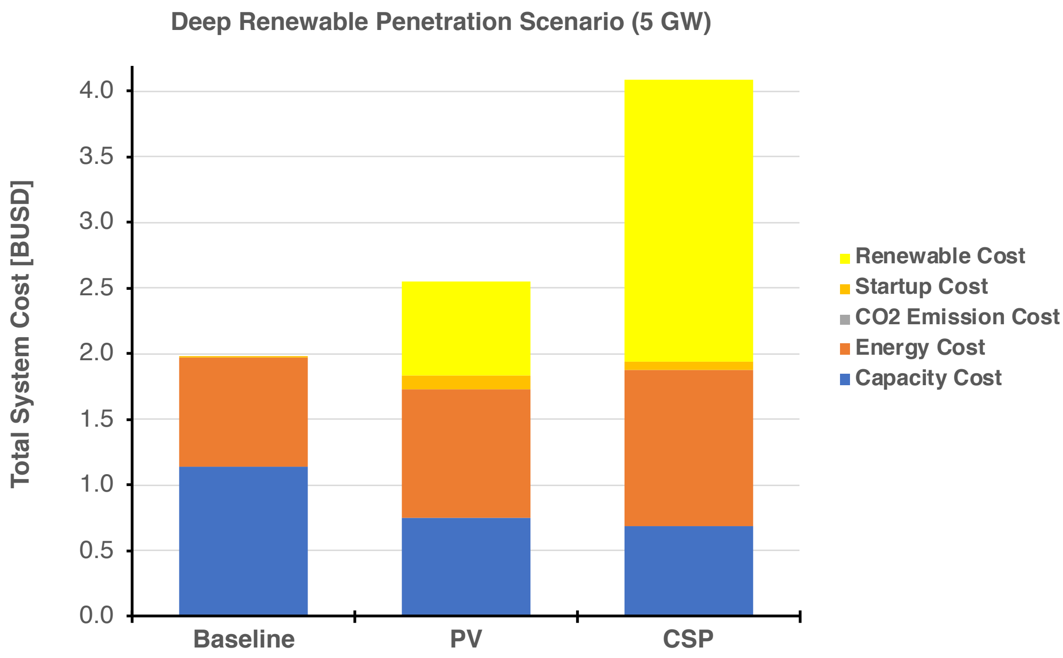

Figure 72: System costs results comparison between the PV and CSP technology models under deep renewable penetration scenarios (5 GW)

1) The cost differential between the two scenarios is massive. The CSP model causes the total system cost to increase by about 1.53 BUSD, which represents a 60% increase in the total system costs compared to the PV technology model. This massive system cost differential is by far dominated by the differential in their respective technology investment costs.
2) The conventional capacity cost is cheaper under the CSP scenario due to having fewer coal assets.
3) The cost of energy is higher under the CSP scenario despite the fact that CSP achieves higher energy penetration levels compared to PV. The differential in energy costs amounts to 214 MUSD, which represents a 22% in energy cost compared to the PV scenario. This further reinforces our earlier observation about the role of renewable profile volatility in inflating the energy cost of recipient systems.
4) Furthermore, interestingly, we note that, although the number of startups increased under the CSP scenario, nevertheless the startup costs of the system dropped by about 40 MUSD. This represents about a 40% reduction in the startup costs relative to the PV scenario. This can be explained by the retirement of the coal assets, whose startup costs are particularly high when compared to the startup costs of other thermal technologies.

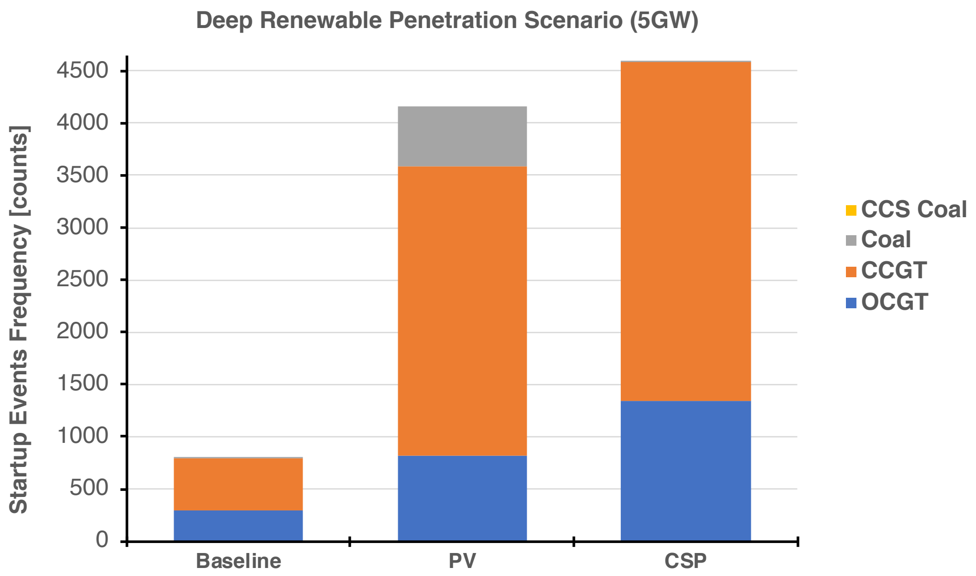

Figure 73: Thermal generation startup activities results comparison between the PV and CSP technology model under deep penetration scenarios (5 GW)

6.4.2 Effect on the perceived carbon cost-effectiveness

Figure 74 shows how the carbon reduction cost-effectiveness of the system changes across a range of different penetration and decarbonisation scenarios for both the PV and CSP technologies.

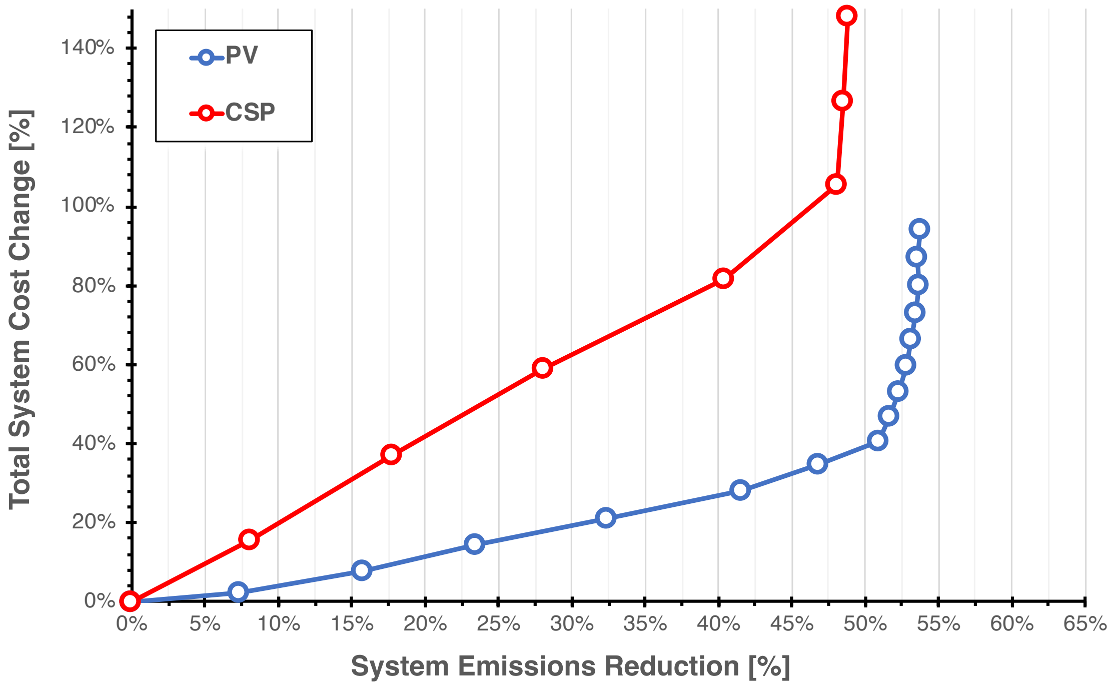

Figure 74: Projected carbon cost-effectiveness trends of the PV and CSP technology models under different decarbonisation levels

It is worth recalling that CSP was able to outperform PV in terms of its ability to save carbon per GW capacity addition because it was able to displace more coal assets compared to PV. Nevertheless, CSP had a significant edge in terms of its cost-effectiveness regarding decarbonising the electric system under consideration. This can be explained by the ability of PV to deliver much cheaper total system costs.

It might be relevant to note that slope of the mostly linear region of the curve seems to be predominantly driven by the capex of the renewable technologies. While the profile characteristics seems to influence the steepness of the second slope of the curve (i.e., beyond the knee point)[112]

Again, this would suggest that the relative system-level cost differentials between the two technologies tend to have more weight in terms of altering their respective carbon cost-effectiveness than their carbon-saving differentials.

6.5 Research Findings, Implications, Insights, and Conclusions

6.5.1 Effect of technological variations on the environmental value of renewables

Our research suggests that the variations in the technical characteristics of renewable technologies can have a large influence on the economics of the decarbonisation process. We found that the strength of this influence depends on the way by which the technical characteristics affect both the long-term *economic* and *environmental* values of renewables.

In analysing the *environmental* value trends of renewables, we found that the mechanisms by which the variations in production profiles of renewables affect the carbon-saving potential change with increased penetration. In particular, we noted that, under the shallow and intermediate penetration level, the carbon-saving potential of renewables tends to be dominated by static factors such as variations in capacity factors across renewable technologies or the direct[113] ‘energy displacement’ mechanism. Overall, we

[112] This note was added to the manuscript after passing my viva examination. I would like to thank my examiners Prof. Peter Taylor and Dr. Iain Staffell for bringing this observation to my attention.

113. Reducing the carbon emissions released from the energy system by directly displacing the energy that would be otherwise generated from carbon-emitting technologies. The environmental value of the renewable generation

noted that, under shallow penetration rates, technologies with higher capacity factors tend to displace more carbon emissions per GW installed. However, under deeper penetration rates, we found that the environmental value tends to be dominated by dynamic factors, such as the shift in the capacity and energy mix as a result of the variations in the flexibility requirements to run the system. The technologies that attract more flexible requirements to run the system tend to achieve higher marginal savings per GW installed as a result of the indirect 'fuel switching' effect or mechanism (i.e., a shift in the fuel consumption trend from mostly coal-based generation to gas-based generation). This explains the ability of PV to achieve more carbon savings than wind technology in the second case when the two technologies achieve comparable capacity factors. Overall, we found that the scale of these dynamic effects is proportional to the renewable penetration levels.

6.5.2 Effect of technological variations on the economic value of renewables

In terms of the economic value of renewables, our results suggest that the relative system-level cost differentials arising from the variation in production profiles of renewables can be quantitatively significant in terms of influencing the economics of the decarbonisation process. Furthermore, our results indicate that renewable technologies not only differ on the *scale* of their relative system-level costs but also vary significantly in the nature and breakdown of their respective system costs.

As indicated in the three cases presented earlier, we discovered that carbon abatement cost-effectiveness is influenced by the relative system-level cost differentials across the different renewable technologies considered.

One relevant insight is that the ability or the potential of renewable technology to save carbon emissions at the system level (i.e., measured in Mton of CO_2 eq basis) does not necessarily guarantee its cost-effectiveness in decarbonising the electric system. One important policy insight is that the failure to internalise the economic value and the system-level cost differentials delivered by renewables in the evaluation process of investment and incentive programmes is likely to lead to misguided or suboptimal long-term policy decisions. Equally, the failure to take into account the additional costs

hinges upon the type of displaced carbon technology. Broadly speaking, the more carbon-intensive the displaced energy, the higher the environmental value delivered by the renewable generation.

required to run a system with a high share of weather-dependent renewables is likely to lead to suboptimal policy and investment decisions as well. At the policy level, this would suggest the following recommendations:

- We recommend policymakers carefully consider both the expected carbon emissions savings and the system-level cost differentials or potential savings of renewables in their analysis and evaluation processes.
- We also recommend policymakers keep a close eye on the changes in the environmental and economic values of renewables as the system decarbonises. The result of our research clearly establishes that both the carbon-savings potential of renewables and their respective cost differentials dynamically change as the system decarbonises.
- This would also suggest that extra caution is required in drawing inferences about the cost-effectiveness of the decarbonisation process of power systems through expanding the use of renewables compared to other conventional low-carbon technologies, such as CCS and nuclear.

6.5.3 Changes to the economic value of renewable capacity

Our results suggest that the economic value of the capacity value tends to be the highest at shallow penetration scenarios. We also found that the capacity value of renewables drops significantly with increased penetration. This tends to wipe the direct economic value that arises from the thermal capacity savings at the system level. This suggests that the system-level savings arising from the direct capacity value of renewable capacity are of little significance in terms of influencing the economics of the decarbonisation process, especially under the deep renewable penetration scenarios. This further suggests that the energy value of renewables might outweigh the capacity value in terms of its contribution to the long-term economic value of renewables.

At the policy level, this thus implies the following:

- The synergies between the production profiles of renewable technologies and electric systems with some degree of correlated demand (i.e., solar technology and system demand with relatively high midday demand) might be overvalued in the long run.

- This would also suggest that renewable assets can be overvalued in terms of their long-term economic value given the fast pace of capacity value depreciation.

6.5.4 Effect of technological variations on energy mix and costs

Our results indicate that the variations in the production profiles of renewables can affect the scale, nature, and mechanisms by which renewable penetration can affect the energy mix and costs.

Our research indicates that, in most cases, the increased renewable penetration leads to a reduction in the variable cost of the system. However, we found that this does not necessarily hold true for all technologies under all penetration scenarios. The mechanism by which the technical characteristics of renewables manifest their effects on the total energy cost can change significantly under deep decarbonisation scenarios.

For example, we found that the penetration of wind technology consistently leads to a decrease in fuel or variable costs at the system level. In contrast, the PV and CSP technologies in some cases could lead to an increase in the system-level variable costs under particularly deep penetration scenarios. This can be explained by the significant shift in the technology capacity mix and the subsequent substantial increase in the energy output levels from more flexible yet more expensive technologies (mostly from coal to CCGT) under the deep PV and CSP penetration scenarios. More specifically, the substantial increase in the flexibility requirement imposed by the deep penetration of PV and CSP would make flexible technologies with mid-Capex, high-Opex technologies (i.e., gas-fired CCGT) more economically viable to meet the baseload demand at the expense of the less flexible high-Capex, low-Opex technologies (i.e., coal-fired steam technology).

In addition, the increased incidence of curtailment tends to limit the effectiveness of renewable generation, causing deeper energy penetration and subsequently contributing to lowering the total energy system costs. These factors combined tend to increase the 'baseline' of the energy costs at the system level. We found the pace of baseload cost escalation hinges upon the volatility level of the residual demand. This in turn depends on the variability of the renewable profile and its respective level of correlation with the system demand. This explains why wind power tends to consistently suppress the total variable energy cost of the system. In fact, we argue that, under deep penetration levels, the volatility of the renewable profile acts as an amplifier to the energy cost of the system.

In addition, we argue that despite the fact renewables enjoy almost a zero-marginal cost at the technology level, this does not necessarily hold true at the system level. The cost externality caused by the variability of the renewable profile can be substantial in some cases. This happens when the increase in the conventional generation costs grow at a much faster pace than the cost savings that arise from the penetration of renewable generation. However, we found this effect to be negligible under the shallow penetration scenario. Although we recognise that this effect might only materialise under particularly deep renewable penetration scenarios that are characterised by a high level of residual demand volatility (i.e., PV and CSP generation), we believe this effect should not be discounted from the possible economic implications of deep renewable decarbonisation.

Furthermore, we argue that this effect might give rise to several serious concerns, particularly in the context of the 'energy-only' market. One possible implication is that this effect increases the level of financial risk exposure that the incumbent thermal plants with the least flexibility characteristics might face as a result of the expected reduction in their utilisation factors. In particular, under these circumstances, incumbent thermal plants will be required to compete not only on a production cost basis but also on their ability to provide system flexibility as well. More research is required to evaluate the extent to which this effect could affect the financial viability of incumbent plants with limited flexibility characteristics.

6.5.5 Effect of technological variations on the flexibility requirement of the electric system

As indicated earlier, our simulations under deep penetration rates reveal that the variations in the generation profiles of renewables can have a large influence on the flexibility requirements of the system. In relation to this point, we summarise our findings in the following points:

First, our results suggest that increased renewable penetration can reduce the effectiveness of thermal generation units, particularly in high penetration scenarios. In particular, we found that a significant increase in thermal plant startups and shutdown frequency reduces the effective dispatchability potential of the incumbent thermal plants, thereby affecting their potential utilisation levels.

Second, our simulations indicate that, under particularly volatile demand conditions, the increased renewable penetration might attract additional investment in conventional dispatchable generation to (1) compensate for the reduced dispatchability of the incumbent thermal plants and (2) maintain the system's ability to respond to rapid upward or downward changes in demand under high renewable penetration scenarios. This would indicate that, in some cases, additional renewable penetration might have a negative marginal capacity credit.

Third, building on the previous point, we identify the flexibility characteristics of thermal units as an additional indirect driver that can influence the capacity value of renewables. Although this might not be a prime driver in terms of affecting the capacity value of renewables under the low and intermediate penetration rates, nevertheless we found evidence to suggest that, under deep penetration scenarios, the inflexibility of thermal plants can further reduce the capacity value of renewable capacity.

Fourth, it is worth noting that although in some cases high penetration of renewables might attract additional generation capacity as a result of the increased flexibility requirements to run the system, we did not find evidence this will eventually lead to increasing carbon emissions at the system level.

Fifth, in analysing the drivers of the increase of the flexibility requirement, we identify the relative level of volatility (or) smoothness of the residual demand as a key determinant that largely dictates the level of flexibility and hence the technology mix needed to integrate the renewable generation.

At the policy level, the previous points mentioned would suggest the following:

- The results underscore the importance of the 'capacity adequacy' issue under the envisioned deep renewable decarbonisation scenarios.
- For energy-only markets, this also might imply the need to introduce a capacity payment mechanism to ensure the realisation of investments in the 'capacity adequacy' of the system, especially because investments in these flexibility assets might not be commercially justified on an energy-output basis as a result of their low utilisation factors.
- Perhaps counter-intuitively, our results suggest that extra renewable curtailment might be needed to reduce the volatility in the residual demand and prevent a large reduction in the operational effectiveness and the displaceability potentials of the incumbent generation fleet. Given the limited scope of this work, further research is needed to confirm the validity of this reasonably informed speculation.

CHAPTER 7

RESEARCH CONCLUSIONS & FUTURE WORK

7.1 Key Research Conclusions

Thematically, the work of this thesis is related to several streams of literature on the economics of renewable energy resources. In addition, several findings of this thesis contribute to the growing body of literature addressing the environmental value of renewables. For brevity, in the following sections, we discuss the key conclusions of our research and their expected contributions to these streams of literature.

7.1.1 Theoretical conclusions

The first key, stream of literature related to our work is the growing body of studies that examines the environmental benefits delivered by renewable technologies. Examples of these studies include Hawkes (2010), Hart and Jacobson (2012), Fell and Linn (2013), Cullen (2013), Kaffine et al. (2013), Wheatley (2013), Marcantonini and Ellerman (2015), Novan (2015), Cullen and Mansur (2017), Thomson et al. (2017), Staffell (2017), Marcantonini and Valero (2017), and O'Mahoney et al. (2017). Importantly, the results of our research corroborate the findings of these studies which reported varying marginal emissions savings potential for different renewable technologies.

In addition, several studies have investigated the economic inefficiencies that raise from allocating production and capacity-based incentives for renewable technologies that deliver different external environmental benefits. Examples of these studies include Novan (2015) and Callaway et al. (2018). Crucially, however, a key outstanding gap identified in this stream of literature is how can a policymaker allocate fair economic incentives for renewable generators delivering varying environmental values at different stages of the system decarbonisation process. One important contribution of our research is the development of a theoretical framework and *specific mathematical metrics* that will help policymakers in designing and allocating optimum subsidy levels for different renewable technologies *at different decarbonisation levels of the system*. To the best of our knowledge, this is the first theoretical framework trailered for this purpose. We believe that using the *ECCE* values of the framework will greatly help policymakers in internalising the heterogeneity of environmental benefits delivered by different renewable technology types or locations in their economic assessments.

7.1.2 Methodological conclusions

Our work is related to many studies that investigated how the modelling methodology of renewable integration studies can affect their results. One key, related stream of literature looks at how differences in modelling methodology can influence the accuracy of carbon saving estimates of renewables such as Hart and Jacobson (2011) and Palmintier and Webster (2016). Yet, another key, related stream of literature to our work focuses on the effect of differences in modelling methodology on electricity mix, investment decisions, and system costs rather than on quantifying the environmental benefits and the carbon savings of renewables. Examples of this stream of literature include De Jonghe et al. (2011), Belderbos and Delarue (2015), and Poncelet et al. (2016). One important contribution of our work is reconciling and linking the insights of these two valuable streams of literature by offering a combined economic and environmental treatment of the subject.

For example, the findings of our research are consistent and complementary to the findings of Palmintier and Webster (2016) who reported a significant difference in the CO_2 emission results of an SC- and a UC-based optimisation models. Relative to their work, however, our work has the advantage of shedding more light on the extent to which can the differentials of carbon emission estimates of the two methods impact the perceived economic effectiveness of renewable to decarbonise the energy system.

Similarly, our work extends the work of Belderbos and Delarue (2015) who compared the optimum capacity mix of a traditional SC model and a more detailed model using mixed-integer linear programming (MILP) for different large-scale penetration scenarios of wind power for the Belgian system. In essence, the results of our study are consistent with Belderbos and Delarue's results which highlight the tendency of the model with operational constraints to invest more in a more flexible generation mix with increased renewable penetration (i.e., a shifting trend from baseload generation towards mid- and peak-load generation). Similar findings have been reported by De Jonghe et al. (2011) who compared the optimum capacity mix of a traditional SC model and a more technically detailed linear programming (LP) model under several wind energy penetration scenarios for the Belgian system. Although their results did not show significant differences in the peak load plant mixes for the two models, they reported a shift in energy output from baseload to mid-load generators in the more technically detailed LP model. In contrast to these studies, however, our study digs a little a bit deeper and explores the individual technical factors that can strongly affect the capacity mix results of renewable decarbonisation studies. For example, in one case study, we explore the effect of including or omitting the minimum running up- and downtimes for the generation plants in unit commitment models as opposed to only comparing the results of renewable integration study of load duration optimisation-based models (i.e., SC models) with temporal optimisation-based models (i.e., UC models). We find that excluding the minimum up- and downtimes of generating units can result, in some cases, in a relatively large difference in the optimum capacity mix of UC models and subsequently on the projected carbon emission savings of renewables under deep decarbonisation scenarios. This in turn, in some cases, alters the carbon abatement cost estimates and the perceived economic competitiveness of renewable technologies to decarbonise energy systems.

Likewise, our modelling work is related to several studies which explored the technical factors affecting the retirement of more baseload plants (i.e., coal) with increased penetration of renewable energy. For example, similar to previous studies, Nweke et al. (2012) and Poncelet et al. (2016) reported that models with low temporal and techno-economic detail tend to overestimate the investments needed in baseload generation and underestimate the operation costs of the systems. In our work, we further extend the scope of their technical analysis by investigating underexplored technical factors that might have a great influence on the retirement of baseload plants. For example, our study identifies the minimum running thermal load (MRTL) of the system or the system's total minimum "rotating load" as a key factor that is likely to have a large influence on the size and timeline of retiring baseload power plants. More importantly perhaps, in some cases, we find that the MRTL level of the system can substantially affect the projections of renewable carbon savings. In one study case, we find that a moderate increase in the MRTL level can significantly reduce the decarbonisation potential of renewable generation and increase the incidences of curtailment, especially for systems with sizable coal generation assets. Additionally, in some cases, a moderate increase in the MRTL level can disproportionally increase the capacity investment and energy output from carbon-intensive units, leading to a large effect on the carbon abatement cost estimates of renewables.

We believe these methodological contributions combined would improve our understanding of the potential shortcomings in the current modelling practices and help identify patterns of possible inaccuracies or biases in renewable decarbonisation results. We think that this will bring more rigour and robustness to the economic treatment of renewables' contributions to climate change

7.1.3 New insights

Another important contribution of this work lies within its new findings and original insights. Drawing on the multiple case studies of the research carried out, we identify several often-overlooked economic implications of the deep decarbonisation of electric systems through expanding the use of renewables. We show that not all renewable technology types can have a suppressing effect on the variable costs of the systems due to their "zero marginal costs." In particular, we identify certain technologies and circumstances in which an increase in renewable penetration can significantly inflate the variable energy costs of the system. More specifically, we find that under deep decarbonisation scenarios, renewable technologies with highly volatile production profiles can act as an amplifier for the variable cost of the systems through (1) reducing the effectiveness of thermal generation units due to the increased start-up and shutting downing activities, and (2) increasing the energy output levels from more flexible and yet more expensive thermal technologies.

In addition, we identify circumstances in which an increased renewable penetration can materially affect the capacity adequacy of electric systems, leading to an increase in capacity investment in thermal flexibility assets. Perhaps more importantly, we find that these additional flexibility assets will not be commercially viable on an energy-output basis. We believe that this might have specific implications for the energy-only markets. We were unable to identify studies in the literature that examined these aspects in sufficient detail. By doing so ourselves, we hope to make a contribution to the literature addressing the economics of renewable decarbonisation of electric systems.

Altogether, we hope that our work will advance the understanding of the economics of renewables and will help policymakers and practitioners in evaluating their economic climate change policies

7.2 Research Limitations

In this the following sections, we summarise the limitations of our research.

7.2.1 Study design limitation

7.2.1.1 Single vs. multiple renewable portfolio simulations

Arguably, one of the potential limitations of our study design is the lack of investigation of the impact of using a portfolio of renewable energy technologies in our study cases. Crucially, however, we believe that there is an impressive volume of research that has reported several technical and economic benefits of simulating a diverse portfolio of renewable technologies to decarbonising energy systems.

In one study, for instance, Hart and Jacobson (2012) used a least-cost engineering dispatch model to investigate the carbon abatement potential of wind turbines, Photovoltaics (PV), Concentrated Solar Power (CSP), and geothermal power in California. They investigated the potential of decarbonising the Californian system using both single and multiple renewable technology portfolios. The results of their work highlighted the technical limitations of achieving deep decarbonisation using a single technology and the necessity of having high levels of flexibility and controllability over the renewable generation. The study also analysed the potential synergy between different renewable resources. Their results indicated that the effect of combining different renewable sources is almost additive under low penetration levels. However, they reported that the potential synergic benefit of combining different renewable resources is most apparent at high penetration levels. For their study, a portfolio of 30% wind and 70% solar was found to have a maximum carbon abatement potential of 79%, compared with 58% and 56% for wind and solar alone, respectively.

Therefore, we believe that the synergic benefits of combining renewable profiles are sufficiently reported in the literature. In our research, however, we tried to depart from the dominant paradigm or practice of comparing single and multiple renewable technologies in the interest of shedding greater light on rather underreported insights. In other words, the single renewable technology simulation was done for research design purposes. In particular, the single technology setting we presented is designed to remove some of the factors that arise from combining two or more renewable resources. For example, in one study case, we investigated the value of renewable technology profiles on the economics of the decarbonisation process. As such, we needed to carry out these scenarios individually to be able to carry out our differential analysis. Likewise, in another case study, we investigated the effect of variability of the renewable technology profile on the economics of the decarbonisation process. Therefore, per se, combining multiple renewable technology profiles with similar shapes (i.e., PV vs. CSP) will make it increasingly difficult to decompose the economic effects of the "profile variability" factor under study.

Furthermore, while investigating hypothetical renewable portfolio options is undoubtedly useful in understanding a range of possible technical and economic synergies for electric systems, nevertheless, this might imply the guaranteed practicality of the large-scale deployment of two or more renewable resources which might not be necessarily available to many countries around the world. Similarly, some countries might be heavily dependent on a single technology such as solar or wind power due to its geographical location or size limitation. Accordingly, it might be argued that investigating such scenarios is not completely unrealistic for countries that share these characteristics.

As indicated earlier, the scenarios presented in our study cases are not meant to be exhaustive, and therefore we acknowledge this limitation. It is feasible that considering alternative technology mix or input data could result in different system costs and different fuel mixes than those reported in our research. However, would many of the qualitative results presented here change noticeably with a greater range of input data? We believe not, but this is definitely an interesting avenue for further research.

7.2.1.2 Analysis perspective: market vs. central planning perspective

Another potential limitation of our study is that our research does not explore the critical questions pertaining to the variations in existing energy market structures and models and their economic implications on different market participants. Instead, we took a central planning perspective to explore the system-wide economic implications of the renewable decarbonisation process rather than focusing on exploring the specific economic effects of a certain market model. For example, our research did not look at how the increased renewable penetration affects the profitability of conventional generators in a liberalised market setting. Similarly, our research did not consider the shifts in market power with increased renewable penetration. In particular, similar to Pérez-Arriaga and Linares (2008), we view that central or *indicative planning* models can be of particular importance in navigating the major sustainability questions facing both traditional systems and liberalised markets, such as exploring the system-wide economic impacts of setting renewable penetration levels and carbon emissions targets. In other words, indicative planning models that are based on a central planning perspective can serve as a complementary instrument to aid decision-makers in liberalised markets refine their understanding of the possible system-wide or long-term economic implications of delivering the hoped-for net-zero energy transition. Nevertheless, it is important to recognise that both models offer a best case solution that real-world decision-makers (in either model) may not achieve in practice. Undoubtedly, however, we will gain a better understanding of the implications of our findings if different market models are studied.

7.2.1.3 Data uncertainty

Another possible caveat of our simulations is that we have taken a deterministic approach in our treatment of the renewable energy profiles. Several studies have reported that the stochastic treatment of renewable generation profiles might impact the carbon predictions of UC models (Hart and Jacobson, 2011). Furthermore, in terms of demand profiles, we relied on historical load profiles, and we assumed nonresponsive, inelastic demand profiles in our simulations. As a result, like other renewable decarbonisation studies, our study does not take into account the possible long-term changes or shifts in electricity consumption patterns. These long-term changes can be driven by several factors, including social, economic, and demographic shifts; climate change impacts; and the anticipated increased electrification of heat and transportation sectors (Auffhammer et al., 2017, Anderson and Torriti, 2018, Staffell and Pfenninger, 2018, Denholm et al., 2019). Furthermore, we also did not explore demand-side management considerations, including load shifting, direct load control, interruptible loads, time-of-use pricing, and the role of digitisation and smart metering in changing demand patterns (Strbac, 2008). However, we believe that taking these considerations into account might be an interesting research topic for a separate PhD thesis.

7.2.1.4 Study scope and system size

Another possible limitation of our research is the scope of study and system size considered. Notably, the scale of the test system considered in this study is relatively small compared to the UK's electric system or other major European[114] countries' electric systems. Therefore, the reader might find keeping this in mind useful when interpreting and drawing inferences from the results presented.

As pointed out earlier we do not assert or imply that the results of the case studies presented in this work are transferable to all electric systems in the same way or to the same extent. Nor are they generalisable to same technologies considered under different electric systems. Instead, the scenarios presented are meant to explore the economics of the renewable decarbonisation process in the system modelled here, typical in load profile of a Gulf Cooperation Council (GCC) country. Yet, additional research will be required to further refine these findings for different electric systems and other renewable technology types. Unquestionably, however, this remains an opportunity for further investigation.

7.2.2 Other Limitations

Another limitation of our research is that the behaviour of a real power system might deviate from the results obtained using least-cost optimisation models because real power systems might have additional constraints that are not captured in this study. These constraints might be technical, such as transmission and congestion constraints, or non-technical, such as issues related to the market structure and mechanism. In this research, however, we focus on the fundamental technical and economic inputs of the power system that have been used extensively in the literature to estimate and predict the carbon emissions of power systems.

Furthermore, as with other renewable decarbonisation studies, several modelling considerations were beyond the scope of our analysis. For example, we did not consider the impact of energy exchange with neighbouring systems or having transmission- or

[114] The classification indicated is meant to be on a geographical basis, not necessarily or strictly based on political or institutional affiliation.

reliability-related constraints. For the renewable technologies, we did not consider the cost associated with the transmission losses or the wheeling charges of renewable power-to-load centres. Likewise, we did not factor in the distribution or transmission investment costs needed to integrate the renewable energy sources into the grid. We also did not take into account the land requirement or issues related to the practicality of the development of renewable generation plants. For the thermal plants, among other things, we did not examine the plants' forced outages and maintenance schedules. Finally, we did not investigate the wear-and-tear aspects of thermal plants due to increased cycling and start-up activities.

Another possible limitation of our work is that we focus only on carbon dioxide as the main environmental externality or negative emission category of power system operation. For example, we did not factor in the other emission types that can be reduced by the expansion of renewables, such as SO_2, NO_X, and PM2.5 (Council, 2010). In other words, we did not explore other emission types that might have negative environmental impacts or their respective GHG impact equivalences. In addition, we did not cover the GHG externalities from a life-cycle perspective. For example, we did not study the CO_2 emissions related to the extraction, processing, and transportation of the plant's fuel or the decommissioning of the generation plants (Hendrickson et al., 2006). Similarly, we did not investigate the indirect and embedded emissions used to manufacture and produce the PV solar panels and the CSP modules.

7.3 Future Work

The limitations we pointed out earlier might serve as a basis for future lines of inquiry. Nevertheless, we are particularly interested in investigating the following research questions and issues.

First, as indicated earlier in the thesis, in our simulations, we did not consider the existence of large-scale storage systems. In our future work, we intend to explore the role of storage systems not only in enabling the integration of renewables but also in facilitating the decarbonisation of energy systems. One relevant worry is that due to economic reasons, the existence of large storage systems might attract disproportionate charging from conventional generation rather than absorbing the excessive renewable generation, thereby contributing to increasing system-wide emissions. In other words, we are interested in investigating the unintended consequences of expanding the use of storage systems in support of renewables from a system-level decarbonisation perspective.

In particular, we would like to investigate the value of storage in maximising the carbon-saving potential of renewables. The guiding question of our planned research is, what is the value of storage in maximising the carbon savings of renewables? In addition, we would like to explore the technical factors that could potentially enhance or limit the storage systems' positive contribution to saving carbon. More specifically, we seek to understand the relative importance of the various technical factors that can affect the ability of storage systems to maximise the carbon savings of renewables.

Second, we would like to investigate the economic implications of the large-scale deployment of storage systems for the economics of the decarbonisation process. In particular, we would like to understand the extent to which storage systems can impact the abatement costs of renewables. More specifically, we seek to establish whether the economic impact of storage systems on the abatement cost of renewables varies across different storage technologies. One particular concern is that storage systems with different technical characteristics might impact the abatement cost of renewables in significantly different ways.

Third, we would like to investigate the impact of storage systems on the energy market. In particular, we would like to investigate the impact of the large-scale deployment of storage systems on energy prices. More specifically, we would like to investigate the following research question: what would large-scale adoption of storage systems do to the profitability of (1) conventional generators and (2) flexibility assets under a deep renewable penetration scenario?

Given the complexity of these questions and issues, at this juncture, we can only hope to get the time and funding needed to pursue them.

APPENDIX A

SUPPLEMENTARY RESULTS

Appendix Overview

In this appendix, we include the extended results for the case studies presented in the core chapters. Moreover, we include some mathematical formulations and we present sensitivity analyses for some of the work carried out.

A.1 Supplementary Results of Chapter 4

A.1.1 PV and CCS technologies case study results

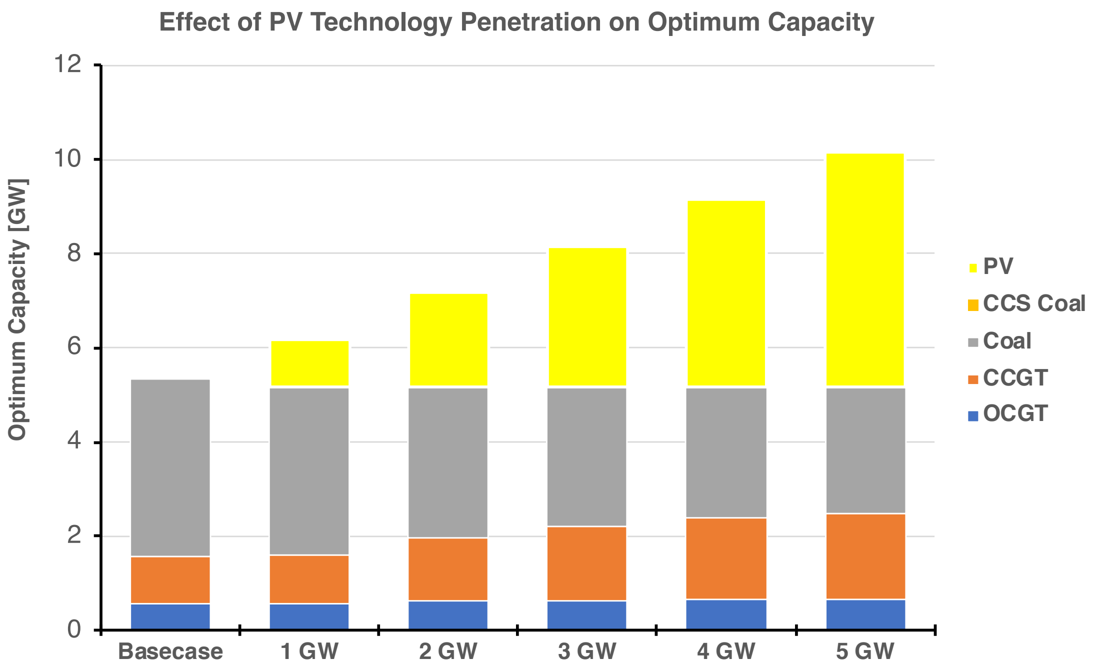

Figure 75: Effect of increased penetration of PV technology on the optimum capacity mix for selected penetration scenarios

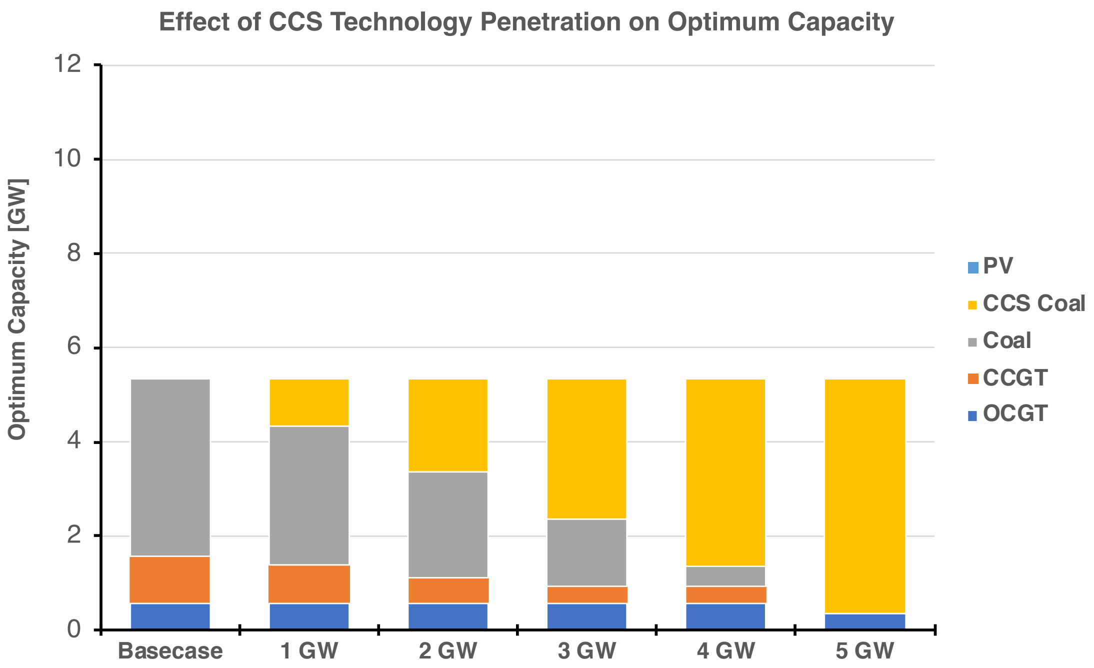

Figure 76: Effect of increased penetration of CCS technology on the optimum capacity mix for selected penetration scenarios

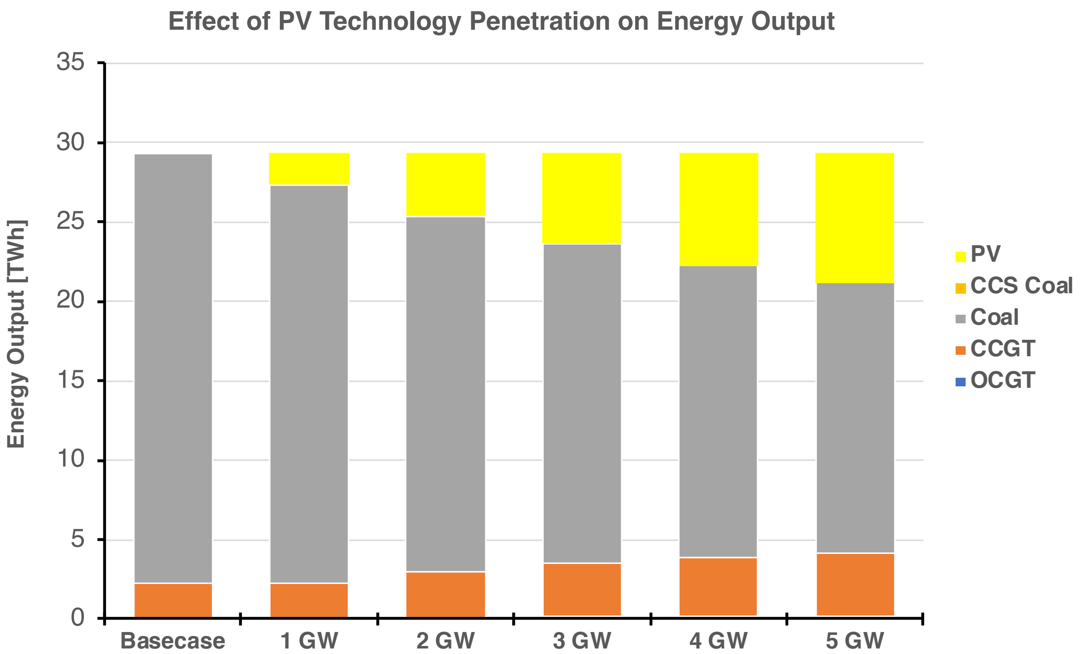

Figure 77: Effect of increased penetration of PV technology on the energy output for selected penetration scenarios

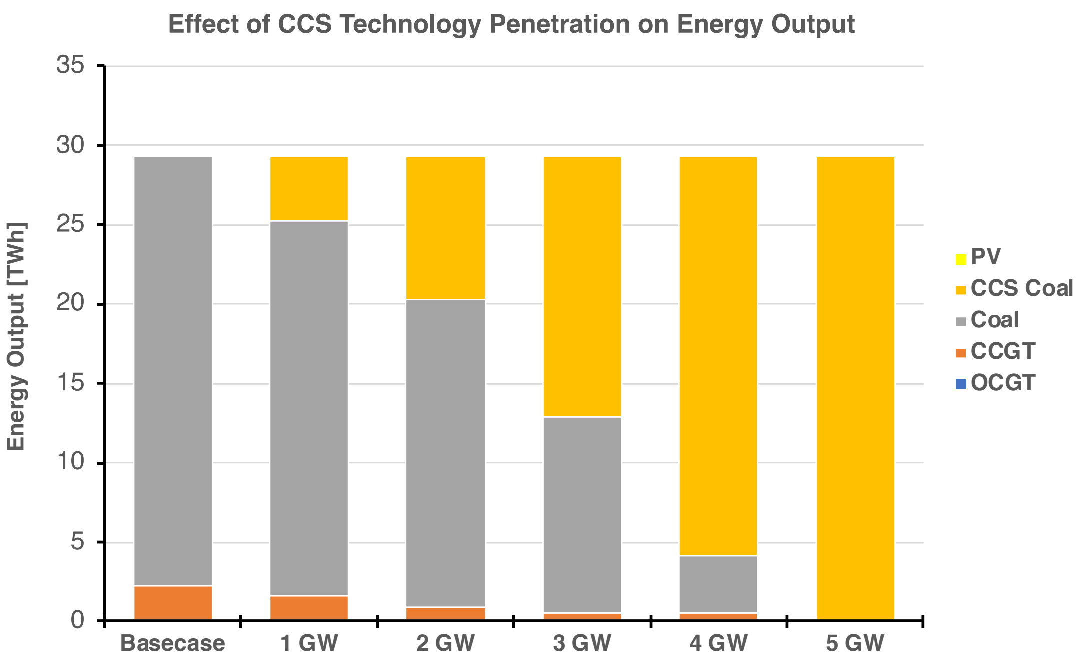

Figure 78: Effect of increased penetration of CCS technology on the energy output for selected penetration scenarios

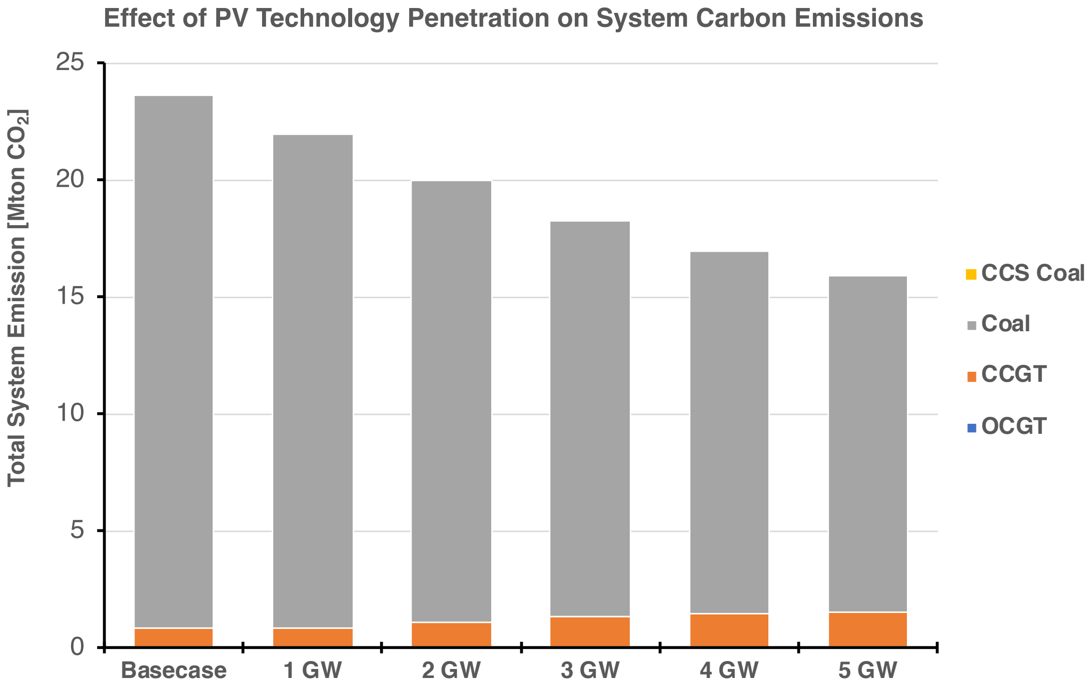

Figure 79: Effect of increased penetration of PV technology on the system's carbon emissions for selected penetration scenarios

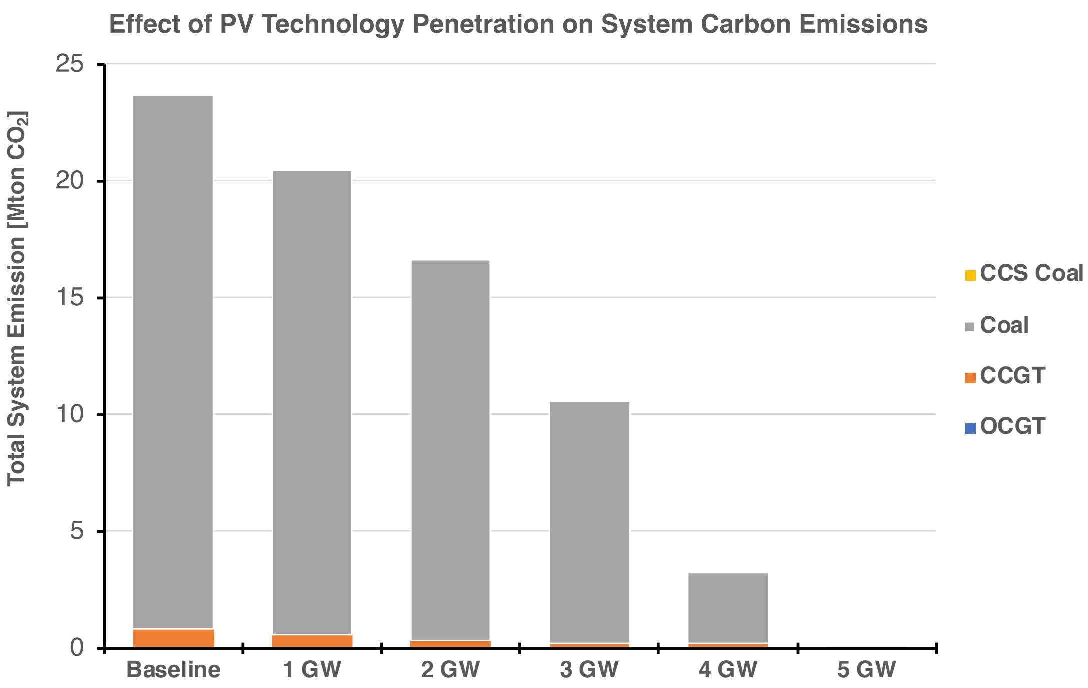

Figure 80: Effect of increased penetration of CCS technology on the system's carbon emissions for selected penetration scenarios

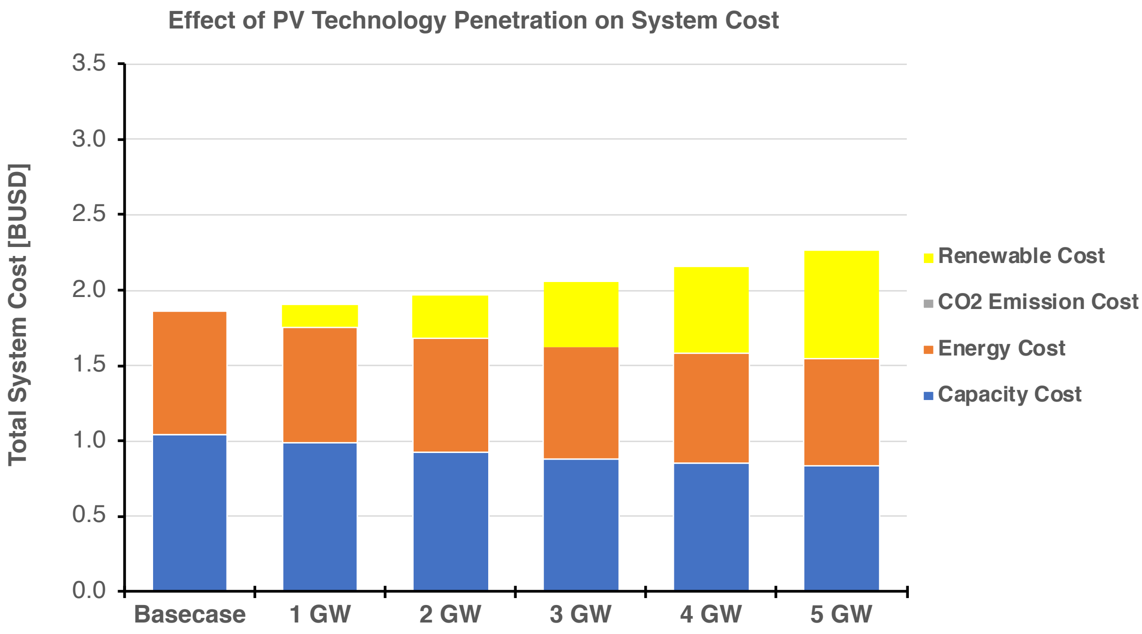

Figure 81: Effect of increased penetration of PV technology on the system's costs for selected penetration scenarios

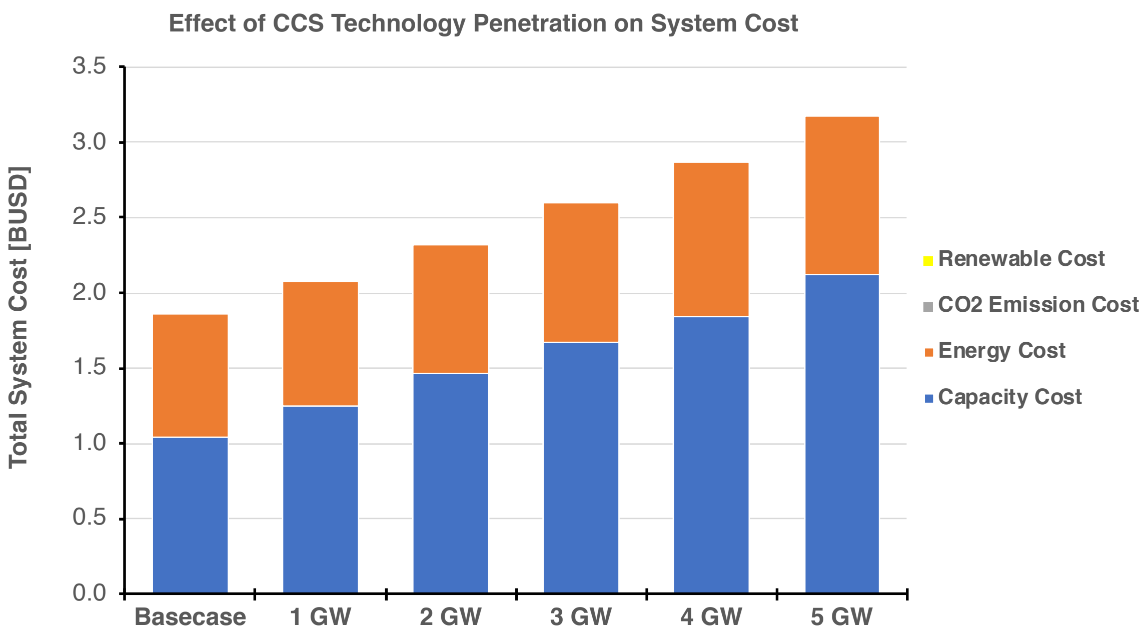

Figure 82: Effect of increased penetration of CCS technology on the system's costs for selected penetration scenarios

Levelised Cost of Energy (LCOE) Derivation

As signified earlier, LCOE indicates the average fixed revenue per unit of electricity generated that would be needed to recover the costs of building, operating, and sometimes the decommissioning of a generating plant over its economic lifetime. Mathematically, this can be expressed by equation (A.1) and (A.2)

$$\sum_{n=0}^{N} \frac{Revenues_n}{(1+r)^n} = \sum_{n=0}^{N} \frac{Costs_n}{(1+r)^n} \tag{A.1}$$

where r is the fixed discount rate

N is the total economic lifetime of the project

That implies,

$$\sum_{n=0}^{N} \frac{LCOE_n \times (E_n)}{(1+r)^n} = \sum_{n=0}^{N} \frac{Costs_n}{(1+r)^n} \tag{A.2}$$

where E_n is the total energy output in year n

$LCOE_n$ is the fixed energy price paid in year n

Therefore, LCOE could be calculated using equation (A.3)

$$LCOE = \frac{\sum_{n=0}^{N} \frac{Costs_n}{(1+r)^n}}{\sum_{n=0}^{N} \frac{(E_n)}{(1+r)^n}} \tag{A.3}$$

Assuming that the initial cost of the plant paid up-front. Then the discounting summation starts at n=1 and the LCOE can be re-calculated by equation (A.4)

$$LCOE = \frac{intial\ cost + \sum_{n=1}^{N} \frac{Costs_n}{(1+r)^n}}{\sum_{n=1}^{N} \frac{(E_n)}{(1+r)^n}} \tag{A.4}$$

Studies vary in terms of the economic and technical factors and details included in LCOE calculations. However, key inputs of LCOE calculations typically include overnight capital costs, fuel costs, fixed and variable operations and maintenance (O&M) costs and an assumed utilisation rate for each technology type (EIA, 2013a, EIA, 2019).

A.1.2 Sensitivity analysis of the PV and CCS technologies

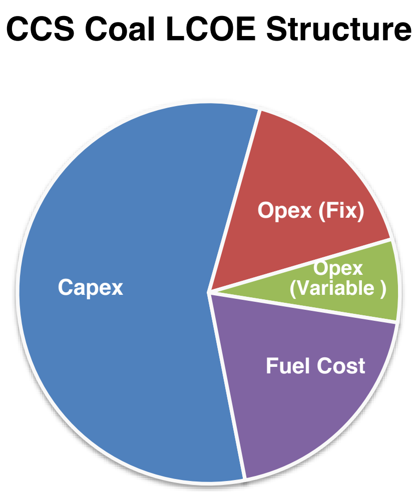

Figure 83: Levelised cost structure of the CCS technology

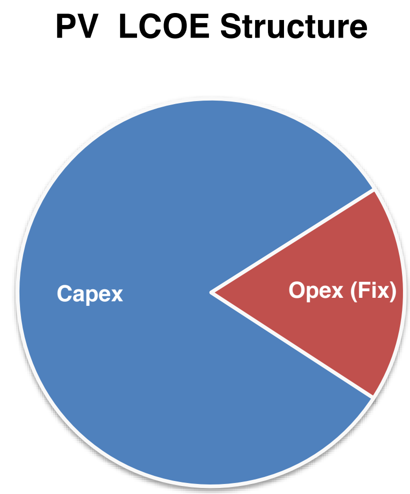

Figure 84: Levelised cost structure of the PV technology

CCS Coal Technology	LCOE	LCOE
	USD/MWh	%
Capex	77.63	57%
Opex (Fix)	21.81	16%
Opex (Variable)	9.51	7%
Fuel Cost	26.28	19%
Total	**135.23**	**100%**

Table 19: Levelised cost structure of CCS technology

PV Technology	LCOE	LCOE
	USD/MWh	%
Capex	60.60	82%
Opex (Fix)	13.42	18%
Total	**74.03**	**100%**

Table 20: Levelised cost structure of PV technology

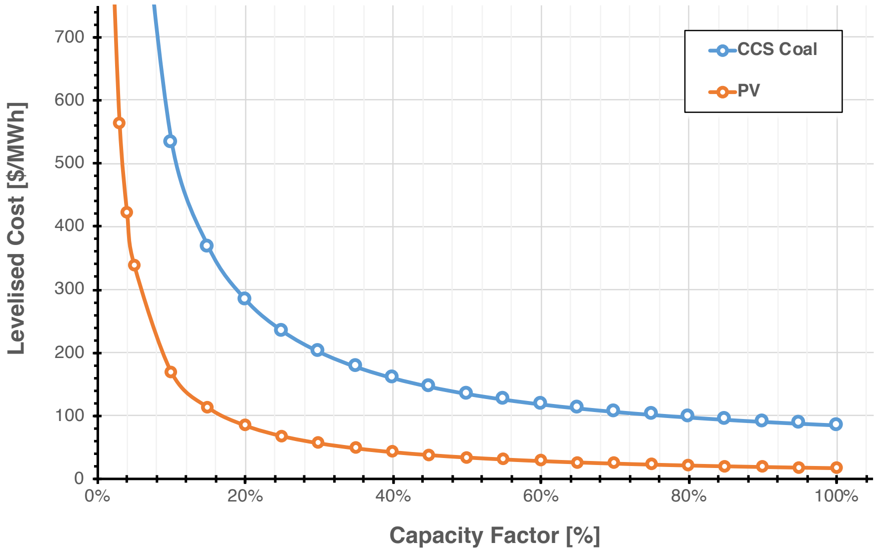

Figure 85: Impact of variations in capacity factor on LCOE for CCS and PV technologies

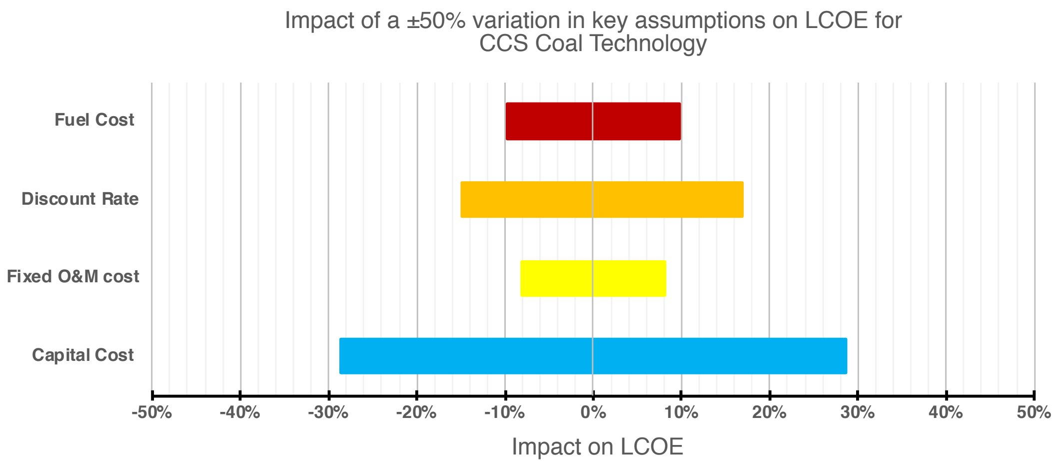

Figure 86: Impact of a ±50% variation in key assumptions on LCOE for CCS Technology

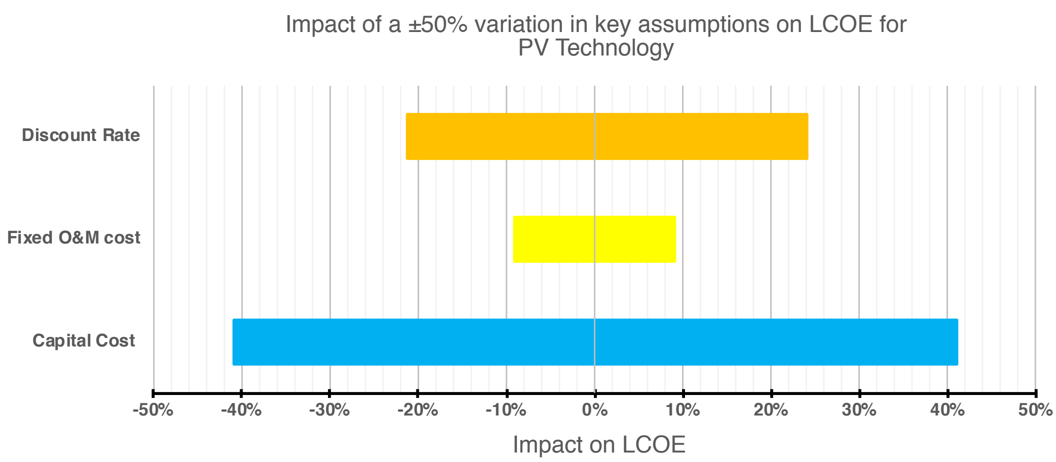

Figure 87: Impact of a ±50% variation in key assumptions on LCOE for PV Technology

A.2 Supplementary Results of Chapter 5

A.2.1 Supplementary results of the effect of choice of modelling methodology case study

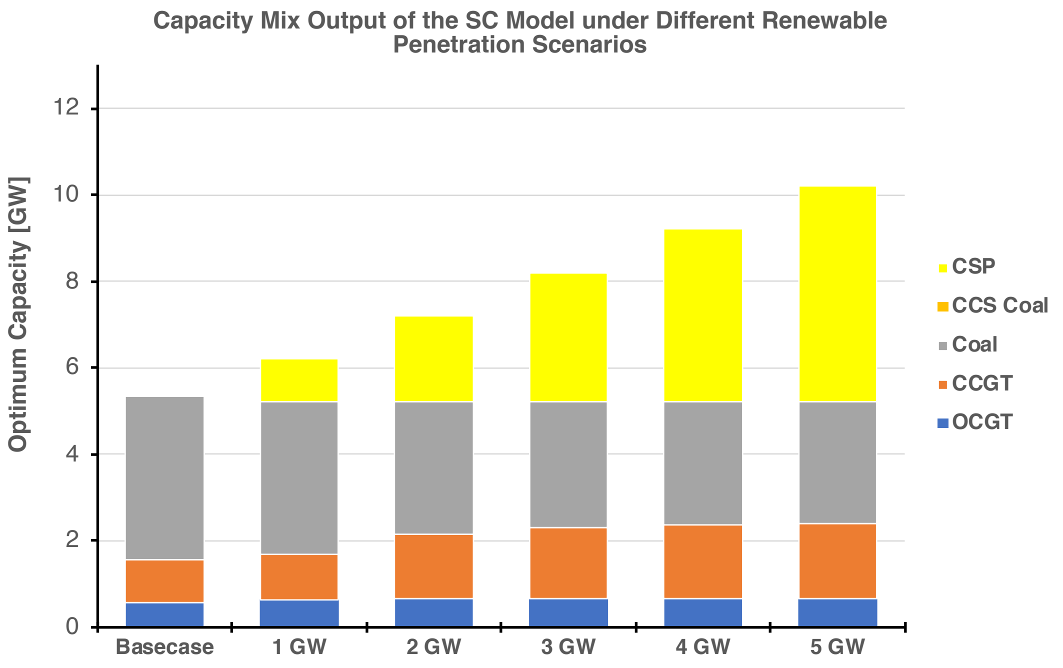

Figure 88: Optimum capacity mix results of the SC model under different penetration scenarios of CSP technology

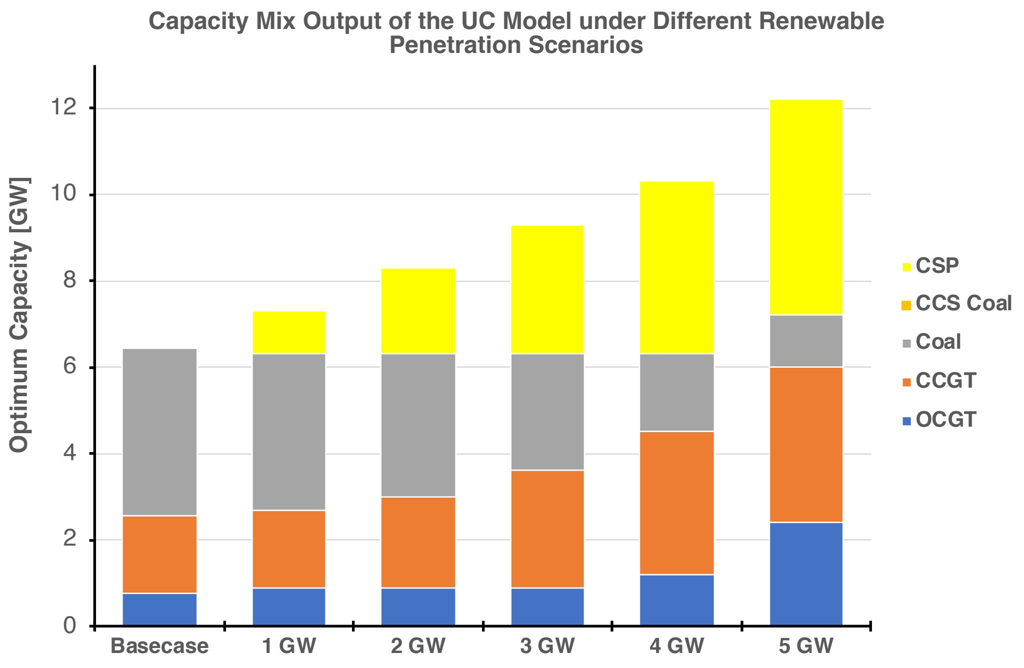

Figure 89: Optimum capacity mix results of the SC model under different penetration scenarios of CSP technology

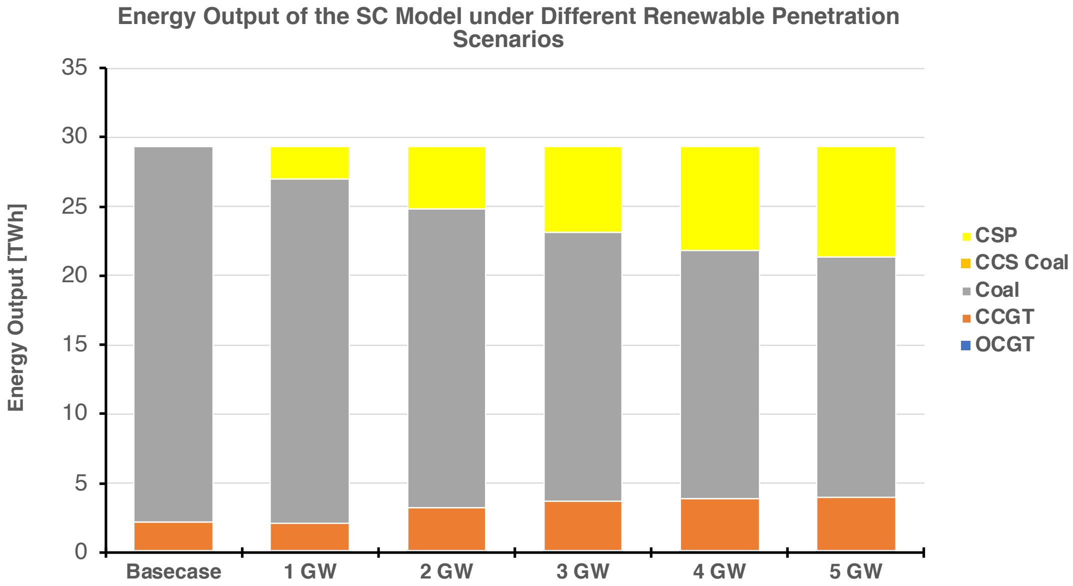

Figure 90: Energy output results of the SC model under different penetration scenarios of CSP technology

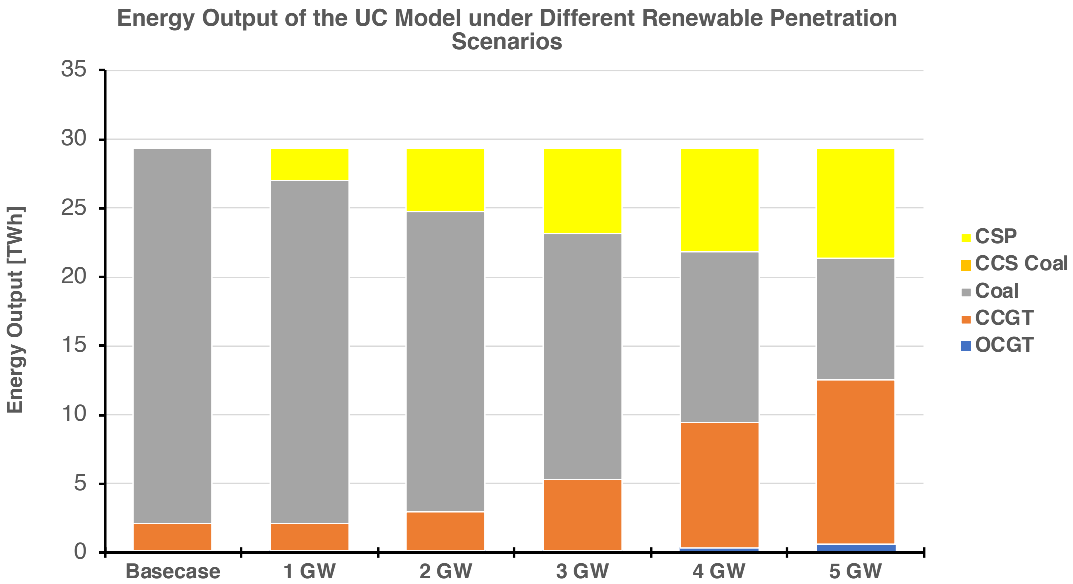

Figure 91: Energy output results of the UC model under different penetration scenarios of CSP technology

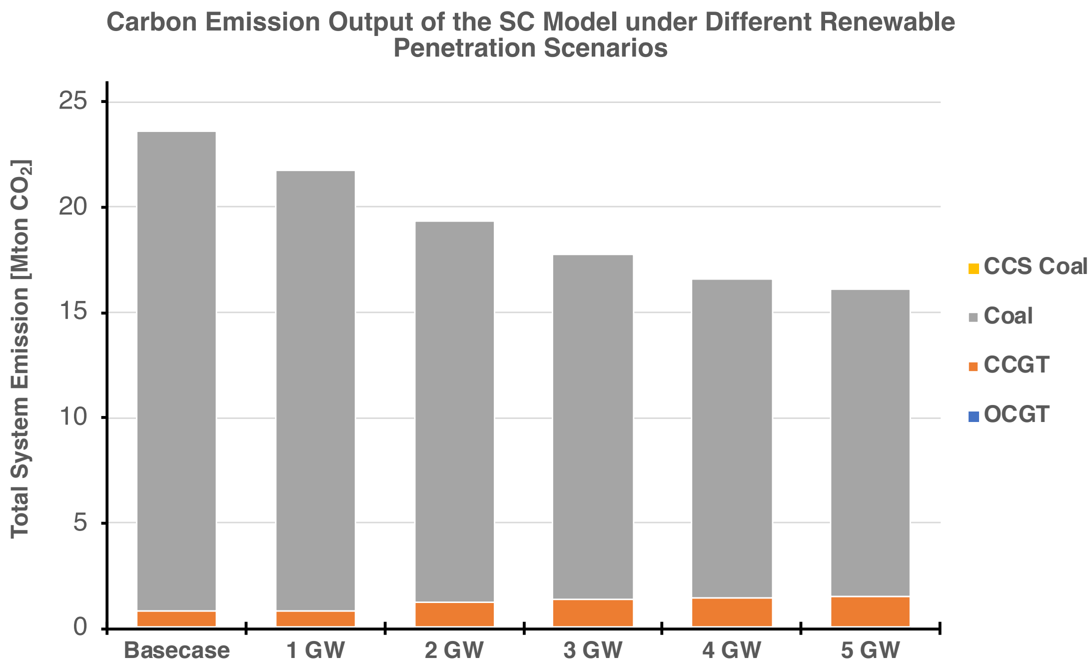

Figure 92: Carbon emission results of the SC model under different penetration scenarios of CSP technology

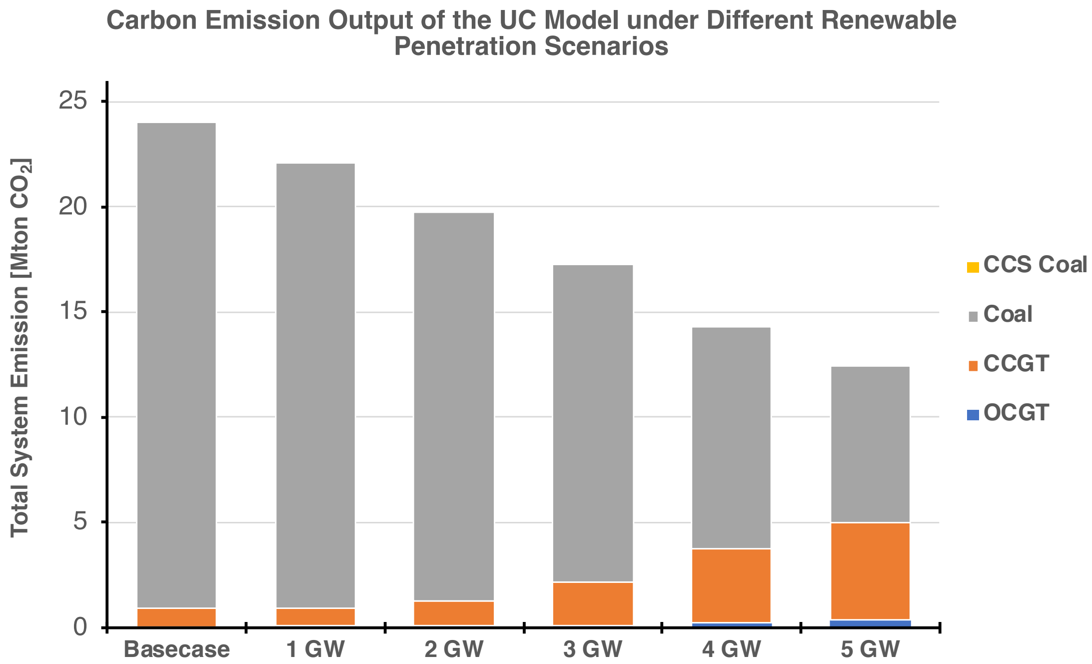

Figure 93: Carbon emission results of the UC model under different penetration scenarios of CSP technology

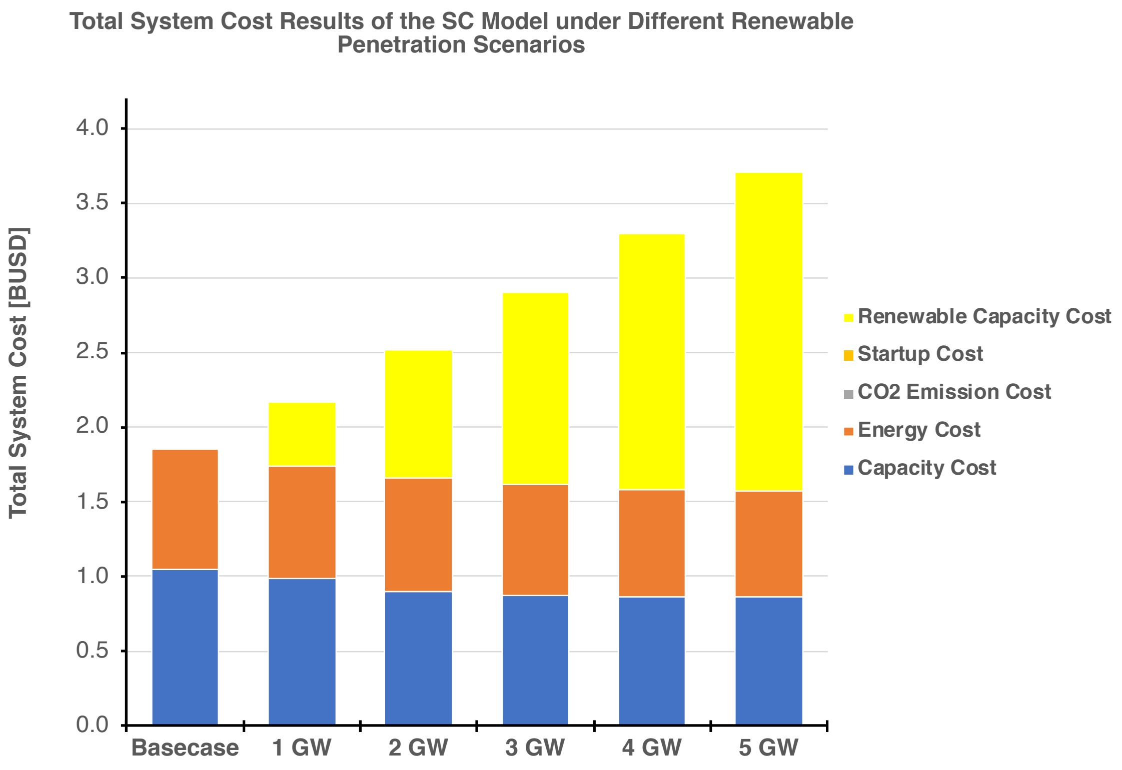

Figure 94: Total system cost results of the SC model under different penetration scenarios of CSP technology

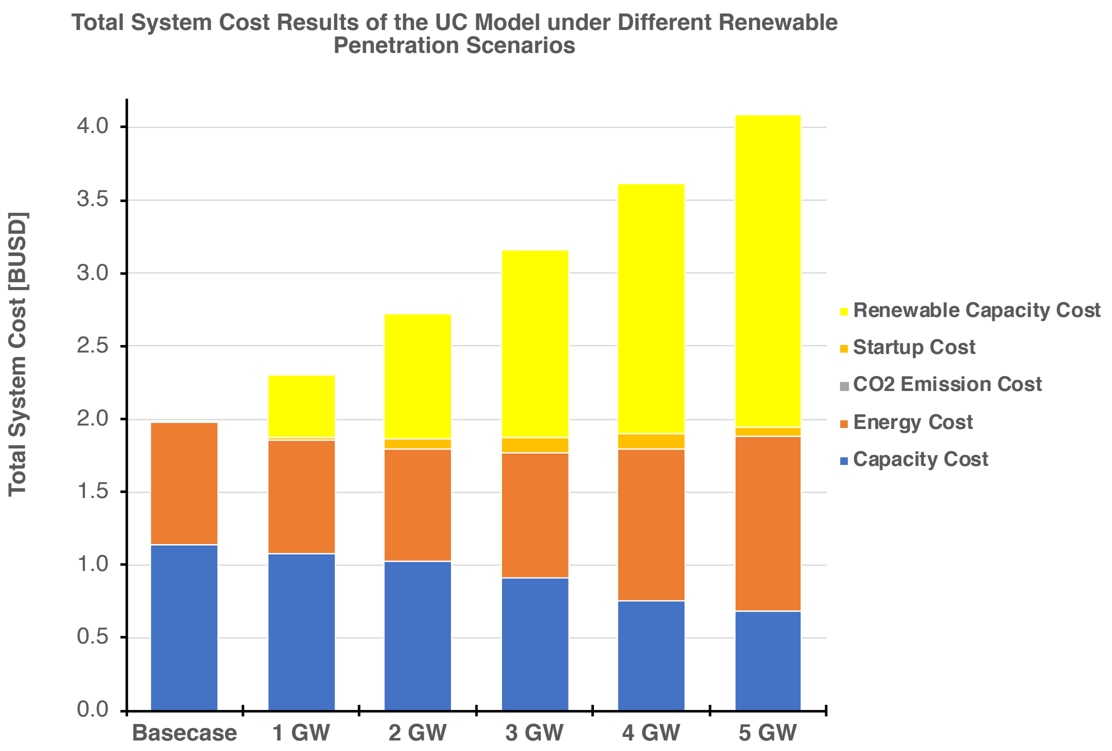

Figure 95: Total system cost results of the UC model under different penetration scenarios of CSP technology

A.2.2 Supplementary results of the minimum running thermal generation effect case study

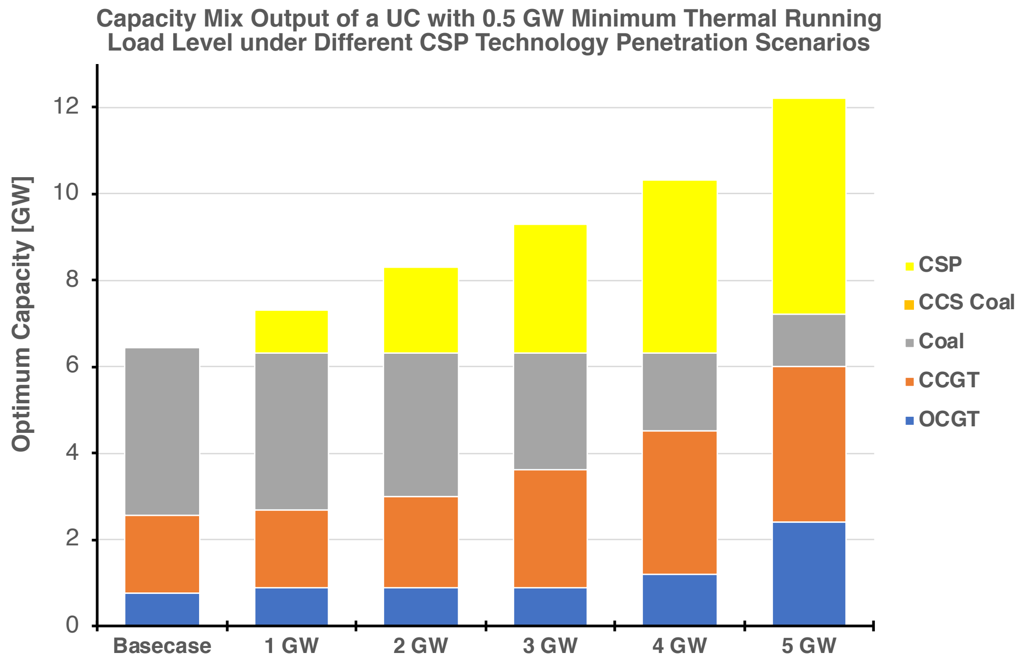

Figure 96: Optimum capacity mix results of a UC model with 0.5 GW minimum thermal running load level under different CSP technology penetration scenarios

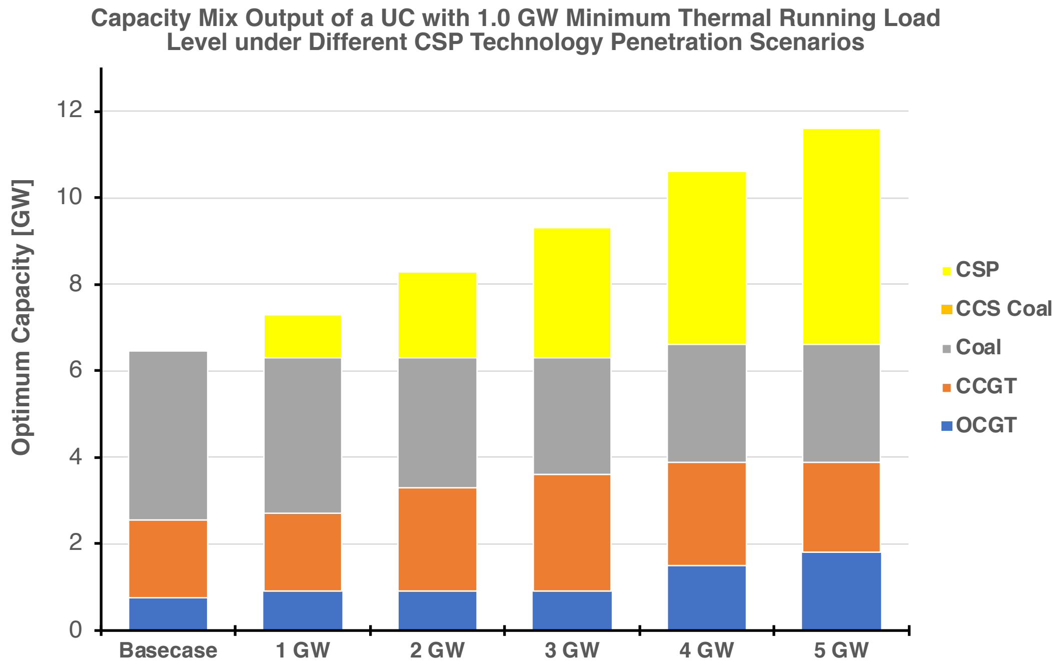

Figure 97: Optimum capacity mix results of a UC model with 1 GW minimum thermal running load level under different CSP technology penetration scenarios

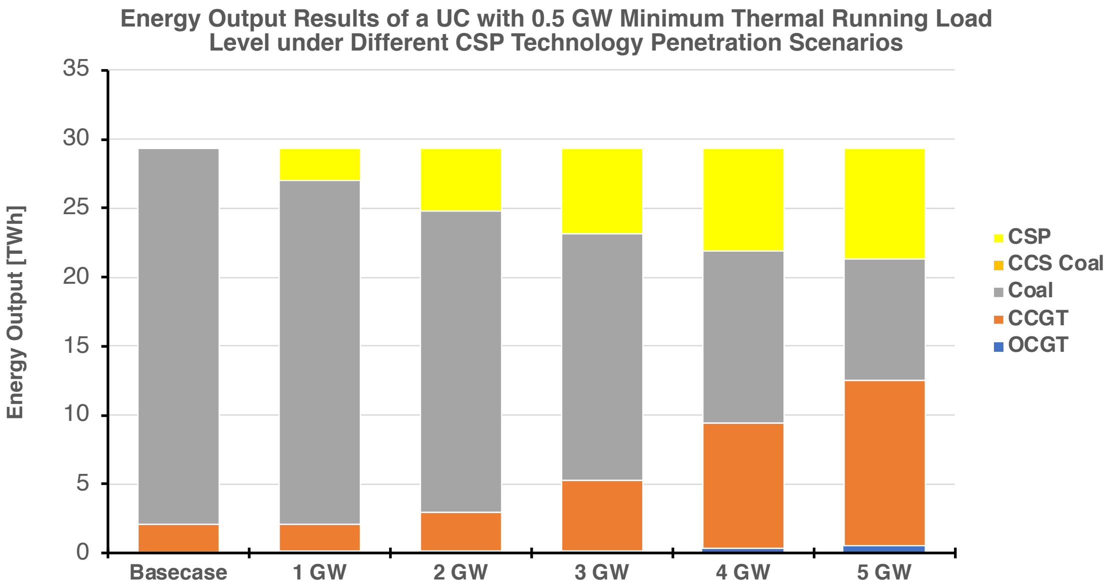

Figure 98: Energy output results of a UC model with 0.5 GW minimum thermal running load level under different CSP technology penetration scenarios

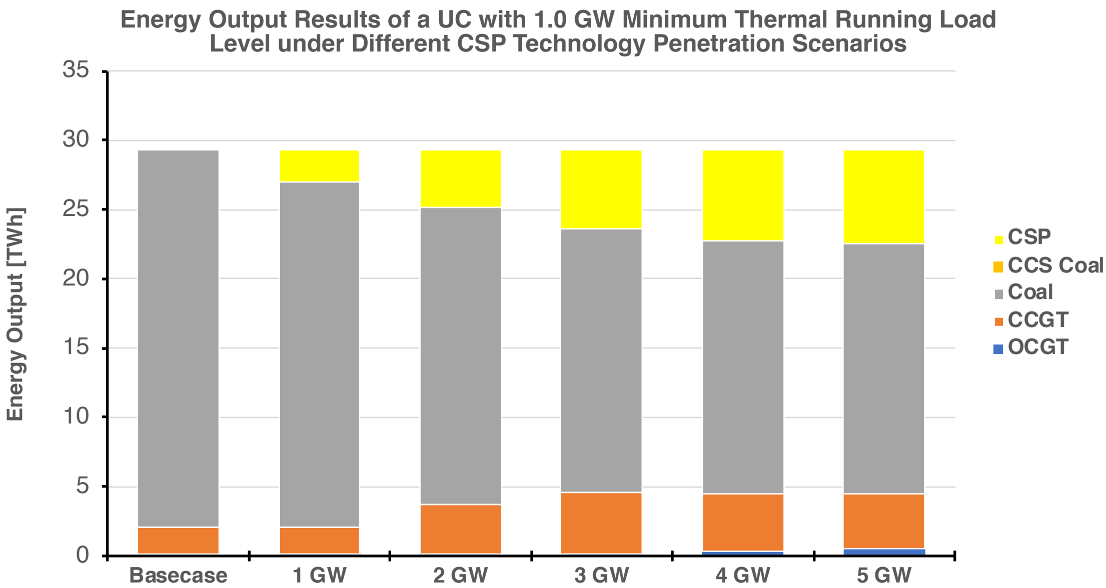

Figure 99: Energy output results of a UC model with 0.5 GW minimum thermal running load level under different CSP technology penetration scenarios

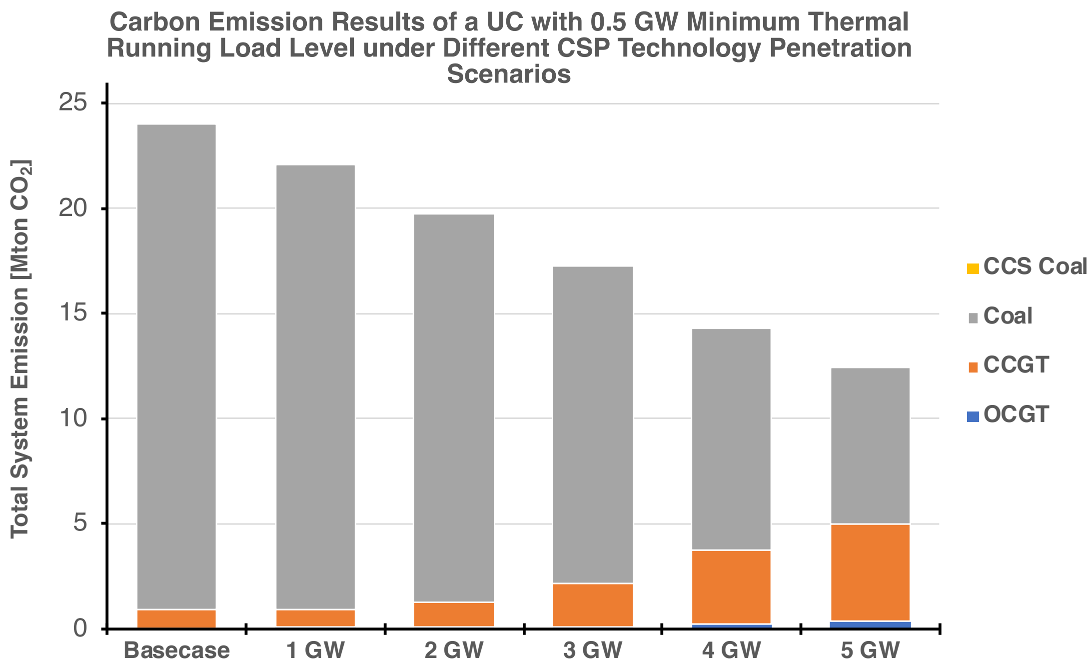

Figure 100: Carbon emission results of a UC model with 0.5 GW minimum thermal running load level under different CSP technology penetration scenarios

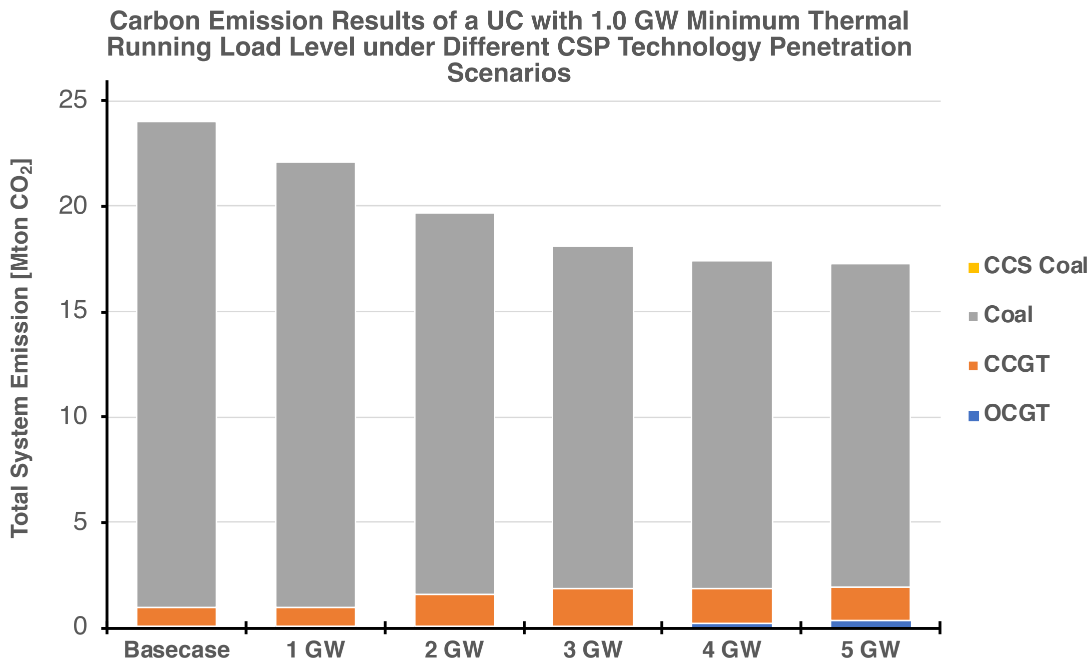

Figure 101: Carbon emission results of a UC model with 1 GW minimum thermal running load level under different CSP technology penetration scenarios

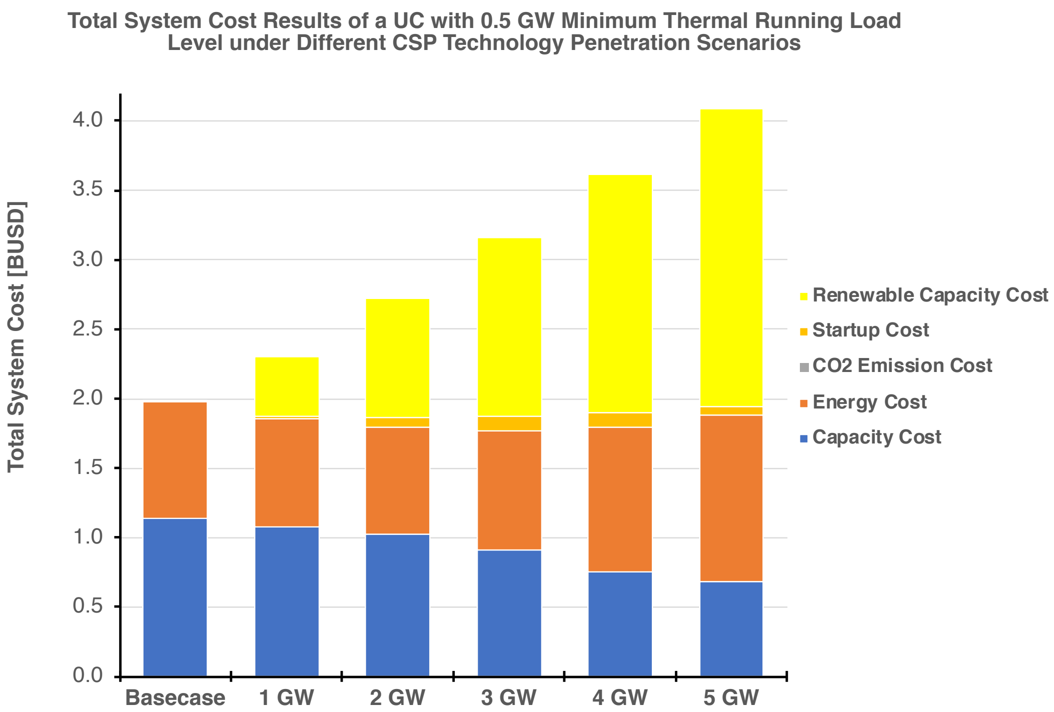

Figure 102: Total system cost results of a UC model with 0.5 GW minimum thermal running load level under different CSP technology penetration scenarios

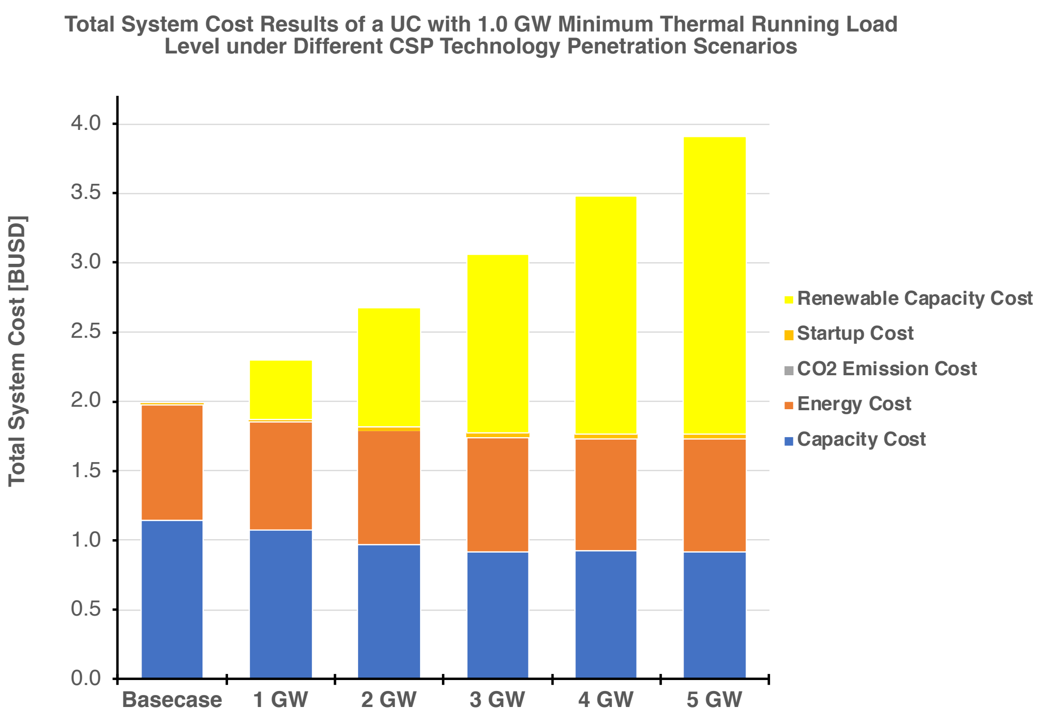

Figure 103: Total system cost results of a UC model with 1 GW minimum thermal running load level under different CSP technology penetration scenarios

A.2.3 Supplementary results of the units' dynamic constraints effect case study

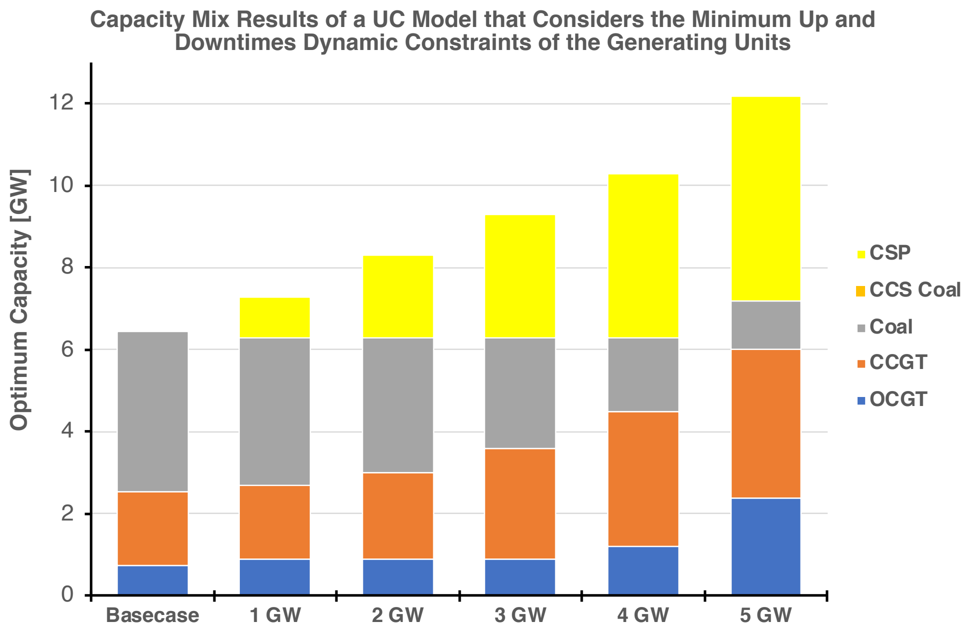

Figure 104: Optimum capacity mix results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

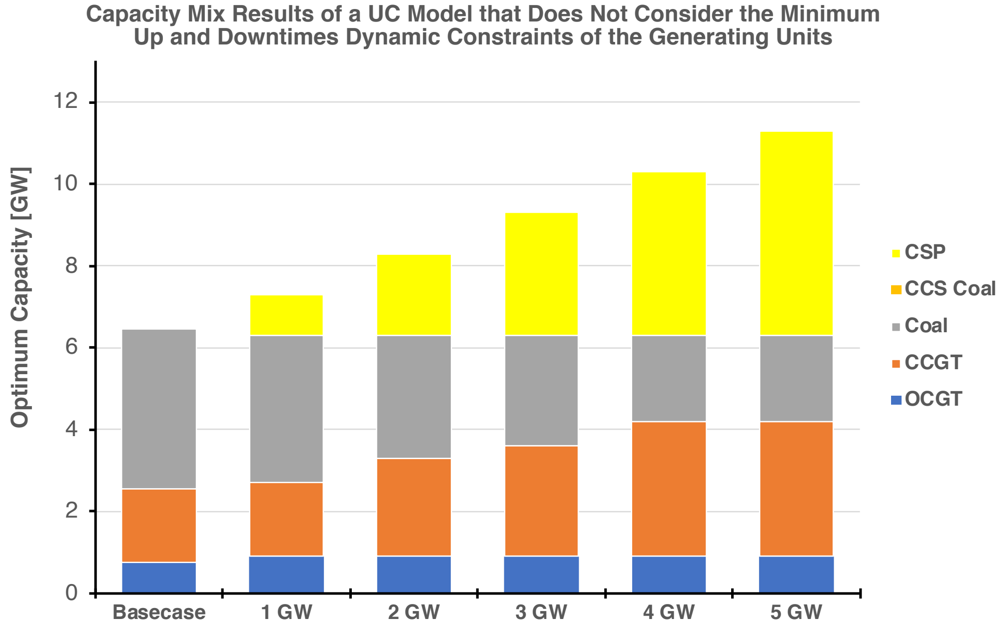

Figure 105: Optimum capacity mix results of a UC model that does not consider the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

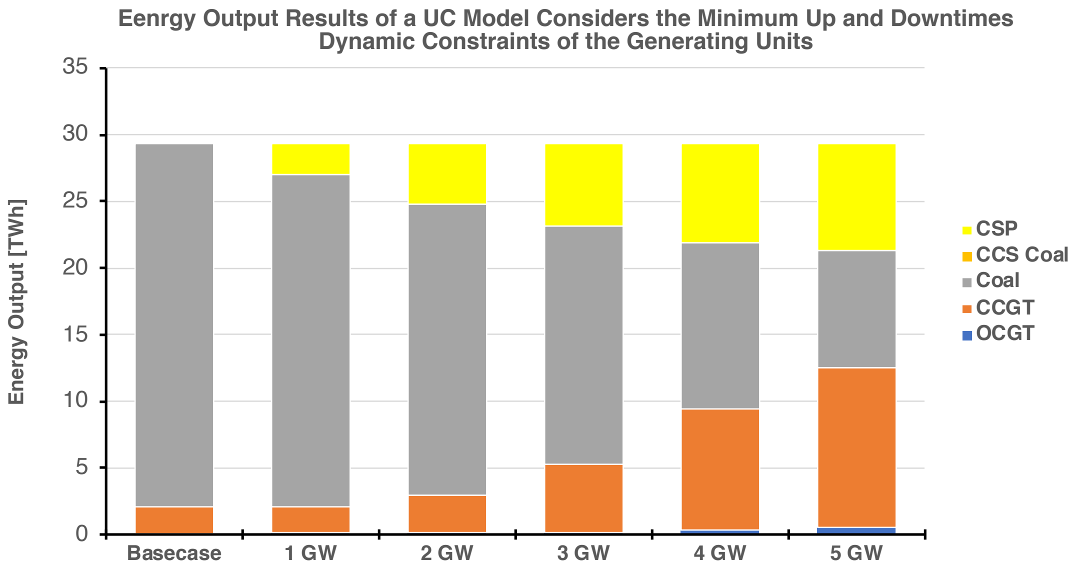

Figure 106: Energy output results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

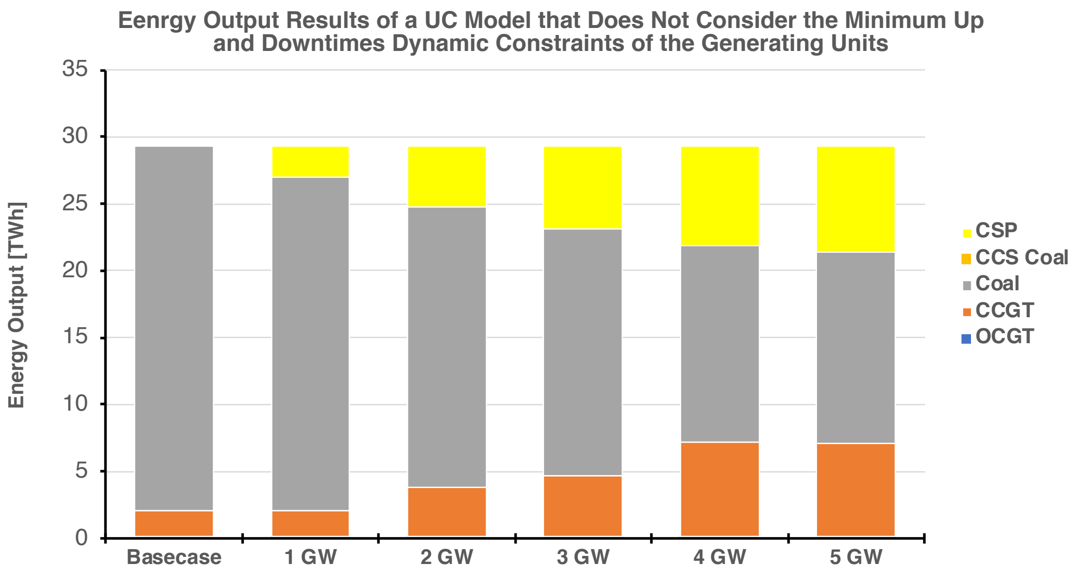

Figure 107: Energy output results of a UC model that does not consider the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

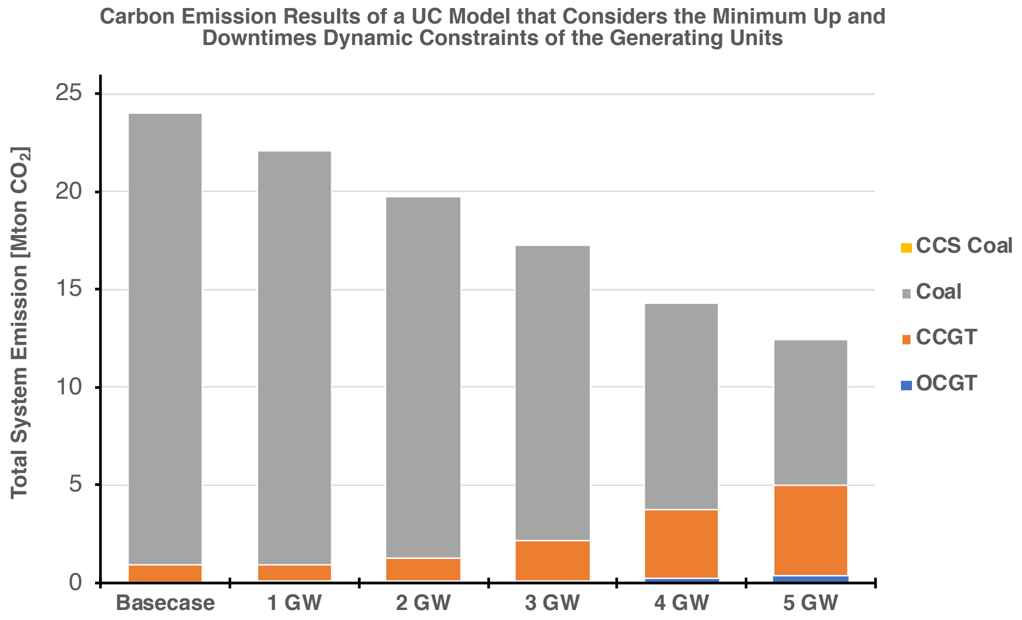

Figure 108: Carbon emission results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

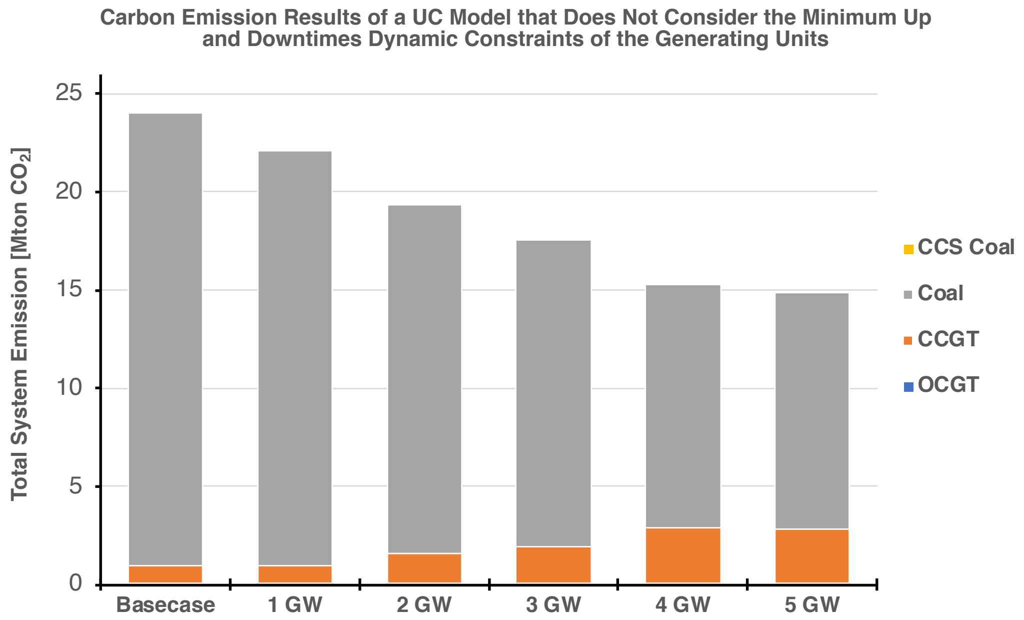

Figure 109: Carbon emission results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

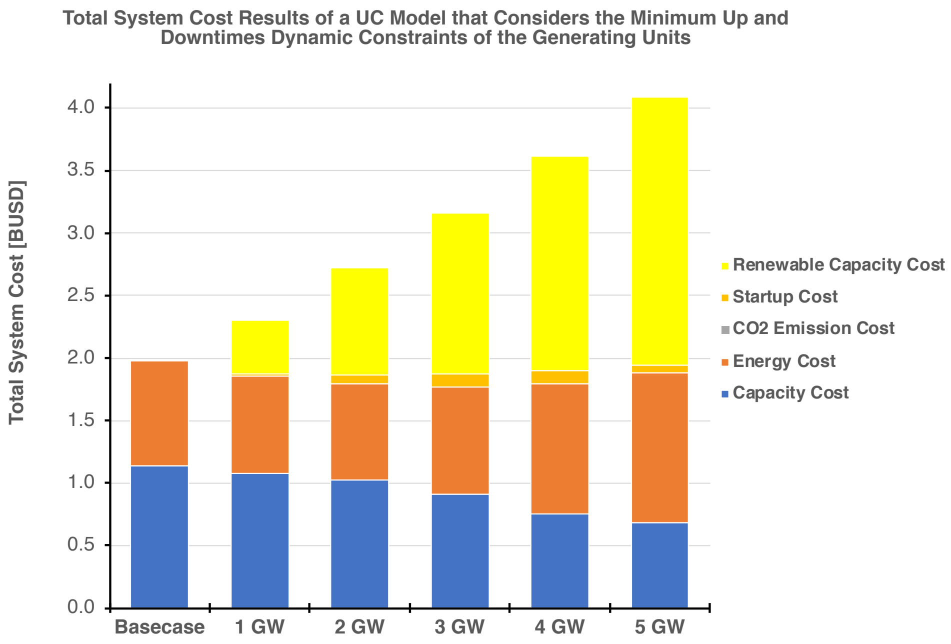

Figure 110: Total system cost results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

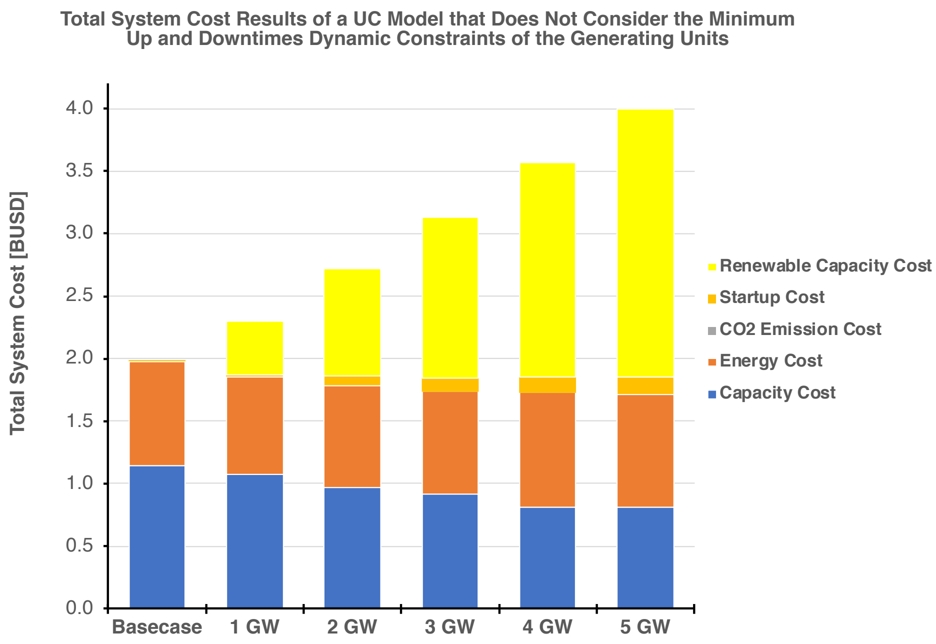

Figure 111: Carbon emission results of a UC model that considers the minimum up and downtimes of thermal generators under different CSP technology penetration scenarios

A.3 Supplementary Results of Chapter 5

A.3.1 Supplementary results of the impacts of renewable technology characteristics on the economics of decarbonisation

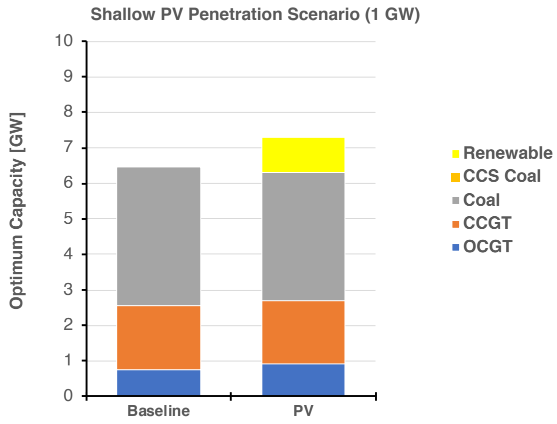

Figure 112: Optimum technology mix results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

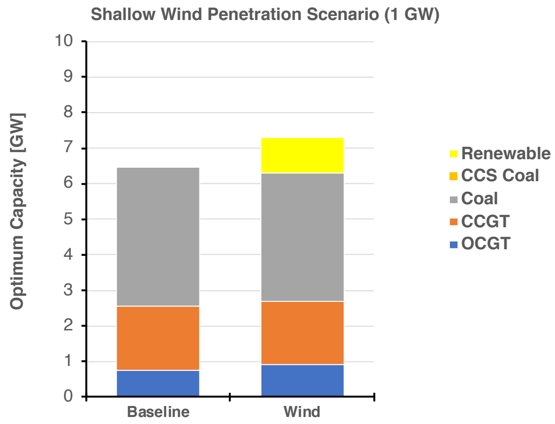

Figure 113: Optimum technology mix results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	PV Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
PV Penetration	0.00	1.00	1.00	-
Total	6.45	6.30	-0.15	-2%

Table 21: Optimum technology mix results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	Wind Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
Wind Penetration	0.00	1.00	1.00	-
Total Thermal	6.45	6.30	-0.15	-2%

Table 22: Optimum technology mix results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

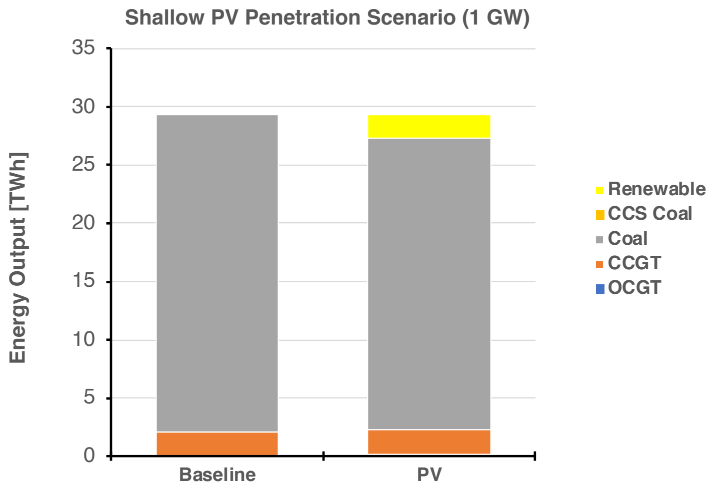

Figure 114:Energy output results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

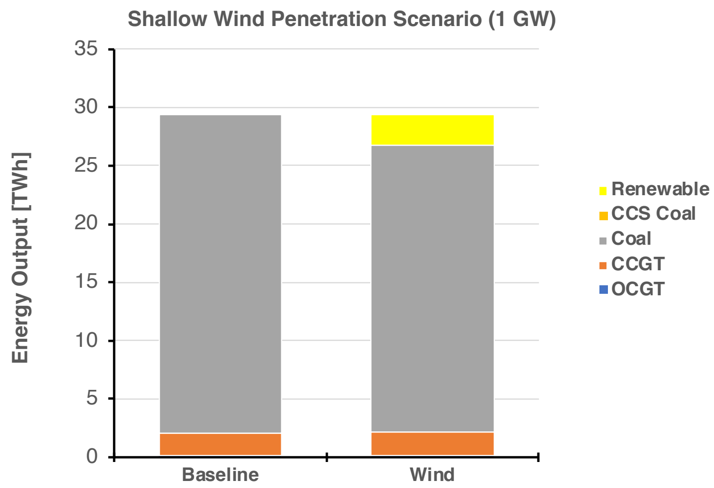

Figure 115: Energy output results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Energy Output [TWh]	PV Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.11	0.16	0.05	44%
CCGT	1.98	2.15	0.17	9%
Coal	27.25	25.03	-2.22	-8%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	0.00	2.00	2.00	-
Total Thermal	29.34	27.34	-2.00	-7%

Table 23: Energy output results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline Energy Output [TWh]	Wind Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.11	0.13	0.01	12%
CCGT	1.98	2.04	0.06	3%
Coal	27.25	24.64	-2.61	-10%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	0.00	2.54	2.54	-
Total Thermal	29.34	26.80	-2.54	-9%

Table 24: Energy output results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

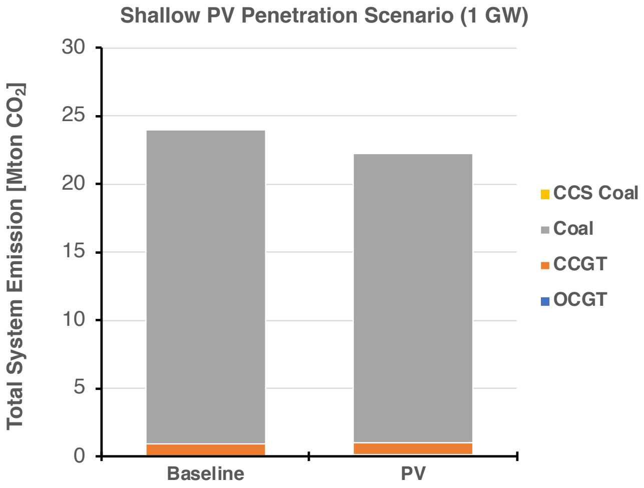

Figure 116: CO_2 emissions results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

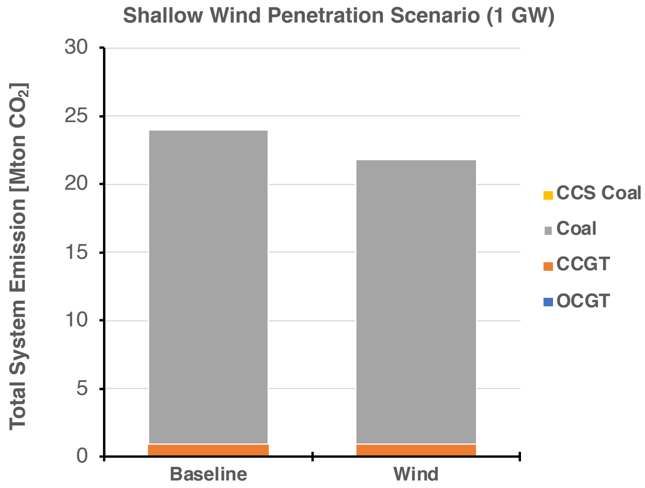

Figure 117: CO_2 emissions results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline	PV		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.07	0.10	0.03	44%
CCGT	0.87	0.93	0.06	7%
Coal	23.06	21.22	-1.84	-8%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	22.24	-1.75	-7%

Table 25: CO_2 emissions results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline	Wind		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.07	0.08	0.01	12%
CCGT	0.87	0.88	0.02	2%
Coal	23.06	20.87	-2.19	-9%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	21.83	-2.16	-9%

Table 26: CO_2 emissions results comparison between the baseline model and the wind technology model under a shallow penetration scenario

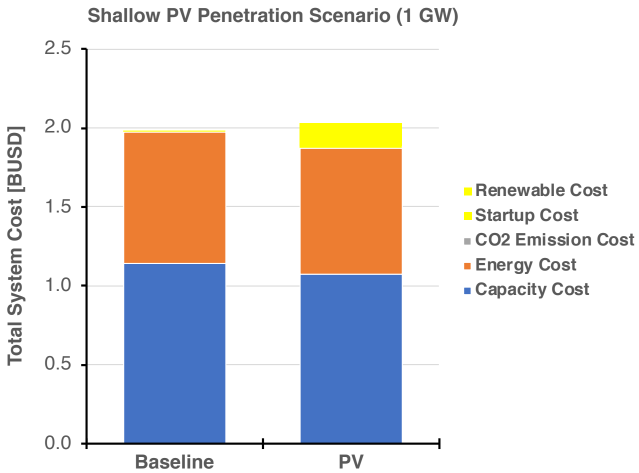

Figure 118: System cost results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

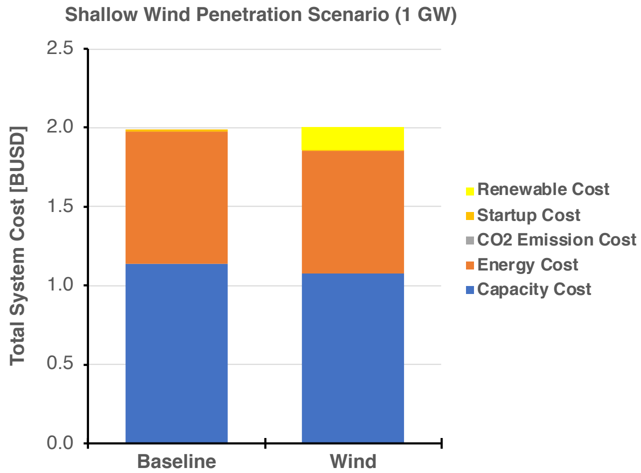

Figure 119: System cost results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	PV Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	801.0	-34.2	-4.1%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	12.9	1.9	17.5%
Renewable Cost	0.0	142.4	142.4	-
Total Cost	1986.4	2029.5	43.1	2.2%

Table 27: System cost results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	Wind Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	778.6	-56.6	-6.8%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	10.5	-0.5	-4.5%
Renewable Cost	0.0	141.0	141.0	-
Total Cost	1986.4	2003.3	16.9	0.9%

Table 28: System cost results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

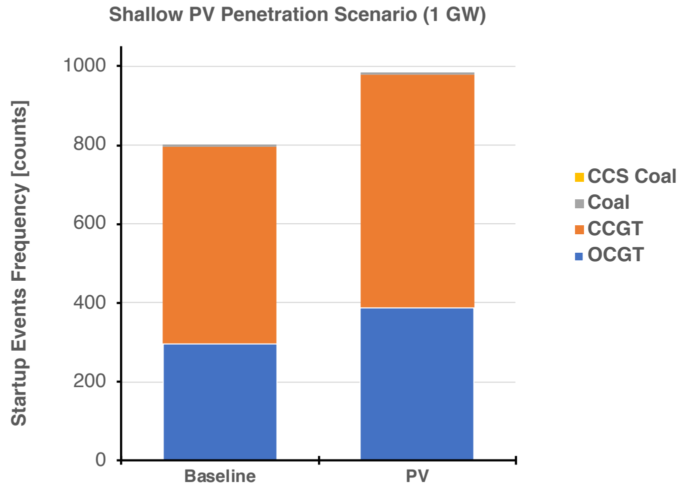

Figure 120: Thermal generation start-up activities results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

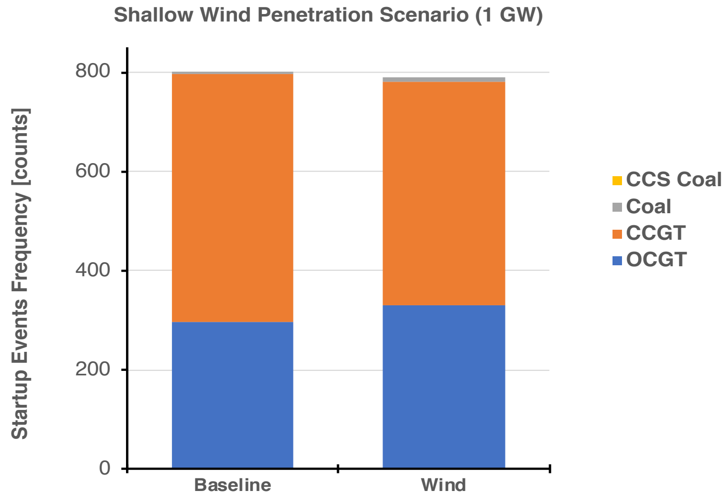

Figure 121: Thermal generation start-up activities results comparison between the baseline model and the wind technology model under a shallow penetration scenario

	Baseline	PV		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	388	92	31%
CCGT	501	592	91	18%
Coal	4	3	-1	-25%
CCS Coal	0	0	0	-
Total	801	983	182	23%

Table 29: Thermal generation startup activities results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline	Wind		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	330	34	11%
CCGT	501	452	-49	-10%
Coal	4	7	3	75%
CCS Coal	0	0	0	-
Total	801	789	-12	-1.5%

Table 30: Thermal generation startup activities results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

Shallow & deep penetration scenarios results

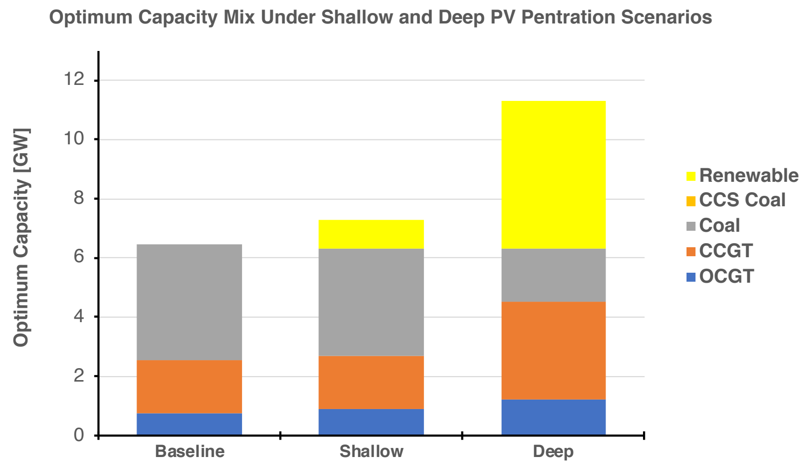

Figure 122: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the PV technology model

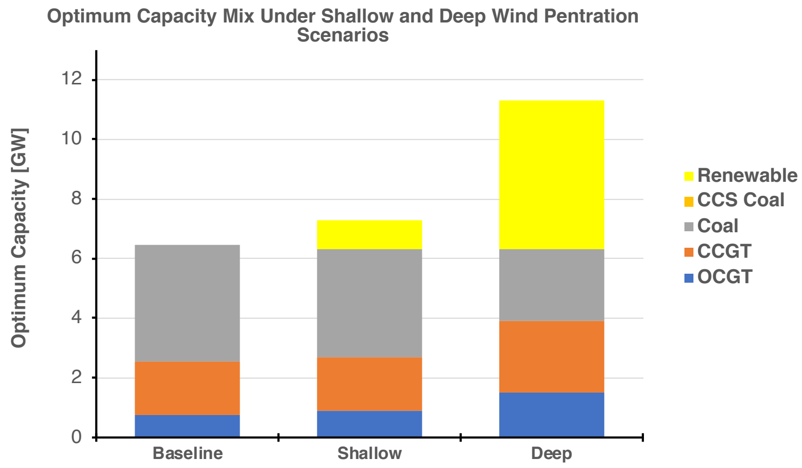

Figure 123: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the wind technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	1.20	0.30	33%
CCGT	1.80	3.30	1.50	83%
Coal	3.60	1.80	-1.80	-50%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	1.00	5.00	4.00	-
Total Thermal	6.30	6.30	0.00	0%

Table 31: Optimum technology mix results comparison between shallow (1 GW) and deep (5GW) penetration scenarios for the PV technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	1.50	0.60	67%
CCGT	1.80	2.40	0.60	33%
Coal	3.60	2.40	-1.20	-33%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	1.00	5.00	4.00	-
Total Thermal	6.30	6.30	0.00	0%

Table 32: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the wind technology model

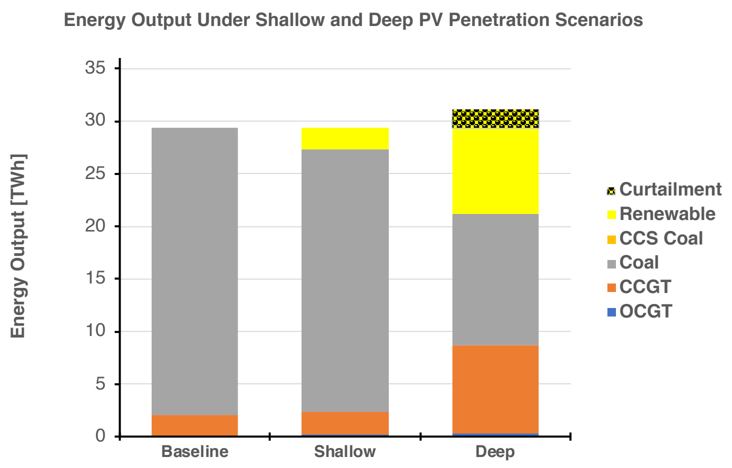

Figure 124: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

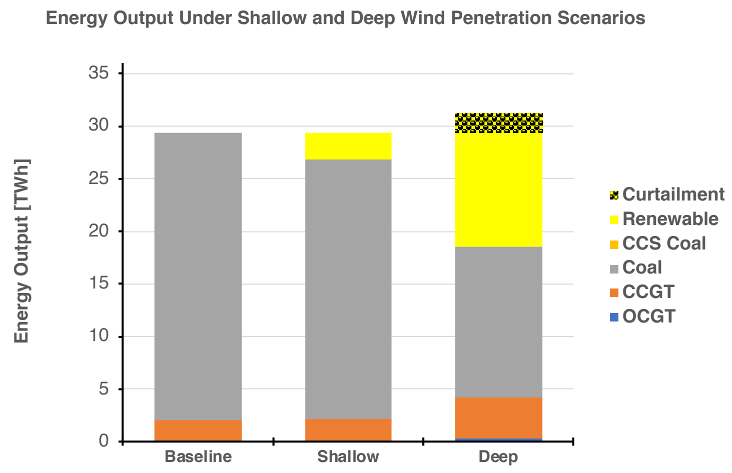

Figure 125: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow Energy Output [TWh]	Deep Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.16	0.30	0.14	84%
CCGT	2.15	8.35	6.21	289%
Coal	25.03	12.51	-12.52	-50%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	2.00	8.17	6.18	-
PV Curtailment	0.00	1.81	1.81	-
Total	29.34	29.34		

Table 33: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow Energy Output [TWh]	Deep Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.12	0.29	0.17	144%
CCGT	2.05	5.05	3.01	147%
Coal	24.64	13.16	-11.47	-47%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	2.54	10.84	8.30	-
Wind Curtailment	0.00	1.85	1.85	-
Total Thermal	29.34	29.34		

Table 34: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

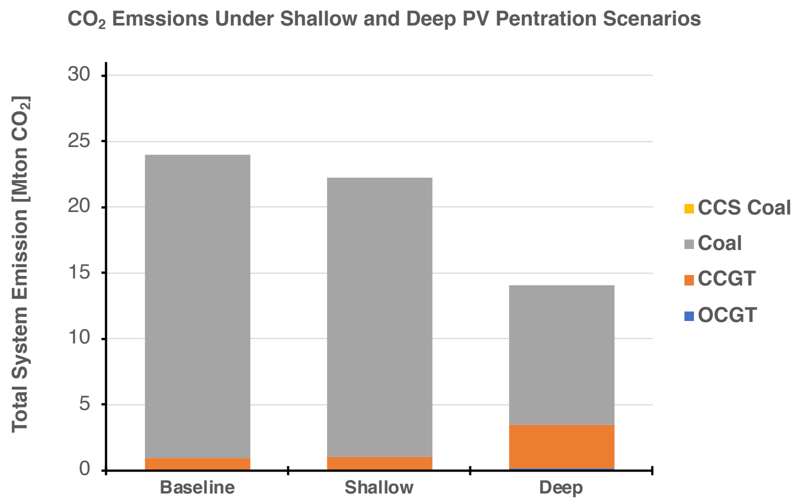

Figure 126: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

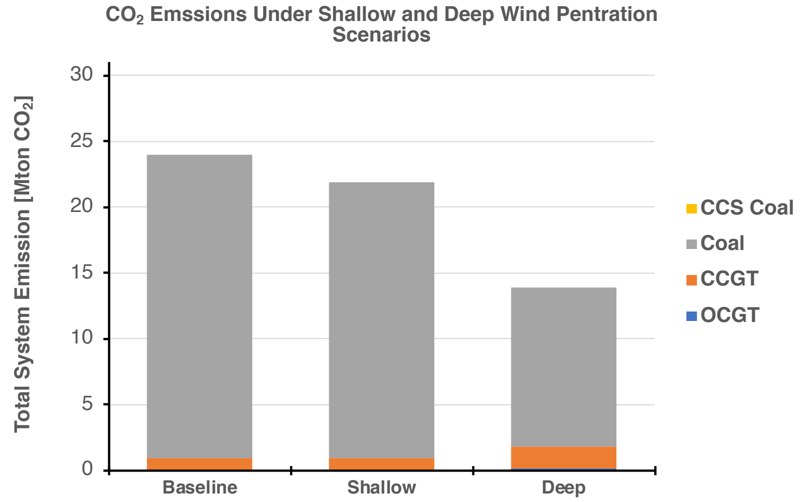

Figure 127: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow	Deep		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.10	0.18	0.08	84%
CCGT	0.93	3.28	2.36	255%
Coal	21.22	10.56	-10.65	-50%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	22.24	14.03	-8.21	-37%

Table 35: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow	Deep		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.08	0.17	0.10	128%
CCGT	0.88	1.60	0.71	80%
Coal	20.87	12.08	-8.79	-42%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	21.83	13.85	-7.98	-37%

Table 36: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

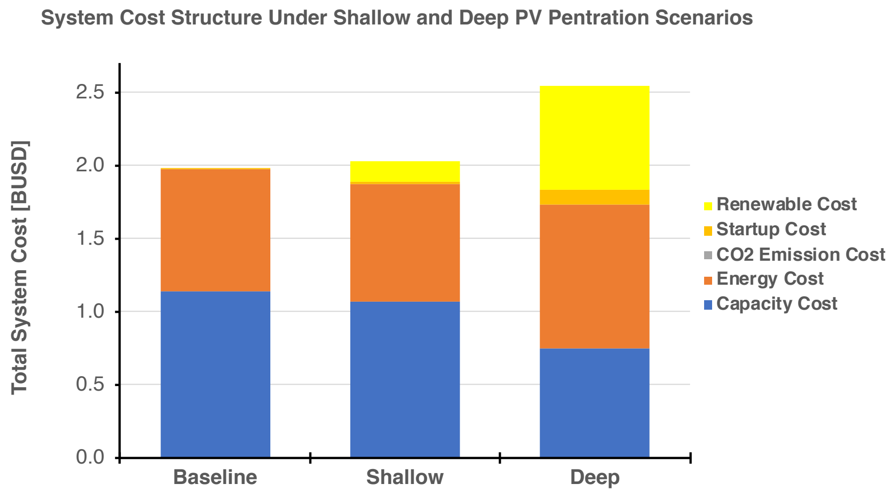

Figure 128: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

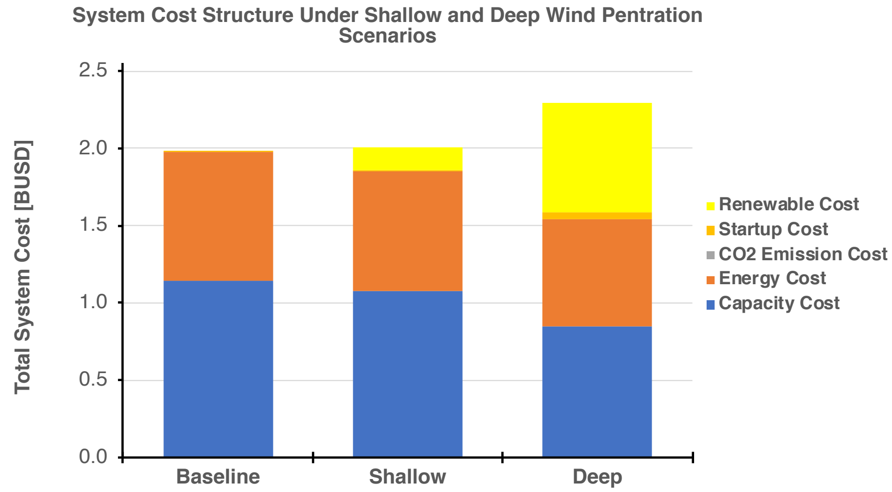

Figure 129: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	749.7	-323.6	-30%
Energy Cost	801.0	984.9	183.9	23%
CO2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	12.9	100.9	88.0	685%
Renewable Cost	142.4	712.1	569.7	400%
Total Thermal	2029.5	2547.4	518.0	25.5%

Table 37: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	848.8	-224.4	-21%
Energy Cost	778.6	691.8	-86.7	-11%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.5	46.1	35.7	341%
Renewable Cost	141.0	705.2	564.1	400%
Total Thermal	2003.3	2291.9	288.6	14.4%

Table 38: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

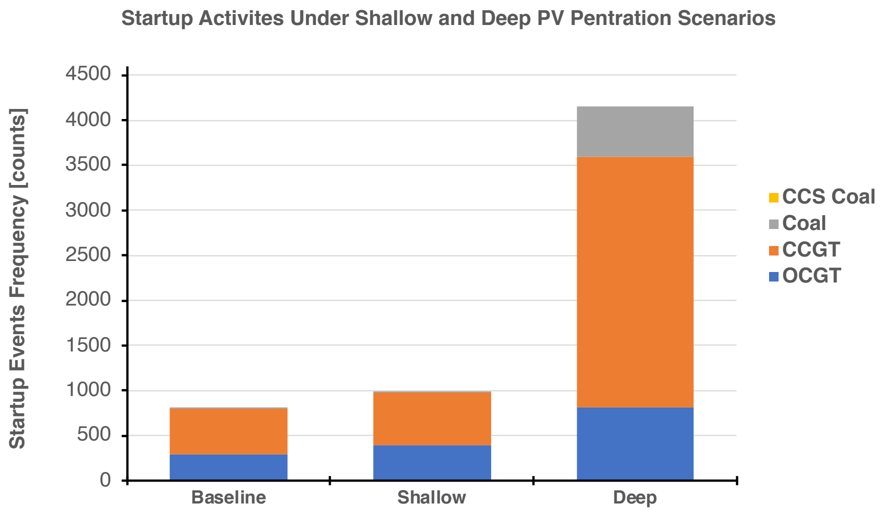

Figure 130: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

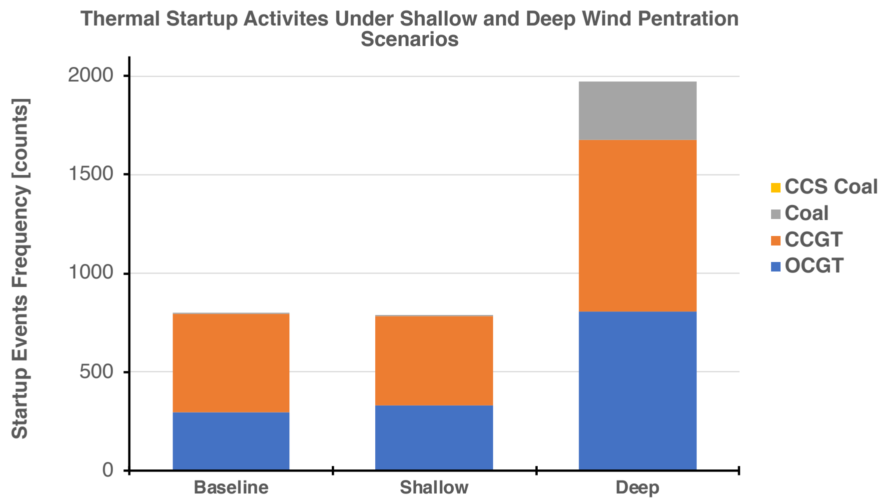

Figure 131: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	388	815	427	110%
CCGT	592	2778	2186	369%
Coal	3	562	559	18633%
CCS Coal	0	0	0	-
Total	983	4155	3172	323%

Table 39: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	330	807	477	145%
CCGT	452	867	415	92%
Coal	7	300	293	4186%
CCS Coal	0	0	0	-
Total	789	1974	1185	150%

Table 40: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

A.3.2 Supplementary results of the impacts of renewable production profiles on the economics of decarbonisation

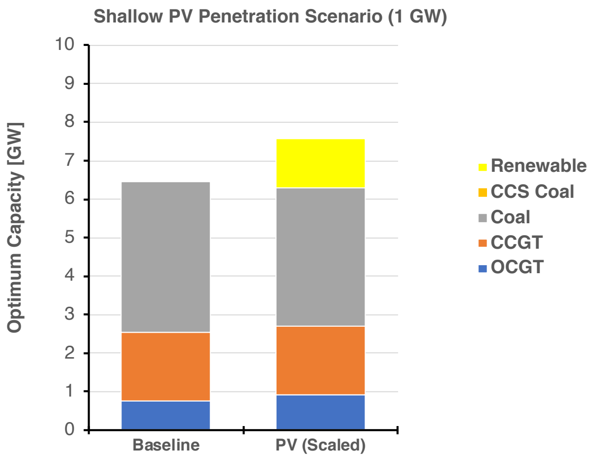

Figure 132: Optimum technology mix results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

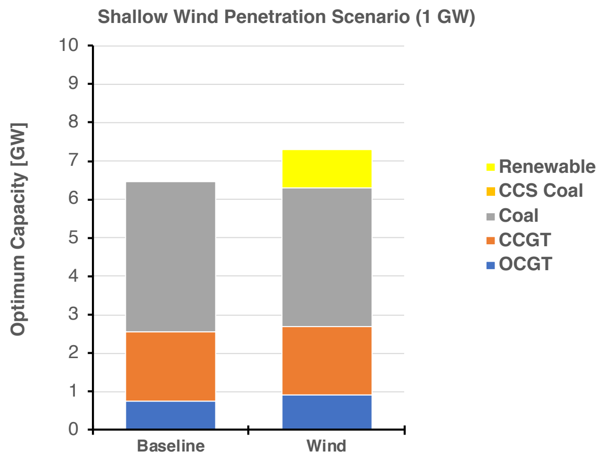

Figure 133: Optimum technology mix results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	PV (Scaled) Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
CCS Coal	0.00	0.00	0.00	-
PV (Scaled) Penetration	0.00	1.27	1.27	-
Total Thermal	6.45	6.30	-0.15	-2%

Table 41: Optimum technology mix results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	Wind Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	0.00	1.00	1.00	-
Total Thermal	6.45	6.30	-0.15	-2%

Table 42: Optimum technology mix results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

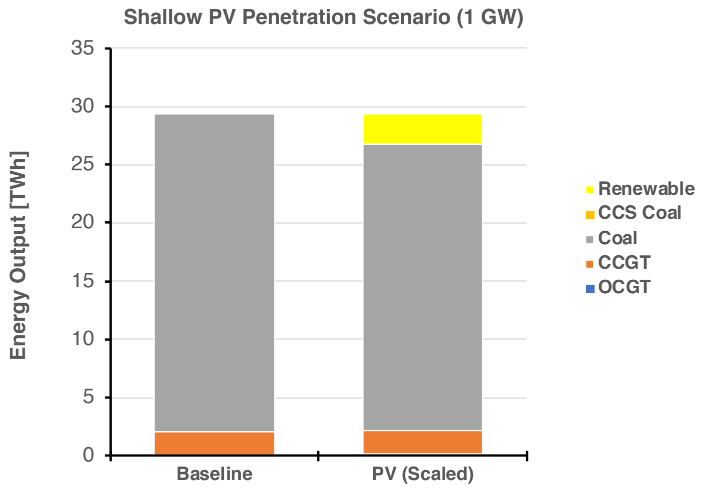

Figure 134:Energy output results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

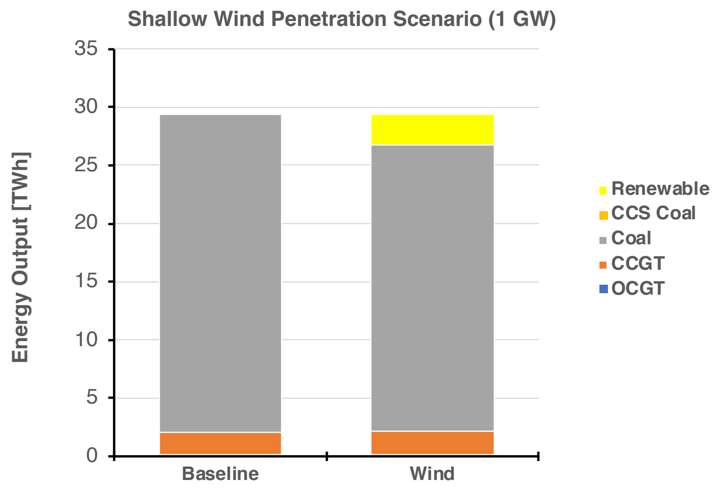

Figure 135: Energy output results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Energy Output [TWh]	PV (Scaled) Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.11	0.15	0.04	36%
CCGT	1.98	2.02	0.04	2%
Coal	27.25	24.63	-2.62	-10%
CCS Coal	0.00	0.00	0.00	-
PV (Scaled) Penetration	0.00	2.54	2.54	-
Total Thermal	29.34	26.80	-2.54	-9%

Table 43: Energy output results comparison between the baseline model and the PV (scaled) technology model under a hallow penetration scenario (1 GW)

	Baseline Energy Output [TWh]	Wind Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.11	0.13	0.01	12%
CCGT	1.98	2.04	0.06	3%
Coal	27.25	24.64	-2.61	-10%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	0.00	2.54	2.54	-
Total Thermal	29.34	26.80	-2.54	-9%

Table 44: Energy output results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

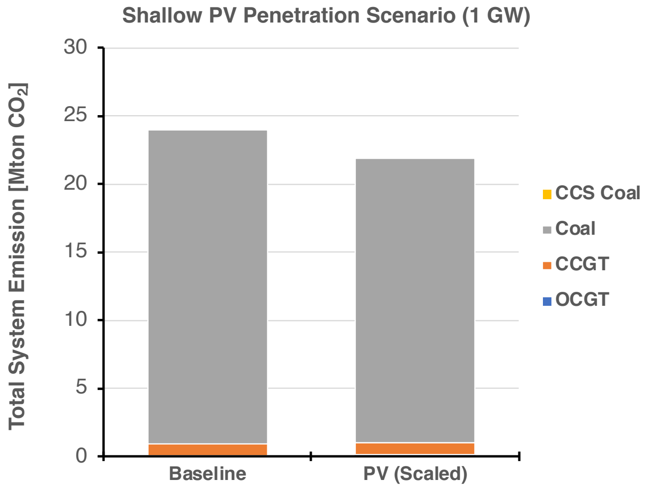

Figure 136: CO_2 emissions results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

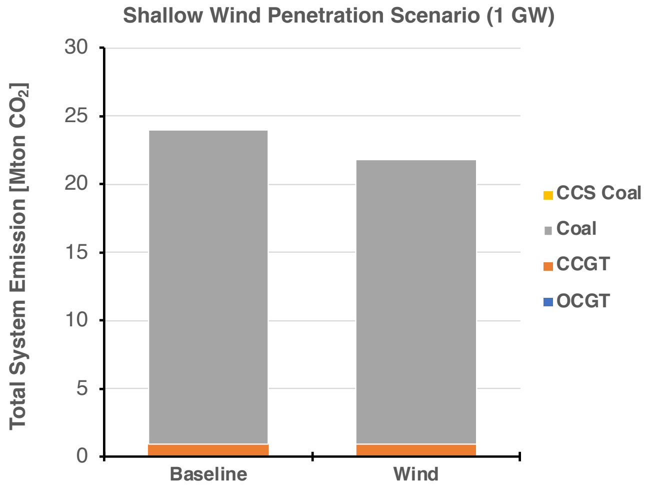

Figure 137: CO_2 emissions results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline CO_2 Emissions [Mton CO_2]	PV (Scaled) CO_2 Emissions [Mton CO_2]	Difference [Mton CO_2]	Difference [%]
OCGT	0.07	0.09	0.02	36%
CCGT	0.87	0.87	0.01	1%
Coal	23.06	20.88	-2.18	-9%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	21.85	-2.15	-9%

Table 45: CO_2 emissions results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

	Baseline CO_2 Emissions [Mton CO_2]	Wind CO_2 Emissions [Mton CO_2]	Difference [Mton CO_2]	Difference [%]
OCGT	0.07	0.08	0.01	12%
CCGT	0.87	0.88	0.02	2%
Coal	23.06	20.87	-2.19	-9%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	21.83	-2.16	-9%

Table 46: CO_2 emissions results comparison between the baseline model and the wind technology model under a shallow penetration scenario

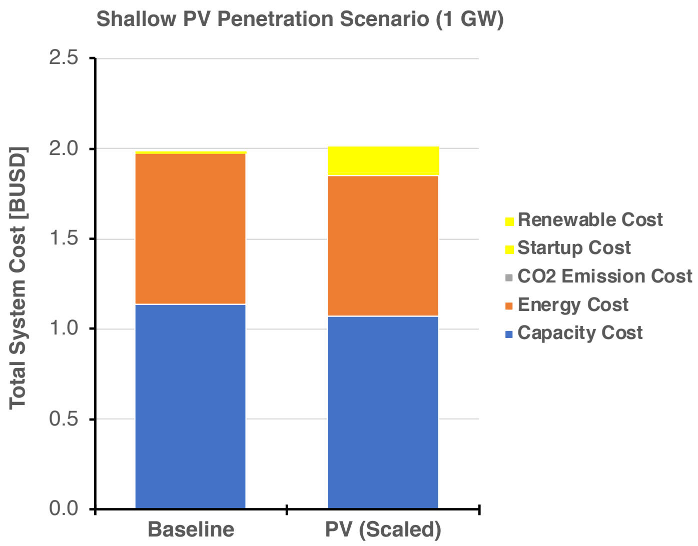

Figure 138: System cost results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

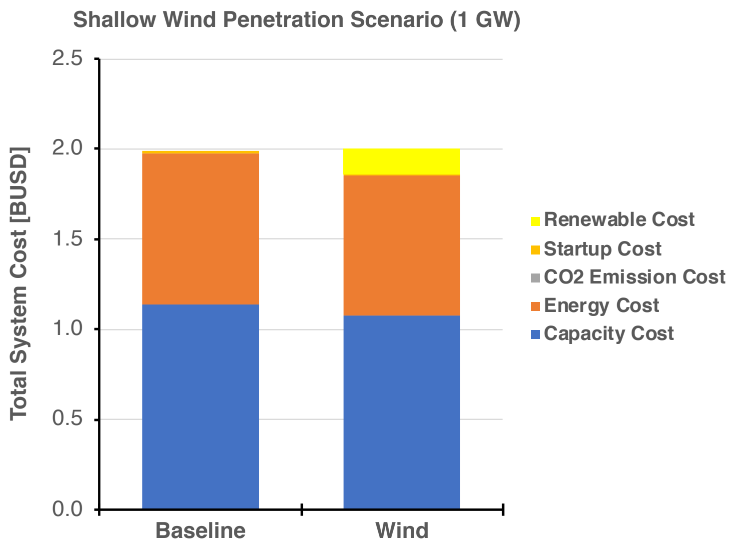

Figure 139: System cost results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	PV (Scaled) Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	779.9	-55.3	-6.6%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	16.4	5.4	49.5%
Renewable Cost	0.0	141.0	141.0	-
Total Cost	1986.4	2010.5	24.1	1.2%

Table 47: System cost results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	Wind Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	778.6	-56.6	-6.8%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	10.5	-0.5	-4.5%
Renewable Cost	0.0	141.0	141.0	-
Total Cost	1986.4	2003.3	16.9	0.9%

Table 48: System cost results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

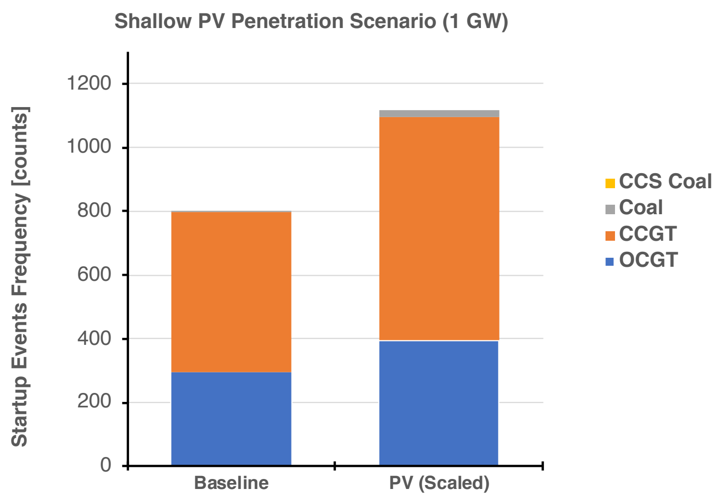

Figure 140: Thermal generation start-up activities results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

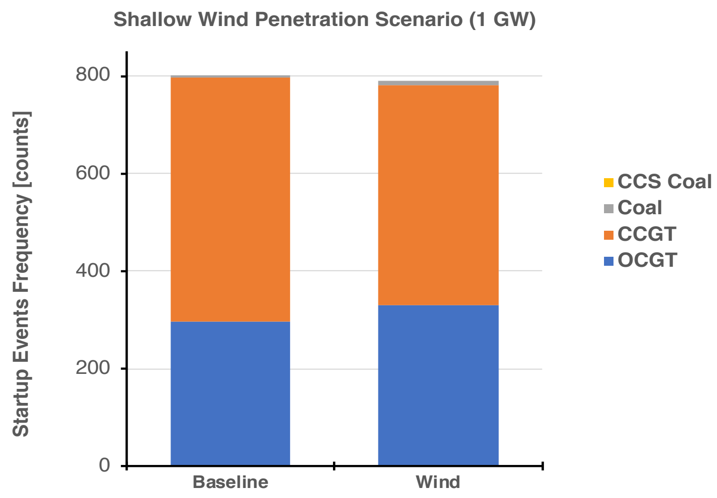

Figure 141: Thermal generation start-up activities results comparison between the baseline model and the wind technology model under a shallow penetration scenario

	Baseline	PV (Scaled)		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	394	98	33%
CCGT	501	701	200	40%
Coal	4	22	18	450%
CCS Coal	0	0	0	-
Total	801	1117	316	39%

Table 49: Thermal generation startup activities results comparison between the baseline model and the PV (scaled) technology model under a shallow penetration scenario (1 GW)

	Baseline	Wind		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	330	34	11%
CCGT	501	452	-49	-10%
Coal	4	7	3	75%
CCS Coal	0	0	0	-
Total	801	789	-12	-1.5%

Table 50: Thermal generation startup activities results comparison between the baseline model and the wind technology model under a shallow penetration scenario (1 GW)

Shallow & deep penetration scenarios results

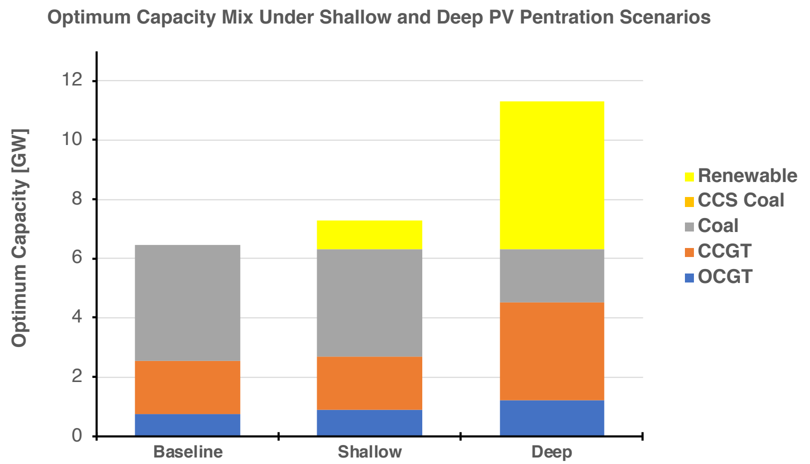

Figure 142: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the PV (scaled) technology model

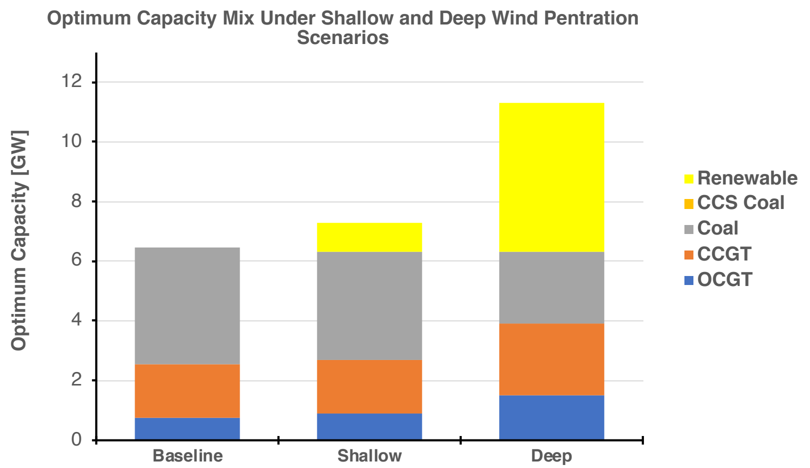

Figure 143: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the wind technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	1.20	0.30	33%
CCGT	1.80	3.90	2.10	117%
Coal	3.60	1.20	-2.40	-67%
CCS Coal	0.00	0.00	0.00	-
PV (Scaled) Penetration	1.27	6.36	5.09	-
Total Thermal	6.30	6.30	0.00	0%

Table 51: Optimum technology mix results comparison between shallow (1 GW) and deep (5GW) penetration scenarios for the PV (scaled) technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	1.50	0.60	67%
CCGT	1.80	2.40	0.60	33%
Coal	3.60	2.40	-1.20	-33%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	1.00	5.00	4.00	-
Total Thermal	6.30	6.30	0.00	0%

Table 52: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the wind technology model

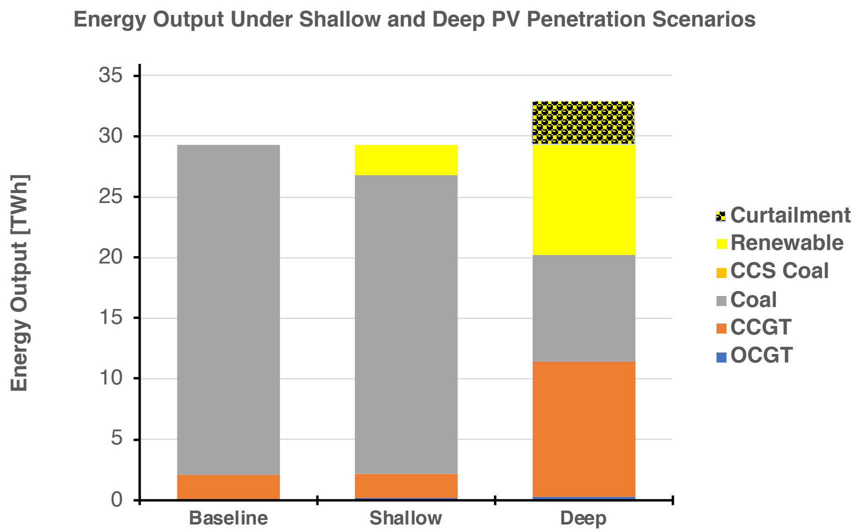

Figure 144: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

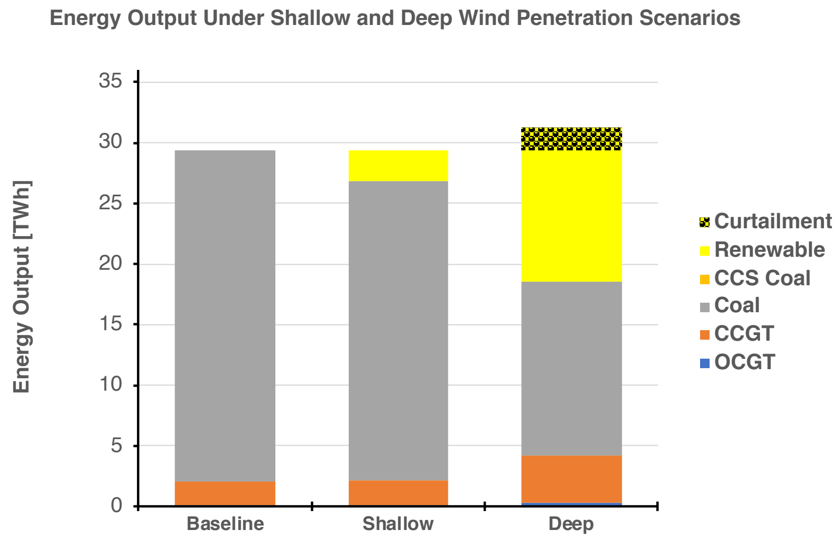

Figure 145: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow Energy Output [TWh]	Deep Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.15	0.29	0.13	88%
CCGT	2.02	11.19	9.17	454%
Coal	24.63	8.75	-15.88	-64%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	2.54	9.11	6.57	-
PV Curtailment	0.00	3.58	3.58	-
Total	29.34	29.34		

Table 53: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

	Shallow Energy Output [TWh]	Deep Energy Output [TWh]	Difference [TWh]	Difference [%]
OCGT	0.12	0.29	0.17	144%
CCGT	2.05	5.05	3.01	147%
Coal	24.64	13.16	-11.47	-47%
CCS Coal	0.00	0.00	0.00	-
Wind Penetration	2.54	10.84	8.30	-
Wind Curtailment	0.00	1.85	1.85	-
Total Thermal	29.34	29.34		

Table 54: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

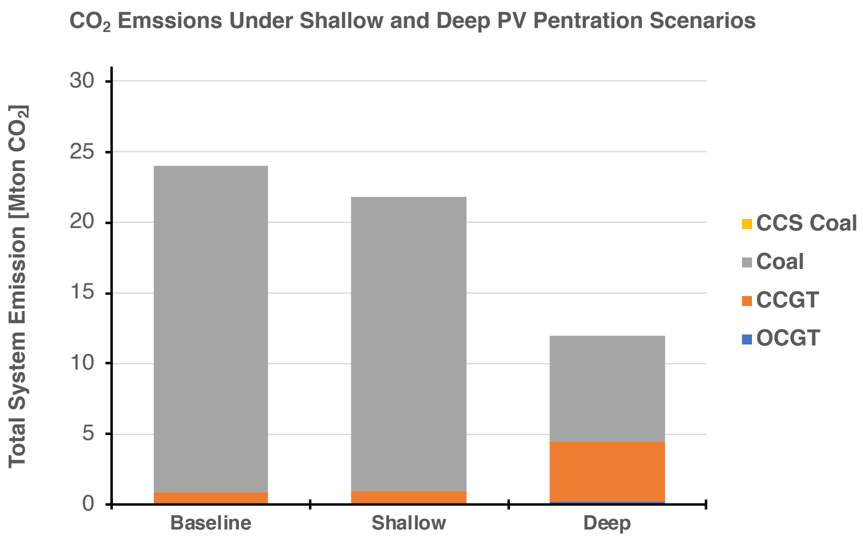

Figure 146: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

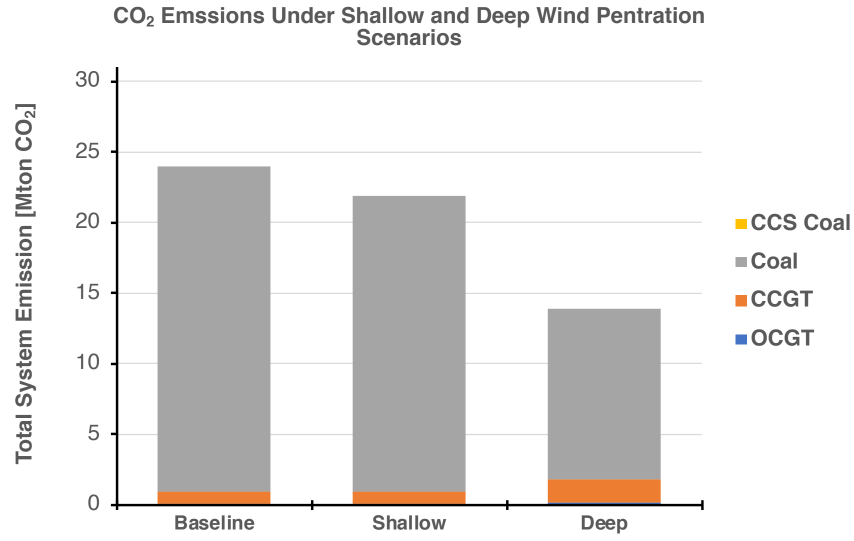

Figure 147: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow CO_2 Emissions [Mton CO_2]	Deep CO_2 Emissions [Mton CO_2]	Difference [Mton CO_2]	Difference [%]
OCGT	0.09	0.18	0.08	88%
CCGT	0.87	4.34	3.47	398%
Coal	20.88	7.41	-13.47	-65%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	21.85	11.93	-9.92	-45%

Table 55: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

	Shallow CO_2 Emissions [Mton CO_2]	Deep CO_2 Emissions [Mton CO_2]	Difference [Mton CO_2]	Difference [%]
OCGT	0.08	0.17	0.10	128%
CCGT	0.88	1.60	0.71	80%
Coal	20.87	12.08	-8.79	-42%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	21.83	13.85	-7.98	-37%

Table 56: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

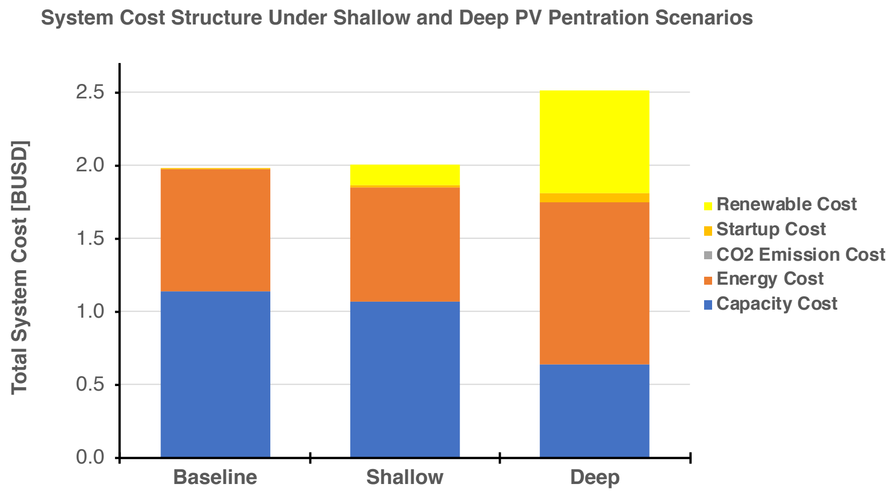

Figure 148: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

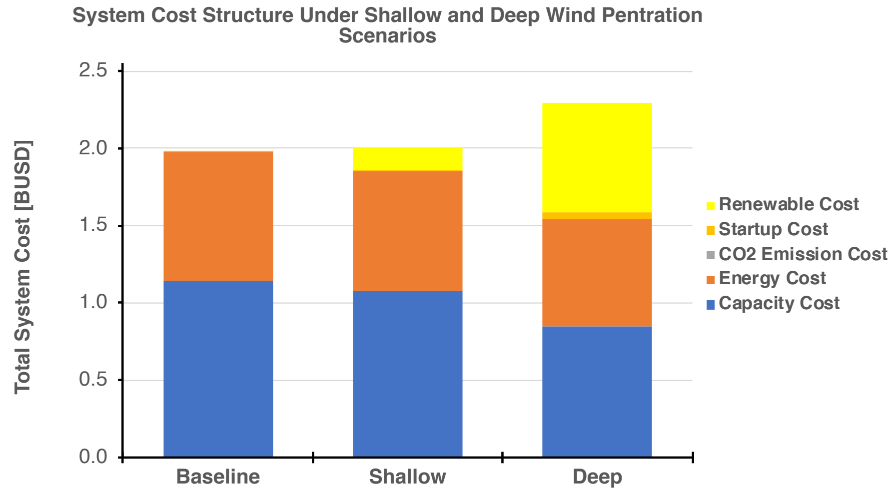

Figure 149: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	644.0	-429.3	-40%
Energy Cost	779.9	1103.9	324.1	42%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	16.4	61.2	44.8	274%
Renewable Cost	141.0	705.2	564.1	400%
Total Thermal	2010.5	2514.3	503.8	25.1%

Table 57: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	848.8	-224.4	-21%
Energy Cost	778.6	691.8	-86.7	-11%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.5	46.1	35.7	341%
Renewable Cost	141.0	705.2	564.1	400%
Total Thermal	2003.3	2291.9	288.6	14.4%

Table 58: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

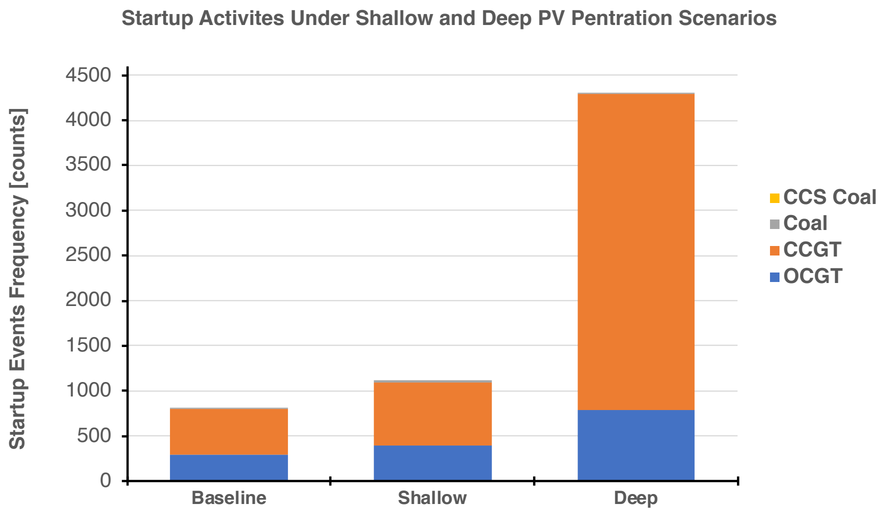

Figure 150: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

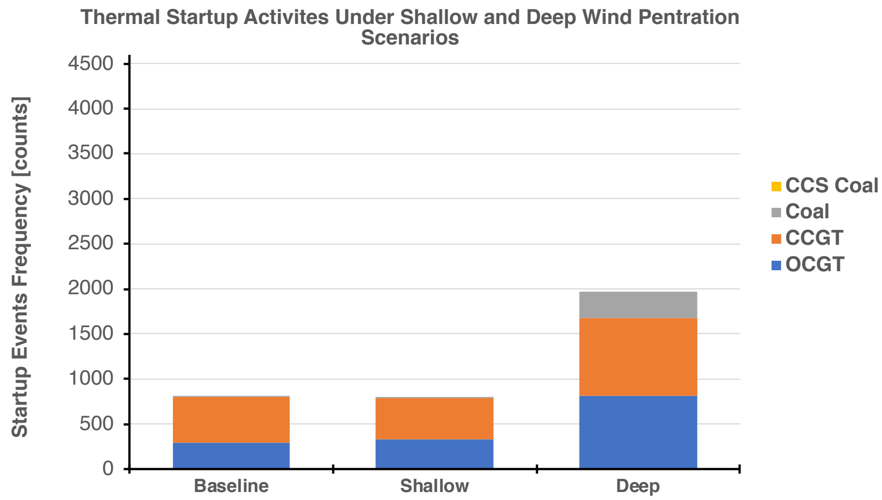

Figure 151: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	394	785	391	99%
CCGT	701	3510	2809	401%
Coal	22	1	-21	-95%
CCS Coal	0	0	0	-
Total	1117	4296	3179	285%

Table 59: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV (scaled) technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	330	807	477	145%
CCGT	452	867	415	92%
Coal	7	300	293	4186%
CCS Coal	0	0	0	-
Total	789	1974	1185	150%

Table 60: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the wind technology model

A.3.3 Supplementary results of the impacts of renewable production profile variability on the capacity and flexibility requirements of an electric system

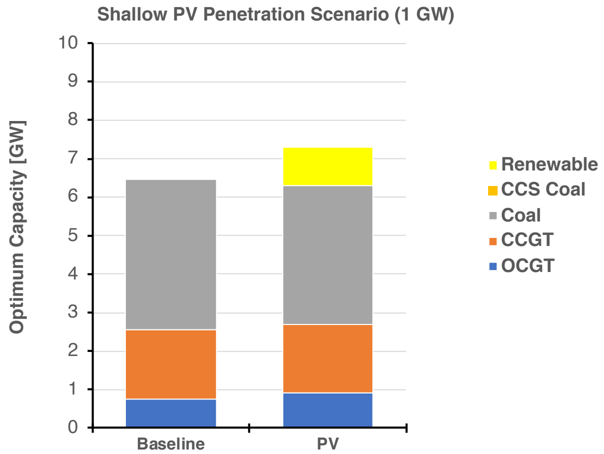

Figure 152: Optimum technology mix results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

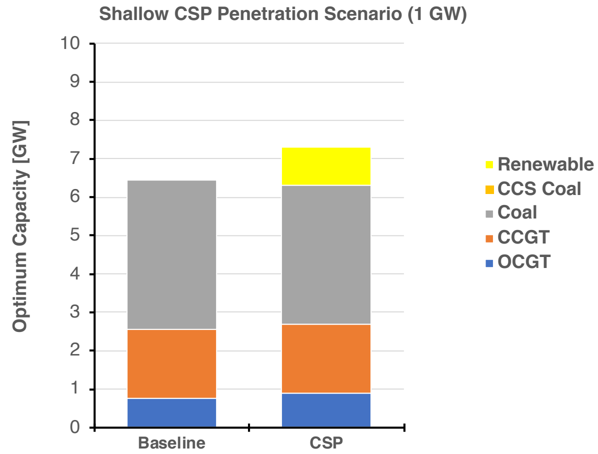

Figure 153: Optimum technology mix results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	PV Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
PV Penetration	0.00	1.00	1.00	-
Total	6.45	6.30	-0.15	-2%

Table 61: Optimum technology mix results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline Capacity Mix [GW]	CSP Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.75	0.90	0.15	20%
CCGT	1.80	1.80	0.00	0%
Coal	3.90	3.60	-0.30	-8%
CSP Penetration	0.00	1.00	1.00	-
Total Thermal	6.45	6.30	-0.15	-2%

Table 62: Optimum technology mix results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

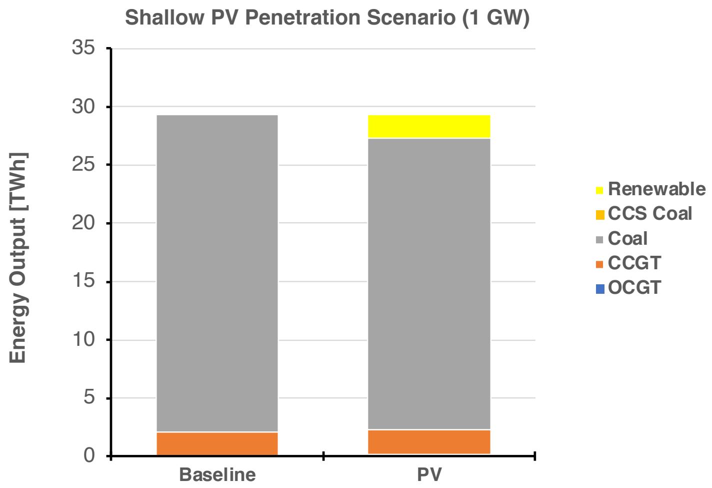

Figure 154:Energy output results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

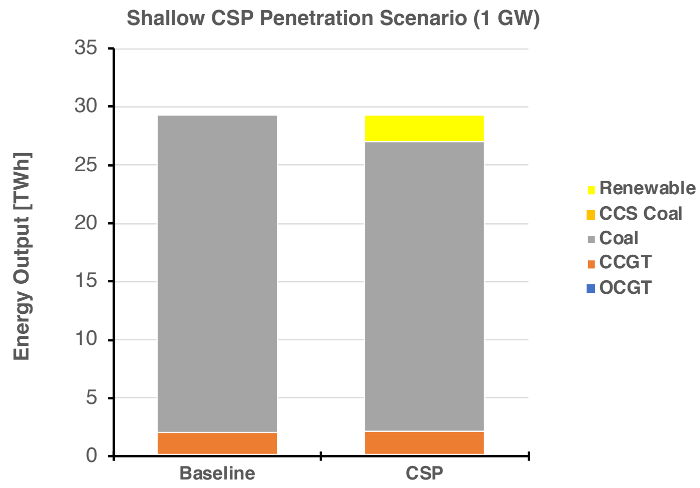

Figure 155: Energy output results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

	Baseline	PV		
	Energy Output	Energy Output	Difference	Difference
	[TWh]	[TWh]	[TWh]	[%]
OCGT	0.11	0.16	0.05	44%
CCGT	1.98	2.15	0.17	9%
Coal	27.25	25.03	-2.22	-8%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	0.00	2.00	2.00	-
Total Thermal	29.34	27.34	-2.00	-7%

Table 63: Energy output results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline	CSP		
	Energy Output	Energy Output	Difference	Difference
	[TWh]	[TWh]	[TWh]	[%]
OCGT	0.11	0.15	0.03	30%
CCGT	1.98	1.97	0.00	0%
Coal	27.25	24.91	-2.35	-9%
CCS Coal	0.00	0.00	0.00	-
CSP Penetration	0.00	2.32	2.32	-
Total Thermal	29.34	27.02	-2.32	-8%

Table 64: Energy output results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

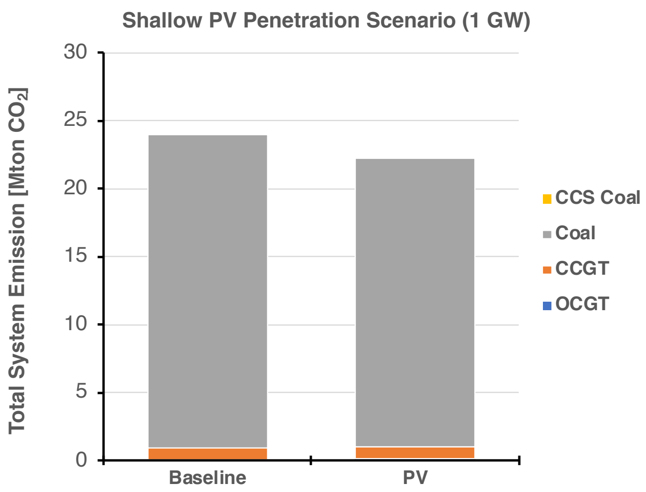

Figure 156: CO_2 emissions results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

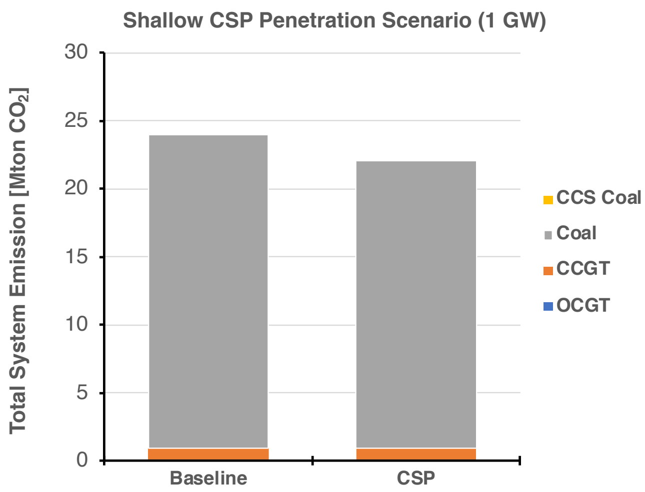

Figure 157: CO_2 emissions results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

	Baseline	PV		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.07	0.10	0.03	44%
CCGT	0.87	0.93	0.06	7%
Coal	23.06	21.22	-1.84	-8%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	22.24	-1.75	-7%

Table 65: CO_2 emissions results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline	CSP		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.07	0.09	0.02	30%
CCGT	0.87	0.86	-0.01	-1%
Coal	23.06	21.11	-1.95	-8%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	23.99	22.06	-1.93	-8%

Table 66: CO_2 emissions results comparison between the baseline model and the CSP technology model under a shallow penetration scenario

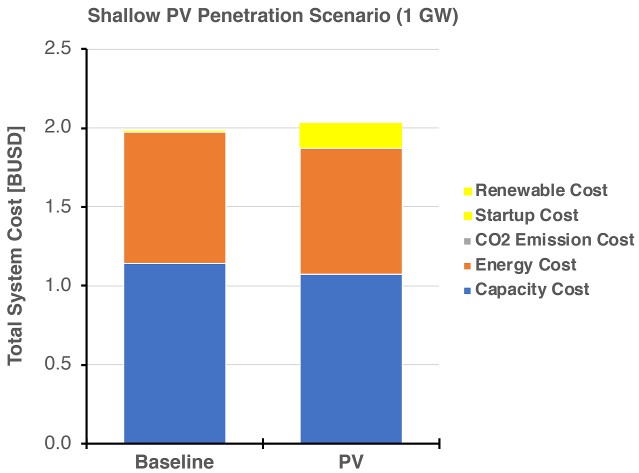

Figure 158: System cost results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

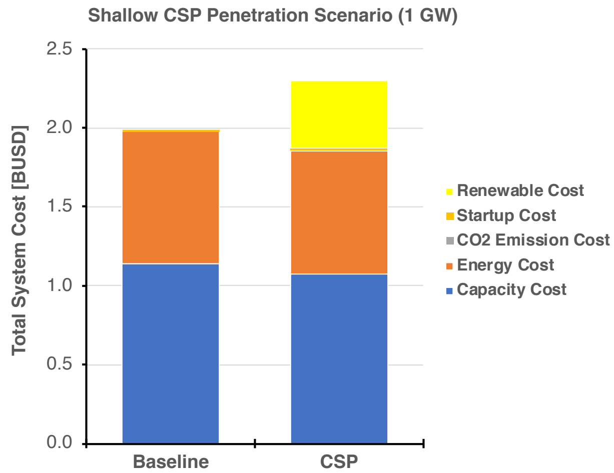

Figure 159: System cost results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	PV Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	801.0	-34.2	-4.1%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	12.9	1.9	17.5%
Renewable Cost	0.0	142.4	142.4	-
Total Cost	1986.4	2029.5	43.1	2.2%

Table 67: System cost results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline Cost [MUSD]	CSP Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1140.3	1073.2	-67.0	-5.9%
Energy Cost	835.2	782.9	-52.2	-6.3%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	10.9	13.9	2.9	26.8%
Renewable Cost	0.0	428.3	428.3	-
Total Cost	1986.4	2298.3	311.9	15.7%

Table 68: System cost results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

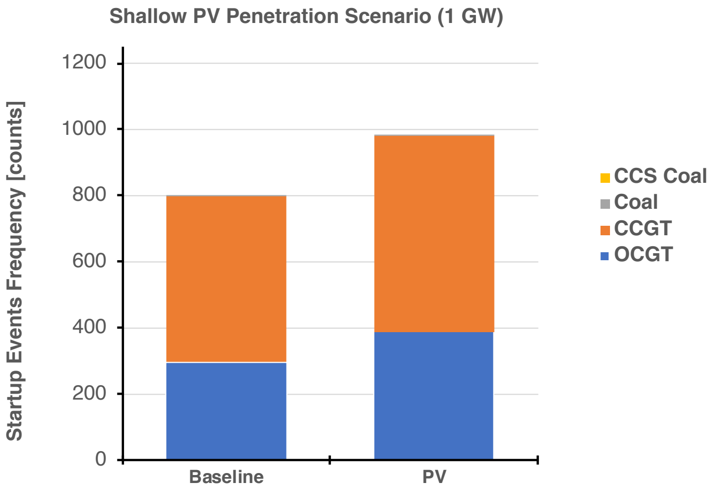

Figure 160: Thermal generation start-up activities results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

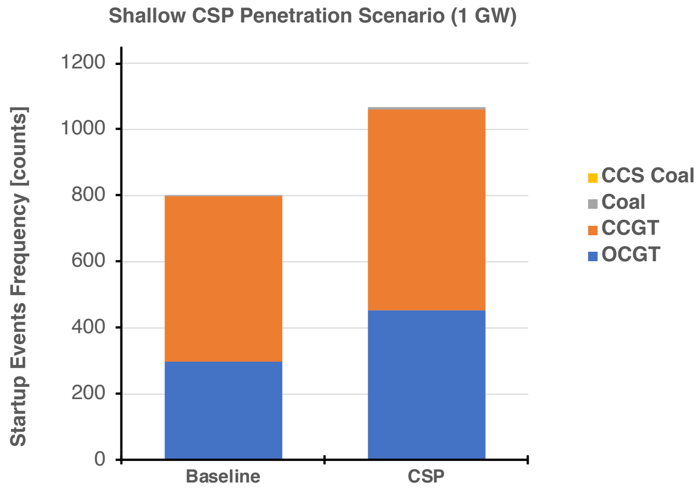

Figure 161: Thermal generation start-up activities results comparison between the baseline model and the CSP technology model under a shallow penetration scenario

	Baseline	PV		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	388	92	31%
CCGT	501	592	91	18%
Coal	4	3	-1	-25%
CCS Coal	0	0	0	-
Total	801	983	182	23%

Table 69: Thermal generation startup activities results comparison between the baseline model and the PV technology model under a shallow penetration scenario (1 GW)

	Baseline	CSP		
	Startups Frequency [Counts]	Startups Frequency [Counts]	Difference [Counts]	Difference [%]
OCGT	296	330	34	11%
CCGT	501	452	-49	-10%
Coal	4	7	3	75%
CCS Coal	0	0	0	-
Total	801	789	-12	-1.5%

Table 70: Thermal generation startup activities results comparison between the baseline model and the CSP technology model under a shallow penetration scenario (1 GW)

Shallow & deep penetration scenarios results

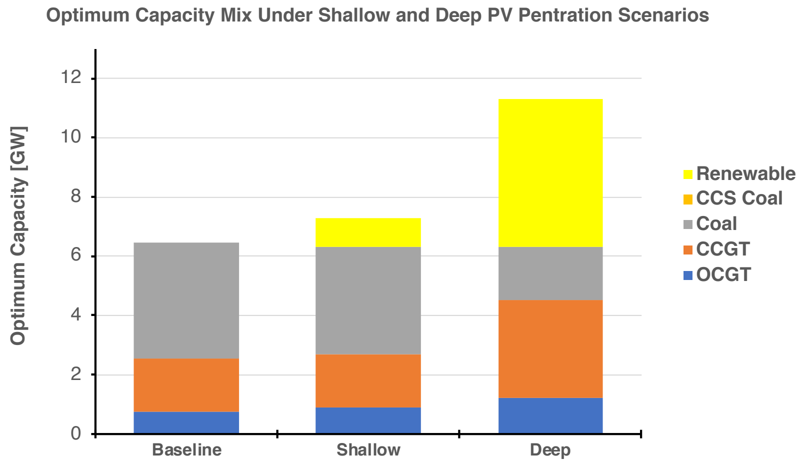

Figure 162: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the PV technology model

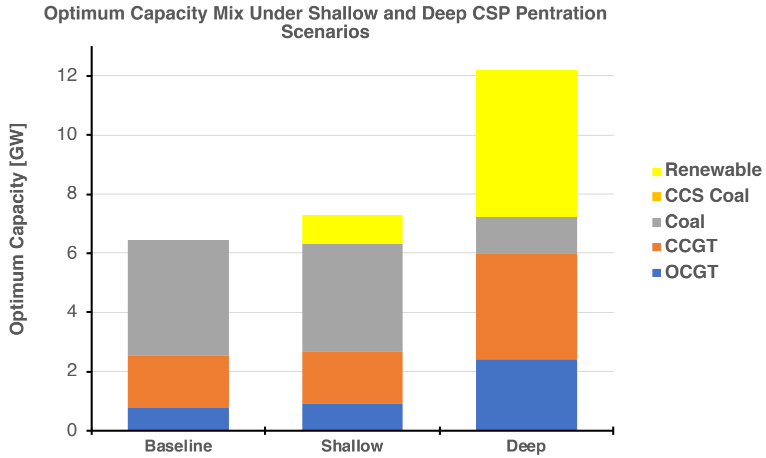

Figure 163: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the CSP technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	1.20	0.30	33%
CCGT	1.80	3.30	1.50	83%
Coal	3.60	1.80	-1.80	-50%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	1.00	5.00	4.00	-
Total Thermal	6.30	6.30	0.00	0%

Table 71: Optimum technology mix results comparison between shallow (1 GW) and deep (5GW) penetration scenarios for the PV technology model

	Shallow Capacity Mix [GW]	Deep Capacity Mix [GW]	Difference [GW]	Difference [%]
OCGT	0.90	2.40	1.50	167%
CCGT	1.80	3.60	1.80	100%
Coal	3.60	1.20	-2.40	-67%
CCS Coal	0.00	0.00	0.00	-
CSP Penetration	1.00	5.00	4.00	-
Total Thermal	6.30	7.20	0.90	14%

Table 72: Optimum technology mix results comparison between shallow (1 GW) and deep (1 GW) penetration scenarios for the CSP technology model

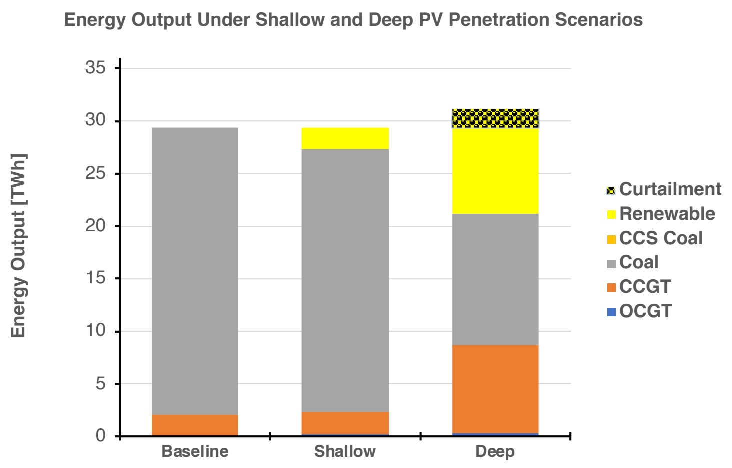

Figure 164: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

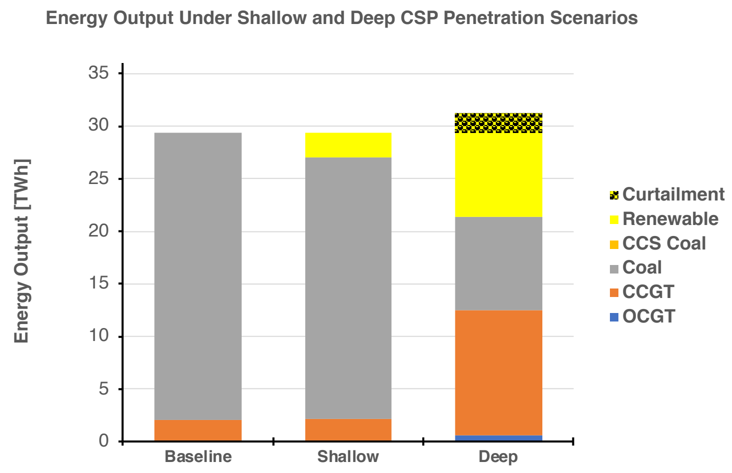

Figure 165: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

	Shallow	Deep		
	Energy Output	Energy Output	Difference	Difference
	[TWh]	[TWh]	[TWh]	[%]
OCGT	0.16	0.30	0.14	84%
CCGT	2.15	8.35	6.21	289%
Coal	25.03	12.51	-12.52	-50%
CCS Coal	0.00	0.00	0.00	-
PV Penetration	2.00	8.17	6.18	-
PV Curtailment	0.00	1.81	1.81	-
Total	29.34	29.34		

Table 73: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow	Deep		
	Energy Output	Energy Output	Difference	Difference
	[TWh]	[TWh]	[TWh]	[%]
OCGT	0.15	0.59	0.45	305%
CCGT	1.97	11.93	9.96	505%
Coal	24.91	8.83	-16.08	-65%
CCS Coal	0.00	0.00	0.00	-
CSP Penetration	2.32	7.99	5.67	-
CSP Curtailment	0.00	1.85	1.85	-
Total Thermal	29.34	29.34		

Table 74: Energy output results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

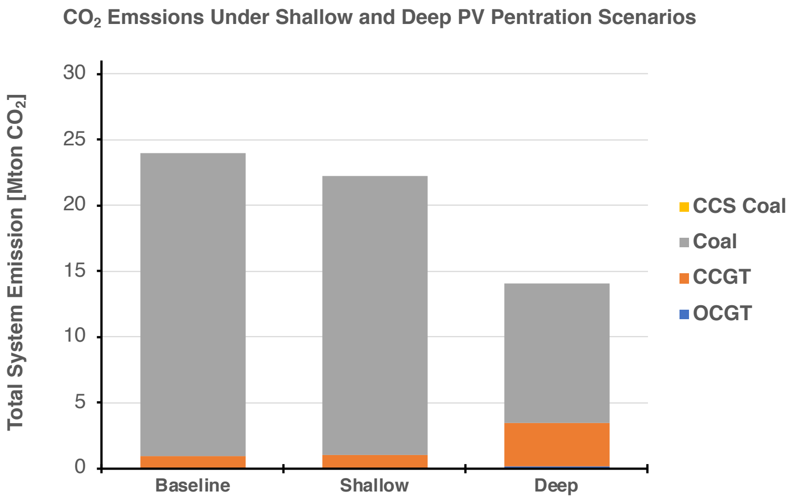

Figure 166: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

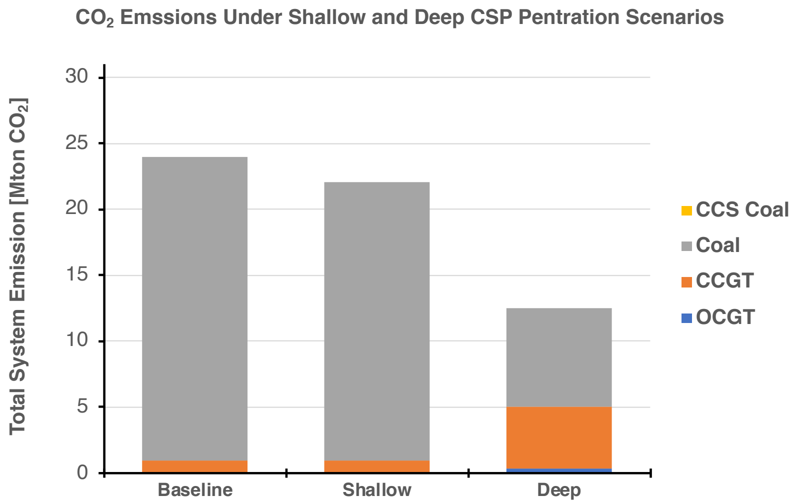

Figure 167: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

	Shallow	Deep		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.10	0.18	0.08	84%
CCGT	0.93	3.28	2.36	255%
Coal	21.22	10.56	-10.65	-50%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	22.24	14.03	-8.21	-37%

Table 75: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow	Deep		
	CO_2 Emissions	CO_2 Emissions	Difference	Difference
	[Mton CO_2]	[Mton CO_2]	[Mton CO_2]	[%]
OCGT	0.09	0.36	0.27	305%
CCGT	0.86	4.62	3.76	437%
Coal	21.11	7.47	-13.64	-65%
CCS Coal	0.00	0.00	0.00	-
Total Thermal	22.06	12.45	-9.60	-44%

Table 76: Carbon emissions results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

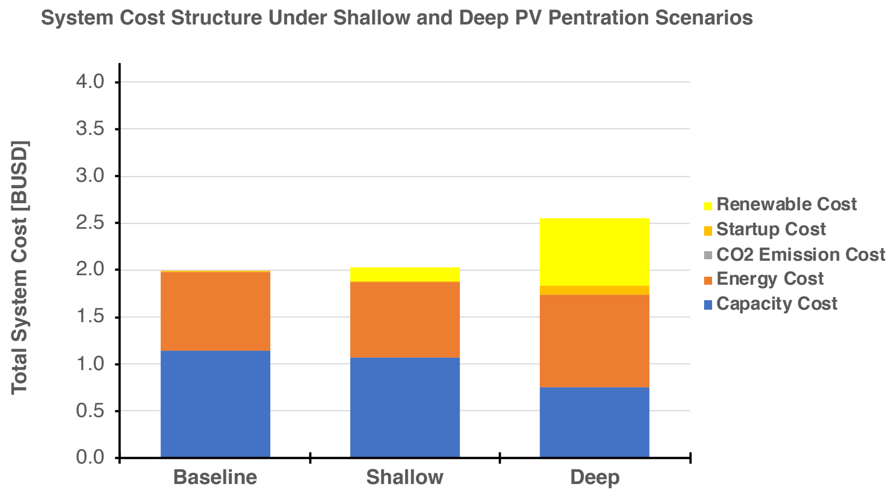

Figure 168: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

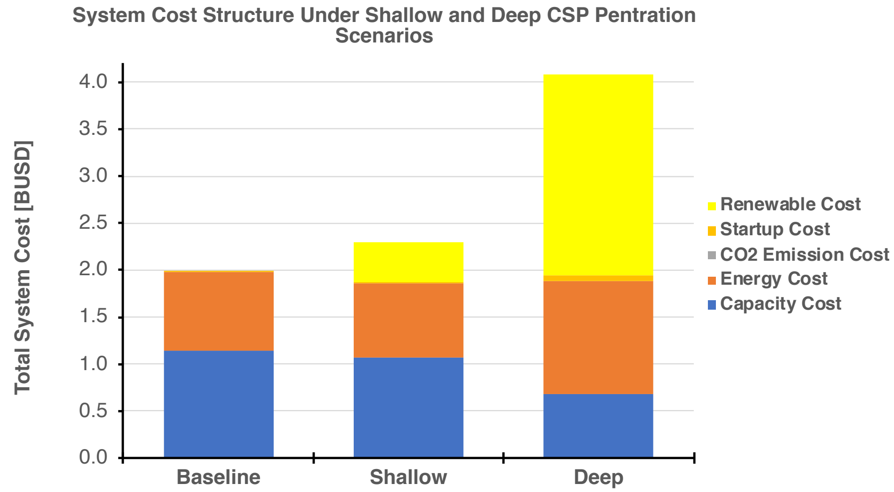

Figure 169: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	749.7	-323.6	-30%
Energy Cost	801.0	984.9	183.9	23%
CO2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	12.9	100.9	88.0	685%
Renewable Cost	142.4	712.1	569.7	400%
Total Thermal	2029.5	2547.4	518.0	25.5%

Table 77: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow Cost [MUSD]	Deep Cost [MUSD]	Difference [MUSD]	Difference [%]
Capacity Cost	1073.2	683.3	-389.9	-36%
Energy Cost	782.9	1199.1	416.2	53%
CO_2 Emission Cost	0.0	0.0	0.0	-
Startup Cost	13.9	60.5	46.6	336%
Renewable Cost	428.3	2141.5	1713.2	400%
Total Thermal	2298.3	4084.4	1786.1	77.7%

Table 78: System cost results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

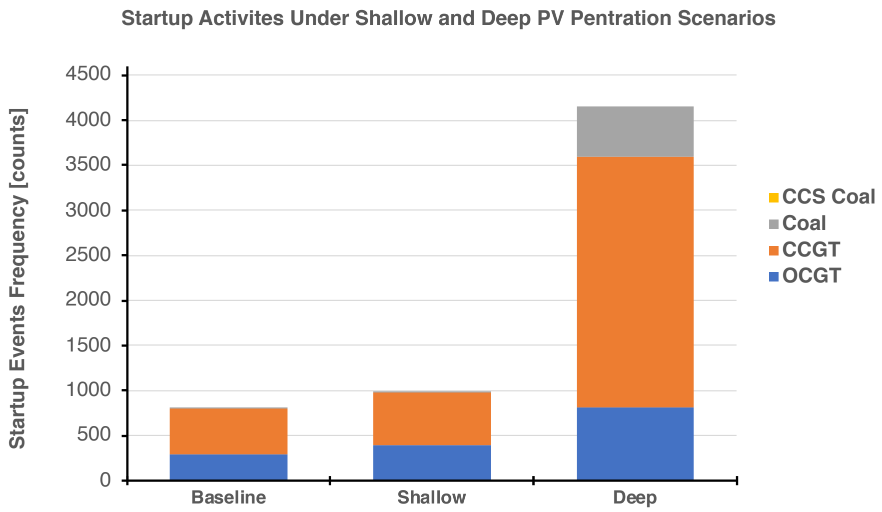

Figure 170: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

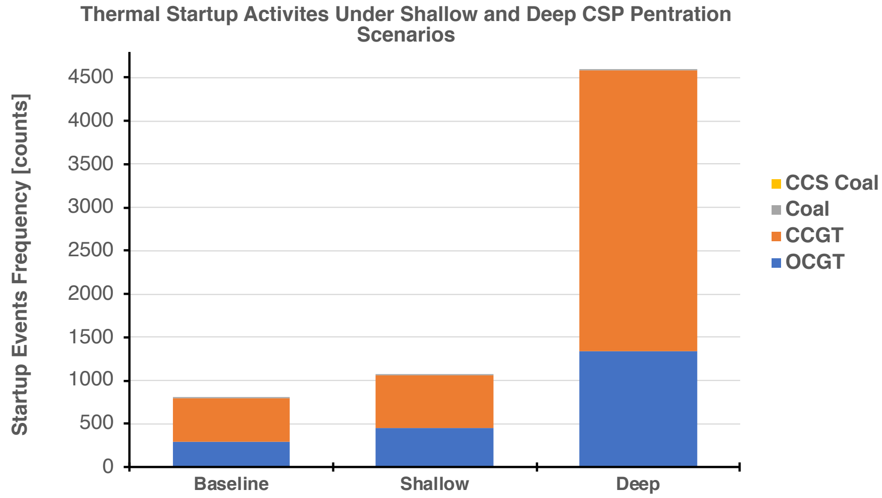

Figure 171: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	388	815	427	110%
CCGT	592	2778	2186	369%
Coal	3	562	559	18633%
CCS Coal	0	0	0	-
Total	983	4155	3172	323%

Table 79: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the PV technology model

	Shallow	Deep		
	Startups Frequency	Startups Frequency	Difference	Difference
	[Counts]	[Counts]	[Counts]	[%]
OCGT	452	1340	888	196%
CCGT	609	3240	2631	432%
Coal	7	4	-3	-43%
CCS Coal	0	0	0	-
Total	1068	4584	3516	329%

Table 80: Thermal generation startup activities results comparison between shallow (1 GW) and deep (5 GW) penetration scenarios for the CSP technology mode

APPENDIX B

MODELLING NOTES

Appendix Overview

In this appendix. we include selected GAMS codes and routines used to carry out the simulation work of the thesis. In addition, we include selected GAMS codes used to automate the prepressing of the input data and postprocessing of the simulation results.

```
$Ontext
==========================================================================================
The core programs and routines of the Screening Curve (SC) and Unit Commitment (UC) models

The unit commitment model is based on the clustering formualtion. The coded program is loosely
based on Palmintier BS, Webster MD. Heterogeneous Unit Clustering for Efficient Operational
Flexibility Modeling. IEEE Transactions on Power Systems. 2014

==========================================================================================
$Offtext

*=========================================================================================
* Definitions of Sets
*=========================================================================================
SETS
t                          | Time Frame (i.e. hours mins or secs)                /1*8760/
g                          | Conventional Generation Plant or Units
reng                       | Renewable Generation Plants
;

*=========================================================================================
* Declaration of Parameters and Scalars
*=========================================================================================

*-----------------------------------------------------------------------------------------
PARAMETERS
*-----------------------------------------------------------------------------------------
Demand(t)                  | MW              | Demand level                        | Given
DemandEff(t)               | MW              | Effective demand                    | Calculated
PV(t)                      | MW              | PV AC prodcution level              | Given
ExcessPV(t)                | MW              | Excessive PV                        | Calculated
TotalExcessPV              | MW              | Total excessive PV                  | Calculated
CSP(t)                     | MW              | CSP production level                | Calculated
ExcessCSP(t)               | MW              | Excessive Demand                    | Calculated
TotalExcessCSP             | MW              | Total excessive CSP                 | Calculated
HeatRate(g)                | Btu\kWh         | Heatrate of thermal plants          | Given
ThermEfficiency(g)         | %               | Efficiency rate                     | Calculated
Capex(g)                   | USD\kW          | Capital cost                        | Given
CapexAnn(g)                | USD\kW-yr       | Annualized Capitl Cost              | Calculated
OpexFix(g)                 | USD\kW-yr       | Operation Fixed Cost                | Given
TotalFix(g)                | USD\MWh-yr      | Total fixed cost                    | Calculated
OpexVar(g)                 | USD\MWh         | Operating cost                      | Given
FuelCost(g)                | USD\MWh         | Fuel cost                           | Calculated
CarbonCost(g)              | USD\MWh         | Carbon cost                         | Calculated
TotalVar(g)                | USD\MWh         | Operting+Fuel+Carbon                | Calculated
DiscountRate(g)            | %               | Discount rate                       | Given
LifeTime(g)                | Yrs             | Economic lifetime                   | Given
FuelPrice(g)               | USD\MMBTu       | Fuel pries                          | Given
CO2EmissionFactor(g)       | kg\kWh          | Emssions rate                       | Given
TotalDemand                | GWh             | Total system demand                 | Calculated
MaxDemand                  | MW              | Maximum system demand               | Calculated
MinDemand                  | MW              | Maximum system demand               | Calculated
RenCapex(reng)             | USD\kW          | Capital cost                        | Given
RenDiscountRate(reng)      | %               | Discount rate                       | Given
RenLifeTime(reng)          | Yrs             | Economic lifetime                   | Given
RenOpexFix(reng)           | USD\kW-yr       | Operation Fixed Cost                | Given
RenCapexAnn(reng)          | USD\kW-yr       | Annualized Capitl Cost              | Calculated
RenTotalFix(reng)          | USD\MWh-yr      | Total fixed cost                    | Calculated
RenPentPer(reng)           | %               | Penetration level                   | Given
RenInstalledCap(reng)      | MW              | Installed Capacity                  | Calculated
SumPV                      | GWh             | Annual energy produced              | Calculated
SumCSP                     | GWh             | Annual energy produced              | Calculated
Tech(g)                    | Type            | CCGT OCGT CCS_COAL                  | Given
Fuel(g)                    | Type            | Gas Coal Uranuim                    | Given
UnitSize(g)                | MW              | Unit rated capacity                 | Given
MinStableGen(g)            | %               | As % of rated power                 | Given
StartupCost(g)             | USD\MW\Start    | Unit Startup Cost                   | Given
MinUpTime(g)               | h               | Minimum Up hours                    | Given
MinDownTime(g)             | h               | Minimum Down hours                  | Given
a(g)                       | %               | Part-loading cofficient             | Given
b(g)                       | %               | Part-loading cofficient             | Given
c(g)                       | %               | Part-loading cofficient             | Given
FuelCO2EmissionRate(g)     | Kg\MMBTu        | CO2 content of Fuel                 | Given
NoLoadFuel(g)              | P.U.\h          | No-load cofficient tech-specifc     | Given
IncFuel(g)                 | P.U.\MWh        | Incremantal fuel cofficient tech-specifc | Given
NoLoadFuelCost(g)          | USD\hr          | No Load Fuel Cost                   | Calculated
IncrementalFuelCost(g)     | USD\MWh         | Incremental Fuel Cost               | Calculated
NoLoadCarbonEm(g)          | Ton\hr          | No Load Fuel Cost                   | Calculated
IncrementalCarbonEm(g)     | Ton\MWh         | Incremental Fuel Cost               | Calculated
NoLoadCarbonCost(g)        | USD\hr          | No Load Fuel Cost                   | Calculated
IncrementalCarbonCost(g)   | USD\MWh         | Incremental Fuel Cost               | Calculated
*-----------------------------------------------------------------------------------------
SCALARS
*-----------------------------------------------------------------------------------------
GasPrice                   | USD\MMBTu       | Assumed gas price                   | Given
CoalPrice                  | USD\MMBTu       | Assumed coal price                  | Given
GasEmissionFactor          | Kg\MMBTu        | Gas CO2 emission content            | Given
CoalEmissionFactor         | Kg\MMBTu        | Coal CO2 emission content           | Given
CarbonTax                  | USD\MWh         | Assumed CO2 Tax                     | Given
PVPentPer                  | %               | Penetration level as % of total laod | Given
CSPPentPer                 | %               | Penetration level as % of total laod | Given
PVPentAbs                  | MW              | Penetration level                   | Given
CSPPentAbs                 | MW              | Penetration level                   | Given
MinThermalGen              | MW              | Minimum running thermal generation  | Given
SystSpinningReserve        | %               | As % of the total load              | Given
ExtraRenReserve            | %               | As % of the total renewable generation | Given
;

*=========================================================================================
* Values assigment of key parameters
*=========================================================================================

* ---------------------------------------------------------------------------------------
* Fuel prices, tax and emissions information
* ---------------------------------------------------------------------------------------
CarbonTax=                   0;
*-----------------------------
GasPrice=                   10;
*-----------------------------
CoalPrice=                2.19;
*-----------------------------
SystSpinningReserve=       0.2;
*-----------------------------


* ---------------------------------------------------------------------------------------
* Renewable energy penetration and flexibility assumptions
* ---------------------------------------------------------------------------------------
PVPentPer=                 eps;   PVPentAbs=eps;
*-----------------------------
CSPPentPer=                eps;   CSPPentAbs=eps;
*-----------------------------
MinThermalGen=             500;
*-----------------------------


*=========================================================================================
* Data Import Intialisation
*=========================================================================================
$ include Data_Import.gms
$ include Definition_of_Additional_Parameters.gms
*=========================================================================================
```

Figure 172: Selected GAMS code used for implementing the SC and UC models

```
*==================================================================================================
*==================================================================================================
* Definition of Variables, Equations for the Screening Curve Model (SC)
*==================================================================================================
*==================================================================================================

VARIABLES
TotalSysCostSC              | M-USD        | Total system cost                          | Variable
;

POSITIVE VARIABLES
TotalSysVarCostSC           | M-USD        | Total system variable cost                 | Variable
TotalSysFixCostSC           | M-USD        | Total system fixed cost                    | Variable
PowerOutputSC(g,t)          | MW           | Generators power output                    | Variable
InstalledCapacitySC(g)      | MW           | Installed capacity                         | Variable

;
*==================================================================================================
* Definition of Screening Curve Model Equations
*==================================================================================================
EQUATIONS

EqTotalCostSC               | Total cost is the sum of all variable and fixed costs
EqTotalFixedSC              | Total investment and fixed maintenance cost
EqTotalVarCostSC            | Total fuel variable maintance and emission costs
EqDemandSupplyBalSC(t)      | Supply must meet demand at all times
EqCapacityCheckSC(g,t)      | Generators output can not exceed installed capacity at anytime
;
*==================================================================================================
EqTotalCostSC..            TotalSysCostSC =e= (TotalSysFixCostSC + TotalSysVarCostSC);
*--------------------------------------------------------------------------------------------------
EqTotalFixedSC..           TotalSysFixCostSC =e=
                           sum[g, TotalFix(g)*InstalledCapacitySC(g)]/1000000 +
                           sum[reng, RenTotalFix(reng)*RenInstalledCap(reng)]/1000000;
*--------------------------------------------------------------------------------------------------
EqTotalVarCostSC..         TotalSysVarCostSC =e=
                           sum[(t,g), TotalVar(g)*PowerOutputSC(g,t)]/1000000;
*--------------------------------------------------------------------------------------------------
EqCapacityCheckSC(g,t)..   PowerOutputSC(g,t) =l= InstalledCapacitySC(g);
*--------------------------------------------------------------------------------------------------
EqDemandSupplyBalSC(t)..   sum[g,PowerOutputSC(g,t)] =e= DemandEff(t);
*==================================================================================================
model ScreeingCurveModel    /  EqTotalCostSC
                               EqTotalFixedSC
                               EqTotalVarCostSC
                               EqDemandSupplyBalSC
                               EqCapacityCheckSC/;
```

Figure 173: Selected GAMS code used for implementing the SC model

```
*==========================================================================================
* Definition of Variables for the Unit Commitment Model (NLF) Model
*==========================================================================================

VARIABLES

TotalSysCostNLF           | M-USD        | Total system cost                       | Variable
TotalSysVarCostNLF        | M-USD        | Total system variable cost              | Variable
TotalSysFixCostNLF        | M-USD        | Total system fixed cost                 | Variable
PowerOutputNLF(g,t)       | MW           | Generators power output                 | Variable
UnitCountsNLF(g)          | #            | Number of units to be built             | Variable
;

POSITIVE VARIABLES
StartedUnitsNLF(g,t)      | #            | Number of started units                 | Variable
StoppedUnitsNLF(g,t)      | #            | Number of stopped units                 | Variable
;

INTEGER VARIABLES
OnlineUnitsNLF(g,t)       | #            | Number of units to be built             | Variable
;

*==========================================================================================
*==========================================================================================
* Definition of Unit Commitment Model Equations (No-Load Formulation NLF)
*==========================================================================================
*==========================================================================================

EQUATIONS

EqTotalCostNLF            | Total cost is the sum of all variable and fixed costs
EqTotalFixedNLF           | Total investment and fixed maintenance cost
EqTotalVarCostNLF         | Total fuel variable maintance and emission costs
EqDemandSupplyBalNLF(t)   | Supply must be equal demand at all times
EqCapMaxCheckNLF(g,t)     | Generators output can not exceed thier maximum power limits
EqCapMinCheckNLF(g,t)     | Generators output shall exceed minimum loading limits
EqUnitsCheckNLF(g,t)      | Generators numbers can not exceed installed capacity
EqReserveCheckNLF(t)      | Generators must meet reserve requirment
EqStartStopLogicNLF(g,t)  | Generators cannot stop and start simultaneously
EqMinUpTimeNLF(g,t)       | Generators minimum up time constrain
EqMindownTimeNLF(g,t)     | Generators minimum down time constrain
;
*==========================================================================================
*------------------------------------------------------------------------------------------
EqTotalCostNLF..          TotalSysCostNLF =e= (TotalSysFixCostNLF + TotalSysVarCostNLF);
*------------------------------------------------------------------------------------------
EqTotalFixedNLF..         TotalSysFixCostNLF =e=
                          sum[g, TotalFix(g)*UnitCountsNLF(g)*UnitSize(g)]/1000000 +
                          sum[reng, RenTotalFix(reng)*RenInstalledCap(reng)]/1000000;
*------------------------------------------------------------------------------------------
EqTotalVarCostNLF..       TotalSysVarCostNLF =e= sum[(t,g),
                          NoLoadFuelCost(g)*OnlineUnitsNLF(g,t)+
                          IncrementalFuelCost(g)*PowerOutputNLF(g,t)+
                          NoLoadCarbonCost(g)*OnlineUnitsNLF(g,t)+
                          IncrementalCarbonCost(g)*PowerOutputNLF(g,t)+
                          OpexVar(g)*PowerOutputNLF(g,t)+
                          StartupCost(g)* UnitSize(g)* StartedUnitsNLF(g,t)]/1000000;
*------------------------------------------------------------------------------------------
EqCapMaxCheckNLF(g,t)..   PowerOutputNLF(g,t) =l= OnlineUnitsNLF(g,t)*UnitSize(g);
*------------------------------------------------------------------------------------------
EqCapMinCheckNLF(g,t)..   PowerOutputNLF(g,t) =g=
                          OnlineUnitsNLF(g,t)*MinStableGen(g)*UnitSize(g);
*------------------------------------------------------------------------------------------
EqDemandSupplyBalNLF(t).. sum[g,PowerOutputNLF(g,t)] =e= DemandEff(t);
*------------------------------------------------------------------------------------------
EqUnitsCheckNLF(g,t)..    OnlineUnitsNLF(g,t) =l= UnitCountsNLF(g);
*------------------------------------------------------------------------------------------
EqReserveCheckNLF(t)..    sum[g,OnlineUnitsNLF(g,t)* UnitSize(g)] =g=
                          (1+SystSpinningReserve)*DemandEff(t) ;
*------------------------------------------------------------------------------------------
EqStartStopLogicNLF(g,t).. OnlineUnitsNLF(g,t)=e=
                          OnlineUnitsNLF(g,t-1)+ StartedUnitsNLF(g,t)- StoppedUnitsNLF(g,t);
```

```
*------------------------------------------------------------------------------------------
EqMinUpTimeNLF(g,t)..     OnlineUnitsNLF(g,t)
                          =g=
                          StartedUnitsNLF(g,t)   +
                          StartedUnitsNLF(g,t-1)  $ (MinUpTime(g)>1) +
                          StartedUnitsNLF(g,t-2)  $ (MinUpTime(g)>2) +
                          StartedUnitsNLF(g,t-3)  $ (MinUpTime(g)>3) +
                          StartedUnitsNLF(g,t-4)  $ (MinUpTime(g)>4) +
                          StartedUnitsNLF(g,t-5)  $ (MinUpTime(g)>5) +
                          StartedUnitsNLF(g,t-6)  $ (MinUpTime(g)>6) +
                          StartedUnitsNLF(g,t-7)  $ (MinUpTime(g)>7) +
                          StartedUnitsNLF(g,t-8)  $ (MinUpTime(g)>8) +
                          StartedUnitsNLF(g,t-9)  $ (MinUpTime(g)>9) +
                          StartedUnitsNLF(g,t-10) $ (MinUpTime(g)>10)+
                          StartedUnitsNLF(g,t-11) $ (MinUpTime(g)>11);
*------------------------------------------------------------------------------------------
EqMindownTimeNLF(g,t)..   UnitCountsNLF(g) - OnlineUnitsNLF(g,t)
                          =g=
                          StoppedUnitsNLF(g,t)   +
                          StoppedUnitsNLF(g,t-1)  $ (MinDownTime(g)>1) +
                          StoppedUnitsNLF(g,t-2)  $ (MinDownTime(g)>2) +
                          StoppedUnitsNLF(g,t-3)  $ (MinDownTime(g)>3) +
                          StoppedUnitsNLF(g,t-4)  $ (MinDownTime(g)>4) +
                          StoppedUnitsNLF(g,t-5)  $ (MinDownTime(g)>5) +
                          StoppedUnitsNLF(g,t-6)  $ (MinDownTime(g)>6) +
                          StoppedUnitsNLF(g,t-7)  $ (MinDownTime(g)>7) +
                          StoppedUnitsNLF(g,t-8)  $ (MinDownTime(g)>8) +
                          StoppedUnitsNLF(g,t-9)  $ (MinDownTime(g)>9) +
                          StoppedUnitsNLF(g,t-10) $ (MinDownTime(g)>10)+
                          StoppedUnitsNLF(g,t-11) $ (MinDownTime(g)>11);

*==========================================================================================

model UnitCommitmentNoLoadFormulation  / EqTotalCostNLF
                                         EqTotalFixedNLF
                                         EqTotalVarCostNLF
                                         EqCapMaxCheckNLF
                                         EqCapMinCheckNLF
                                         EqDemandSupplyBalNLF
                                         EqUnitsCheckNLF
                                         EqReserveCheckNLF
                                         EqStartStopLogicNLF
                                         EqMinUpTimeNLF
                                         EqMindownTimeNLF
                                         / ;
```

Figure 174: Selected GAMS code used for implementing the UC model

```
$Ontext
=========================================================================================
Filename    :  Post-Processing.gms
Descriptiom :  A file to be used in conjuction with Unit Commitment Model to help compile and
               present the results of the model
=========================================================================================

$Offtext



*========================================================================================
* A) General Parameters and Stats
*========================================================================================
Parameters

TotalDemandEff            | GWh            | Total net demand [residual demand]      | Calculated
TotalPVGen                | GWh            | Yearly generation of 1MW PV [PV profile] | Calculated
EffPV(t)                  | GWh            | PV generation time series [scaled]      | Calculated
EffCSP(t)                 | GWh            | CSP generation time series [scaled]     | Calculated
SumEffPV                  | GWh            | Yearly total PV generation              | Calculated
SumEffCSP                 | GWh            | Yearly total CSP generation             | Calculated
SumSerPV                  | GWh            | Total generation injected to grid       | Calculated
SumSerCSP                 | GWh            | Total generation injected to grid       | Calculated
TotalRenCost              | M-USD          | Total renewable energy cost             | Calculated
ResidualLoadStDev         | MW             | Residual load votalitiy measure (SD)    | Calculated
ResidualLoadStAvrg        | MW             | Residual load average                   | Calculated

;
*========================================================================================

Scalars

n                         | GWh            | Total number of demand values           | Calculated

;

*========================================================================================
* B) Screening curve model
*========================================================================================

PARAMETERS

EnergycostSC              | USD\MWh        | System energy unit cost                 | Calculated
SumInsatlledCapacitySC    | MW             | System's total installed capacity       | Calculated
EnergyServedSC(g)         | GWh            | Energy served per generator             | Calculated
TotalEnergyServedSC       | GWh            | Total energy served by all generators   | Calculated
FuelConsumptionSC(g,t)    | MMBTU          | Fuel Consumption (Instant)              | Calculated
CO2EmissionSC(g,t)        | Ton            | CO2Emission (Instant)                   | Calculated
GenFuelConsumptionSC(g)   | MMBTU          | Fuel Consumption per gen                | Calculated
GenCO2EmissionSC(g)       | Ton            | CO2Emission per gen                     | Calculated
GenCO2EmissionPercSC(g)   | %              | CO2Emission per gen as % of total       | Calculated
SystemCO2EmissionSC       | kg\MWh         | System Emission intensity               | Calculated
TotalCO2EmissionSC        | Ton            | Total System Emission                   | Calculated
GenCapacityCostSC(g)      | M-USD          | Total Capacity Cost                     | Calculated
GenEnergyCostSC(g)        | M-USD          | Total Energy Cost                       | Calculated
GenEmissionCostSC(g)      | M-USD          | Total Emission Cost                     | Calculated
EnergyServedPercSC(g)     | %              | Total energy served                     | Calculated
LoadFactorSC(g)           | %              | Average utilisation factor              | Calculated
InstalledCapPercSC(g)     | %              | Installed capacity as % of total        | Calculated
EnergyServedPerSC(g)      | %              | Energy served as % of total             | Calculated
;

* Scenarios related parameters
*========================================================================================
PARAMETERS

EnergycostchangeSC        | %              | System energy unit cost change          | Calculated
TotalSysCostChangeSC      | %              | Total system cost change                | Calculated
TotSystemCapCostChangeSC  | %              | Total system capacity cost change       | Calculated
TotalCO2EmissionChangeSC  | %              | Total System Emission change            | Calculated

;
*========================================================================================


*========================================================================================
* C) Unit Commitment (No Load Formulation)
*========================================================================================

PARAMETERS

EnergycostNLF             | USD\MWh        | System energy unit cost                 | Calculated
InstalledCapacityNLF(g)   | MW             | Installed capacity per generator type   | Calculated
SumInsatlledCapacityNLF   | MW             | Installed capacity per generator type   | Calculated
EnergyServedNLF(g)        | GWh            | Energy served by each generator         | Calculated
TotalEnergyServedNLF      | GWh            | Total energy served by all generators   | Calculated
InstalledCapPercNLF(g)    | %              | Installed capacity as % of total        | Calculated
EnergyServedPerNLF(g)     | %              | Energy served as % of total             | Calculated
LoadFactorNLF(g)          | %              | Average utilisation factor              | Calculated
CO2EmissionNLF(g,t)       | Ton            | CO2Emission per gen (instant)           | Calculated
GenCO2EmissionNLF(g)      | Ton            | CO2Emission per gen                     | Calculated
GenCO2EmissionPercNLF(g)  | %              | CO2Emission per gen as % of total       | Calculated
SystemCO2EmissionNLF      | kg\MWh         | System Emission intensity               | Calculated
GenCapacityCostNLF(g)     | Ton            | Total System Emission                   | Calculated
GenEnergyCostNLF(g)       | M-USD          | Total Energy Cost                       | Calculated
GenEmissionCostNLF(g)     | M-USD          | Total Emission Cost                     | Calculated
TotalCO2EmissionNLF       | Ton            | Total System Emission                   | Calculated
GenCountsNLF(g)           | N.O.           | Number of generators built              | Calculated
GenStartupCostNLF(g)      | M-USD          | Total startup c ost                     | Calculated
GenStartupsCountsNLF(g)   | N.O.           | Total startup cost                      | Calculated
GenStopsCountsNLF(g)      | N.O.           | Total startup cost                      | Calculated
SpinningRerseveNLF(g,t)   | MW             | Spinning reserve                        | Calculated
GenSpinReserveNLF(g)      | MW             | Spinning reserve                        | Calculated
GenSpinReservePercNLF(g)  | %              | Spinning reserve as % of total          | Calculated
TotalSpinningReserveNLF   | MW             | Total System Spinning reserve           | Calculated
PlantOnBarNLF(t)          | MW             | Total Plant on Bar                      | Calculated
Starts(g,t)               | MW             | Starts per type                         | Calculated
;


* Scenarios related parameters
*========================================================================================
PARAMETERS

EnergycostchangeNLF       | %              | System energy unit cost change          | Calculated
TotalSysCostChangeNLF     | %              | Total system cost change                | Calculated
TotSystemCapCostChangeNLF | %              | Total system capacity cost change       | Calculated
TotalCO2EmissionChangeNLF | %              | Total System Emission change            | Calculated


;
```

Figure 175: Selected GAMS code used in conjunction with the SC and UC models to help postprocess the main results of the model

```
$Ontext
=========================================================================================
Filename    :  Excel_Scenario_Report.gms
Description :  A file to be used in conjuction with Unit Commitment Model to help compile and
               present the results of the model
=========================================================================================
$Offtext


*========================================================================================
* A) Screening curve model
*========================================================================================

$OnDotL
*========================================================================================
* 1. Descriptve Stats
*========================================================================================
SolutionSummartySC("System energy unit cost","USD\MWh",""            ,s)       = EnergycostSC;
SolutionSummartySC("System Emission intensity","kg\MWh",""            ,s)     = SystemCO2EmissionSC;
SolutionSummartySC("System's total installed capacity","MW",""       ,s)   = SumInsatlledCapacitySC;
SolutionSummartySC("Peak Load","MW",""       ,s)                           = MaxDemand;
SolutionSummartySC("Minimum Load","MW",""       ,s)                        = MinDemand;
SolutionSummartySC("Total Load","GWh",""       ,s)                         = TotalDemand;
SolutionSummartySC("Energy served by thermal generation","GWh",""       ,s)   = TotalEnergyServedSC;
*---------------------------------------------------------------------------------------»
-
SolutionSummartySC("Total System Cost","M-USD",""       ,s)                = TotalSysCostSC;
if
((TotalSysCostSC-SolutionSummartySC("Total System Cost","M-USD","","S001"))=0,
SolutionSummartySC("Total System Cost Change","M-USD",""       ,s)= eps;
else
SolutionSummartySC("Total System Cost Change","M-USD",""       ,s)=
(TotalSysCostSC-SolutionSummartySC("Total System Cost","M-USD","","S001"))/
         SolutionSummartySC("Total System Cost","M-USD","","S001");
);

*---------------------------------------------------------------------------------------»
-
SolutionSummartySC("Total System Emissions","M-Ton",""       ,s)           = TotalCO2EmissionSC;
if
((TotalCO2EmissionSC-SolutionSummartySC("Total System Emissions","M-Ton","","S001"))=0,
SolutionSummartySC("Total System Emissions reduction","M-Ton",""       ,s)= eps;
else
SolutionSummartySC("Total System Emissions reduction","M-Ton",""       ,s)=
-(TotalCO2EmissionSC-SolutionSummartySC("Total System Emissions","M-Ton","","S001"))/
         SolutionSummartySC("Total System Emissions","M-Ton","","S001");
);
*========================================================================================
* 2. Scenario Details
*========================================================================================
SolutionSummartySC("Natural Gas Price","USD/MMBtu",""       ,s)            = GasPrice;
SolutionSummartySC("Coal Price","USD/MMBtu",""       ,s)                   = CoalPrice;
SolutionSummartySC("Carbon Floor Price","USD/Ton",""       ,s)             = CarbonTax;
*========================================================================================
* 3. Renewable Stats
*========================================================================================
SolutionSummartySC("Penetration level as % of total laod ","%","PV"     ,s)     = PVPentPer;
SolutionSummartySC("Penetration level as % of total laod ","%","CSP"    ,s)     = CSPPentPer;
SolutionSummartySC("Energy generated","GWh","PV"    ,s)                    = SumEffPV;
SolutionSummartySC("Energy generated","GWh","CSP"    ,s)                   = SumEffCSP;
SolutionSummartySC("Energy served (injected to the grid)","GWh","PV"    ,s)     = SumSerPV;
SolutionSummartySC("Energy served (injected to the grid)","GWh","CSP"    ,s)    = SumSerCSP;
SolutionSummartySC("Energy spilled (curtailed)","GWh","PV"    ,s)          = TotalExcessPV;
SolutionSummartySC("Energy spilled (curtailed)","GWh","CSP"    ,s)         = TotalExcessCSP;
*========================================================================================
* 4.Capacity, Energy and Emissions
*========================================================================================
SolutionSummartySC("Optimum Capacity","MW",g,            s)             = InstalledCapacitySC(g);
SolutionSummartySC("Optimum Capacity","MW","Total",      s)       = sum(g,InstalledCapacitySC(g));
SolutionSummartySC("Optimum Capacity","%",g,            s)              = InstalledCapPercSC(g);
SolutionSummartySC("Energy served per generator","GWh",g,            s)       = EnergyServedSC(g);
SolutionSummartySC("Energy served per generator","GWh","Total"      ,s)= sum(g,EnergyServedSC(g));
SolutionSummartySC("Energy served per generator","%",g,              s)     = EnergyServedPerSC(g);
SolutionSummartySC("Fleet Utilization Factor","%",g,                 s)       = LoadFactorSC(g);
SolutionSummartySC("CO2 Emission Generated","Ton",g,                 s      = GenCO2EmissionSC(g);
SolutionSummartySC("CO2 Emission Generated","Ton","Total",      s)    = sum(g,GenCO2EmissionSC(g));
SolutionSummartySC("CO2 Emission Generated","%",g,             s)        = GenCO2EmissionPercSC(g);
SolutionSummartySC("Number of plants","n",g,                   s)               = eps;
SolutionSummartySC("Number of plants","n","Total",             s)               = eps;
*========================================================================================
* 5. Conventional generation costs
*========================================================================================
SolutionSummartySC("Capacity Cost","M-USD",g,            s)                 = GenCapacityCostSC(g);
SolutionSummartySC("Capacity Cost","M-USD","Total",      s)          = sum(g,GenCapacityCostSC(g));
SolutionSummartySC("Energy Cost","M-USD",g,            s)            = max(GenEnergyCostSC(g),eps);
SolutionSummartySC("Energy Cost","M-USD","Total",      s)              = sum(g,GenEnergyCostSC(g));
SolutionSummartySC("CO2 Emission Cost","M-USD",g,                s)       = GenEmissionCostSC(g);
SolutionSummartySC("CO2 Emission Cost","M-USD","Total",      s)      = sum(g,GenEmissionCostSC(g));
SolutionSummartySC("Startup Cost","M-USD",g,                s)                  = eps;
SolutionSummartySC("Startup Cost","M-USD","Total",      s)                      = eps;
*========================================================================================
* 6. Renewable Energy Cost
*========================================================================================
SolutionSummartySC("Renewable Capacity Cost","M-USD","Total",      s)          = TotalRenCost;
*========================================================================================
* 6.  Flexibility parameters
*========================================================================================
SolutionSummartySC("Spinning reserve as percentage of total load","%","Total",s)
         = SystSpinningReserve;
SolutionSummartySC("Startups counts","n",g,               s)                = eps;
SolutionSummartySC("Startups counts","n","Total",         s)                = eps;
SolutionSummartySC("Stops counts","n",g,                  s)                = eps;
SolutionSummartySC("Stops counts","n","Total",            s)                = eps;
SolutionSummartySC("Minimum loading","%",g,               s)                = eps;
SolutionSummartySC("Minimum thermal generation","MW",""      ,s)            = MinThermalGen;
SolutionSummartySC("Spinning reserve contribution","%",g,    s)             = eps;
*========================================================================================
* 7.  Additional Calculations
*========================================================================================
SolutionSummartySC("Penetration levels","%","PV"    ,s)    = PVPentAbs;
SolutionSummartySC("Penetration levels","%","CSP"   ,s)    = CSPPentAbs;
SolutionSummartySC("Penetration level as % of total load ","%","PV"    ,s)    =
         SumSerPV/10/TotalDemand;
SolutionSummartySC("Penetration level as % of total load ","%","CSP"   ,s)    =
         SumSerCSP/10/TotalDemand;
SolutionSummartySC("PV  Energy Generation as % of total load ","%","PV"    ,s)
         = SumEffPV/10/TotalDemand;
SolutionSummartySC("CSP Energy Generation as % of total load ","%","CSP"   ,s)
         = SumEffCSP/10/TotalDemand;
SolutionSummartySC("Residual Demand Votality Index","MW","SD"   ,s)
         = ResidualLoadStDev;



*SolutionSummarty("___________________________","______","______"  ,s)  =0.0000000000000000001;
```

Figure 176: Selected GAMS code used in conjunction with the SC model to help compile and present the results of the model in an excel format

```
*==========================================================================================
* 1. Descriptve Stats
*==========================================================================================
SolutionSummartyNLF("System energy unit cost","USD\MWh",""            ,s)          = EnergycostNLF;
SolutionSummartyNLF("System Emission intensity","kg\MWh",""            ,s)  = SystemCO2EmissionNLF;
SolutionSummartyNLF("System's total installed capacity","MW",""       ,s)= SumInsatlledCapacityNLF;
SolutionSummartyNLF("Peak Load","MW",""      ,s)                              = MaxDemand;
SolutionSummartyNLF("Minimum Load","MW",""      ,s)                           = MinDemand;
SolutionSummartyNLF("Total Load","GWh",""      ,s)                            = TotalDemand;
SolutionSummartyNLF("Energy served by thermal generation","GWh",""      ,s)= TotalEnergyServedNLF;
*------------------------------------------------------------------------------------------
SolutionSummartyNLF("Total System Cost","M-USD",""      ,s)                   = TotalSysCostNLF;
if
((TotalSysCostNLF-SolutionSummartyNLF("Total System Cost","M-USD","","S001"))=0,
SolutionSummartyNLF("Total System Cost Change","M-USD",""      ,s)= eps;
else
SolutionSummartyNLF("Total System Cost Change","M-USD",""      ,s)=
(TotalSysCostNLF-SolutionSummartyNLF("Total System Cost","M-USD","","S001"))/
SolutionSummartyNLF("Total System Cost","M-USD","","S001");
);
*------------------------------------------------------------------------------------------
SolutionSummartyNLF("Total System Emissions","M-Ton",""      ,s)              =
TotalCO2EmissionNLF;
if
((TotalCO2EmissionNLF-SolutionSummartyNLF("Total System Emissions","M-Ton","","S001"))=0,
SolutionSummartyNLF("Total System Emissions reduction","M-Ton",""      ,s)= eps;
else
SolutionSummartyNLF("Total System Emissions reduction","M-Ton",""      ,s)=
-(TotalCO2EmissionNLF-SolutionSummartyNLF("Total System Emissions","M-Ton","","S001"))/
SolutionSummartyNLF("Total System Emissions","M-Ton","","S001");
);

*==========================================================================================
* 2. Scenario Details
*==========================================================================================
SolutionSummartyNLF("Natural Gas Price","USD/MMBtu",""      ,s)               = GasPrice;
SolutionSummartyNLF("Coal Price","USD/MMBtu",""      ,s)                      = CoalPrice;
SolutionSummartyNLF("Carbon Floor Price","USD/Ton",""      ,s)                = CarbonTax;
*==========================================================================================
* 3. Renewable Stats
*==========================================================================================
SolutionSummartyNLF("Penetration level as % of total laod ","%","PV"    ,s)    = PVPentPer;
SolutionSummartyNLF("Penetration level as % of total laod ","%","CSP"   ,s)    = CSPPentPer;
SolutionSummartyNLF("Energy generated","GWh","PV"   ,s)                        = SumEffPV;
SolutionSummartyNLF("Energy generated","GWh","CSP"   ,s)                       = SumEffCSP;
SolutionSummartyNLF("Energy served (injected to the grid)","GWh","PV"   ,s)    = SumSerPV;
SolutionSummartyNLF("Energy served (injected to the grid)","GWh","CSP"   ,s)   = SumSerCSP;
SolutionSummartyNLF("Energy spilled (curtailed)","GWh","PV"   ,s)              = TotalExcessPV;
SolutionSummartyNLF("Energy spilled (curtailed)","GWh","CSP"   ,s)             = TotalExcessCSP;
*==========================================================================================
* 4.Capacity, Energy and Emissions
*==========================================================================================
SolutionSummartyNLF("Optimum Capacity","MW",g,           s)            = InstalledCapacityNLF(g);
SolutionSummartyNLF("Optimum Capacity","MW","Total",      s)     = sum(g,InstalledCapacityNLF(g));
SolutionSummartyNLF("Optimum Capacity","%",g,           s)             = InstalledCapPercNLF(g);
SolutionSummartyNLF("Energy served per generator","GWh",g,           s)      = EnergyServedNLF(g);
SolutionSummartyNLF("Energy served per generator","GWh","Total"  ,s)  = sum(g,EnergyServedNLF(g));
SolutionSummartyNLF("Energy served per generator","%",g,          s)      = EnergyServedPerNLF(g);
SolutionSummartyNLF("Fleet Utilization Factor","%",g,           s)           = LoadFactorNLF(g);
SolutionSummartyNLF("CO2 Emission Generated","Ton",g,            s)      = GenCO2EmissionNLF(g);
SolutionSummartyNLF("CO2 Emission Generated","Ton","Total",  s)     = sum(g,GenCO2EmissionNLF(g));
SolutionSummartyNLF("CO2 Emission Generated","%",g,          s)     = GenCO2EmissionPercNLF(g);
SolutionSummartyNLF("Number of plants","n",g,              s)      = max(UnitCountsNLF(g),eps);
SolutionSummartyNLF("Number of plants","n","Total",        s)        = sum(g,UnitCountsNLF(g));
*==========================================================================================
* 5. Conventional generation costs
*==========================================================================================
SolutionSummartyNLF("Capacity Cost","M-USD",g,           s)             = GenCapacityCostNLF(g);
SolutionSummartyNLF("Capacity Cost","M-USD","Total",      s)       = sum(g,GenCapacityCostNLF(g));
SolutionSummartyNLF("Energy Cost","M-USD",g,          s)         = max(GenEnergyCostNLF(g),eps);
SolutionSummartyNLF("Energy Cost","M-USD","Total",      s)           = sum(g,GenEnergyCostNLF(g));
SolutionSummartyNLF("CO2 Emission Cost","M-USD",g,            s)      = GenEmissionCostNLF(g);
SolutionSummartyNLF("CO2 Emission Cost","M-USD","Total",      s)   = sum(g,GenEmissionCostNLF(g));
SolutionSummartyNLF("Startup Cost","M-USD",g,                s)          = GenStartupCostNLF(g);
SolutionSummartyNLF("Startup Cost","M-USD","Total",      s)         = sum(g,GenStartupCostNLF(g));
*==========================================================================================
* 6. Renewable Energy Cost
*==========================================================================================
SolutionSummartyNLF("Renewable Capacity Cost","M-USD","Total",      s)          = TotalRenCost;
*==========================================================================================
* 6.  Flexibility parameters
*==========================================================================================
SolutionSummartyNLF("Spinning reserve as percentage of total load","%","Total",s)
= SystSpinningReserve;
SolutionSummartyNLF("Startups counts","n",g,                s)        = GenStartupsCountsNLF(g);
SolutionSummartyNLF("Startups counts","n","Total",            s) = sum(g,GenStartupsCountsNLF(g));
SolutionSummartyNLF("Stops counts","n",g,                     s)          = GenStopsCountsNLF(g);
SolutionSummartyNLF("Stops counts","n","Total",               s)    = sum(g,GenStopsCountsNLF(g));
SolutionSummartyNLF("Minimum loading","%",g,                  s)               = MinStableGen(g);
SolutionSummartyNLF("Minimum thermal generation","MW",""     ,s)                 = MinThermalGen;
SolutionSummartyNLF("Spinning reserve contribution","%",g,    s)       = GenSpinReservePercNLF(g);
*==========================================================================================
* 7.  Additional Calculations
*==========================================================================================
SolutionSummartyNLF("Penetration levels","%","PV"    ,s)    = PVPentAbs;
SolutionSummartyNLF("Penetration levels","%","CSP"   ,s)    = CSPPentAbs;
SolutionSummartyNLF("Penetration level as % of total load ","%","PV"    ,s) =
SumSerPV/10/TotalDemand;
SolutionSummartyNLF("Penetration level as % of total load ","%","CSP"   ,s)
=SumSerCSP/10/TotalDemand;
SolutionSummartyNLF("PV  Energy Generation as % of total load ","%","PV"    ,s)
=SumEffPV/10/TotalDemand;
SolutionSummartyNLF("CSP Energy Generation as % of total load ","%","CSP"   ,s)
=SumEffCSP/10/TotalDemand;
SolutionSummartyNLF("Residual Demand Votality Index","MW","SD"   ,s)= ResidualLoadStDev;
*==========================================================================================

*==========================================================================================
* D) Time Based
*==========================================================================================

ResidualLoad("Residual Demand","MWh",t,s)                              = DemandEff(t);
SystemLoad("Residual Demand","MWh",t,s)                                = Demand(t);
PVGenerated("PV Energy generated","GWh",t,s)                           = SumEffPV;
CSPGenerated("CSP Energy generated","GWh",t,s)                         = SumEffCSP;
PVConsumed("PV Energy served (injected to the grid)","GWh",t,s)        = SumSerPV;
CSPConsumed("CSP Energy served (injected to the grid)","GWh",t,s)      = SumSerCSP;
PVSpilled("PV Energy spilled (curtailed)","GWh",t,s)                   = TotalExcessPV;
CSPSpilled("CSP Energy spilled (curtailed)","GWh",t,s)                 = TotalExcessCSP;
PlantOnBar("Plant On Bar","MW",t,s)                                    = PlantOnBarNLF(t);
PlantOnBarperType("Plant On Bar",g,t,s)                                = max(OnlineUnitsNLF(g,t),eps);
StartsCountsPerType("Starts",g,t,s)                                    = StartedUnitsNLF(g,t)
```

Figure 177: Selected GAMS code used in conjunction with the UC model to help compile and present the results of the model in an excel format

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