# Mitigating risk of emissions in energy planning and the operational implications

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## ABSTRACT

There is increasing imperative to reduce emissions from global energy systems to avoid catastrophic climate impacts. Much of the work on how countries can meet their emissions reduction targets assumes perfect knowledge of the emissions from energy technologies. This dissertation first implements a model that takes into account emissions uncertainties and evaluates the impacts that uncertainty has on the long term system build out. It is found that an early build out of wind energy reduces the risk of exceeding emissions targets. Given the requirement of high penetrations of wind energy for reducing emissions risk, the second part of this dissertation evaluates the impact that high penetrations of wind energy have on system operations, and the value that storage and dispatchable loads can provide. Finally, this dissertation evaluates the impact that synchronous generation constraints have on system operation, and the optimal operation of storage. All three models are applied to the Alberta, Canada electricity system as a case study.

It is found that building out wind five years earlier for Alberta decreases the risk of missing emissions targets. Allowing nuclear energy in the system results in a lower overall cost and a reduced risk of missing emissions targets. To evaluate the impact that an early and large build out of wind has on the system a medium term model is developed that incorporates curtailment costs into the system operation. This shows that storage and dispatchable loads have the potential to reduce curtailment in the system and that including curtailment costs increases the value provided by between 10 and 60%. The value provided by storage for Alberta is very high at small installed capacities and diminishes with increased capacity while the value provided by dispatchable loads has a much more consistent value at different installed capacities. Finally, when the instantaneous penetration of renewable energy in the system is restricted, it is found that storage for integration of wind generation does not operate in a pre-defined manner but switches between peak shaving and wind shifting depending on the wind resource available in any given week.

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## NOMENCLATURE

| | |
|---|---|
| $a_{i,j}$ | Performance parameters of technologies in the model. |
| $b_i$ | Limits on installed capacity and operating parameters. |
| $c_j$ | Vector of all cost parameters considered by the model. |
| $BC_j$ | Balancing costs as defined by Hirth et al. |
| $c_j^c$ | Curtailment cost per unit energy for generator *j* |
| $C(x_j)$ | Total cost of system for a given decision vector, $x_j$. |
| $C(x_j{}^*)$ | Total minimum cost of the system as determined by deterministic optimization method. |
| $C_C$ | Total curtailment cost |
| $CF_{i,j}$ | Capacity factor for generator *j* in time slice *i* |
| $C_T$ | Total system cost with curtailment costs included |
| $D_i$ | Adjusted demand in time slice *i* to model dispatchable load |
| $D_i^0$ | Initial demand in time slice *i* |
| $E_{i,j}^A$ | Energy available from generator *j* in time slice *i* |
| $E_{i,j}^C$ | Amount of energy constrained for generator *j* in time slice *i* |
| $E_i^D$ | Total demand in each time slice, *i* |
| $E_{i,j}^G$ | Total generation for generator *j* in each time slice *i* |
| $GC_j$ | Grid related costs as defined by Hirth et al. |
| $i$ | Index of time slices in the model |
| $IC$ | Installed capacity of storage |
| $I_j$ | Installed capacity of generator *j* |
| $j$ | Index of decisions (generators) in the model |
| $P$ | Amount of energy the dispatchable load must provide |
| $P_i$ | Power of the dispatchable load in time slice *i* |
| $PC_j$ | Profile costs as defined by Hirth et al. |
| $\bar{r}_j$ | Mean, or expected, value of the uncertain parameter. |
| $r_j(\omega_n)$ | Random sample of the uncertain parameter. |
| $f$ | Risk premium. The extra amount that society is willing to pay to minimize risk. |

| | |
|---|---|
| $F(x_j)$ | Sum of the system cost, $C(x_j)$, and weighted risk. |
| $MaxIC$ | Maximum installed capacity of storage |
| $MaxR_{in}$ | Maximum charge rate for storage |
| $MaxR_{out}$ | Maximum discharge rate for storage |
| N | Number of samples to consider when determining the risk vector. |
| R | Power produced by a given technology in a given time slice |
| $R_{in}$ | Rate of charging of storage |
| $R_{out}$ | Rate of discharging of storage |
| $Ramp_{Down}$ | Amount a given generator can ramp down between time slices |
| $Ramp_{Up}$ | Amount a given generator can ramp up between time slices |
| $R_{max}$ | The maximum risk allowable. |
| $R(x_j, \omega_n)$ | Risk for a given decision, $x_j$, for a single random draw from the probability space, $\omega_n$. |
| $R(x_j)$ | Total risk for a given decision vector, $x_j$. |
| $\rho_r$ | Risk aversion parameter. Used to convert risk into an equivalent cost. |
| $S(t)$ | Storage starting level for a given time slice |
| $S_V$ | Size of infrastructure investment |
| $S_{min}$ | Minimum storage level |
| $SG_{req}$ | Percentage of synchronous generation required in each time slice |
| $t$ | Index to indicate the time slice |
| $\Delta t$ | Size of a given time slice |
| $v$ | Specific value of infrastructure investment to the system, scaled to size of infrastructure investment |
| $v_C$ | Component of the specific value attributable to the inclusion of curtailment cost |
| $V$ | Value of an infrastructure investment to the system |
| $x_j$ | Vector of installed capacities and operating parameters. |
| $x_j^*$ | Optimal (lowest cost) decision vector as identified by deterministic optimization method. |

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10 minute wind, load and hydro data for Alberta for 2011 through 2016 was kindly provided by the Alberta Electricity System Operator. The work Malcolm MacRae did to gather and provide this data made the work on synchronous generation possible.

I am grateful to Pauline Shepherd and Susan Walton for the administrative support.

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Finally, the computing facilities of Westgrid (www.westgrid.ca) and Compute Canada (www.computecanada.ca) were invaluable, as was the GNU Parallel[1] software for running many serial runs in parallel on full nodes of the Compute Canada cluster.

[1] Tange O. GNU Parallel: The Command-Line Power Tool. Login USENIX Mag 2011;2011:42–7.

## DEDICATION

I dedicate this dissertation to the memory of my father, Johannes Henri Gaston Niet. He challenged and inspired me and, without his belief in me, I would never have reached the point of starting, let alone completing, a Ph.D.

# 1. INTRODUCTION

There is clear evidence that human caused carbon dioxide and other climate changing emissions need to be reduced to prevent catastrophic climate impacts. Under the Conference of the Parties 21 (COP21) agreement, 195 countries affirmed their intentions to put in place measures to meet global emissions targets. These countries have provided the United Nations Framework Convention on Climate Change (UNFCCC) with Nationally Determined Contributions (NDCs) committing to specific emissions reductions post 2020 [1]. Much of the work on how countries intend to meet these NDCs is performed using optimization models that are deterministic and assume that newly installed technologies will have performance characteristics similar to existing technologies or that assume exogenous cost reductions [2]. These assumptions are questionable for a number of reasons. For renewable energy sources, sites with the highest availability resource that are near transmission lines tend to be developed first. Future sites may have higher emissions per unit of energy as they may be built with a lower quality resource or will require more capital to access the resource, resulting in either higher embedded emissions or lower amounts of generation. As more renewable energy is brought on board, existing fossil powered generators will cycle more often and operate more often at less than ideal operating points leading to increased emissions from these generators. On the other hand some technologies may become more efficient and newer plants may use updated technology. These factors cause significant uncertainty in the expected emissions of future power systems.

The first part of this work directly addresses the risk of increased emissions due to this uncertainty for the electricity system in Alberta, Canada. Chapter 2 applies a ‘risk premium’, an acceptable increase in the overall system cost that society must pay, to the Alberta electricity system. With the risk premium applied, the model optimizes to determine the system that has the lowest risk of missing the set emissions targets. As detailed in Chapter 2, this work shows that, to reduce the risk of increased emissions, an early and large build out of wind and other renewable energy is required, in addition to other system generation mix changes.

As the amount of energy from wind and other renewables increases, a number of challenges arise. One such challenge is over-generation which occurs when the available renewable energy in the system cannot be absorbed by the current demand. At this point, curtailment of generators occurs. This curtailment increases costs for a variety of reasons including the amortization of capital costs over fewer units of generation and renewable energy credits that cannot be claimed for un-generated energy. Chapter 3 implements a one year operational model to evaluate the impact of high penetrations of wind power and the ability of storage and dispatchable loads to reduce curtailment when wind penetrations are high.

Another challenge associated with high penetrations of wind power is the potential for the instantaneous penetration of wind power, at short time scales, to be too high. This can cause challenges in the grid related to frequency regulation. Though some studies show that renewables, in some circumstances, can provide synchronous generation for frequency regulation, many studies show that there are significant challenges with high penetrations of renewables operating in the system [3–10]. To address the impact of constraining the instantaneous penetration of variable renewable energy on system operation, Chapter 4 presents a study based on a model of a system that has a minimum synchronous generation requirement of 50%.

All three of these studies use adapted versions of the Open Source Energy Modelling System (OSeMOSYS) [11,12] and apply it to the Alberta, Canada electricity system. The Alberta system is similar to many US states and countries such as China in that it is mainly fossil-based with increasing amounts of wind generation in the mix. For Chapter 2 the model is adapted to incorporate a stochastic risk framework. Chapter 3 uses a version that is adapted to calculate and optimize when curtailment costs are included, and Chapter 4 uses a version in which synchronous generation constraints apply. OSeMOSYS code for each of these variations is included in the appendices.

## 1.1 Previous Work

This section provides an overview of the prior works for each chapter. Detailed literature reviews are provided in each chapter to provide full context for the contribution of that chapter. Here we summarize the literature on incorporating risk into energy systems models, then summarize the literature on reducing curtailment and finally review the literature on synchronous generation constraints.

### *1.1.1 The Risk of Increased Emissions*

There are many sources of uncertainty in energy systems modelling, including costs, availability, demand projections and uncertainty in emissions of a given technology [13–17]. These uncertainties create risk. The financial risk of increased costs and of changes in carbon pricing and other government policies are well studied [18–26]. A number of other studies consider the risk posed by uncertainty in the availability of resources [27–29], the risk due to variations in the sensitivity of the earth system to carbon emissions [30–32] and the risks associated with policy uncertainty [33–35]. Various combinations of risks have also been studied [36–46]. None of these studies evaluate the impact that uncertain environmental performance, namely carbon emissions, has on the system and therefore do not consider the potential for the system to exceed identified carbon dioxide emissions targets.

The few studies that do consider environmental performance risk consider the impact on expected carbon dioxide emissions. Parkinson and Djilali [47] use a stochastic programming approach to investigate the risk of increased emissions and how a changing energy mix can hedge against increased emissions. Other studies have used a combined fuzzy logic and stochastic approach to reduce the risk of increased emissions [48], a multi-objective optimization technique to investigate the risks for South Africa [49] and a multi-scenario approach to evaluate the impact of uncertainty in future policies on future emissions [50]. None of these studies consider the potential of nuclear energy to mitigate risk although nuclear is considered a very low emissions technology that could contribute to the reduction of global energy systems emissions.

### *1.1.2 The Value of Infrastructure to Reduce Curtailment*

Having shown, in Chapter 2, that a large build out of wind is required to reduce emissions risks, it is important to consider the impact that large amounts of wind energy have on the system. One major impact on the ability to integrate this generation into the system is the potential for curtailment to occur. Many long term optimization studies investigate the integration of variable renewable (VR) generation into the system mix and consider demand side management, storage and transmission expansion, amongst other flexibility methods [51–69]. These long term studies include costs for integrating VR generation into the system in various ways. Ueckerdt [70] and Hirth et al. [71] have formalized a framework for including integration costs into long term models.

Numerous short and medium term studies have addressed the impact of demand side management [72–75], transmission expansion [74,76] and storage [77,78] on the ability of the system to absorb high penetrations of VR energy. The potential for solar thermal storage [79–81] and power to gas technologies [82–88] have also been studied. These studies focus on the ability of these technologies to reduce variability and/or curtailment in the system but none of these studies consider the cost to the system of curtailing VR energy. Quoilin [89] provides a method for forcing the model to accept any energy generated by VR, thereby not permitting curtailment. This model structure does not allow curtailment and does not allow for costing any curtailment that occurs should the system not be capable of accepting this energy. Ignoring the cost of curtailment potentially under-estimates the challenges associated with integration and also under-values the potential of storage and dispatchable loads for system operation.

### *1.1.3 Synchronous Generation Constraints*

Another potential impact that large amounts of VR generation has on system operations is the impact on frequency regulation in the system. The maintenance of the grid frequency within a narrow range is important for effective operation of modern electricity grids [90]. This is usually performed by ensuring adequate synchronous generation, such as large thermal or natural gas plants, is operational in the system at all times. As more VR generation enters the system, there are questions about how the grid will maintain frequency regulation and whether or not VR generators can contribute to this frequency regulation [3–10].

Section 4.2.2 provides a literature review of the amount of synchronous generation required in a system to maintain frequency regulation. The range of values in the literature varies from between 25% and 75% but are typically close to 50%. If the instantaneous availability of VR generation in the system exceeds this level the VR generation is commonly curtailed [91,92]. Vithayasrichareon et al. [93] studies the requirement for synchronous generation and finds that this requirement increases costs of up to 20% when large amounts of renewable generation are available in the system. As an alternative to curtailing, many studies consider storage [68,78,94–97]. Unfortunately most studies that consider storage as an alternative to curtailing do not include a synchronous generation constraint and, therefore, over-estimate the potential of storage for integrating VR generation. McKenna et al. [98] apply a synchronous generation constraint to a system with large amounts of wind generation and enable storage for this system. They operate the storage in a number of 'typical' ways and do not optimize the operation of the storage system.

#### *1.1.4 OSeMOSYS model*

The research conducted in this dissertation is performed using the OSeMOSYS Energy Modelling System [11,12]. The model is a bottom-up energy-economy model that is technologically explicit and has been applied in many analysis and planning situations. The open source nature of the model and the solver for the model make it accessible and ensures that research done with OSeMOSYS can be reproduced by third parties which is important for informing public policy [99,100]. Initial developments with OSeMOSYS included validation against similar modelling tools such as MARKAL [11] and TIMES-PLEXOS [101]. The model has been applied to a large variety of energy systems analyses including Africa [102,103], Saudi Arabia [104], Bolivia [105], Cypress [106] and many others, and has been used for both electricity and whole system analysis. More recently, the model has been expanded to allow for the modelling of the Climate, Land, Energy and Water nexus and this 'CLEWs' model has been applied to a variety of analyses for countries and regions around the globe [107–111].

As with any complex model, validation is an important consideration. As noted above, the OSeMOSYS model structure and equations have been validated against the MARKAL and TIMES-PLEXOS framework and found to be functionally similar [11,101]. The validation of a specific model and its parameters has, however, not been addressed fully in the literature. Compared to a model of a physical system, where experiments can be used to validate the model, energy systems models are, by definition, models of a potential future. Since future policies, energy prices, climate, weather, etc. are all uncertain, energy systems models will, by definition, not perfectly predict the future. It is also not possible to delay system level decisions until we see what the future holds.

The literature on validation of energy systems models falls into two broad categories. First, there is historical back casting, where the model is compared to historical data to see if it accurately predicts the historical 'future'. For example van Sluisveld et al. [112] model system rates of change and compare the historical rates of change with future required rates of change to meet climate targets. A similar process is used for models that predict demand for systems such as district heating, etc. [113,114]. These validations are more similar to physical system models where the model can be validated with measurements of the real system parameters.

The final class of model validation in the literature consists of using a short term unit commitment model to check if the generator mix suggested by the long term build out plan can match the predicted future demand and resource cycle over a few selected days or weeks in the predicted future. For example Bistline et al. [115,116] compare two different model temporal resolutions and then use a short term model to 'validate' and compare the performance of the two proposed future systems. Again, the predicted future cannot be validated directly but a comparison of two model structures can hopefully identify errors or flaws that may exist in a given long term model output.

In this dissertation the long term model results from Chapter 2 are not validated directly, but the work in Chapters 3 and 4 with a medium and short term model, respectively, provides some validation of the long term results. Other than such validation against similar models as was done in this dissertation there is little literature on how to properly validate energy systems models.

#### *1.1.5 CONTRIBUTION FROM COLLEAGUES*

As noted in the acknowledgements and the published papers, other members of the 2060 Project contributed to parts of the modelling efforts in this dissertation. Specifically, the base Alberta model was developed and published by Benjamin Lyseng in his 2016 paper [117]. Ben gathered the required input parameters for the base Alberta model, including the cost data summarized in Appendix C, and I built a stochastic framework on this base model for the work in Chapter 2. The curtailment cost framework in Chapter 3 was likewise implemented on the Alberta base model and was inspired by a conversation Benjamin Lyseng and I had over a beer in Ireland. Other than having Benjamin present that work for me at the Energy Systems Conference in London, UK in 2017, the entire contribution to this chapter was mine. For Chapter 4, other than some minor inputs from the group on model ideas and building off the same base model of Alberta, the entire work was mine.

## 1.2 Overview and Outline

In Chapter 2 we extend the work on risk by Parkinson and Djilali [47] to evaluate a system that is mainly fossil based rather than the hydro generation based system that they evaluated. The fossil-based system in Alberta is similar to many other jurisdictions making our work more applicable in a broader context. We also implement the method in the OSeMOSYS Open Source Energy Modelling System and provide the code in Appendix A, making it available to other researchers using the OSeMOSYS model. We also include the potential of nuclear power to reduce the emissions risk and evaluate the system implications of allowing nuclear as nuclear is a technology that is generally considered to have very low carbon dioxide emissions.

Having found that large amounts of renewable energy, namely wind, are required to reduce the risk of future emissions, we evaluate the impact this has on system operations in Chapter 3. We first consider the impact that curtailment costs have on system operation and evaluate the value that storage and dispatchable loads provide in reducing these costs. As noted in the literature review, Ueckerdt [70] and Hirth et al. [71] provide a structure to include curtailment costs in long term models but the inclusion of these costs in short and medium term models has not previously been considered. Although other studies have evaluated the benefits that VR generation owners can obtain from reduced curtailment [118] or how curtailment works in the marketplace [59,119], we take a systems level view of the value that storage and dispatchable loads can provide to evaluate the overall impact that curtailment costs have on system operation.

Finally, we consider the impact that synchronous generation requirements have on system operation in Chapter 4. Specifically, while other studies have evaluated storage when synchronous generation constraints are active in the system [98], the optimal operation of storage has not previously been studied. We implement a model where the optimal operation of storage over one week periods, with 10 minute resolution, is evaluated and determine how this impacts the system operating costs, both with and without a synchronous generation constraint. This allows us to evaluate optimal system operation rather than considering exogenous operation of the storage system, providing insights into where storage best provides value.

The last chapter provides a summary of the key contributions and future work.

# 2. Hedging the risk of increased emissions in long term energy planning[2]

## Preamble

The feasibility of meeting emission targets is often evaluated using long range planning optimization models in which the targets are incorporated into the system constraints. These models typically provide one 'optimal' solution that considers only a deterministic representative value of emissions for each technology and do not consider the risk of exceeding expected emissions for a given optimal solution. Since actual emissions for any given technology are uncertain, implementation of an optimal solution carries inherent risk that emissions will exceed the given target. In this chapter, we implement a stochastic risk structure into the OSeMOSYS optimization model to incorporate uncertainty related to the emissions of electricity generation technologies. For a given risk premium, defined as the additional amount that society is willing to pay to reduce the risk of exceeding the cost optimal system's predicted emissions, we determine the generation technology mix that has the lowest risk of exceeding this baseline. We focus on emissions risk since the literature on emissions risk is sparse while the literature on other risks such as policy risks, financial risks and technological risks is extensive.

We apply the model to a case study of a primarily fossil based jurisdiction and find that, when risk is incorporated, solar and wind technologies are built out seven and five years earlier, respectively, and that carbon free technologies such as coal with carbon capture and storage (CCS) become effective alternatives in the energy mix when compared to the 'optimal' solution without consideration of risk, though this does not include the risk of carbon leakage from CCS

[2] The body of this chapter was published in T. Niet, B. Lyseng, J. English, V. Keller, K. Palmer-Wilson, I. Moazzen, B. Robertson, P. Wild and A. Rowe, *Energy Strategy Reviews*, vol. 16, pp. 1–12, Jun. 2017.

technologies. If nuclear is included as a generation option, we find that nuclear provides an effective risk hedge against exceeding emissions.

## 2.1 Introduction

At the Conference of the Parties 21 (COP21), 195 countries affirmed their intentions to put in place measures to meet global emissions targets. The feasibility of meeting emission targets is often evaluated using long range planning models in which the targets are incorporated into the system constraints. This is typically done either by implementing a cap on $CO_2$ emissions [120–122] or by adding constraints, such as renewable energy portfolio standards, renewable energy credits or carbon taxes, that push the system to meet a given emissions target [84,122–124]. In all cases, an 'optimal' solution is found that meets the target at the lowest cost. Most of these studies do not incorporate uncertainty in the levels of emissions from the modelled technologies. As a result, the risk of exceeding the emissions target is not quantified, leaving a gap in the literature as discussed in Section 2.2.1. There are a number of methods that have been used to incorporate uncertainty into long term energy planning models, as discussed in detail in Section 2.2.3.

In this study we apply a stochastic risk enabled version of the Open Source Energy Modelling System (OSeMOSYS) [11,12] to the Alberta, Canada electricity system. The Alberta system is fossil fuel based, similar to many US states and countries such as China and India, making our results more broadly applicable than those Parkinson and Djilali [47] obtained for a hydro based jurisdiction. In addition, we consider how nuclear, a low carbon technology that is often ignored due to political and social considerations, impacts the emissions risk for the Alberta, Canada electricity system.

The stochastic risk enabled version of OSeMOSYS is developed using the stochastic risk framework described by Krey and Riahi [125] and adapted by Parkinson and Djilali [47]. We use this framework to incorporate uncertainty in environmental performance of technologies into OSeMOSYS and assess the risk that emission targets will be exceeded. While Parkinson and Djilali use a custom linear programming model to apply the risk framework we implement this framework in OSeMOSYS. We use OSeMOSYS as it is a widely used energy system model that is open source and, by using this model, we contribute to the code base available for modellers using OSeMOSYS.

Although this study focuses on climate impact emissions risk, there are many other environmental impact risks posed by energy technologies that could be included in a risk framework including air pollution, water use and/or contamination, waste stewardship, wildlife impacts and land use. This study focuses on climate change emissions risk as this is an area that has not been thoroughly studied, as discussed in our literature review, and which has a global impact.

## 2.2 Literature review

Uncertainty is of concern in energy planning because uncertainty creates risk. Uncertain parameters in energy planning include: capital cost of generation technologies; operation and maintenance costs; fuel prices; availability of imported fuels; construction schedules for new plants; demand projections; and uncertainty in the emissions of a given generation technology or generation mix [13–17]. These uncertainties are compounded by the uncertainty of projecting over decadal time frames, as is typical in energy system planning. Quantifying the risk associated with these uncertain parameters requires an understanding of both the methods available for addressing risk in models, as discussed in Section 2.2.3, and of the sources of uncertainty as discussed in Section 2.2.1. One rarely considered source of uncertainty is environmental performance risk, defined as the risk that a given technology's environmental impact is greater than the expected impact. We discuss this in Section 0.

### *2.2.1 Sources of Uncertainty*

As in all modelling, there are many sources of uncertainty in energy system modelling. These include financial uncertainty, resource availability, sensitivity of the climate system to emissions and uncertainty in climate policies as well as uncertainty in future demand for energy services. There has been significant work in each of these areas.

Szolgayová et al. [18] use a portfolio analysis approach to investigate financial uncertainties in a model that considers a simplified set of four technology options. Hunter et al. [19] extend the modelling tool TEMOA to include cost uncertainty. Other examples of models using portfolio analysis methods to consider financial risks include work done by Krey et al. [20], Usher and Strachan [21], Messner et al. [22], Webster et al. [23], Leibowicz [24] and Arnesano et al. [25]. Each of these papers considered the financial risks associated with future energy prices, carbon policies and/or social costs and determined an energy system buildout that hedged the risk of financial losses in the system. Wu and Huang [26] consider the potential for zero marginal cost technologies such as wind and solar to hedge against fossil fuel price risk using a similar method.

Variability in resource availability is a significant source of system uncertainty, both in terms of the ability of renewable resources to meet demand in the short term and in terms of resource constraints on generators in the longer term. Stoyan and Dessouky [27] use a mixed integer programming approach to evaluate various scenarios of resource availability to enhance system planning.  Tan [28] provides a method for incorporating inoperability risks into a linear programming model in which the resource mix is optimised to reduce the risk that demand is not met when energy sources become inoperable due to supply constraints.  Martienez-Mares and Fuerte-Esquivel [29] use a robust optimization approach to consider the impact of wind resource variability on the optimal system.  Each of these three studies is based on a stochastic evaluation of the cost of this variability.

Studies by Loulou et al. [30], Ekholm [31] and Syri et al. [32] investigate uncertainty due to variability in the sensitivity of climate to carbon emissions, and calculate the costs associated with meeting specified climate change temperature targets.  Each of these studies use a stochastic programming model to determine the financially optimal system given this uncertainty in climate sensitivity.

Uncertainties in climate policy also create risks for investors and a number of studies have investigated how decision makers will react to these risks [33–35].  These studies find that uncertainty in policy can undermine the potential benefits of a policy, in particular when policy decisions are short-term or if policy makers do not consider the potential reaction of investors.

There are also a number of studies that consider a combination of uncertainties.  Most of these studies combine cost uncertainty with policy uncertainty and evaluate the financial risk associated with these uncertainties [36–46], either with stochastic programming or interval programming.

However, none of these studies considers uncertainty related to the environmental performance of energy technologies in fossil based jurisdictions nor do any of these studies consider nuclear.

This is summarized in Table 2.1. It is important to fill this gap in the literature since ignoring this uncertainty could lead to systems with higher than predicted emissions, meaning jurisdictions could miss their emissions targets.

**Table 2.1: Uncertainty studies in the literature**

| Uncertainty Considered | Hydro Based Jurisdiction | Fossil Based Jurisdiction | Consideration of Nuclear |
|---|---|---|---|
| **Financial** | Yes [23] | Yes [18–26] | Yes [24] |
| **Resource Availability** | Yes [28] | Yes [27–29] | No |
| **Climate Sensitivity** | Yes [30,32] | Yes [30–32] | No |
| **Climate Policy** | No | Yes [33–35] | Yes [33] |
| **Emissions Levels** | Yes [47] | This study | This study |

### *2.2.2 ENVIRONMENTAL PERFORMANCE UNCERTAINTY*

As outlined above, few studies consider uncertain environmental performance of alternative energy system realizations. In this chapter we define environmental performance uncertainty as the uncertainty in the environmental impact of a given technology. This could be due to variability in pollutant emissions such as carbon dioxide, uncertainty in the amount of water use, uncertainty about the impact of construction to name a few.

There are a small number of studies in the literature that address environmental performance risk. Parkinson and Djilali [47] investigate the impact of uncertain environmental performance of energy technologies, as defined by their carbon dioxide emissions, on the potential of these technologies to hedge against climate impact risk in British Columbia, Canada, using a stochastic programming approach. Li et al. [48] use a combined fuzzy and stochastic approach to consider uncertain environmental performance, again as defined by greenhouse gas emissions, in combination with other uncertainties, to reduce the risk that a generic energy system would fail to meet specified emission targets. Heinrich et al. [49] use a multi-objective optimization technique to investigate how uncertain technological parameters in their model influence environmental impact risks for the South African energy system. They specifically consider the uncertainty in emissions from power plants for each technology as well as the efficiency of each technology and include these in their multi-objective optimization model. Kanudia et al. [50] use a multi-scenario framework to evaluate the impact of uncertainty in future policy on the overall climate impact of the energy system in Quebec, Canada.

### *2.2.3 RISK METHODS IN ENERGY SYSTEM MODELS*

Ascough et al. [126] provide an overview of different methods of addressing risk in energy-economic models. Krey and Riahi [125] note that most of these approaches are for 'stylized models' that lack an explicit technology representation as defined as the ability to model the efficiency and operating parameters of a specific technology. Examples of models that include technology-explicit representations include multi-objective optimization [49], near optimal techniques [127,128], monte-carlo simulation [129] and stochastic optimization methods originally developed for financial portfolio analysis [125].

Incorporating risk in a multi-objective optimization model requires defining objectives for the model that are expected to reduce the perceived risk. The multi-objective optimization then determines a set of possible decisions that meet these policy objectives. Near optimal techniques, including model generated alternatives (MGA), do not explicitly take into consideration risk and uncertainty, but allow for the policy decision maker to choose from a number of near optimal options that are all unique. These unique solutions allow the decision maker to choose which of the near optimal solutions meets non-specified constraints or objectives of the decision maker. Neither multi-objective optimization and near optimal techniques take uncertainty and risk into consideration endogenously; therefore, this method was not chosen for this study.

Monte-Carlo simulation techniques do allow the modeller to take risk into consideration endogenously, similar to financial portfolio risk methods. However, Monte-Carlo methods find an optimal solution to large number of random problems but do not guarantee that all of these solutions are feasible and can be implemented. This approach is useful for many energy system modelling questions but is not directly applicable to the consideration of increased risk of emissions.

Portfolio analysis uses a stochastic approach to develop expected distributions for the future value of the potential investments. A risk model is then used to choose an investment portfolio that balances the financial risk of this uncertainty with the initial cost of the investment. When applied to energy systems modelling, this approach considers the uncertainty in the cost of future energy supply rather than the uncertainty in future value of investments. Krey and Riahi [125] demonstrate that the risk methods applied to portfolio analysis can be incorporated into energy-economic models. They provide three alternative formulations of a risk-based stochastic linear programming problem and show that these formulations are numerically equivalent. Parkinson and Djilali [47] argue that, for policy decisions, the formulation that minimizes risk for a given risk premium provides the greatest benefit to the policy maker by providing a direct link between the risk and the cost of a policy decision. The risk premium is a factor that indicates the additional cost that society is willing to pay to reduce the exposure to risk. Parkinson and Djilali adapt the financial risk structure to the quantification of environmental performance risk and, more specifically, the risk of increased carbon dioxide emissions. As this method has already been applied to the risk of increased carbon dioxide emissions it fits well with the purpose of this study.

Based on this review of the literature, we find that financial portfolio analysis, as presented by Krey and Riahi [125], provides an effective method for addressing risk in energy systems models. It allows the modeller to quantify risks in the model structure and determine generation portfolio decisions that hedge against these risks endogenously. Furthermore, although many authors have investigated cost and other uncertainties, little work has been done to quantify the risk of excess emissions. Parkinson and Djilali [47] adapt the financial portfolio analysis methodology to address the risk of excess emissions. In this study, we extend the work of Parkinson and Djilali by implementing the method they use in the OSeMOSYS Open Source Energy Modelling System, making it available to anyone wishing to consider risk in energy systems modelling. We apply the methods to a case study of the electricity system in Alberta, Canada to investigate strategies by which the risk of excess emissions can be reduced. While Parkinson and Djilali focus on British Columbia, Canada, a jurisdiction with large hydro resources, we look at Alberta, Canada, a jurisdiction that has predominantly fossil generation in the energy mix that is similar to many US states and countries such as China and India. In addition, we expand the analysis to consider the risk mitigation potential of nuclear energy and investigate how that impacts both risk and cost.

## 2.3 Methodology

We implement a techno-economic linear programming model to investigate uncertainty and risk hedging strategies and technologies following the work by Krey and Riahi [125] and Parkinson and Djilali [47]. Such models are based on the generic linear programming problem formulation:

$$Min\ C(x_j) = \sum_j (c_j x_j) \tag{1}$$

$$s.t. \sum_j (a_{i,j} x_j) \leq b_i\ \forall\ i \tag{2}$$

$$x_j \geq 0\ \forall\ j \tag{3}$$

The objective of the problem, as defined in Equation 1, is to find the solution vector, $x_j$, that minimizes the sum of $c_j x_j$, where $j$ represents the set of all possible decisions. In energy systems models, $c_j$, the vector comprising the cost parameters, is often separated into capital, fixed and operating costs while $x_j$, the vector comprising the decision variables, is often separated into new capacity and operating decision vectors. The subscript $j$ then represents new capacity and operating decisions for each technology in the model. The performance parameters for the technologies are $a_{i,j}$ and the activity or installed capacities are restricted by $b_i$ as shown in Equation 2.

This general formulation has been implemented in a number of techno-economic energy system modeling tools, including MESSAGE [130,131], Times/MARKAL [132] and, more recently, the Open Source Energy Modelling System (OSeMOSYS) [11,12].

The optimal deterministic system cost, $C(x_j^*)$, is defined as the total minimized system cost, as determined by Equation 1, for the system realization, $x_j^*$, with no consideration of risk. A risk measure, $R(x_j)$, is then introduced that represents the total risk that a given decision vector, $x_j$, will result in higher total cost than $C(x_j^*)$. Three different approaches to incorporate risk into linear programming models are described by Krey and Riahi [125]:

1. Minimize the weighted sum, $F(x_j)$, of the total system cost and the risk measure. This is the approach implemented in MESSAGE by Messner [22] and discussed by Dantzig [133]. A *risk aversion factor*, $\rho_r$, is introduced that, when multiplied by the risk, $R(x_j)$, of the solution vector converts the risk into an equivalent cost, as shown in Equation 4.

$$\min F(x_j) = C(x_j) + \rho_r R(x_j) \tag{4}$$

2. Minimize the risk measure subject to a maximum expected total system cost. In this case, a *risk premium*, *f*, is introduced that represents the extra amount that society is willing to pay, above the optimal deterministic system cost, $C(x_j{}^*)$, to reduce risk below that which is associated with the optimal deterministic solution.

$$\min R(x_j) \ s.t. \ C(x_j) \leq (1+f)C(x_j{}^*) \tag{5}$$

3. Minimize the total system cost under constrained risk. In this case, the cost of the system is minimized subject to a maximum acceptable level of risk, $R_{max}$.

$$\min C(x_j) \ s.t. \ R(x_j) \leq R_{max} \tag{6}$$

All three approaches use a risk parameterization that is stochastically determined by successive draws from the probability space, as discussed by Hazell [134]. Hazell's approach is based on cost uncertainty, where the total absolute deviation of cost for a single draw, from the expected value for each set of draws, is used to measure the financial risk of the solution associated with that draw.

Krey and Riahi [125] show that these three approaches are numerically equivalent in that one can choose a *risk aversion factor*, a *risk premium* or a limit on the level of risk which will result in the same decision vector. For financial risk, the risk measure and the cost parameter in the model are both monetary, so the structure with the *risk aversion factor* provides insights for financial decisions. For energy systems analysis, where the risk measure may correspond to non-monetary risks, the structure with the *risk premium* allows for a clear connection between the reduction of a given risk and the monetary cost. Parkinson and Djilali [47] observe that the *risk premium* can be considered the cost of hedging to reduce risk. The third structure, where cost is minimized for a given level of risk, allows the modeller to obtain marginal costs from the model which is not possible with the first two formulations, but does not allow for a direct link between increased costs and reduced risk [125]. As we are interested in the increased cost to mitigate climate impact risk, we utilize the *risk premium* structure to obtain insights into climate impact risks.

To incorporate the *risk premium* model structure into a linear programming model, Krey and Riahi provide a risk metric, the "*upper mean absolute deviation*", as defined in Equations 7 and 8. Equation 7 provides a measure of the risk for a given decision vector, $x_j$, for one random draw from the probability distributions of the performance variable, $r_j(\omega_n)$, for each element in the decision vector. This risk measure is then summed, in Equation 8, to give the risk based on $N$ random draws from the probability distributions of each performance variable. This overall risk, as given by Equation 8, corresponds, for financial risk, to the expected underestimation of the system cost [22]. For our purposes, this can be considered as the expected underestimation of the system emissions of the deterministic model, which we term "risk" in the remainder of this chapter.

$$R(x_j, \omega_n) = \max\{0, \textstyle\sum_j [r_j(\omega_n) - \bar{r}_j] x_j\} \tag{7}$$

$$R(x_j) = \frac{1}{N} \textstyle\sum_n R(x_j, \omega_n) \tag{8}$$

When applied to the risk of increased carbon dioxide emissions, as we do in this chapter, $\bar{r}_j$ is the vector of average values of carbon dioxide emissions for each technology and $r_j(\omega_n)$ is the vector of random draws from the probability distribution of carbon dioxide emissions for each technology. The difference between these two parameters is multiplied by the decision vector, $x_j$, to find the risk for that decision vector and random draw. Equation 8 gives the risk based on $N$ random draws from the probability distributions of the emissions of each generation technology. A sufficient number of random draws must be taken to ensure convergence of the model while keeping it to a minimum to reduce computation time.

As discussed earlier, the decision vector, $x_j$, for most energy system models is comprised of new capacity and operating decisions. Here, we consider only the portion of the decision vector, $x_j$, which corresponds to the operation decisions. $\bar{r}_j$ is then the vector of average lifecycle emissions per unit of generation for each technology while $r_j(\omega_n)$ is the vector of predicted lifecycle emissions per unit of generation for a technology for random draw $n$.

For each random draw, $n$, we sum only the downside risk (*i.e.* the chance that the emissions are higher than expected) to obtain $R(x_j, \omega_n)$, the risk of emissions exceeding the expected level. The risk for each of the random draws are then summed to find the risk based on $N$ random draws, $R(x_j)$. A single optimization is then performed to minimize this risk.

For the linear programming GNU MathProg code, as implemented in OSeMOSYS, please refer to Appendix A.

## 2.4 Case Study – Methods

The risk framework described above is incorporated into the Open Source Energy Modelling System (OSeMOSYS) [11,12]. We then implement into this risk-enabled version of OSeMOSYS a model of the electrical energy system for Alberta, Canada. The Alberta model was originally developed in OSeMOSYS by Lyseng et al. [117] and was recently updated to include policy announcements made by the Alberta government in late 2015 [135,136]. This section provides a brief description of the general model structure. For those parameters not described here please refer to Lyseng et al. [117].

Figure 2.1 shows the general structure of the Alberta model, with generators that contribute to the reserve margin shown on the left. The reserve margin ensures that there is enough dispatchable generation in the generation mix to meet the demand for times when non-dispatchable generation such as wind and solar are not available. It is also used to ensure the system has energy available to meet projected peak loads since the time slice structure for long term optimization averages out some of these peaks.

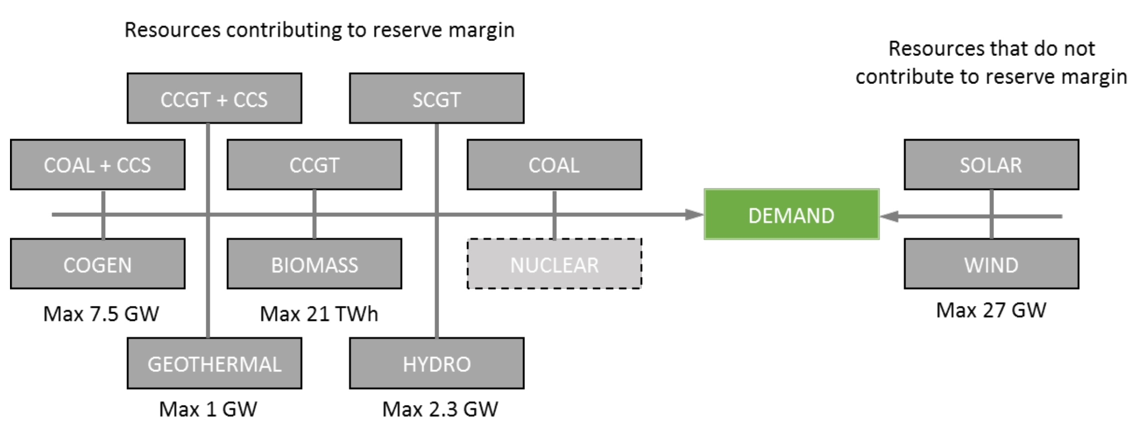


**Figure 2.1: Diagram of generation options in the modeled Alberta system. Generators on the left contribute to the reserve margin. Generators on the right (i.e. wind and solar) do not.**

The generation options that contribute to the energy mix in Alberta include coal fired generation (COAL), natural gas fired combined cycle turbines (CCGT), simple cycle natural gas fired turbines (SCGT), and natural gas fired cogeneration with heat production plants for industrial loads (COGEN). Carbon capture and sequestration (CCS) can be implemented on either a CCGT natural gas plant or a coal plant and is implemented as two additional technologies available in the model. Generator performance and cost data are taken from the U.S. Energy Information Agency [137] while capacity limits are based on data from the Alberta Electricity System Operator (AESO) [138]. Biomass is limited in the amount of energy available each year while the other forms of generation are limited in terms of maximum installed capacity.

Nuclear is currently not considered a generation option by the Alberta Electricity System Operator (AESO), as outlined in their long term plan [138]. Accordingly, a first set of model runs was performed without nuclear as a generation option. A second set of model runs with nuclear enabled was then performed to compare the risk profiles with and without nuclear.

The current Alberta system is reliant on coal and natural gas with smaller amounts of wind and hydro making up the balance. The natural gas in Alberta is split between cogeneration providing heat and power to industry and conventional natural gas generators, both simple cycle and combined cycle, meeting much of the remaining load. The model structure implemented by Lyseng et al. is a lumped system model, with no consideration of transmission which follows from the Alberta Electricity System Operator (AESO) mandate to, “plan for a transmission system that is free of constraints” [139]. We optimize over the period 2010 through 2060 using a high-demand, average-demand and low-demand time slice for each season based on the AESO demand growth forecast [138]. Each season is three months long, for a total of 12 time slices per year.  The size of the time slices varies from 283 hours for the shortest peak time slice to 1201 hours for the longest off peak time slice.

In fall 2015, Alberta made the announcement that existing coal generation will be retired and that 30% of all generation will be from renewable sources by 2030 [136].  A \$30/ $tCO_2$ carbon tax will be implemented and will be used to fund incentives for renewable sources.  The carbon tax will apply to any emissions from a generator that exceeds the level of emissions of a theoretical best in class, high efficiency natural gas plant, expected to be 0.4 $tCO_2$/MWh in 2018, decreasing to 0.3 $tCO_2$/MWh in 2030.

We implement this policy by eliminating residual coal capacity in 2030 and applying the \$30 carbon tax on emissions above the best in class standard, starting in 2018 at 0.4 $tCO_2$/MWh and decreasing linearly to 0.3 $tCO_2$/MWh in 2030.  With these policies in place, we increase the renewable energy credit (REC) until the 30% generation level is met.  Lyseng et al. [135] found that a REC of \$25/MWh was sufficient to obtain 30% generation from renewable sources by 2040 and we, therefore, implement a \$25/MWh REC in this study.  Although there is no specified overall emissions limit applied, there are emissions targets implied by these policies. Our model similarly does not apply a specific emissions limit on the system but determines the level of emissions with these policies in place.

Distributions of the emission intensities were created based on the review of lifecycle emissions performed by the IPCC [140, Annex II], as shown in Figure 2.2.  Lognormal distributions were fit to the percentiles published by the IPCC following the work by Parkinson and Djilali [47]. For each random draw, *n*, we obtain the predicted lifecycle emissions per unit of generation for each technology from these distributions.

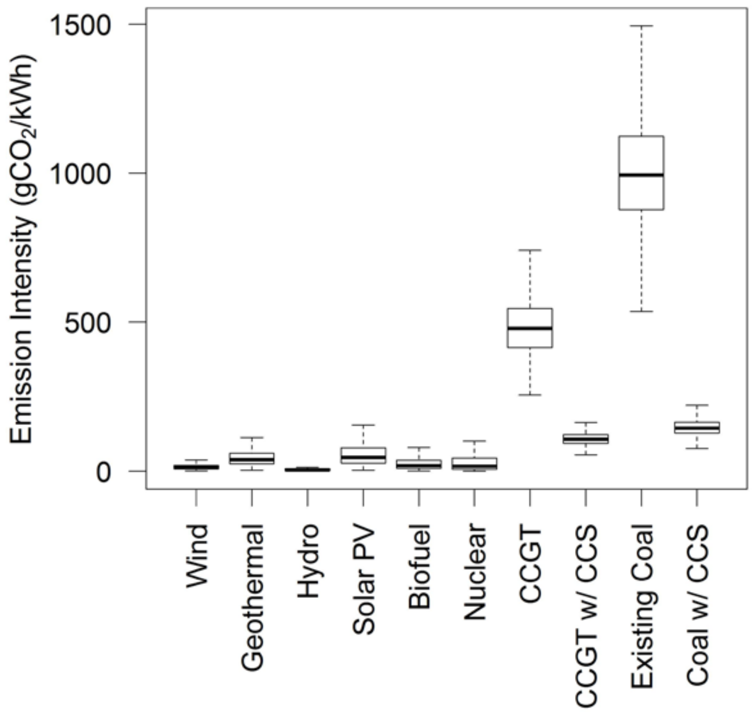


**Figure 2.2: Distribution of emission intensity for various generation technologies (after [47]) The boxes show the 25th to 75th percentiles while the whiskers show the 95% probability limits of the lognormal distribution.**

Three technologies shown in Figure 2.2 require elaboration. First, the emissions from solar are based on the IPCC study findings for Solar Photovoltaic (PV) rather than Concentrated Solar Power (CSP). This is consistent with the expectations that Alberta will have distributed PV rather than CSP. Neither the Alberta Energy System Operator (AESO) nor the Canadian Solar Energy Industries Association mention CSP in their plans for the foreseeable future, while both mention Solar PV as a viable technology [138,141].

The IPCC study provides only a single emissions distribution for each of coal and natural gas, although there are multiple generating technologies for each of these fuels. We assume that the IPCC figures are for the worst generator using a given fuel, namely existing coal plants and typical SCGT plants. Emissions from other plants that use the same fuel are scaled down based on their relative conversion efficiency.

Data for carbon capture and storage (CCS) provided by the IPCC is sparse since there are few systems in operation to quantify the emissions. The IPCC provides simply a minimum and maximum value for these technologies rather than a distribution. We assume that the distribution of emissions from plants with CCS follow a similar shape as for those without CCS. We linearly scale the distribution for plants without CCS such that the minimum of the resulting distribution matches the minimum provided by the IPCC for plants with CCS.

## 2.5 Case Study – Results

As noted above, two sets of analyses were performed. First, following the Alberta Electricity System Operator projections, we consider the case without nuclear as a generation option. We then allow nuclear as a generation option and compare the results. In both cases, we constrain our model to meet the newly announced Alberta policies discussed earlier.

### *2.5.1 SYSTEM WITHOUT NUCLEAR*

The analysis is first performed without implementation of the risk framework. Figure 2.3 shows the resulting installed capacity for each technology, over time, as a stacked area plot.

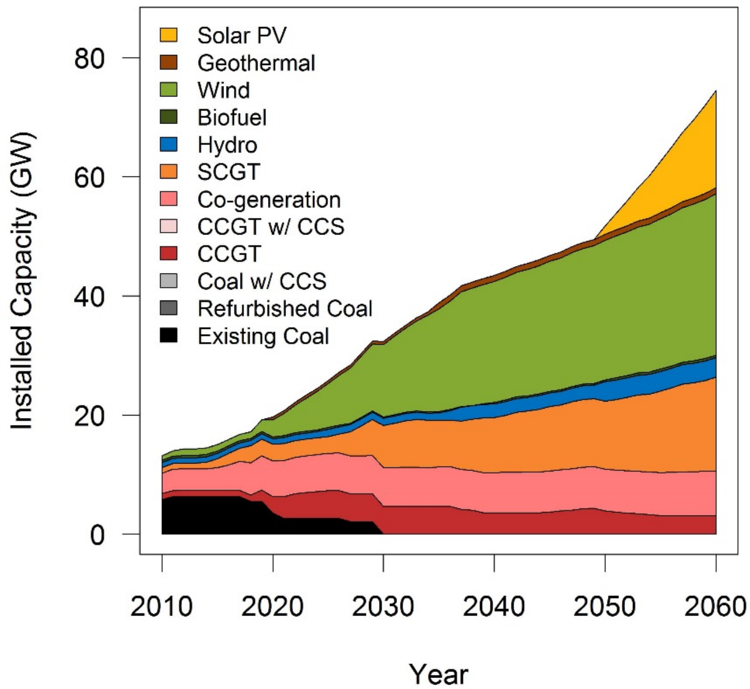


**Figure 2.3: Installed generation capacity over time for system with no consideration of risk.**

As shown in this figure, coal is mostly pushed out of the system in 2020 by CCGT with only a small amount of residual coal capacity lasting until 2030. Due to reserve margin requirements, SCGT is installed as backup for the large amounts of renewable generation being installed. A large build out of wind begins in the year 2019, with solar entering the generation mix in 2050.

When a 5% risk premium is applied, there is a clear shift in generation technologies, as shown in Figure 2.4. The build out of wind starts four years earlier, and the build out of solar starts eight years earlier. Co-generation expands slowly in the first 20 years, then remains flat until approximately 2040, when it starts to be slowly reduced due to coal with CCS entering the system, eliminating CCGT entirely.

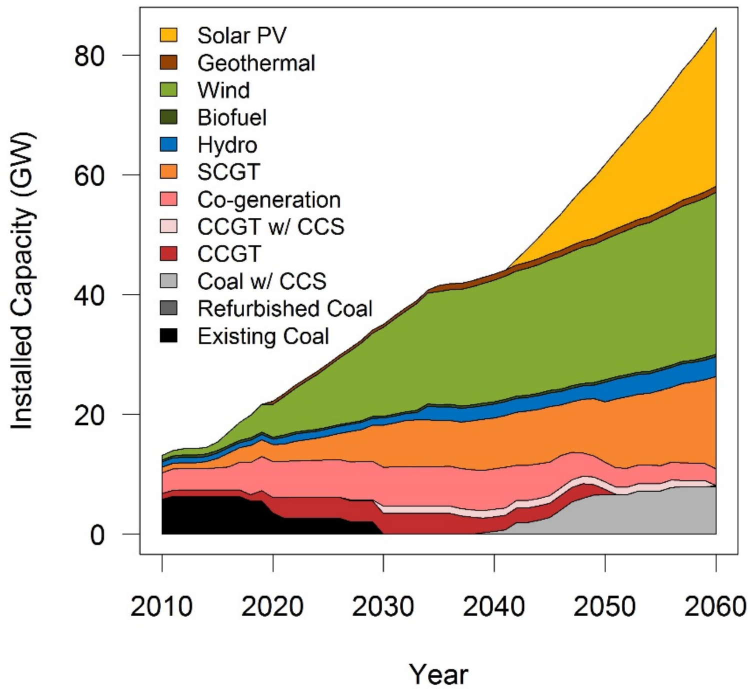


**Figure 2.4: Installed generation capacity over time for system with 5% risk premium.**

Figure 2.5 shows the installed capacity in the year 2050 for each of the modelled risk premiums. The increase in solar capacity is clearly seen – each increase in risk premium causes a clear increase in the amount of solar installed. Also notable in this figure is that small increases in risk premium cause coal with CCS to become more attractive while combined cycle natural gas and co-generation become less attractive. The use of SCGT to meet the reserve margin is less prevalent at higher risk premiums due to installation of coal with CCS.

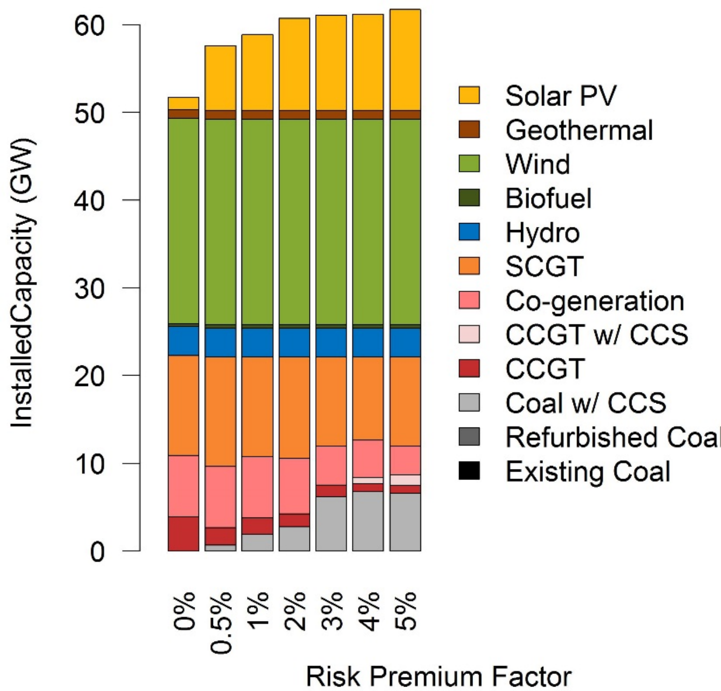


**Figure 2.5: Installed capacity by technology at various levels of risk premium in the year 2050.**

The large amount of SCGT capacity installed by the model is rarely used for generation, as shown in Figure 2.6. It is installed to ensure that generation for peak periods is always available even when variable resources such as wind or solar are unavailable. It is important to highlight that our model lacks the short time-scale resolution to show the operational characteristics for short term peak generators but does include the requirement to install peaking generation. Other than the clear absence of any generation by SCGT, as shown in Figure 2.6, the operational capacity factor for each generator remains approximately the same for each risk premium level.

As the risk premium increases, the amount of potentially asynchronous generation such as PV and Wind in the system increases to nearly 50% of the total generation. We expect that, if there was such a large build out of wind and PV in Alberta, that many of the wind turbines installed would be installed with synchronous generators as this is both technically feasible and done in some existing wind turbine installations [142]. In addition, PV installations could be connected to the grid with synchronous inverters, further mitigating this impact. Finally, the SCGT installations, though not used for significant generation, would likely be called upon for grid balancing duties which should allow for grid stability even with such a large amount of wind and PV generation.

The current risk framework considers only the risk associated with generation emissions, and not the risk associated with construction emissions. Given the large quantity of new construction predicted by the model, these emissions and their associated risk may be significant. In addition, our model does not quantify all of the uncertainty related to the technical potential of carbon capture technologies nor the long term stability of the stored carbon.

The Alberta average load in 2050 is under 19 GW, with a peak near 30 GW, whereas the total installed capacity in 2050 varies from approximately 55 GW for the base model to over 60 GW for the 5% risk premium. This apparent over-building results from the requirement for dispatchable generation to meet the reserve margin combined with the lower risk of carbon dioxide emissions from wind and solar. To reduce the emissions risk, more solar is installed, but the same level of dispatchable generation is installed to ensure system reliability.

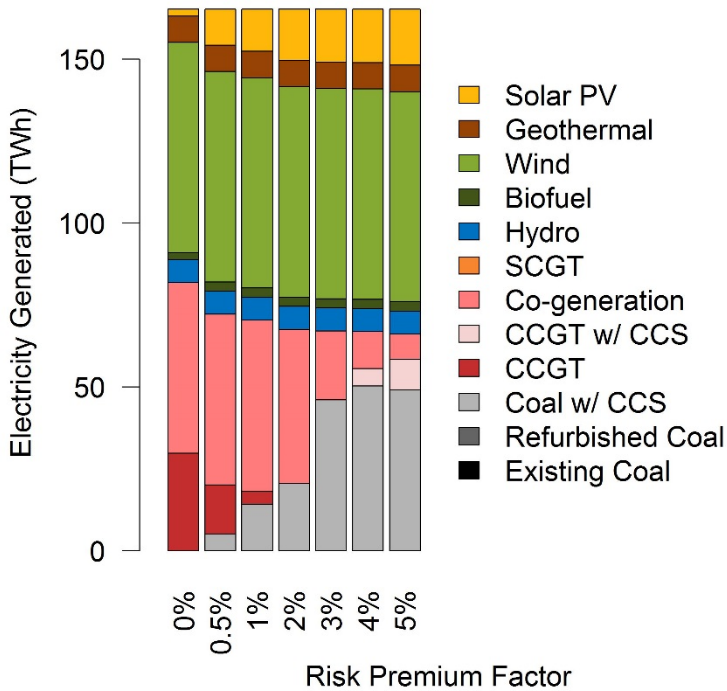


**Figure 2.6: Generation by technology at various levels of risk premium in the year 2050.**

Figure 2.7 shows the distribution of realized emissions for each of the risk premiums simulated, showing a clear trend of reduced emissions with increased risk premium. The distribution of emissions is compressed at higher risk premium, indicating a reduced risk of exceeding expected emissions.

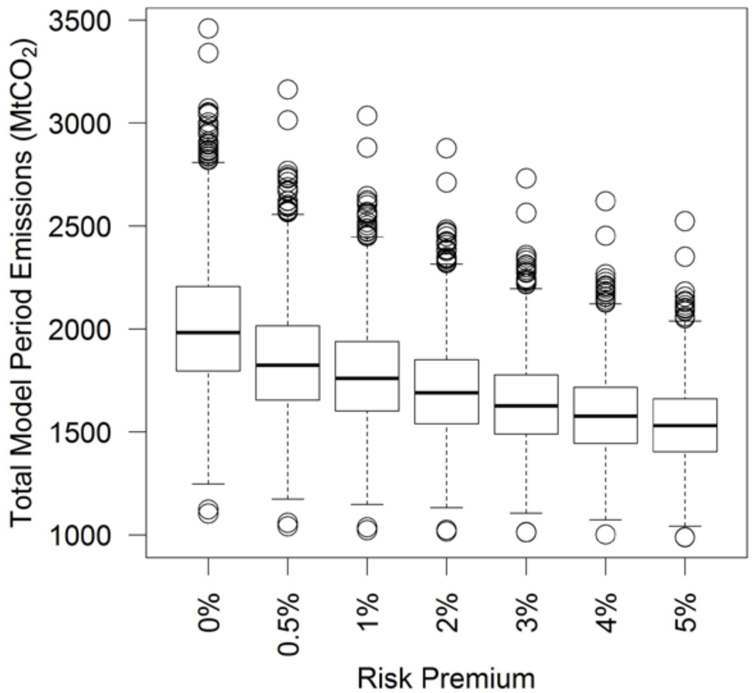


**Figure 2.7: Total model period emissions for each random realization at various levels of risk premium.**

### *2.5.2 NUCLEAR AVAILABLE AS A GENERATION OPTION*

Figure 2.8 shows the installed capacity for each technology on a stacked area graph with no consideration of risk, but with nuclear enabled.

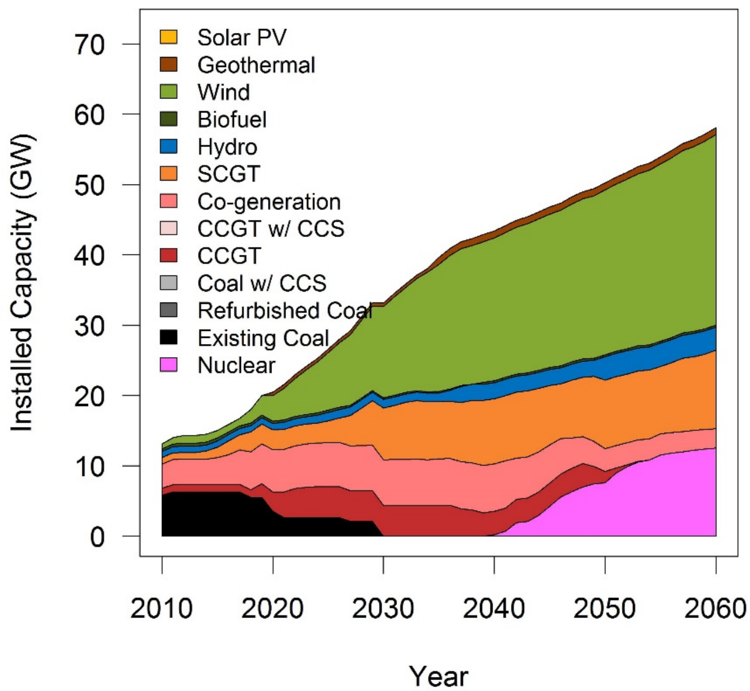


**Figure 2.8: Installed generation capacity over time for system with no consideration of risk and nuclear as a generation option.**

When compared with Figure 2.3, the major change with nuclear available is the absence of solar generation from the mix. Other notable changes include the reduction of SCGT buildout after 2040 which is replaced by nuclear capacity and the complete elimination of CCGT capacity by 2055.

When a 5% risk premium is applied, there is a significant shift in the generation mix, as shown in Figure 2.9, relative to the model with no consideration of risk. Wind comes on line approximately five years earlier while nuclear replaces cogeneration and coal entirely. The additional nuclear is installed and has very low emissions and very low variability in terms of the predicted emissions. This means it is a cost effective risk hedge for the model to choose. Additional SCGT is installed to meet the reserve margin.

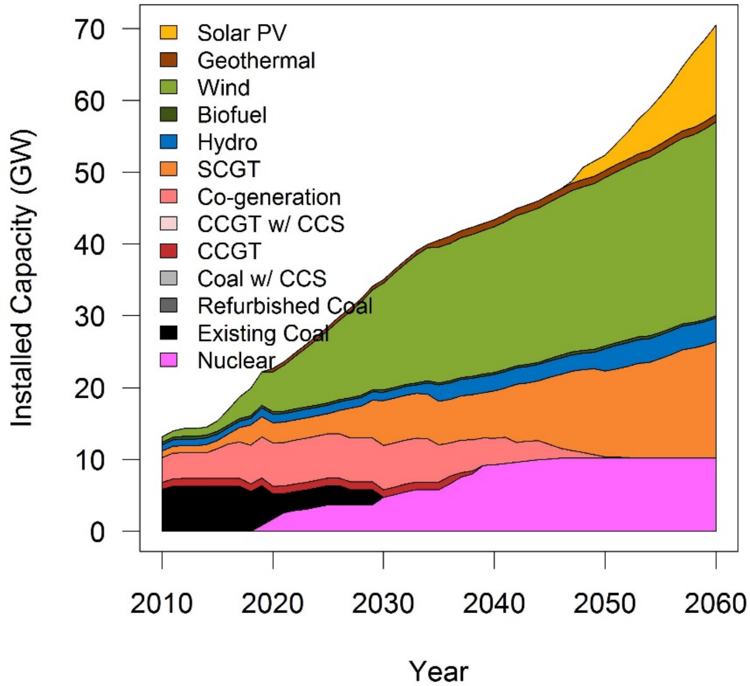


**Figure 2.9: Installed generation capacity over time for system with 5% risk premium and nuclear as a generation option.**

Figure 2.10 shows the installed capacity in 2050 for each of the risk premiums considered. In the existing AESO projections case, where nuclear is unavailable, the installation of solar increases steadily with the risk premium, as shown in Figure 2.5. When nuclear is available, solar is installed in 2050 and only when the risk premium rises to 4%.

Figure 2.10 shows that the generation mix changes little with increases in the risk premium over 1%. The generation mix, once coal and natural gas are pushed out, remains largely nuclear and wind, with SCGT meeting the reserve margin. Small amounts of other technologies comprise the remaining generation mix.

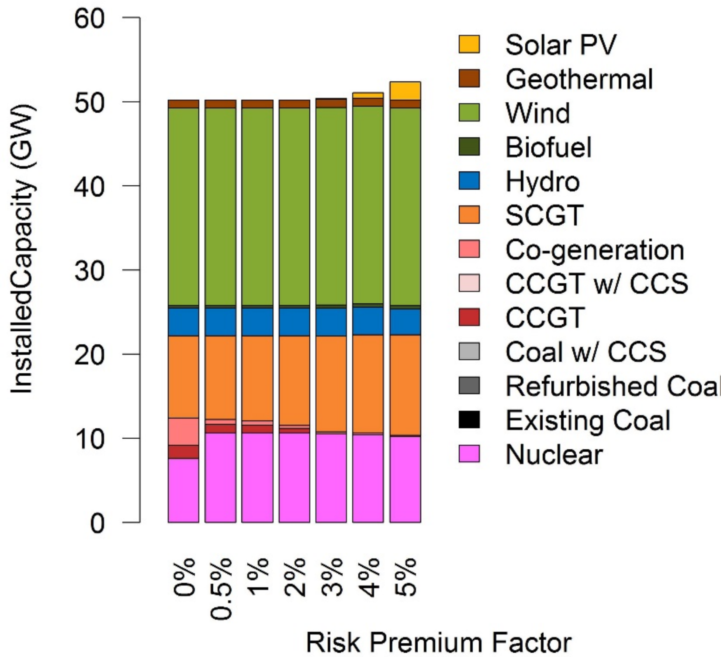


**Figure 2.10: Installed capacity by technology at various levels of risk premium in the year 2050 for system with nuclear available.**

In comparison to the case where nuclear is not available in the model, the total installed capacity for the system is quite different with nuclear available. As shown in Figure 2.5, the 2050 installed capacity rises from 55 GW for the base model to over 60 GW for the 5% risk premium under the current no nuclear policy. When nuclear is available the total amount of generation is reduced to around 50 GW, and an increase is seen only when the risk premium rises to 5%. With nuclear available it is more sensible to use nuclear to replace natural gas generation up to a 4% risk premium rather than installing more wind and/or solar. Since nuclear meets the system reserve margin, it can replace natural gas rather than adding to the installed capacity of the system.

As is the case without nuclear in the mix, when nuclear is enabled, SCGT technologies are installed to meet the reserve margin, but do not significantly contribute to the energy produced, as shown in Figure 2.11. This figure shows that two types of generation, nuclear and wind, dominate across all risk premium levels. For the case with no consideration of the emissions risk, co-generation remains as a generation option meeting a portion of the heat demand for the oil sands. However, this is pushed out with only a 0.5% risk premium and is replaced by nuclear. Nuclear would likely also be able to supply this heat demand, so would be a reasonable replacement for co-generation. As the risk premium increases, small amounts of other technologies such as biomass and solar come in to the mix, but wind and nuclear comprise the majority of the generation in the system in all cases.

One consideration for this generation mix would be the interaction between nuclear and wind generation. Nuclear is not generally considered agile, so the coupling with variable wind generation might be technically challenging. Figure 2.10 shows that there is a significant amount of SCGT installed to meet peaking loads, but this generation is never used in the model due to the low resolution of the time slices, as seen in Figure 2.11. In actual operation the SCGT might be called upon to meet the ramping requirements in the system. It is also possible that, with new nuclear technologies, that nuclear could meet the ramping requirements. Adaptations in existing plants and design features of new plants promise to allow nuclear to follow loads or find ways of using excess energy from nuclear for other uses [143,144]. In addition, reactors in France have been used for load following to an extent for many years and upgrades and new technologies will increase these capabilities over time [145,146].

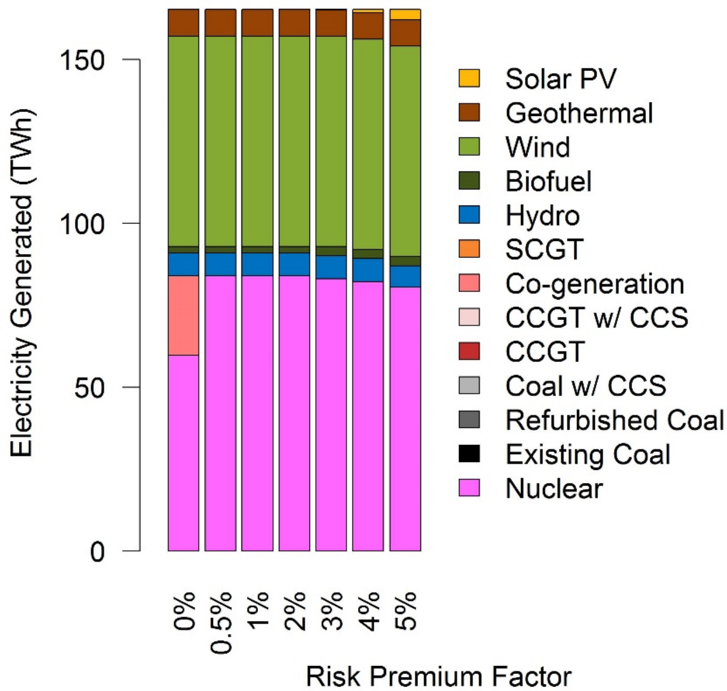


**Figure 2.11: Generation by technology at various levels of risk premium in the year 2050 for system with nuclear available.**

Figure 2.12 shows the distributions of realized emissions for all 2000 random realizations of the generation emissions profiles. As was the case with the current no nuclear AESO projection, there is a clear trend of reduced average emissions with an increased risk premium. There is, however, notable difference between the trend with nuclear available and the trend with the current AESO projections without nuclear (Figure 7).

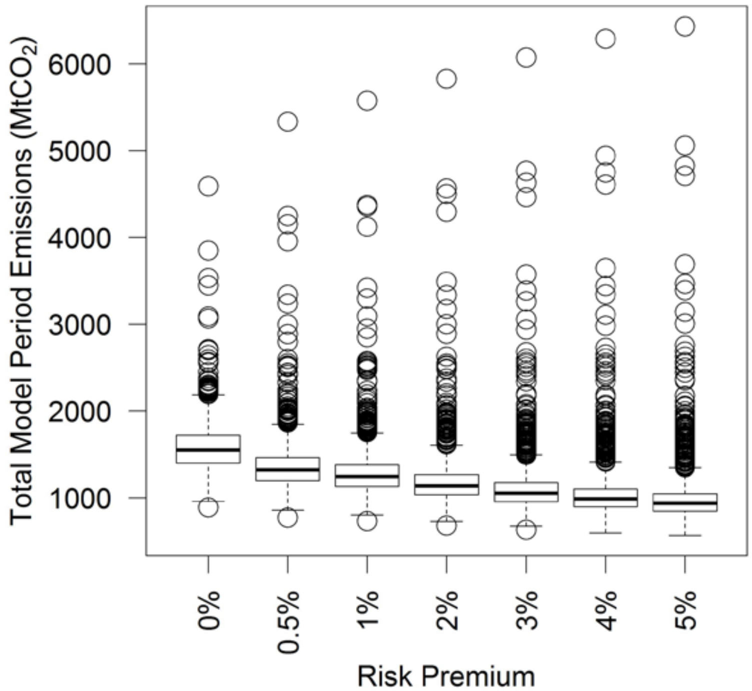


**Figure 2.12: Total model period emissions for each random realization at various levels of risk premium for system with nuclear available.**

For the case with no nuclear (Figure 2.7), as the risk premium increases, average emissions and the high emission outliers follow the same decreasing trend and the maximum high emissions case is approximately 3500 $MtCO_2$. When nuclear generation is available (Figure 2.12), the trend of average emissions show this same decreasing trend, with the average at each risk premium around 500 $MtCO_2$ lower than that without nuclear available. However, there are a number of high emissions outliers, which are as high as 4500 – 6000 $MtCO_2$. Both risk and average emissions are reduced, but there is a low probability (*i.e.* less than 10 in 2000 or less than 0.5%) that the emissions are higher. This is because the system relies on only two generation technologies. If either of the technologies produces emissions toward the upper end of its distribution, for a given random realization, the total emissions for that realization are high.

### 2.5.3 *COST AND RISK COMPARISON*

It is illustrative to compare the cost and risk for each risk premium for the systems with and without the option of nuclear generation. Figure 2.13 shows the Pareto optimal risk versus cost curves with and without nuclear available. This figure shows that the risk and cost are significantly lower for all situations where nuclear is available.

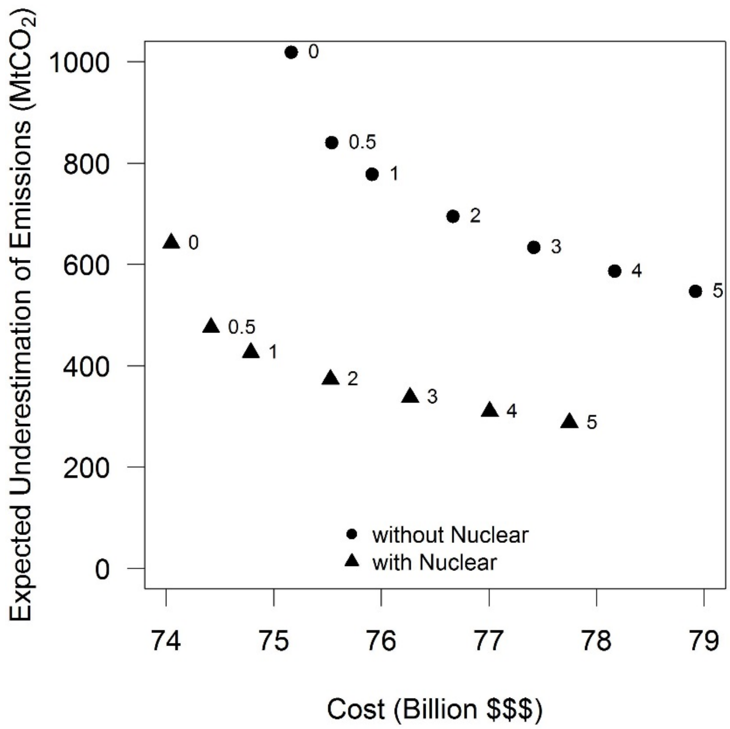


**Figure 2.13: Model calculated risk versus system cost for all risk premium levels for the system with and without nuclear.**

Figure 2.13 shows that the risk with nuclear, at a 0.5% risk premium, is lower than the risk without nuclear at a 5% risk premium. Although there is much public controversy about nuclear safety, nuclear generation provides a cost effective hedge against climate emissions risk.

## 2.6 Discussion

We have used a stochastic risk framework and applied it to carbon emissions in an electrical system represented by the province of Alberta, Canada, a predominantly fossil based system, and have included nuclear as a risk mitigation technology.

We find that, for the system without the availability of nuclear in the generation mix, a 5% risk premium starts the build out of wind 5 years earlier, and the build out of solar photovoltaic 7 years earlier than the base model, ending up with significantly more installed solar in 2050 than without the risk premium. In the year 2040, coal with carbon capture and storage comes into the energy mix and replaces co-generation as a less risky alternative. Parkinson and Djilali [47] did not include carbon capture technologies in their model so the results cannot be compared directly, but their model also showed an increase in wind generation with increased risk premium and, similar to our results, they found an increase in SCGT to meet the reserve margin. Their model showed run of river and pumped hydro taking up the bulk of the generation while, in our model, CCS came in at higher risk premiums and pushed out CCGT. Since they analysed a primarily hydro based jurisdiction, using pumped storage and run of river technologies is possible. In the Alberta context, there is no significant potential for either run of river or pumped storage. This shows that jurisdictions with different potential energy sources need to be analysed separately. Our analysis could be extrapolated to similar fossil based jurisdictions such as many US states and countries such as India and China.

Although current climate policies eventually incent additions of renewables, additional policies that provide for earlier adoption of solar power and wind could provide a risk hedge against future emissions if nuclear is not considered an option. A policy to encourage earlier wind adoption would need to be implemented almost immediately, while the policy to encourage solar adoption would need to take effect in the early 2040s. Investments in the development of coal with CCS or other unproven low carbon technologies that can meet baseload with lower emissions risk could provide future benefits. Although this technology is not installed by the model until the early 2040s, similar to solar, the potentially lengthy research and development timelines would indicate that policy action sooner rather than later is needed. Using a risk framework to look at carbon dioxide emissions could allow decision makers to implement policies that are more effective, given the timelines for some technologies.

With nuclear available for the system there is little power generated by any technology other than wind and nuclear, though some flexible generation in the system would be needed for system stability. This could be met by building nuclear generation able to ramp and follow load, though we acknowledge that this could increase costs. If nuclear is considered an option for Alberta, the focus should be on getting the best performance out of the combination of wind and nuclear. Even without a risk premium applied, allowing nuclear reduces costs and reduces the risk of increased emissions and is installed starting around 2040. With a significant shift in social/political will, having nuclear generation operational in Alberta as early as 2020, and contributing significantly by 2030 reduces the emissions risk significantly if a 5% risk premium is applied. This is consistent with the results found by Kanudia et al. using a multi-scenario framework [50], who found that, when nuclear was available, it was always fully utilized in their model. We realize that a significant political and social shift would be required to allow nuclear to contribute to the Alberta power system in 2020, so early policy action would be needed to realize the full benefit of nuclear as a risk hedge if a 5% risk hedge is implemented as policy.

Our results show that nuclear is a cost effective risk hedge against increases in carbon dioxide emissions even without a risk premium applied. The 0% risk premium with nuclear case has the same emissions risk as the 3% risk premium without nuclear case, but at a 5% lower cost. As discussed in the literature review, there has been significant research into the cost uncertainty of nuclear but our results indicate that there is room for capital cost escalation in nuclear and it would still provide an effective risk hedge against increased emissions.

As noted in the literature review, very little work has been published on the risk of increased emissions in energy system modelling. More studies that investigate this space would provide more comparisons and allow for more detailed policy direction.

## 2.7 Future Work

The model described above has a number of limitations that could be addressed in future work. The main limitation is that emissions from a number of technologies such as wind and solar occur only at the installation phase and not when the technology generates electricity. The current implementation of the model uses expected emissions per kWh generated, or levelized emissions, and therefore disadvantages these technologies. Separating out the risk associated with construction emissions will allow us to address this limitation.

The model implementation above uses Coal with CCS as a proxy for a low-emissions dispatchable/baseload generator. At this point CCS technology is still developing and there are unknown risks with the technology including the possibility of leakage from the stored carbon. Incorporating this risk into the model could alter the results and provide interesting insights.

In this study we investigated how to hedge against the risk of increased emissions while most studies on risk consider only financial risks. Developing a framework for incorporating both financial and emissions risks into the model would potentially provide insights into how to mitigate both financial and emissions risks and allow for more nuanced policy decisions.

Finally, expanding the study to include the entire energy system, not just the electricity system, would make the analysis more general. There may be some interesting trade-offs in terms of how to meet the given demand for these three services within this model framework.

# 3. VALUING INFRASTRUCTURE INVESTMENTS TO REDUCE CURTAILMENT[3]

### Preamble

Curtailment due to high penetrations of variable renewable (VR) capacity leads to increased costs borne by the electricity system. These curtailment costs can be implicitly included as integration costs in long term models but to date have not been included in short or medium term models in the literature. We implement curtailment cost tracking into a medium term version of the OSeMOSYS linear programming model and show how the inclusion of curtailment costs adds to the value proposition when considering infrastructure investments to reduce curtailment. Infrastructure investments such as storage and dispatchable load technologies are considered for a system with high wind penetration.

We find that including curtailment costs in the value of storage and dispatchable loads adds significantly to the value of that infrastructure to the system, depending on the curtailment cost and the penetration level of wind power. Ignoring curtailment costs potentially under-values investments to reduce curtailment. No other works compare the value of curtailment to investment in storage or dispatchable load technologies.

## 3.1 Introduction

High penetrations of variable renewable (VR) capacity, such as wind and solar, can lead to curtailment of the VR generator due to the limited ability of the electricity grid to receive this power [51]. Curtailment leads to increased costs that are either borne by the electricity system operator, if the contract with the VR generator is *must take*, or by the owner of the generator.

[3] The body of this chapter was published in T. Niet, B. Lyseng, J. English, V. Keller, K. Palmer-Wilson, B. Robertson, P. Wild and A. Rowe, *Energy Strategy Reviews*, vol. 22, pp. 196–206, November 2018.

These costs, which we term *curtailment costs,* include: contractual requirements for direct payment to the operator of the generator; loss of renewable energy credits (RECs); and increased life cycle cost of the VR energy because capital and fixed costs are amortized over a lower amount of generation. As an example, in Germany in 2015, wind generators were paid an average of €53/MWh to curtail their generation [147].

Previous studies such as Ueckerdt [70] and Hirth et al. [71] implicitly include curtailment costs within integration costs in long term models but the explicit inclusion of curtailment costs in a short and medium term optimization models is not present in the literature. With the increased penetration of VR generation, and the corresponding increase in VR curtailment, this can no longer be justified.

In this study, we use a curtailment-enabled model to value infrastructure investments that reduce curtailment. Two types of infrastructure investment are used to demonstrate the applicability of the method: storage and dispatchable loads. Other studies have evaluated how VR generation owners can benefit from reduced curtailment [118] or how curtailment schemes work in the marketplace [59,119]. We take a system-level view and consider the overall system value that specific infrastructure investments provide when curtailment costs are included in a one year system model. This allows us to value investments in storage or dispatchable load technologies when curtailment costs are included in the model.

## 3.2 Literature Review

We first review the literature on integration of VR generation into power systems and find that, although integration costs are considered in some long term studies, short and medium term studies focus primarily on reducing curtailment and not on the cost that curtailing imposes on the system.  Model frameworks that have been used to evaluate VR energy integration costs are then presented and we show how integration costs for long term models can implicitly include curtailment costs, but that shorter term studies do not include curtailment costs.  Finally, a discussion of model time scales is provided.

### *3.2.1 Integration of VR generation in Power Systems*

There is much research on integrating VR generation into power systems.  Much of this work focusses on long term optimization of the generation mix rather than on short and medium term impacts of curtailment.  These studies address the efficacy of demand side management and grid enhancements, such as storage, transmission expansion or increased flexibility, to increase the long term penetration of VR generation.  We provide a brief review of these studies before reviewing the literature on curtailment in short and medium term studies.

In long term studies, the effect of demand side management, transmission expansion and storage on the penetration of VR energy have been addressed.  Salpkari et al. [66] model demand side management of heating loads and other flexibility solutions to increase VR penetration for a system in Finland.  Lamadrid et al. [67] assess the effects of investments in transmission on the ability of the grid to integrate VR generation and find a corresponding increase in VR penetration with transmission expansion.  Denholm and Hand [68] study the effect of ramping capability of non-VR generators on VR penetration and show that a more flexible system allows more VR generation in the system.  Studies of storage often optimize the size of the storage system and, in some cases, other generators to meet a given demand with specified costs for both the generators and the storage system [51–65].  Braff et al. [69] present a method for sizing hybrid wind/storage installations to obtain the highest market value from the power sold.  As noted above, these long term studies can include integration costs using the framework presented by Ueckerdt [70] and Hirth et al. [71].

As in long term studies, short and medium term studies have addressed the effect of demand side management, transmission expansion and storage on the penetration of VR energy. Arteconi et al. [72] evaluate the use of active heating demand response to deal with VR variability and find that demand response reduces system operating costs and curtailment. Xiong et al. [73] consider controlled heating loads in Northeast China to enable reduced wind curtailment. Brouwer et al. [74] compare the system cost when the system is permitted to curtail VR generation with the system cost of adding demand response, storage or interconnection for a system with high penetrations of intermittent resources. They find that only curtailment and demand response are economically viable. Denholm et al. [75] investigate load shifting, demand response and increased ramping flexibility in a system with 50% solar energy penetration and show that implementing these technologies reduces curtailment. Although each of these studies considers demand response investments to reduce curtailment, none place an economic value on the curtailment when it occurs.

Only two studies were identified that consider transmission expansion in short or medium term models and the impact on curtailment. Lamy et al. [76], rather than considering transmission expansion explicitly, compare potential VR generation locations when transmission constraints are included and find that different locations have different levels of curtailment. As noted above, Brouwer et al. [74] compare the system cost when the system is permitted to curtail VR generation with the system cost of interconnection and find that transmission expansion to reduce curtailment is not economically viable. Neither of these studies consider the cost to the system of curtailing generation.

There are many studies of the impacts of storage investments on the curtailment of VR generation. Johnson et al. [77] evaluate storage batteries to determine the value of reducing curtailment and transmission requirements. This value is used to determine storage cost curves based only on the value of the additional revenue from energy sales that is enabled by including battery storage. Denholm [78] evaluates energy storage to reduce curtailment and shows that even medium duration storage, on the order of 4 – 8 hours, results in significantly reduced curtailment. The value of the thermal storage that is integral to concentrated solar power plants and its effect on VR curtailment has also been studied [79–81]. Other works evaluate the potential for power-to-gas technologies to reduce curtailment [82–88]. All these studies optimize the size of storage infrastructure but none explicitly considers the value of resulting curtailment reduction.

To summarize, integration costs for VR generation have been included in some long term energy planning models, but the cost of curtailment can, at best, be only implicitly included in these models. In the short and medium term, most studies have only considered the reduced curtailment that can be achieved with infrastructure investments but not the cost of curtailing this generation.

### *3.2.2 Integration Costs and Model Frameworks*

To show how long term models implicitly include curtailment costs but that shorter term studies, to date, have not included them we first provide a review of the major work on integration costs in long term models. This is followed up with a review of the few papers that discuss integration costs in shorter term models and shows how our addition of curtailment costs into shorter term modelling contributes to the energy modelling literature.

For long term energy planning, Hirth et al. [71] provide a summary of VR integration costs, noting that these costs are a combination of increased requirements for balancing services, increased cycling of thermal plants, reduced utilization of capital stock and other system level impacts. They organise these costs into three categories:

1. *Balancing costs* reduce the value of VR generation due to deviations of actual VR generation from forecast generation. These costs include the requirement to have standby generators available should the VR generation not meet the forecast and the costs of curtailing generators should the VR generator produce more than forecast.
2. *Profile cost* is the differential market value of VR generation due to the timing of the generation. At times of high VR penetration, the price of energy may be depressed due to the effect of VR energy on the market. VR generators, therefore, may provide lower value on average than dispatchable generators.
3. *Grid related costs* are the differential market value of VR generation due to the location of the generation and restrictions and losses in transmission.

Ueckerdt et al. [70] shows how these costs vary with different penetrations of VR generation in the system. Ueckerdt et al. also mention the costs of over-generation, acknowledging that curtailment in the system increases costs. However, they do not explicitly include this cost in their models as long term systems modelling, with long time slices, average the availability of the VR generator, meaning that curtailment rarely occurs.

In long term optimizations the integration costs, as defined by Ueckerdt [70] and Hirth et al. [71], are added exogenously to account for the costs associated with high penetrations of VR energy in the system. The total cost, as defined by Ueckerdt [70] and Hirth et al. [71], becomes:

$$C = \sum_j \left(c_j x_j + PC_j + BC_j + GC_j\right) \tag{9}$$

where $PC_j$ are the profile costs, $BC_j$ are the balancing costs and $GC_j$ are the grid related costs for each technology as defined by Hirth et al. [71] and $c_j x_j$ is the cost implication for each decision, $x_j$. The general model structure is discussed in more detail in Section 3.3.2. Curtailment of VR generation is rarely represented in these long term optimizations because, in typical time slice frameworks, the availability of VR generation is averaged over long time periods.

When the optimization framework is used on shorter time frames, with shorter time slices, the optimization structure can be modified to include most integration costs explicitly, by adding transmission constraints, ramping restrictions, etc., as presented by Quoilin et al. [89]. Profile costs, other than the over-production cost, are accounted for by the supply stack with increasing costs as VR generation is less available. Balancing costs are included in the model by parameters such as the reserve margin and ramping restrictions while grid related costs are incorporated with transmission restrictions in the model formulation. The model formulation of Quoilin et al. restricts curtailment, by requiring the system to take all VR energy but does not allow curtailment or include the cost of any curtailment.

### *3.2.3 Model Time Scales*

As discussed above, shorter term models that consider curtailment have, to date, only considered the reduction of curtailment in the system, and not the costs that this curtailment imposes. There are generally two classes of shorter term models in the literature, dispatch models that consider the balancing of the grid on a very short term basis of a day or two and others that consider medium term load shifting and storage systems using multi-hour time scales.

Dispatch models that consider balancing of the grid on very short time frames, on the order of minutes, are used to model the operation of the grid on short time frames. Due to computational complexities, these models generally simulate periods of 24 hours or less [148–151]. Due to this 24 hour period these models are unable to capture optimal operation of medium term (i.e. daily or weekly) storage or longer term load shifting across days.

Models that consider medium term storage or load shifting usually use yearly model periods with hourly or multi-hour time steps. This approach allows them to capture load shifting of tens of hours as contemplated by Kousksou et al. [152]. Ellison et al. use a medium term scheduling model to determine impacts of outages on the Oahu, Hawaii electricity system and use "temporal simplification" over a one year period. Combined with other model approaches they find that load shifting provides value from energy storage [153]. Stenzel et al. discuss using battery electrical storage on Graciosa Island in the Azores to reduce diesel use with an hourly model and find that they can reduce environmental impacts by over 40% [154]. Komarnicki et al. model the use of energy storage over varying time scales including multi-hour load shifting applications to demonstrate how storage can be used to increase flexible operation of smart grids [155].

For this work we use a one-year model period and three hourly time slices to enable our model to evaluate daily and weekly load shifting.

## 3.3 Methods

We model an electricity system whose generation mix is comprised primarily of must-run natural gas co-generation, natural gas combined cycle and natural gas simple cycle generation and wind generation with lesser amounts of other renewable generation, namely hydro, geothermal and biomass. The system is based on the electricity system in Alberta, Canada, which is a fossil fuel dominated jurisdiction in which wind energy penetration is significant and growing. This generation mix is similar is to the energy systems of many US states and countries such as China and India. Unlike some of these other systems, however, in Alberta, large-scale cogeneration is a significant fraction of capacity and, because of thermal demands, the flexibility of the system is limited.

The following sections describe the system representation, numerical methods, data sources and implementation details and, finally, the case studies considered in the analysis.

### *3.3.1 System Representation*

Figure 3.1 is a representation of the system model in which dispatchable generation types are grouped together and wind is the only VR generation type. Additional options to manage system variability and cost are storage and dispatchable load. The conventional generation technology mix in terms of capacity is assumed to be fixed. The penetration of VR is varied independently from the available storage and dispatchable load. System operation is determined for a range of capacities of curtailment reducing technology, using a fixed demand profile. The resulting dispatch and operating costs are determined by cost minimization.

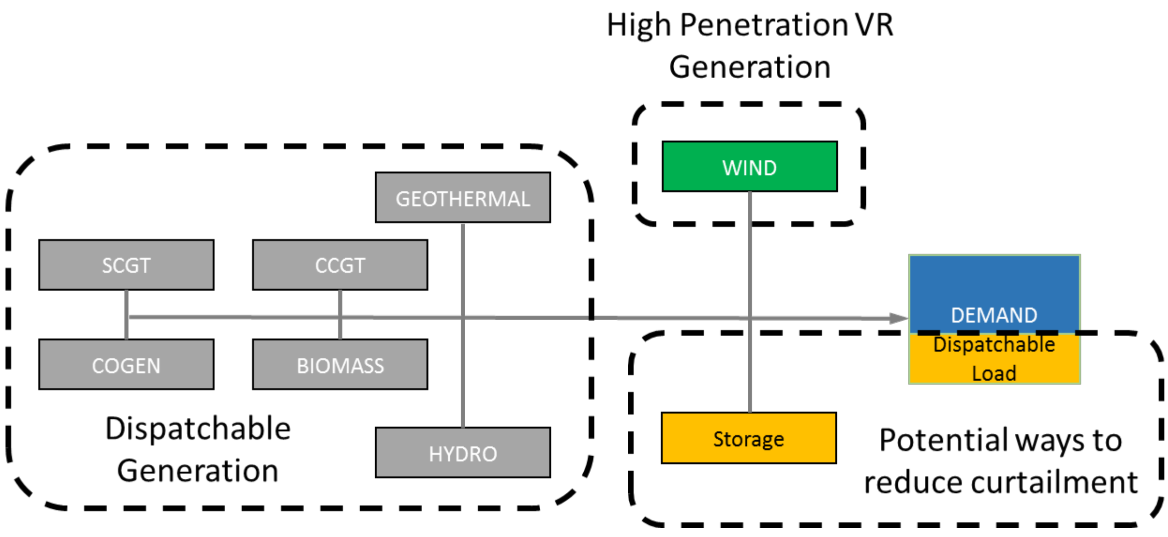


**Figure 3.1: Diagram of generation options in the modeled system. The wind resource is the VR in the system and the installed capacity of wind is varied.**

### *3.3.2 Numerical Model*

A linear programming model is chosen to optimize the overall system cost and provide the optimal operation of the system. This model minimizes the overall system cost, including curtailment cost, based on the generic problem formulation:

$$Min\ C = \sum_j \left(c_j x_j\right) \tag{10}$$

$$s.t. \sum_j (a_{i,j} x_j) \leq b_i\ \forall\ i \tag{11}$$

$$x_j \geq 0\ \forall\ j \tag{12}$$

The objective of the problem, as defined in Equation 10, is to find the solution vector, $x_j$, that minimizes the sum of $c_j x_j$, where $j$ represents the set of all possible decisions. In energy systems models, $c_j$, the vector comprising the cost parameters, is often separated into capital, fixed and operating costs while $x_j$, the vector comprising the decision variables, is often separated into new capacity and operating decision vectors. The subscript $j$ then represents new capacity and operating decisions for each technology in the model. The performance parameters for the technologies are $a_{i,j}$ and the activity or installed capacities are restricted by $b_i$ , as shown in Equation 11. This general formulation has been implemented in a number of techno-economic energy system modeling tools, including MESSAGE [130,131], Times/MARKAL [132] and, more recently, the Open Source Energy Modelling System (OSeMOSYS) [11,12].

The basic model formulation, as shown in Equations 10 through 12 explicitly excludes curtailment costs as the amount of generation in each time slice is permitted to exceed the demand due to the inequality in Equation 11. This is implemented in most models as an inequality that ensures that the sum of the generated energy, $E^G_{i,j}$, for each generator, $j$, is greater than or equal to the total demand, $E^D_i$, in in each time slice, $i$, as shown in Equation 13.

$$E_i^D \leq \sum_j E_{i,j}^G \tag{13}$$

This works when there is no curtailment cost in the model as the optimization algorithm will reduce the variable costs and therefore not over-generate. When curtailment costs are included in the model the inequality in Equation 13 must be changed to an equality to prevent over-generation as shown in Equation 14. This is computationally less efficient, but ensures that the sum of the generated energy, $E^G_{i,j}$, for each generator, $j$, is equal to the total demand, $E^D_i$, in in each time slice, $i$, thereby eliminating any excess generation.

$$E_i^D = \sum_j E_{i,j}^G \tag{14}$$

With this modification, the model is no longer permitted to over-generate energy above the demand curve. We can then calculate the cost of curtailment with an additional cost term in the objective function, namely the average curtailment cost. Thus, $c_j$, the vector comprising the cost parameters, includes capital, $c_{j,c}$, fixed, $c_{j,f}$, operating, $c_{j,o}$, and curtailment costs, $c_{j,e}$. To calculate curtailment cost, we start by defining the available energy, $E_{i,j}^{A}$, from generator $j$ in time slice $i$ as:

$$E_{i,j}^{A} = I_j CF_{i,j} \tag{15}$$

where $I_j$ is the installed capacity of generator $j$ and $CF_{i,j}$ is the capacity factor for generator $j$ in time slice $i$.

The amount of constrained energy for generator $j$ in time slice $i$, $E_{i,j}^{C}$, can then be calculated as:

$$E_{i,j}^{C} = E_{i,j}^{A} - E_{i,j}^{G} \tag{16}$$

where $E_{i,j}^{G}$ is the utilized energy from generator $j$ in time slice $i$, as determined by the model. The total curtailment cost, $C_C$, for this amount of energy is then calculated as:

$$C_C = \sum_{i,j}\left(c_j^c E_{i,j}^{C}\right) \tag{17}$$

Where $c_j^c$ is the average curtailment cost per unit of energy for generator $j$, the portion of the cost, $c_j$, that is associated with curtailing. The costs for each generator in each time slice, $i$, are summed to get the total curtailment cost over the model period. This term is added to Equation 10 to yield a total system cost that includes curtailment cost, $C_T$.

$$C_T = \sum_j\left(c_j x_j\right) + C_C \tag{18}$$

Equations 14 through 18 are implemented in the OSeMOSYS energy modelling system [11,12].

To illustrate the benefit of including curtailment costs in a medium term model, we investigate the impact of installing technologies that reduce the need for curtailment. More specifically, we consider a dispatchable load and an energy storage system. We do not include the costs of the additional technology in the objective function; instead we determine the reduced system cost with the technology installed. We then post calculate the value of this infrastructure to the system as:

$$V = C_T^0 - C_T \tag{19}$$

where $C_T^0$is the cost without the infrastructure and $C_T$ is the reduced cost with the infrastructure. We then normalize Equation 19 for the installed capacity of the infrastructure, $S_V$, to get the value per unit of installed capacity, $v$, as:

$$v = \frac{C_T^0 - C_T}{S_V} \tag{20}$$

The proportion of the value that is contributed by the curtailment cost, $C_C$, is calculated as:

$$v_C = \frac{C_C^0 - C_C}{S_V} \tag{21}$$

Equations 19 through 21 are not implemented in OSeMOSYS but are used to analyse the model outputs.

### *3.3.3 MODEL IMPLEMENTATION AND DATA*

The curtailment cost framework described above is implemented into the Open Source Energy Modelling System (OSeMOSYS) [11,12], a freely available energy systems model. This model was chosen due to its availability and its general acceptance in the energy modelling community. The GLPK model equations, as implemented in OSeMOSYS, are included in the Appendix. Using this framework, we develop a model of an electricity system whose generation mix is comprised primarily of must-run natural gas co-generation, natural gas combined cycle and natural gas simple cycle generation and wind generation with lesser amounts of other renewable generation, namely hydro, geothermal and biomass.

The model is based on a generation mix for Alberta for 2030 as determined using a long term optimization of the Alberta system by Lyseng et al. [117] and updated to include policy announcements by the Alberta government in late 2015 [135,136] which include 30% of energy from renewable resources by 2030. Table 3.1 shows the generation capacities included in the existing generation portion of the model, as shown in Figure 3.1. These capacities are as determined by Lyseng et al. [117,135] to meet an average load of 14.3 GW, which is the 2030 load projected by the Alberta Electricity System Operator (AESO) [138]. Generator performance data are taken from the U.S. Energy Information Agency [137]. The load profile is taken from the 2013 Alberta system load and is scaled to the AESO predicted 14.3 GW average load [56]. The model is based on 2920 3-hour timeslices that cover a one year period.

**Table 3.1: Generator Capacity for 30% Renewables [117]**

| Generator | Acronym | Installed Capacity |
|---|---|---|
| Simple Cycle Gas Turbine | SCGT | 6.7 GW |
| Combined Cycle Gas Turbine | CCGT | 4.3 GW |
| Co-generation (heat and power) | COGEN | 5.53 GW |
| Biomass | BIOMASS | 0.24 GW |
| Hydropower | HYDRO | 0.9 GW |
| Geothermal Power | GEOTHERMAL | 0.5 GW |
| Wind | WIND | 10.6 GW |

### *3.3.4 Case Studies*

For each infrastructure investment we consider nine cases, each comprised of a unique combination of installed wind capacity and curtailment costs as shown in Table 3.2. Curtailment cost values are assumed to fall within the range of US$15/MWh to US$100/MWh, as found in the literature [71,147,156–158]. Three levels of wind capacity are considered, representing 75%, 110% and 150% of the 14.3 GW average projected load for 2030. This corresponds approximately to obtaining 30%, 45% and 60% of the yearly energy from wind power, respectively.

**Table 3.2: Combinations of VR Capacity and Curtailment Cost Modelled**

| Case Study Name | Wind Capacity | Curtailment Cost |
|---|---|---|
| 30%, $35 | 10.6 GW | $35/MWh |
| 30%, $65 | 10.6 GW | $65/MWh |
| 30%, $100 | 10.6 GW | $100/MWh |
| 45%, $35 | 15.9 GW | $35/MWh |
| 45%, $65 | 15.9 GW | $65/MWh |
| 45%, $100 | 15.9 GW | $100/MWh |
| 60%, $35 | 21.2 GW | $35/MWh |
| 60%, $65 | 21.2 GW | $65/MWh |
| 60%, $100 | 21.2 GW | $100/MWh |

Two infrastructure investments cases are modeled. First, a storage system with 80% round trip efficiency is used to illustrate avoided curtailment cost for investments in storage. Second, a dispatchable/interruptible load is modelled to illustrate the avoided curtailment costs for flexible demand. In both cases the infrastructure investment is assumed to have no cost such that the difference in the total system cost can be used to estimate the value of the infrastructure investment for the system. The curtailment costs are determined for each installed capacity of storage or dispatchable load.

#### *3.3.4.1 Infrastructure Investment in Storage*

To model storage, the OSeMOSYS storage equations described in [12] are used with two modifications. First, a constraint is added that requires the net energy transferred into storage to match the net energy transferred out of storage, ensuring that the storage system is refilled to its starting level at the end of the model period. A second modification, a restriction on the maximum stored energy, is added to restrict the installed capacity.

A round trip efficiency of 80% is assumed and is implemented as 89.44% efficiency for both the input and the output. This efficiency is within the typical range of both battery and pumped hydro storage systems [159]. Table 3.3 shows the maximum storage size and the corresponding time that this amount of storage could meet the average load. No constraint is placed on the maximum power input or output to storage as we are considering medium term storage capacities and the expected charging and discharging power of these technologies, at the scale we are considering, would easily meet the power needs in the system at any given time [160–162].

**Table 3.3: Maximum Storage Sizes and Hours of Storage**

| Run number | Storage capacity (GWh) | Hours of storage at average load |
|---|---|---|
| 1 | 0 | 0 |
| 2 | 250 | 17 |
| 3 | 500 | 35 |
| 4 | 750 | 52 |
| 5 | 1000 | 70 |
| 6 | 1500 | 105 |
| 7 | 2000 | 140 |
| 8 | 2500 | 175 |

##### *3.3.4.2 Infrastructure Investment in Dispatchable Load*

To implement a dispatchable load we increase the overall demand, $D_i$, by a capacity that represents the power of the dispatchable load, $P_i$, in each time slice as shown in Equation 22.

$$D_i = D_i^0 + P_i \tag{22}$$

This allows excess wind power to be utilized to meet the demand as shown in green in Figure 3.2.

We then introduce a generator that is constrained to produce the additional annual energy added to the demand by Equation 22, $P$, as shown in Equation 23.

$$P = \sum_i P_i \tag{23}$$

This generator will reduce the operation of the other generators in the system in that time slice, as shown in yellow in Figure 3.2. This implicitly addresses the bounce back effect that often occurs with demand response initiatives.

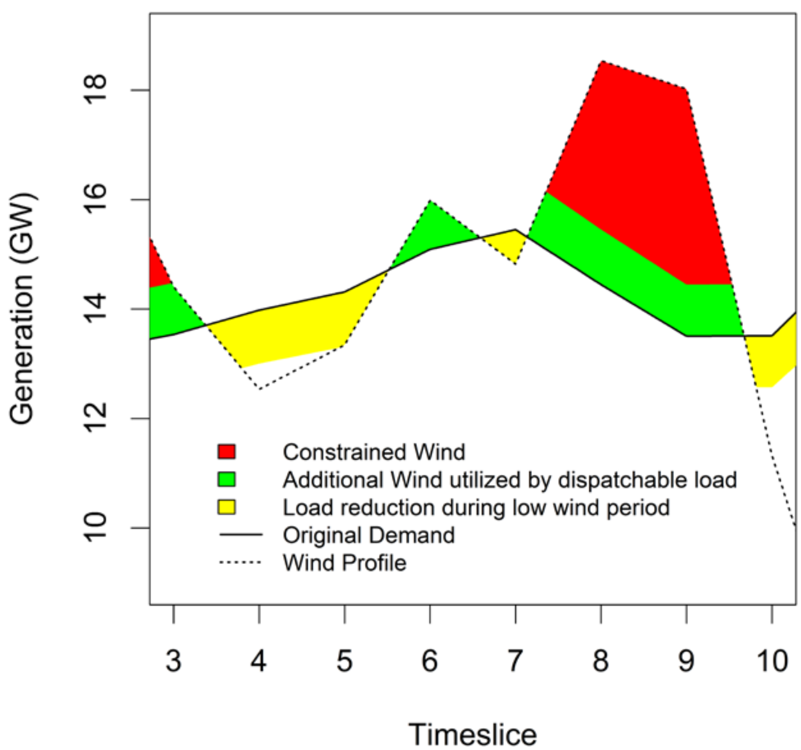


**Figure 3.2: Implementation of dispatchable load in OSeMOSYS (other generators omitted for clarity).**

Table 3.4 shows the maximum power of the dispatchable load and the corresponding percent of average load that is modelled as flexible in the system.

**Table 3.4: Maximum dispatchable load power and percent of average load**

| Run number | Dispatchable Load (GW) | Percent of Average Load (%) |
|---|---|---|
| 1 | 0 | 0.0% |
| 2 | 0.1 | 0.7% |
| 3 | 0.2 | 1.4% |
| 4 | 0.3 | 2.1% |
| 5 | 0.4 | 2.8% |
| 6 | 0.5 | 3.5% |
| 7 | 0.75 | 5.2% |
| 8 | 1 | 7.0% |
| 9 | 1.5 | 10.5% |
| 10 | 2 | 14.0% |
| 11 | 2.5 | 17.5% |
| 12 | 3 | 21.0% |
| 13 | 4 | 28.0% |
| 14 | 5 | 35.0% |

## 3.4 Results

The inclusion of curtailment costs adds between 10% and 60% to the value that storage and dispatchable loads provide to the system depending on the combination of curtailment cost and wind penetration level. This value comes from both a reduction in curtailment and a reduction in operating costs for other generators in the system. We first present the results for investments in storage, and then for investments in a dispatchable load.

### *3.4.1 Valuing Investments in Storage*

Figure 3.3 shows generation for 480 hours (20 days) of the year with 60% installed wind capacity and no storage installed. It can be seen that, with this much wind installed, and no storage capability, there is a large amount of curtailment, shown in red, where the available wind exceeds the demand.

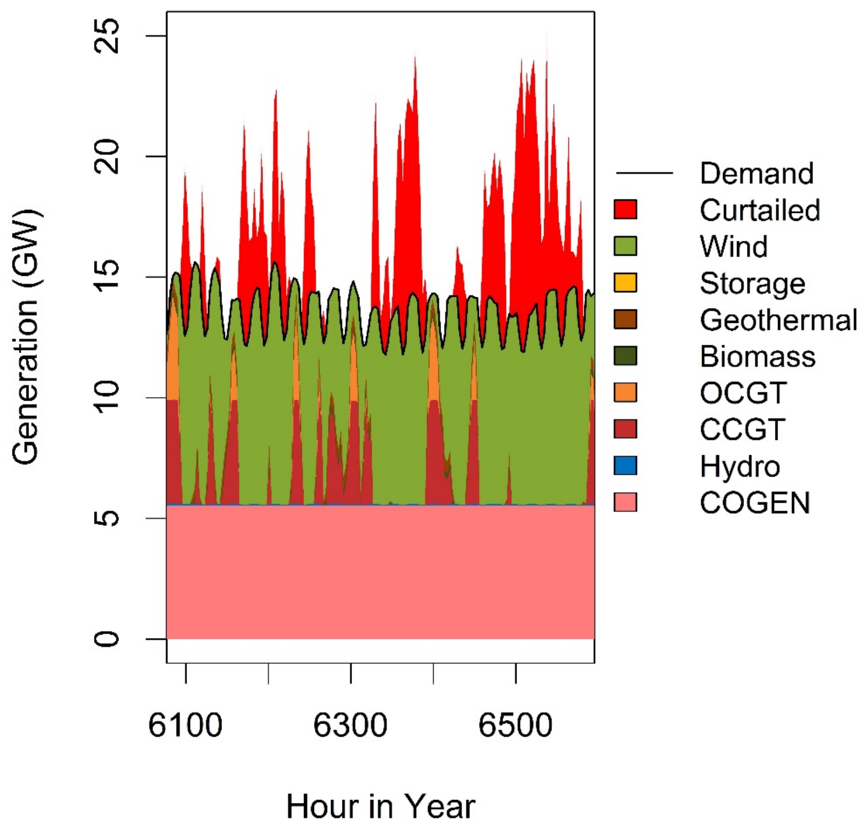


**Figure 3.3: Generation over time for system with 60% wind, no storage.**

Figure 3.4 shows the same information, but with 35 hours of storage installed and the reduced curtailment that occurs with storage available. The wind generation in dark green above the demand line is used to charge the storage system while the bright green areas under the demand line indicate times when the storage system is meeting the demand. Storage reduces both the requirement to curtail wind and the reliance on fossil generation. This can be seen by comparing the difference between the natural gas generation shown in Figure 3.3 and that shown in Figure 3.4.

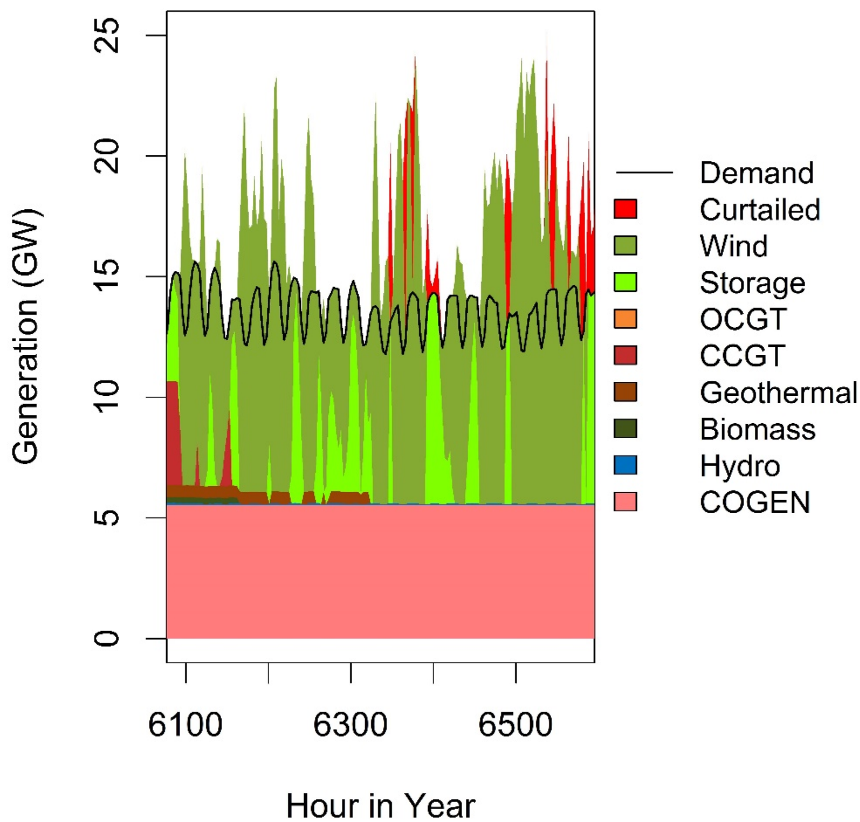


**Figure 3.4: Generation over time for system with 60% wind, 35 hours of storage.**

Figure 3.5 shows the annual generation by each generator with 60% wind for each level of storage modelled. As expected, with increased storage there is decreased curtailment. The reduction in fossil generation (OCGT and CCGT) is also apparent. Generation above the demand line occurs as there is wind power that would have been curtailed that is used to charge the storage system at times of high wind. The demand is then met, at times with low wind, by the stored energy, as shown in light green in Figure 3.5.

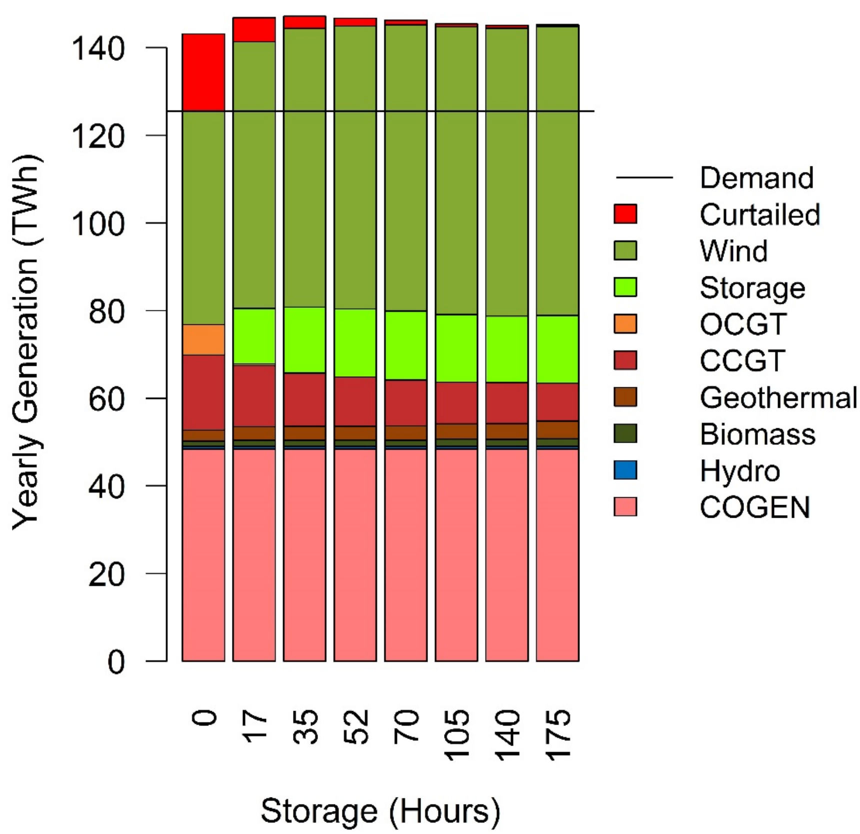


**Figure 3.5: Energy production/curtailment vs. storage size, 60% wind**

Table 3.5 shows the amount of wind curtailment as a percent of available wind energy for the different installed storage capacities as well as the reduction in natural gas use for each case with a $65 curtailment cost. Smaller amounts of storage, on the order of a few days, decreases the curtailment and natural gas use significantly but that there are diminishing returns with larger amounts of storage capacity.

Figure 3.6 shows the value of storage, as a function of storage capacity, for the three wind penetration levels, as defined in Equation 35. The value of storage is higher with higher curtailment costs and higher wind penetration levels, with a diminishing benefit as the storage capacity is increased.

**Table 3.5: Energy production and curtailment vs. storage size, $65 curtailment cost**

| Storage Hours | 30% Wind | | 45% Wind | | 60% Wind | |
|---|---|---|---|---|---|---|
| | % Curtailed | NG Reduction | % Curtailed | NG Reduction | % Curtailed | NG Reduction |
| **0** | 1.51% | 0.00% | 15.67% | 0.00% | 36.22% | 0.00% |
| **17** | 0.03% | 1.96% | 0.64% | 11.17% | 9.31% | 17.14% |
| **35** | 0.01% | 1.97% | 0.19% | 11.93% | 4.36% | 20.43% |
| **52** | 0.00% | 1.97% | 0.03% | 12.29% | 2.69% | 21.75% |
| **70** | 0.00% | 1.97% | 0.08% | 12.45% | 1.54% | 22.79% |
| **105** | 0.00% | 1.97% | 0.03% | 12.54% | 0.89% | 23.99% |
| **140** | 0.00% | 1.97% | 0.03% | 12.54% | 0.80% | 24.22% |
| **175** | 0.00% | 1.97% | 0.03% | 12.54% | 0.50% | 25.11% |

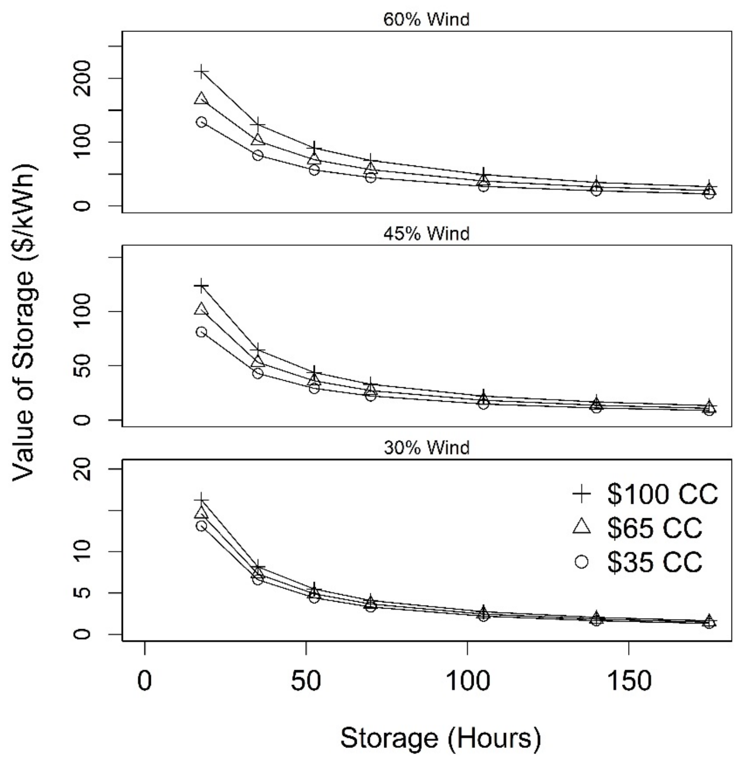


**Figure 3.6: Value of storage vs storage size, 25 year storage life.**

This figure can be used to determine storage size for given cost of a storage technology. For example, if the curtailment cost is $65, and our storage technology costs $50/kWh, there is no value to the system with only 30% wind penetration. At 45% wind penetration, it would be cost effective to install approximately 40 hours of storage, while at 60% wind penetration it is cost effective to install significantly more, around 75 hours.

For Figure 3.6 we have amortized over a 25 year period as a typical storage lifetime. The actual amortization time required to assess a given storage system would depend on the lifetime of that specific technology.

The proportion of the value that is contributed by the curtailment cost was found to have almost no sensitivity to the installed storage capacity. The proportion was found to be as low as 12% of the total value for the 30% wind, $35 curtailment cost case and as high as 50% of the total value for the 60% wind, $100 curtailment cost case. For all cases ignoring the curtailment cost would significantly underestimate the value that storage could provide to the system.

### *3.4.2 VALUING INVESTMENTS IN DISPATCHABLE LOAD*

Figure 3.7 shows the results for a 1 GW dispatchable load and 30% wind penetration. In this figure the original demand line is shown in black. Wind generation that is used by the dispatchable load is shown as generation above the original demand line. The corresponding times when the dispatchable load is turned off are shown unshaded under the original demand line.

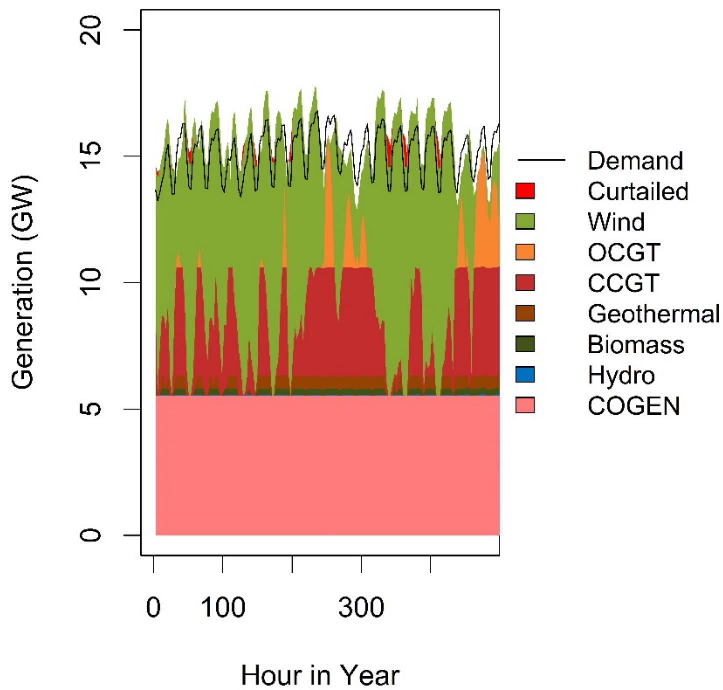


**Figure 3.7: Generation over time for system with 30% wind, 1 GW dispatchable load.**

Figure 3.8 shows the same information as Figure 3.4, but for 60% wind penetration and a 3 GW dispatchable load. There are much larger periods where excess wind can be utilized as shown by the larger green band above the demand line. The amount of time when the demand is reduced due to this demand shifting is correspondingly larger as well.

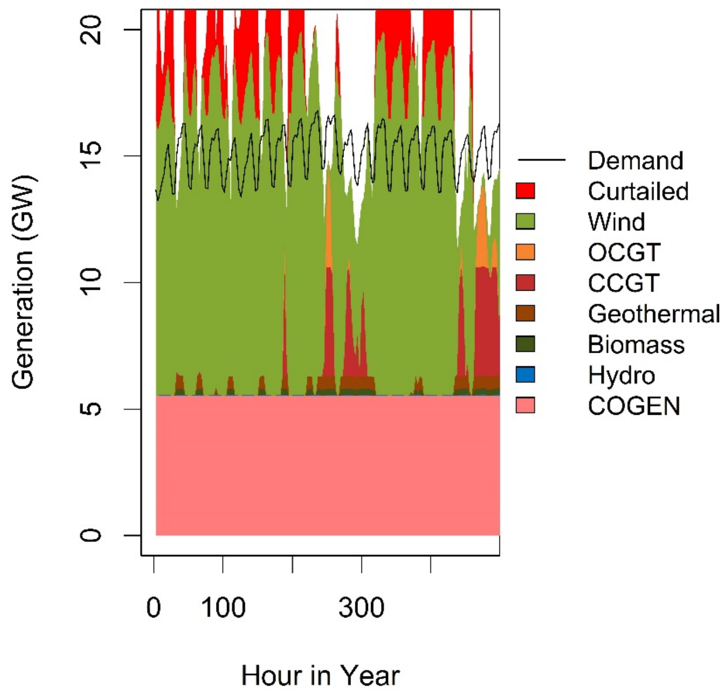


**Figure 3.8: Generation over time for system with 60% wind, 3 GW dispatchable load.**

Figure 3.9 shows the generation by technology for the dispatchable load for 60% wind. The shape of this graph is notably different than the graph in Figure 3.5, the corresponding figure for storage. With storage, the initial installation allows wind to generate above the demand and therefore the total generation increases since there are losses in the storage system. For the dispatchable load, the curtailment decreases with increasing dispatchable load. The generation by OCGT and CCGT decrease correspondingly.

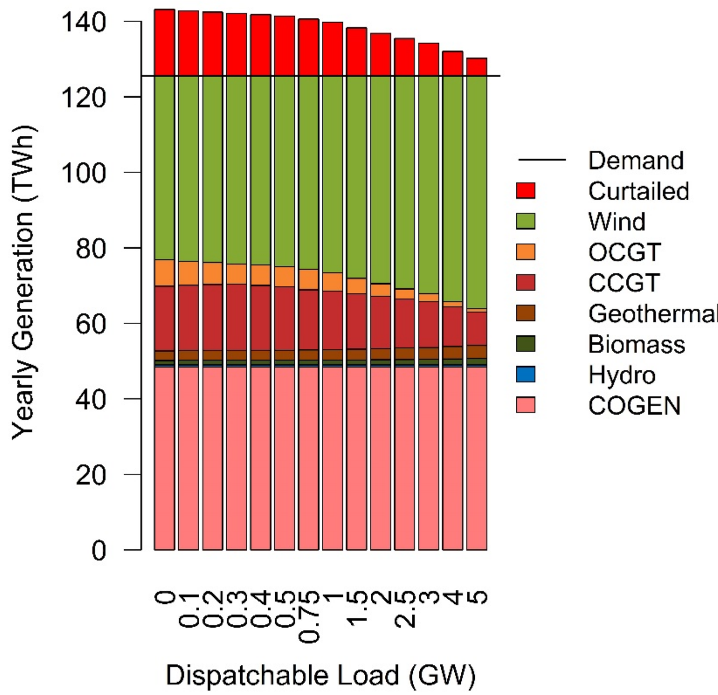


**Figure 3.9: Energy production/curtailment vs. dispatchable load, 60% wind.**

Table 3.6 shows the amount of wind curtailment as a percent of available wind energy for the different installed dispatchable load capacities as well as the reduction in natural gas use for each wind capacity with a $65 curtailment cost. Increasing amounts of dispatchable load provide increasing reductions in curtailment and use of natural gas, especially for high installed wind capacities. This is in contrast to storage, where additional capacity past a certain point does not provide any benefit to the system.

Figure 3.10 shows the value of dispatchable load as a function of capacity. For the low wind penetration the diminishing rate of return for increased investments is clearly seen. There is more variability in the shape of these curves when compared to the value of storage curves. The value still has a declining benefit with high penetration, but the curves are generally flatter, and there are shifts in the curve as the dispatchable load displaces different value generation.

As with Figure 3.6, Figure 3.10 can be used to determine the capacity of dispatchable load that would provide value to the system. If the operating cost of a dispatchable load is $300 per kW per year, and we expect a $65 curtailment cost, at 60% wind we might want to install as much of this dispatchable load as possible, in the 45% wind case, it would be cost effective to install around 2.5-3 GW of dispatchable load and in the 30% wind case it is not clear any value to the system can be obtained.

**Table 3.6: Energy production and curtailment vs. storage size, $65 curtailment cost**

| **Dispatchable Load** | **30% Wind** | | **45% Wind** | | **60% Wind** | |
|---|---|---|---|---|---|---|
| | Wind Curtailed | NG Reduction | Wind Curtailed | NG Reduction | Wind Curtailed | NG Reduction |
| **0** | 1.51% | 0.00% | 15.67% | 0.00% | 36.22% | 0.00% |
| **0.1** | 1.35% | 0.28% | 15.03% | 0.67% | 35.24% | 0.90% |
| **0.2** | 1.21% | 0.56% | 14.42% | 1.33% | 34.28% | 1.79% |
| **0.3** | 1.08% | 0.82% | 13.82% | 1.97% | 33.35% | 2.59% |
| **0.4** | 0.95% | 1.08% | 13.25% | 2.61% | 32.43% | 3.08% |
| **0.5** | 0.84% | 1.33% | 12.68% | 3.23% | 31.55% | 3.57% |
| **0.75** | 0.61% | 1.92% | 11.34% | 4.74% | 29.41% | 4.75% |
| **1.0** | 0.43% | 2.46% | 10.11% | 5.56% | 27.42% | 6.22% |
| **1.5** | 0.19% | 3.43% | 7.94% | 6.83% | 23.79% | 9.01% |
| **2.0** | 0.08% | 3.94% | 6.17% | 7.96% | 20.57% | 11.58% |
| **2.5** | 0.04% | 3.97% | 4.71% | 8.93% | 17.71% | 13.94% |
| **3** | 0.02% | 3.98% | 3.49% | 9.68% | 15.17% | 16.13% |
| **4** | 0.00% | 3.99% | 1.78% | 10.99% | 10.94% | 19.91% |
| **5** | 0.00% | 3.99% | 0.78% | 11.72% | 7.61% | 23.05% |

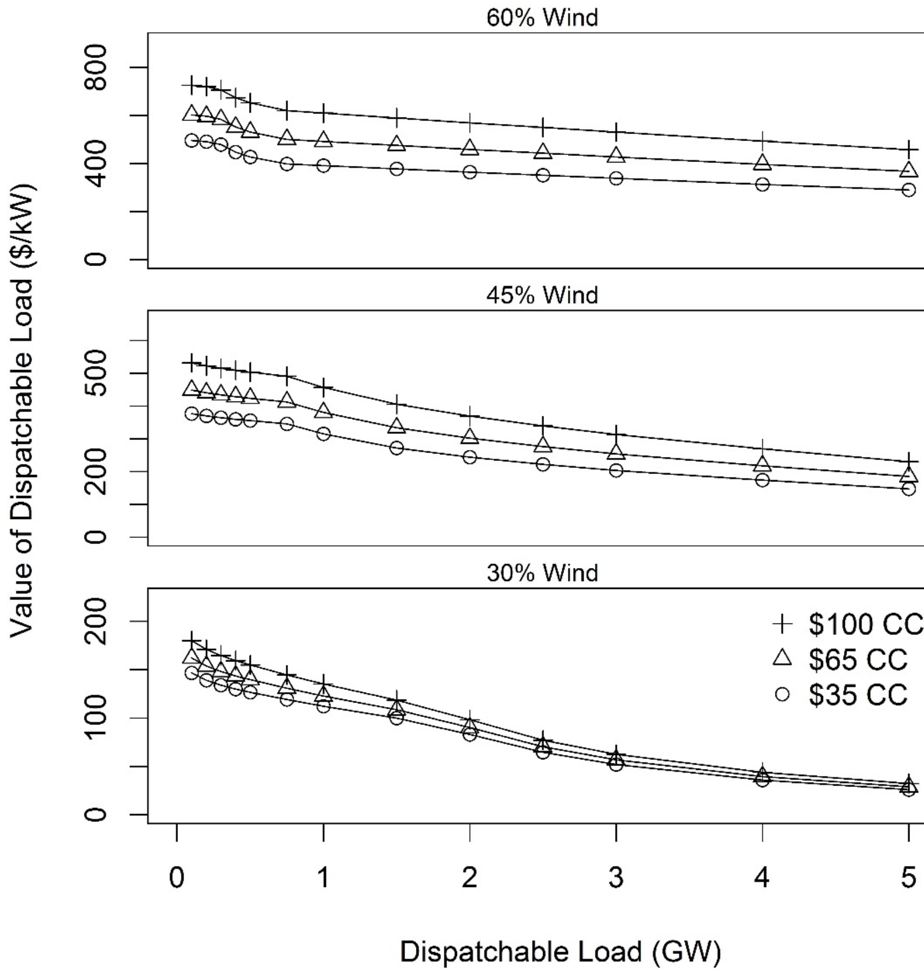


**Figure 3.10: Value of dispatchable load, per year.**

The proportion of the value of a dispatchable load that is contributed by the curtailment cost was found to have somewhat more sensitivity to installed dispatchable capacity than to installed storage capacity, but the variation was still small. The proportion was found to be as low as 10% of the total value for the 30% wind, $35 curtailment cost case and as high as 60% of the total value for the 60% wind, $100 curtailment cost case. For all cases ignoring the curtailment cost would significantly underestimate the value that a dispatchable load could provide to the system.

## 3.5 Discussion

Curtailment cost inclusion in the model adds anywhere from 10% to 60% to the value provided by infrastructure investments in storage and dispatchable loads. The proportion provided from the curtailment cost is higher with higher curtailment costs and higher wind penetration levels. Inclusion of the cost of curtailment in an energy system model allows calculation of the benefit an infrastructure investment might have in reducing this cost and can incentivize the installation of curtailment reducing technologies. Ignoring this cost potentially under-values the benefits that these infrastructure investments provide.

Two recent papers have done similar work, but from a different perspective. Johnson et al. [77] perform a valuation for storage in a system but do not include curtailment costs and Braff et al [69] calculate the return on investment for a given storage cost and size.

Johnson et al. [77] consider the delivered value of the energy from a wind farm with and without storage and calculate the value that the storage system can provide in both reducing curtailment and reducing transmission costs. They find that up to 8 hours of storage attached to a wind farm and priced at between $50 and $75/kWh would provide value by reducing transmission costs and reducing curtailment. Although our results are not directly comparable, our results would imply that Johnson et al. underestimate the value of the storage system by anywhere from 10% to 50%. We find that, at a cost of $75/kWh for storage, as much as 25 hours of storage would be cost effective for a $65 curtailment cost and over 40 hours of storage would be cost effective with a $100 curtailment cost. Our curve for $35 of curtailment cost does not extend above $30/kWh at 17 hours of storage but is curving sharply upwards. We expect that future work at shorter time scales will show a higher value for storage than Johnson et al. found.

Braff et al. [69] consider the size of storage for a wind farm that would provide a positive return on investment and find that, for investments in storage between 0 and 4 hours, there is often a return on investment but, as the storage size increases past 4 hours, the return rapidly becomes negative. Braff et al. studies the wind farm perspective in a similar way to Johnson et al. above so it is not unexpected that they find value of storage to be much lower than either Johnson et al.'s or our work. If a system perspective and the curtailment cost was included in Braff's work we expect they would find higher amounts of storage would provide value.

The variation in value for storage compared to dispatchable load is also interesting. The value of a dispatchable load is fairly constant across a large range of installed capacities while the value of storage infrastructure diminishes with increased installed capacity. In a market based electricity system like Alberta and many others around the world this has policy implications for investors. For dispatchable loads it makes no significant difference if your competitor also installs a dispatchable or controllable load system as you can still recoup the investment. For storage, on the other hand, the value of the investment depends significantly on the other storage available in the system. As such, getting investment and financing for storage would be much more difficult as it is more risky to invest in storage.

The ability of OSeMOSYS to incorporate calculation of curtailment costs allows for the consideration of infrastructure investments that reduce curtailment and the calculation of the value that these infrastructure investments provide. Lund [163] provides a review of methods of enhancing system flexibility to reduce VR curtailment. Each of the methods they discuss would reduce the curtailment cost to the system and the method we describe could be used to value any of these methods. Some specific methods that enhance system flexibility and could be assessed with our curtailment cost model include demand side management/resources and active demand response [164], load management and responsive loads such as hot water tanks, and electricity storage [159].

### *3.5.1 LIMITATIONS*

We model the medium term value of an infrastructure investment with the consideration of curtailment costs. Since our model is a medium term model it was not possible to optimize the generation mix in the model as is done in a long term model. The long term value of an infrastructure investment such as storage or dispatchable load will change based on the changes in the generation mix. We see our method being applied to evaluate the projected generation mix found with a long term model to see if storage or dispatchable load would provide additional value that a long term model cannot incorporate.

Although we utilize average curtailment costs that have been seen in various locations for the current study, corresponding to a curtailment payment contracted to the system, the method can easily be adapted to incorporate different levels of curtailment cost. This could be done by implementing a curtailment cost 'supply stack' similar to the way a supply stack is incorporated into OSeMOSYS for generation technologies. The specifics of a given curtailment cost structure would depend on the contracts, ownership and impacts of constraining in a specific system.

Our model optimizes infrastructure operation as part of the overall system. It is not possible to include the market dynamics of the Alberta, Canada market and how storage or dispatchable loads would interact with the market in such an optimization model. The return on investment for the infrastructure owner was therefore not considered as part of this study. Although we find that storage and dispatchable loads provide value to the overall system, we do not model how the infrastructure owner would benefit from this value or how the savings would be transferred to the owner.

The storage system modelled did not consider maximum power of the storage inputs and outputs but just the capacity of the storage system to maintain the average load. Adding a constraint on storage power and other operating constraints is easy to incorporate using the existing OSeMOSYS storage equations but was not done for this chapter due to the medium term nature of the storage system modelled. For medium term storage technologies such as batteries, at the scale contemplated in this chapter, the available power would exceed that required based on existing battery technologies. For different technologies incorporating this into the model would require characterization of the specific storage system being contemplated.

Finally, dispatchable loads provide significant benefit to the system but, again, the specifics of a real dispatchable load were not modelled in this paper, but a generic dispatchable load was modelled to illustrate the approach. The OSeMOSYS equations presented by Welsch et al. [12] could be used to model a dispatchable load to match a specific application, and the features of this specific application could be programmed into the model.

## 3.6 Conclusions

We have used a curtailment cost enabled model and applied it to two case studies, one considering the value of storage and one considering the value of a dispatchable load. This method provides an effective method for calculating the value of avoided curtailment costs for an investment in infrastructure such as storage and dispatchable loads. Investments in storage and in dispatchable loads are effective ways to reduce constrained wind energy in the system modelled and to provide value to infrastructure investments. This finding confirms that of other published works. Other published works, however, do not consider the cost of constraining these generators while we include this cost into our model. To date no other works have compared the value of curtailment in the valuation of storage and dispatchable loads in an energy system with high penetration of variable renewable energy.

As governments set higher and higher targets for wind and renewable energy, the curtailment of these generators will become more and more common. As discussed in the literature review, existing works mainly consider ways of reducing curtailment without considering the added value that reduced curtailment costs have for the system. By enabling OSeMOSYS to include the calculated cost of constraining in the model structure we allow for the consideration of the value of avoided curtailment cost to the system operator. This model structure will allow for more effective valuation of infrastructure investments such as storage and dispatchable loads from a system perspective.

# 4. Impact of instantaneous renewable penetration limits on grid operations and storage value

## Preamble

High penetrations of renewable energy are causing system management challenges such as maintaining adequate frequency regulation and the forced curtailment of variable renewable energy. These challenges increase operational costs and reduce the environmental benefits provided by renewable energy. Many future scenario modelling studies, including some calling for 100% renewable energy powered systems, take no consideration of these challenges. In this study the operational characteristics of a generation portfolio with high penetrations of wind power is evaluated with consideration of a minimum synchronous generation constraint. Performance of the system is evaluated with and without storage. The restrictions on instantaneous penetration of renewable energy such as wind increases costs, decreases the energy penetration of the renewable energy source and increases carbon emissions. Including storage allows for increased wind utilization, decreased operating costs and increased penetration of renewable energy with diminishing returns as the storage capacity is increased. Storage power has little impact on the value that storage provides to the system. Technologies that allow high instantaneous penetrations of variable renewable energy would reduce the impact of these system limitations.

## 4.1 Introduction

The continuing reduction in the cost of variable renewable energy (VRE) generators has forecasters predicting that a significant share of new generation coming online worldwide will come from renewables such as wind and solar [165]. There are some studies that suggest that it would be feasible to build systems powered entirely by VRE generation [166–169]. As the penetration of VRE generation increases, challenges to the operation of the grid become more significant including increased ramping events [170] and increased need for maintaining synchronous generation for frequency regulation [93,171]. This has implications for system costs for integrating these generators and, when not integrated effectively, can reduce the emission reductions provided by these technologies [98].

Another challenge posed by high penetrations of VRE generation is curtailment. With high penetrations, the ability of the grid to absorb VRE generation can be limited. This can lead to curtailment of VRE generators, reducing the environmental benefits [172,173] and imposing costs on the system such as lost renewable energy credits or reduced generation over which to amortize capital costs [174]. Electricity storage is often considered for reducing curtailment and, thereby, increasing utilization of VRE generation [78,96,97]. Many studies that evaluate storage as a tool to reduce curtailment consider neither the effects of synchronous generation requirements that impose a limit on the instantaneous penetration of renewables nor the impacts of curtailment costs. Omission of these factors can result in over-estimation of the emission reductions and operational advantages of storage.

In this study we utilize an optimization model to evaluate the impact of synchronous generation requirements and curtailment costs on the operation and emissions reductions that storage provides in a system with a high penetration of wind power. We utilize a modified version of the Open Source Energy Modelling System (OSeMOSYS) [11,12] that has been adapted for short time step modelling and that incorporates the cost of curtailment [174]. We implement ramping and synchronous generation constraints into this model. We evaluate systems with nominal VRE energy penetration levels of 30%, 45% and 60% and assess the impact that synchronous generation constraints and curtailment costs have on the system with and without storage.

## 4.2 Literature Review

Before reviewing the literature we need to define the term penetration as used in the literature. There is the energy penetration of the renewable resource, as the percent of total generation over the full model period provided by renewable generation, and the instantaneous penetration at a given time which impacts grid frequency regulation. In this chapter we will use the term energy penetration when referring to the percentage of generation from renewables over the model period, and the term penetration will generally refer to instantaneous penetration.

The literature on renewable penetration can be divided into three broad areas. First the ability of wind power to contribute to synchronous generation, then the literature on the amount of synchronous generation required for frequency regulation, and finally, the use of storage as a flexibility option.

### *4.2.1 Synchronous Generation*

In modern electricity grids there is a requirement to keep the frequency within a narrow range to ensure reliability. This is most often achieved by having large conventional synchronous generators such as coal or natural gas turbines providing the bulk of the electricity. These generators operate at a fixed speed and, due to their mechanical inertia, can absorb and compensate for variations in demand and adjust if there are outages, ensuring that the frequency does not vary outside of the permitted range.

As the penetration of VRE in a system increases, there are uncertainties about how the grid will respond [10]. Some studies conclude that wind turbines can provide primary frequency response and that modern, variable speed wind turbines are able to provide system inertia [3–6]. Other studies show that having high penetrations of wind power in the system puts the system at risk of frequency variations outside of the allowable bounds even with modern wind turbines [7–10]. For this study we consider wind generation to be non-synchronous and implement a synchronous generation constraint on the system to evaluate the impact this has on system operation.

#### *4.2.2 Allowable Non-synchronous Generation Penetration*

There are numerous studies that evaluate the minimum level of synchronous generation required to ensure adequate frequency regulation. Wang et al. [171] find that there is a requirement to restrict the amount of non-synchronous variable renewable generation in the European interconnect to as low as 25% during times of low load and as high as 60% during periods of high load due to the risk of frequency variations should a generator outage occur. The permissible penetration is lower during periods of low load as fewer generators are operating on the system so a potential generator outage has a larger impact during periods of low load. For periods of average load, the VRE penetration that could be accommodated is 40-50%.

Nahid-Al-Masood et al. [7] estimate the permissible non-synchronous penetration level based on frequency regulation contingency and the ability of the grid to handle generator outages. For the grid in south-east Australia, they find that the allowable non-synchronous penetration level is in the 5-20% range with a maximum allowable level of 45% in situations where there was high load and therefore large amounts of synchronous generation were running. This is somewhat lower than the results from Yan et al. [8] who investigate the impact of high penetrations of non-synchronous generation in the Australian National Energy Market and find that in certain circumstances a 59% penetration of non-synchronous generation can cause severe interconnection trips and some load shedding. A case where 71% of the generation was non-synchronous was associated with an unacceptable frequency drop when a synchronous generator tripped and it was noted that this was not an acceptable operational configuration for the system.

O'Sullivan et al. [175] studied the impact of very high non-synchronous penetration in Ireland and finds that above around 40% penetration there were a number of situations where frequency regulation of the grid under existing operating strategies was not maintained. McGarrigle et al. [176] finds that high levels of non-synchronous penetration, up to 75%, reduced curtailment of wind capacity, but did not evaluate the impact on the frequency of the grid. For the 75% penetration, they cite an EIRGrid study [177] that found that a 60-80% penetration level is technically achievable but states, "the integrity of the frequency response and the dynamic stability of the power system are compromised at high instantaneous penetrations of wind" above about 50-60%. This is consistent with the EIRGrid system non-synchronous penetration (SNSP) requirement of 50%, which was temporarily increased to 55% in a 2015 test [178].

There are several studies that discuss requirements for 100% renewable systems. Papaefthymiou et al. [179] state that, "in order to reach higher shares of variable renewables, specific actions should be taken to ensure that there is sufficient system inertia." They continue by stating, "Key strategies for tackling this challenge is to enable converter-connected units to provide inertia, or to keep synchronous units online to provisions system services". Delucchi and Jacobson [169,180,181] have published a number of papers considering 100% renewable energy systems but do not discuss the requirements for frequency regulation. These studies have caused some significant discussions in the literature as to the feasibility of these high levels of renewable energy penetration [182,183].

Some studies have much lower restrictions on variable renewable penetration. Gevorgian et al. [184] conclude that the US Western Interconnection should require wind generation to provide primary frequency response (PFR) services usually provided by synchronous generators even with current wind penetration levels. The current instantaneous level of wind penetration in WECC is approximately 15% during periods of light load [185] and FERC requirements provide a frequency response exception for wind power unless the system integration study identifies a specific requirement [186]. Ledesma et al. [187] model the optimal curtailment of non-synchronous wind generation on the island of Tenerife and find that, to reduce curtailment, the system must either be strengthened with additional synchronous generation or by allowing the voltages to fluctuate more than currently accepted in the system, even with the current generation mix. Neither system is near the 50% non-synchronous penetration level.

The range of allowable non-synchronous generation in the grid required to maintain operational stability and frequency regulation reported in the literature varies from as low as 25% to as high as 75%, as summarized in Table 4.1. The variation in values depend mostly on the assumed acceptable variation in frequency and voltage that the system operator can accept, with higher permissible variation in frequency and voltage allowing for more non-synchronous generation in the generation mix. Some grid operators have hard limits for allowable non-synchronous generation but in many systems this is an emerging problem as the penetration of wind power in most large systems is relatively small. As shown in Table 4.1, for most modern grids, a 50% limit is typical without significant investments in infrastructure to provide frequency regulation.

**Table 4.1: Summary of Allowable Levels of Non-synchronous Generation in the Literature**

| Study Author(s) | System Studied | Low | Typical | Max | Ref. |
|---|---|---|---|---|---|
| Wang et al. | European Interconnect | 25% | 40-50% | 60% | [171] |
| Nahid-Al-Masood et al. | SE Australia | | 5-29% | 45% | [7] |
| Yan et al. | Australia | | | 59% | [8] |
| O'Sullivan et al. | Ireland | | 40% | | [175] |
| EIRGrid | Ireland | | 50-60% | 60-80% | [177] |
| Gevorgian et al. | WECC North America | | 15% | | [184] |

### *4.2.3 Options for Mitigating System Challenges*

A number of options are discussed in the literature for mitigating the impact of high levels of non-synchronous generation in the system. Miller et al. [91] study the use of wind curtailment to maintain grid frequency and find that wind in the eastern US interconnect could provide frequency regulation if governor control of the generators was implemented. Olson et al. [92] perform a similar study for California and find that curtailment should be the 'default' solution against which other solutions can be compared. Neither study considers the cost of curtailment nor do they consider the environmental impact of curtailing renewable generation.

Storage is discussed in the literature as a method for mitigating the impact of high penetrations of renewable energy in the grid, but few of these studies include synchronous generation requirements as part of their evaluation. Barnhart et al. [94] evaluate the energy return on energy invested for systems with variable renewables and energy storage and find that storage systems can increase the energy return if batteries are able to provide over 10,000 charge discharge cycles. O'Dwyer and Flynn [95] explore the system costs associated with ramping and conventional plant cycling and find that storage can benefit the system but that energy only markets often make storage uneconomical. Root et al. [96] evaluate how storage can reduce curtailment in the electricity grid and increase payback of variable renewable costs. Bitaraf and

Rahman [97] evaluate the ability to use demand response and storage to reduce wind curtailment and find that the combination of demand response and storage allows for reduced curtailment. Denholm [78] also evaluates energy storage to reduce curtailment and finds that storage can increase grid flexibility and reduce curtailment while Denholm and Hand [68] find that energy storage in the Texas, US system can increase variable renewable penetration above 50% with curtailment less than 10% when storage is included. All of these studies consider storage in the context of reducing variable renewable curtailment but none include synchronous generation constraints as part of their evaluation.

Overall, the literature on reducing curtailment rarely considers the synchronous generation requirements for frequency regulation. Only two systems level studies have been found that consider the impacts of synchronous generation constraints on overall system operation. Vithayasrichareon et al. [93] consider the impact of ramping constraints and minimum synchronous generation constraints on operational costs of the system. They find that ramping constraints have a minimal impact on overall operational costs but that minimum synchronous generation constraints have a large impact of up to 20% when renewable penetration reaches 85%. Their study uses 30 minute time steps and does include the cost of curtailment, nor do they consider storage and how that would impact system operation.

McKenna et al. [98] considers both synchronous generation and storage in the same system. They study the impact of storage on the $CO_2$ emissions of the Ireland electrical grid with high penetrations of wind power under synchronous generation constraints. They assume 'typical' storage operation in three ways: operation of storage for peak demand shifting, operation of storage for peak wind shifting, and operation of storage following the existing operation of pumped hydro storage in the Ireland system.  They compare this to a ‘base case’ with purely random operation of the storage system.  They do not optimize the operation of storage but simulated how the storage would operate under these assumptions.  They find, with low wind penetration in the system, that storage could actually increase $CO_2$ emissions but with high penetrations of wind that emissions decrease.  They evaluate the system operation on a 30 minute time step.

To evaluate the value of storage we implement a 50% synchronous generation constraint as well as implementing a cost for curtailment of wind energy and evaluate the optimal operation of a system.  Following the recommendation of Deane et al. [188] and Hidalgo Gonzáles et al. [189], who both note that sub-hourly resolution is necessary to capture the full impact of variable renewable generation, and therefore storage, we model down to 10 minute resolution.

## 4.3 Methods

We model an electricity system where most of the demand is met by natural gas and fossil fired generators based on the electricity system in Alberta, Canada projected to 2030.  High penetrations of wind energy are forecast to be built and this is included in our model along with small amounts of other renewables, namely hydro, geothermal and biomass.  A significant portion of the load is met by natural gas co-generation that must run to meet industrial heating loads.  Similar to the projected future energy systems of many US states and countries such as China, the system is fossil-dominated with high energy penetrations of wind energy of around 50%.  Unlike other systems, however, the Alberta system includes large scale cogeneration which, due to thermal demands of industry reduces the flexibility.

The following sections describe the system representation, numerical methods, data sources and implementation details and, finally, the scenarios considered in the analysis.

### *4.3.1 System Representation*

Figure 4.1 shows the system representation with existing dispatchable generation grouped together and VR generation grouped separately. The VR generation could be any technology but the most common are wind and solar and, for this study, we consider a system with only wind power in the mix. Technologies to manage system variability are shown in a third group and include storage and dispatchable loads, though for this study we consider only storage. Conventional generation capacity and demand are fixed while the capacity of VR generation and storage are varied independently. For each case, optimal system operation is determined using cost minimization over a period of one week assuming perfect foresight and 10 minute temporal resolution.

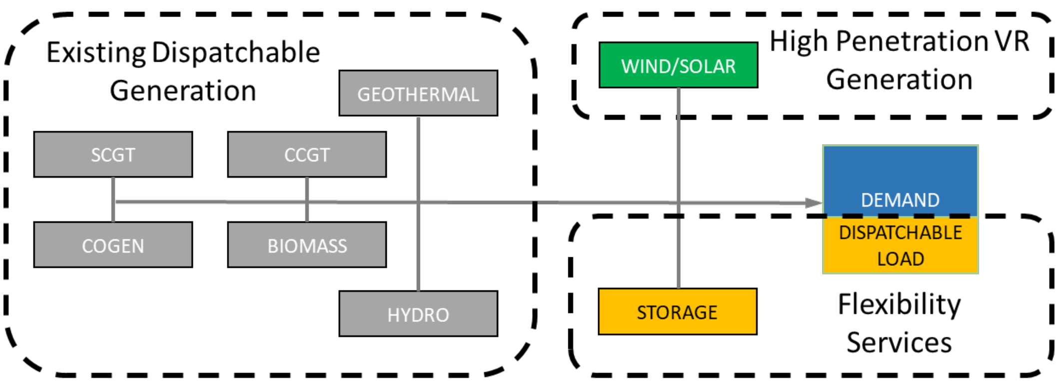


**Figure 4.1: Generation options in the system. Wind is the VR in the system.**

### *4.3.2 Numerical Model*

Three new numerical methods are incorporated into the model. First, the structure for valuing curtailment as presented in Chapter 3, second a new set of storage constraints are developed and third, ramping constraints are added to the model. For details of the structure for valuing curtailment please refer to our previous work [174]. This section describes the storage and the ramping constraints developed for this work.

#### *4.3.2.1 Storage Modelling*

OSeMOSYS comes with a set of equations for the modelling of storage for long term energy planning [12]. These equations create a simplified version of a daily load profile within a series of long term time slices to model cyclic daily nature of storage usage. As we are modelling short term storage with consecutive short term time slices these equations are computationally inefficient and were replaced for this work with a simpler storage system model.

We start by tracking the starting storage level for each time slice based on the charging and discharging rates for each time slice as shown in Equation 24.

$$\forall_t : S(t) = S(t-1) + [R_{in}(t-1) - R_{out}(t-1)]\Delta t \tag{24}$$

where $S$ is the starting level of storage for a given time slice, $t$, and $R_{in}$ and $R_{out}$ are the rate at which the storage system is being charged or discharged, respectively, and $\Delta t$ is the size of the time slice.

To reduce the impact of end effects on the model, and to prevent the model from dumping stored energy at the end of the model period, we constraint the storage system to refill back to the starting level at the end of the model period as in Equation 25. This is done by requiring that the total amount of energy stored over the full model period must match the amount of energy removed from storage.

$$\sum_t R_{in}(t) - \sum_t R_{out}(t) = 0 \tag{25}$$

Equation 26 constrains the storage level, $S$, at the start of each time slice to be above the minimum storage charge percentage, $S_{min}$, and below the overall installed storage capacity, $IC$, respectively.

$$\forall_t: S_{min} \leq S(t) \tag{26}$$

$$\forall_t: S(t) \leq IC \tag{27}$$

We need to also include a restriction on the maximum installed capacity, $MaxIC$, to ensure the installed capacity does not exceed the exogenously determined maximum capacity, as implemented in Equation 28.

$$\forall_t: IC \leq MaxIC \tag{28}$$

And finally, we need to restrict the maximum rate at which we can charge and discharge the storage system, as in Equations 29 and 30, where $MaxR_{in}$ and $MaxR_{out}$ are the exogenously determined maximum charging and discharging rates, respectively.

$$\forall_t: R_{in}(t) \leq MaxR_{in} \tag{29}$$

$$\forall_t: R_{out}(t) \leq MaxR_{out} \tag{30}$$

#### *4.3.2.2 Ramping Constraints*

We implement ramping constraints by restricting the change in generator output, $R$, between time steps for specified technologies, as shown in Equations 31 and 32.

$$\forall_t: R(t) - R(t+1) \geq Ramp_{Down} \times IC \tag{31}$$

$$\forall_t: R(t) - R(t+1) < Ramp_{Up} \times IC \tag{32}$$

where $Ramp_{Down}$ and $Ramp_{Up}$ are the maximum percentage change in output for a given generator per time slice with installed capacity $IC$.

#### *4.3.2.3 Synchronous Generation Constraint*

Synchronous generation is constrained to 50% of the operating capacity to ensure system stability. This is implemented by first calculating the total generation operating in the system and then requiring that 50% comes from generators that are tagged as providing synchronous generation, as shown in Equation 33.

$$\forall_t: \sum_{g,SG=1} R(t) \geq SG_{req} \sum_{g} R(t) \tag{33}$$

where $g$ is the index of generators, $SG$ is the tag indicating if the generator provides synchronous generation, and $SG_{req}$ is the required level of synchronous generation. This constraint is active for every time slice, ensuring that for every period there is sufficient synchronous generation operating in the system.

### *4.3.3 Model Implementation and Data*

The simplified storage equations, the ramping constraints described above, and the synchronous generation constraint, along with the curtailment cost framework from Chapter 3, are implemented into the Open Source Energy Modelling System (OSeMOSYS) [11,12]. Using this tool, we model an electricity system whose generation mix is primarily must-run natural gas co-generation, natural gas combined cycle and natural gas simple cycle generation and wind generation with lesser amounts of other renewable generation, namely hydro, geothermal and biomass.

The base model for this study is from a long term optimization of the Alberta, Canada electricity system by Lyseng et al. [117] that was updated with policy announcements by the Alberta government in 2015 [135,136]. The 2015 policies included a 30% renewable energy target by 2030. We consider the system as a single node system with no interconnections to other jurisdictions.  Although there are some transmission restrictions within the Alberta system, in general the system is built to reduce these restrictions to a minimum [139].  The interconnections that Alberta has with other jurisdictions are generally small other than a 1.2 GW line to British Columbia [190].  Gevorgian et al. [184] note that the current wind penetration level in the western interconnect is already causing challenges with frequency regulation in the interconnected system.  We therefore assume that, as with other NERC regulations that are applied to each balancing authority in the western interconnect, any synchronous generation constraint that is applied in the future would also be applied to each balancing authority.  As such, we consider Alberta as a stand alone system.

We project to the year 2030 to obtain a system with large amounts of renewable capacity. Generation capacities as determined by Lyseng et al. [117] to meet the average 14.3 GW load, as projected by the Alberta Electricity System Operator (AESO) for 2030 [138], are included as existing generation in the model (see Table 4.2).  Performance data for generators are taken from the U.S. Energy Information Agency [137].  We obtained 10 minute resolution load data from AESO [191].  We use this to model one week periods using the profiles from 2011 to 2016, scaled to the 14.3 GW average load, for a total of 312 separate model runs per scenario evaluated.

**Table 4.2:  Existing Capacity in the Model [117]**

| Generator | Acronym | Installed Capacity |
|---|---|---|
| Simple Cycle Gas Turbine | SCGT | 6.7 GW |
| Combined Cycle Gas Turbine | CCGT | 4.3 GW |
| Co-generation (heat and power) | COGEN | 5.53 GW |
| Biomass | BIOMASS | 0.24 GW |
| Hydropower | HYDRO | 0.9 GW |
| Geothermal Power | GEOTHERMAL | 0.5 GW |
| Wind | WIND | 10.6 GW |

### 4.3.4 WIND RESOURCE

We construct 10 minute wind profile data following the same method presented in our previous work [192]. The province of Alberta has a total land area of 662,000 km$^2$, approximately twice the size of Germany. Due to the influence of the Rocky Mountains to the south west, there are essentially four wind regimes in the province, one in the northern half of the province and three in the south where the mountains impact the geography. To effectively model the dispersed wind regime we start with per wind farm 10 minute resolution wind generation data from AESO for the period from 2011 – 2016 [191]. We choose four newer, high capacity factor, wind farms, one located in each wind region of the province, as typical for that region and assume equal build out in each region. Specifically, we use Soderglen, Magrath, Chin-Chute and Wintering Hills as the typical wind farms in each region as they have the high capacity factor expected from wind farms in the future with larger, high capacity wind turbines [193].

The four wind farms are chosen as they have geographic dispersion which has been shown to be beneficial in high VRE penetration scenarios [194,195]. Wintering Hills was commissioned in 2012 so no generation data for that location is available for 2011. In place of Wintering Hills we use the generation data from Ghost Pine for 2011 and scale it to adjust for the fact that Ghost Pine is an older wind farm and has a lower average capacity factor than Wintering Hills.

Table 4.3 shows characteristic statistics for the Alberta 2011-2016 10 minute wind data compared to hourly 2001-2004 data for Nordic countries as published by Holttinen [194]. The higher mean and median values for Alberta are justifiable for newer, larger turbine designs being installed [193]. The standard deviation is also higher when compared to most of the Nordic countries which is likely due to the smaller geographic region of Alberta and the higher, larger turbines being installed. The mean over the standard deviation, minimum and maximum values seem to fall within the range expected when compared to Holttinen's work, indicating that the results of our study would be applicable in other jurisdictions.

**Table 4.3: Statistics of 10 minute wind power capacity factor. Six years for Alberta are compared to the Nordic Countries as reported by Holttinen [194].**

| Statistic | Mean | Median | Std. Dev. | Std.Dev./ Mean | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Denmark | 22.2 | 14.6 | 21.2 | 0.95 | 0 | 92.7 |
| Finland | 22.3 | 17.5 | 17.6 | 0.79 | 0 | 91.1 |
| Norway | 32.3 | 29.2 | 19.6 | 0.61 | 0 | 93.1 |
| Sweden | 23.5 | 18.6 | 18.3 | 0.78 | 0 | 95 |
| Nordic Combined | 25.1 | 22.4 | 14.5 | 0.58 | 1.2 | 86.5 |
| 2011 Alberta | 36.3 | 31.5 | 27.9 | 0.77 | 0 | 107 |
| 2012 Alberta | 36.2 | 23.2 | 27.3 | 0.75 | 0 | 99.9 |
| 2013 Alberta | 33.6 | 28.5 | 26.4 | 0.79 | 0 | 97.6 |
| 2014 Alberta | 33.4 | 27.5 | 26.6 | 0.80 | 0 | 97.6 |
| 2015 Alberta | 34.2 | 27.6 | 27.6 | 0.80 | 0 | 99.1 |
| 2016 Alberta | 36.0 | 31.4 | 27.7 | 0.77 | 0 | 99.7 |
| 2011-2016 Alberta | 35.0 | 29.8 | 27.3 | 0.78 | 0 | 107 |

### *4.3.5 Ramping and Synchronous Generation Constraints*

To implement ramping constraints AESO generation data is used for the year 2016 and the 85$^{th}$ percentile ramp event for one of each type of generator (i.e. open cycle gas turbine, biomass, etc.) is used as an estimated ramping ability for that type of generator [196]. The 85$^{th}$ percentile is used to avoid unexpected outages and errors in the data skewing the results. This provided the ramping restriction values shown in Table 4.4 for cogeneration, open cycle and combined cycle natural gas turbines as well as for biomass power plants. We model the combined generation capacity by type of generator rather than individual generator to provide an upper bound for the case when all the generators of that type ramp together. All other generators are assumed to be able to ramp 100% of their output within a 10 minute period.

Alberta does not state a specific synchronous generation constraint in their Generation Standard for Planning [197]. However, as discussed above, a 50% synchronous generation constraint is consistent with the requirements in many jurisdictions. Table 4.4 shows the technologies that contribute as synchronous generation in the Alberta grid. Other generators in the system, namely wind, are considered not to provide synchronous generation.

**Table 4.4: Synchronous generators in the Alberta system and their 10 minute ramping capability**

| Generator | Ramp Up (%/10 min) | Ramp Down (%/10 min) |
|---|---|---|
| Gas Fired Co-generation | 3.8 | 3.7 |
| Combined Cycle Gas Turbine | 3.8 | 3.7 |
| Open Cycle Gas Turbine | 83 | 83 |
| Biomass (based on Coal) | 3.0 | 2.2 |
| Hydro Generation | Unlimited | Unlimited |
| Geothermal | Unlimited | Unlimited |

### *4.3.6 SCENARIOS*

We consider nine scenarios, as shown in Table 4.5, and evaluate the impact of the synchronous generation constraint on the system costs, emissions and renewable penetration level. The impact of storage is also evaluated for each scenario. Costs for curtailing wind generation are assumed to fall within the range of US$15/MWh to US$100/MWh, as found in the literature [71,147,156–158]. As discussed in our previous work [174], these could be capital costs that are amortized over lower amounts of generation, renewable energy credits that are not achieved, or other operational costs associated with curtailing.

The base installed capacity of wind is 10.6 GW which, in the base model, allowed for 30% of the generated energy to be produced by renewables. We scale the installed capacity up to 15.9 GW and 21.2 GW and, since these are 1.5 and 2 times the installed capacity we name these scenarios

45% and 60% as the nominal amount of generation expected from renewables in these scenarios. For the wind profiles used, this corresponds to wind, if fully utilized, providing up to 26%, 39% and 52% of the total system load, respectively, with the remaining renewable energy coming from hydro and biomass.

**Table 4.5: VR Capacity and Curtailment Cost Combinations Modelled**

| Scenario Name | Wind Capacity | Curtailment Cost | Theoretical Maximum Wind Energy Penetration |
|---|---|---|---|
| 30%, $35 | 10.6 GW | $35/MWh | 25.8% |
| 30%, $65 | 10.6 GW | $65/MWh | 25.8% |
| 30%, $100 | 10.6 GW | $100/MWh | 25.8% |
| 45%, $35 | 15.9 GW | $35/MWh | 38.7% |
| 45%, $65 | 15.9 GW | $65/MWh | 38.7% |
| 45%, $100 | 15.9 GW | $100/MWh | 38.7% |
| 60%, $35 | 21.2 GW | $35/MWh | 51.6% |
| 60%, $65 | 21.2 GW | $65/MWh | 51.6% |
| 60%, $100 | 21.2 GW | $100/MWh | 51.6% |

Following on Denholm and Hand's work on flexibility and its value to the system [68], we model a storage system with 80% round trip efficiency to illustrate the ability of investments in storage to reduce curtailment. We assume the storage system will be installed at no cost to the system and use the reduction in total system cost with storage available as compared to the baseline cost without storage to estimate the value for the system.

#### *4.3.6.1 Infrastructure Investment in Storage*

We model a storage system with 80% round trip efficiency. This is implemented by assuming losses are evenly split between the charging and discharging systems. Each is modelled as having an 89% efficiency. This is within the typical performance range of battery storage systems and pumped hydro storage systems, the two systems most likely to be deployed for grid scale storage [159]. When discharging, the storage system can contribute to the amount of synchronous generation on the system.

Komarnicki et al. [155] provide a summary of technologies for grid scale electrical storage. They identify two technologies that would provide storage capacity at the scale necessary to reduce VRE curtailment: batteries and pumped hydro storage. They also provide a summary of the power to capacity ratios of these technologies. Even though there is some variation in the power to capacity ratio for these technologies, their data shows that most generators of these types fall within a relatively narrow band. Based on their data we model the storage power at 0.1 MW/MWh of storage to represent typical pumped hydro storage power to capacity ratios and at 1 MW/MWh of storage to represent typical battery storage power ratios. We compare these two cases with the situation where storage power is unconstrained for each of the scenarios in Table 4.5. We model storage capacity from 3 GWh to 250 GWh, corresponding to 0.2 to 17.5 hours of storage.

## 4.4 Results

We first present the impact of the synchronous generation constraint on the system in terms of cost, carbon dioxide emissions from the system and the amount of wind curtailment without storage. We then evaluate the impact that storage has on the system and the operation of storage in the system. We finish with a discussion of the value that storage provides and how constraining the storage power impacts this value.

### 4.4.1 *Costs, Emissions and Curtailment*

Figure 4.2 shows the operation of the system for a week with large amounts of wind available and with synchronous generation constraint removed. There is a large amount of wind generation, shown in green, and there is so much wind in the system that during much of the week wind is curtailed, as shown in red above the demand line. Hydro, geothermal, CCGT and OCGT fill in the few gaps that are not powered by wind. It can be seen that, for most of this week the only synchronous generation in the system is the cogeneration which would likely not be adequate to maintain frequency regulation in the system. The significant amount of curtailed wind is an added cost to the system.

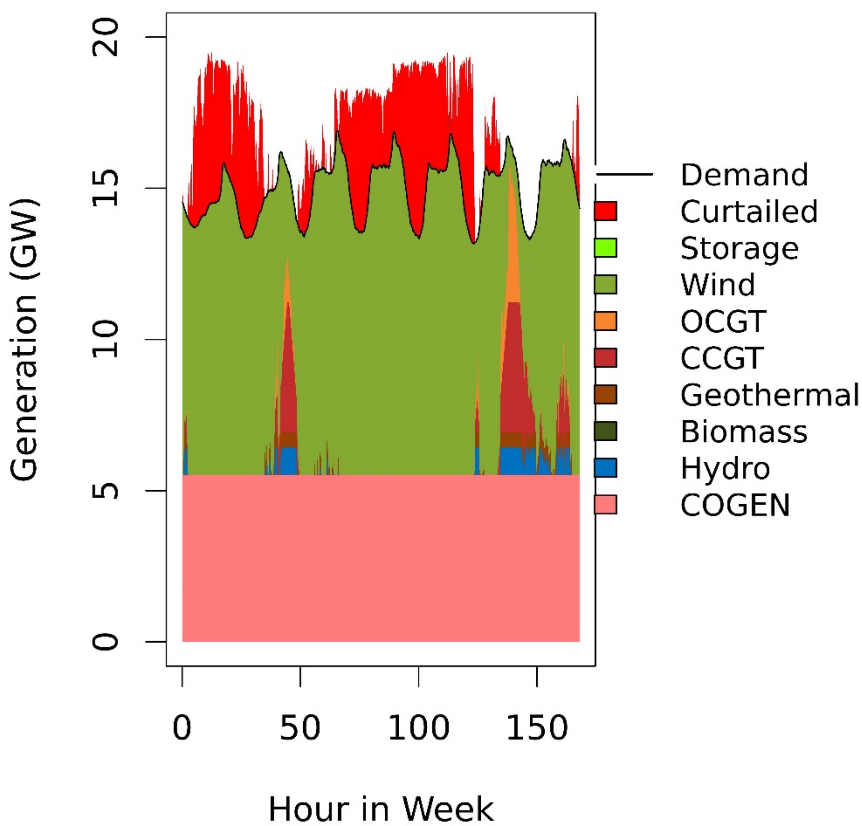


**Figure 4.2: Generation with no SG restriction active (60% renewables, $65 curtailment cost, no storage).**

Figure 4.3 shows the same week, but with the synchronous generation constraint applied. Two major changes are visible in this figure when compared to Figure 4.2. First, there is significant additional generation by CCGT throughout the entire week to meet the synchronous generation constraint. This increases both the variable costs incurred and the emissions from burning fossil fuels. Second, the amount of wind generation curtailed is much higher as it is not possible to absorb that extra energy in the system while maintaining the synchronous generation. This impacts the cost effectiveness of the wind generation.

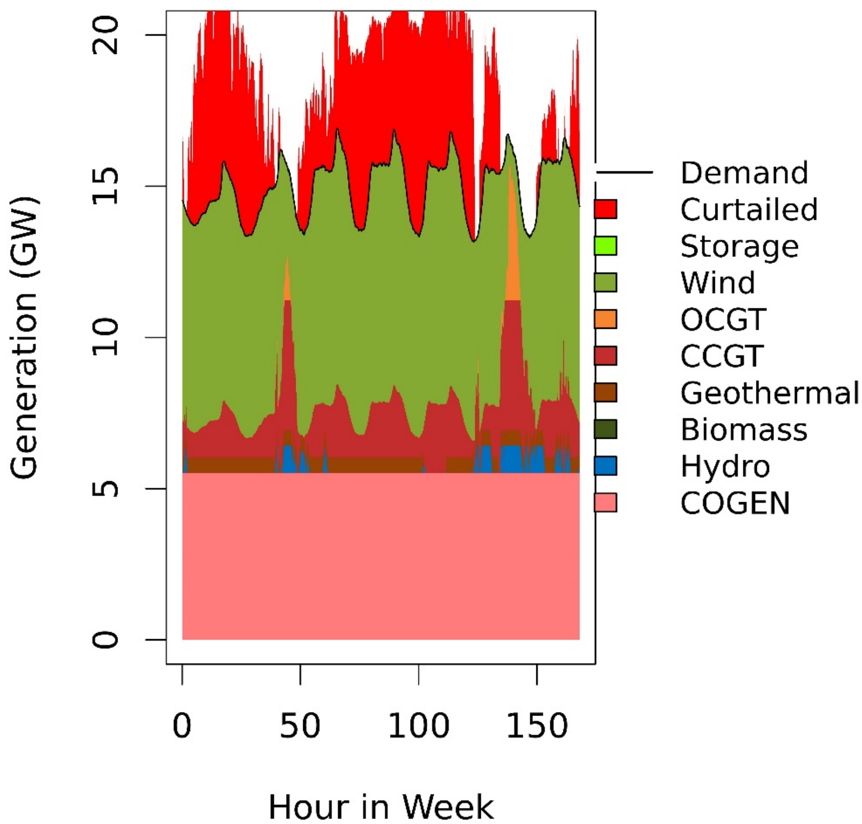


**Figure 4.3: Generation with SG restriction active (60% renewables, $65 curtailment cost, no storage).**

Table 4.6 shows the operational costs, emissions and percent of wind generation curtailed for the three different wind penetrations modelled, with and without the synchronous generation constraint applied for the system without storage. The remainder of this section provides insights into the results provided in Table 4.6.

**Table 4.6: Operational costs, emissions and percent of available wind generation curtailed for each level of wind penetration with no storage in the system**

| Wind | Curtailment Cost ($/MWh) | Synchronous Constraint | Operational Cost ($M/year) | Cost %Δ | $CO_2$ Emissions ($MtCO_2$) | Percent Wind Energy Curtailed |
|---|---|---|---|---|---|---|
| **30%** | $35 | N/A | 12,000 | | 32.0 | 1.8% |
| | $35 | 50% | 12,200 | 1.3 | 32.3 | 6.0% |
| | $65 | N/A | 12,000 | | 32.0 | 1.8% |
| | $65 | 50% | 12,200 | 1.4 | 32.3 | 6.0% |
| | $100 | N/A | 12,000 | | 32.0 | 1.8% |
| | $100 | 50% | 12,200 | 1.4 | 32.3 | 6.0% |
| **45%** | $35 | N/A | 10,400 | | 28.3 | 15.8% |
| | $35 | 50% | 10,800 | 4.8 | 29.3 | 28.7% |
| | $65 | N/A | 10,400 | | 28.3 | 15.7% |
| | $65 | 50% | 10,900 | 5.0 | 29.3 | 28.8% |
| | $100 | N/A | 10,400 | | 28.3 | 15.7% |
| | $100 | 50% | 11,000 | 5.2 | 29.3 | 28.7% |
| **60%** | $35 | N/A | 9,500 | | 26.3 | 36.0% |
| | $35 | 50% | 10,100 | 7.0 | 27.6 | 55.0% |
| | $65 | N/A | 9,600 | | 26.3 | 36.0% |
| | $65 | 50% | 10,300 | 7.3 | 27.6 | 55.0% |
| | $100 | N/A | 9,700 | | 26.3 | 36.0% |
| | $100 | 50% | 10,400 | 7.5 | 27.6 | 55.0% |

Similar to Vithayasrichareon et al. [93], we find that a synchronous generation requirement in the system increases costs. Vithayasrichareon et al. found an increase in costs of 20% with an 85% renewable energy penetration level while we find an increase in costs as low as 1.3% for a 30% renewable energy penetration and as high as 7.25% for a 60% wind energy penetration level as shown in Table 4.6 and summarized in Figure 4.4. The lower cost increases found in our work can be explained by the proportion of must run generation in the Alberta system, which provide approximately 30% synchronous generation in the system at all times.

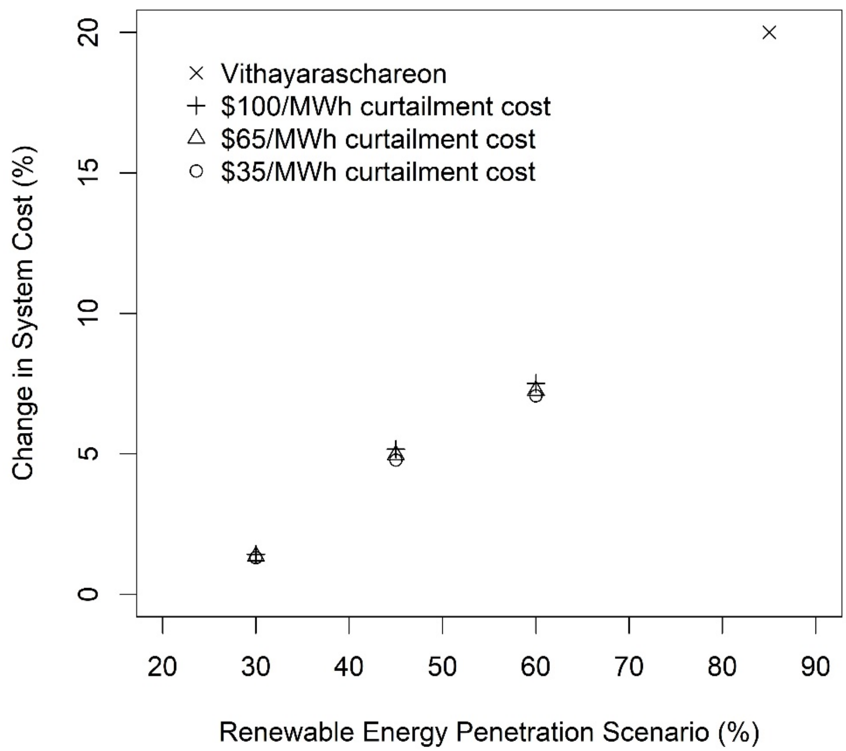


**Figure 4.4: System cost increases due to synchronous generation requirements.**

Vithayasrichareon et al. [93] provide absolute numbers for the amount of wind curtailed, not a relative percentage, which makes it hard to compare their numbers to the curtailment in a different system, but they found significant increases in the amount curtailed with higher renewable energy penetration and with higher synchronous generation requirements. As shown in Table 4.6, we find that, for the 30% penetration level, curtailment goes from just under 2% to just over 6% of the total wind available while for the 60% wind penetration level curtailment goes from around 36% up to 55%.

Vithayasrichareon et al. report renewable energy penetration level and how this is reduced by a synchronous generation constraint. For a 60% theoretical renewable energy scenario they find that the actual penetration with a 50% synchronous generation constraint is only 50% of the energy in the system provided by renewables rather than the desired 60%. We find a similar result. For our nominal 60% renewable energy penetration scenario without the synchronous generation constraint, 52% of the system load could be met by wind, with another 4.2% provided by other renewables in the mix. However, the resulting wind energy penetration level is only 38% when the synchronous generation constraint is active, and when combined with other renewables, we get only 42% of the energy provided by renewables, indicating that the synchronous generation constraint significantly reduces the ability of wind to meet demand.

This both impacts the economics of wind generation and the environmental benefits provided by having low emissions generation in the system. As shown in Table 4.6, with a synchronous generation requirement we find that emissions increase by 1% for 30% renewables, 3.5% for 45% renewables and 5% for 60% renewables due to increased operation of the natural gas generators to meet the synchronous generation requirements of the system. The results in this section indicate that having cost effective approaches for providing inertia in the system that are not fossil fuel powered will be important for meeting future emissions targets.

### *4.4.2 Impact of Storage*

When storage is enabled in the system, we find that curtailment is reduced and that the storage provides value to the system by reducing generation by natural gas generators. We consider only the situation with the synchronous generation constraint active. Figure 4.5 provides the decrease in operational cost, $CO_2$ emissions and percent wind energy penetration for the case with 60% wind and a \$65/MWh curtailment cost for the system with varying levels of storage. Other scenarios have similar results.

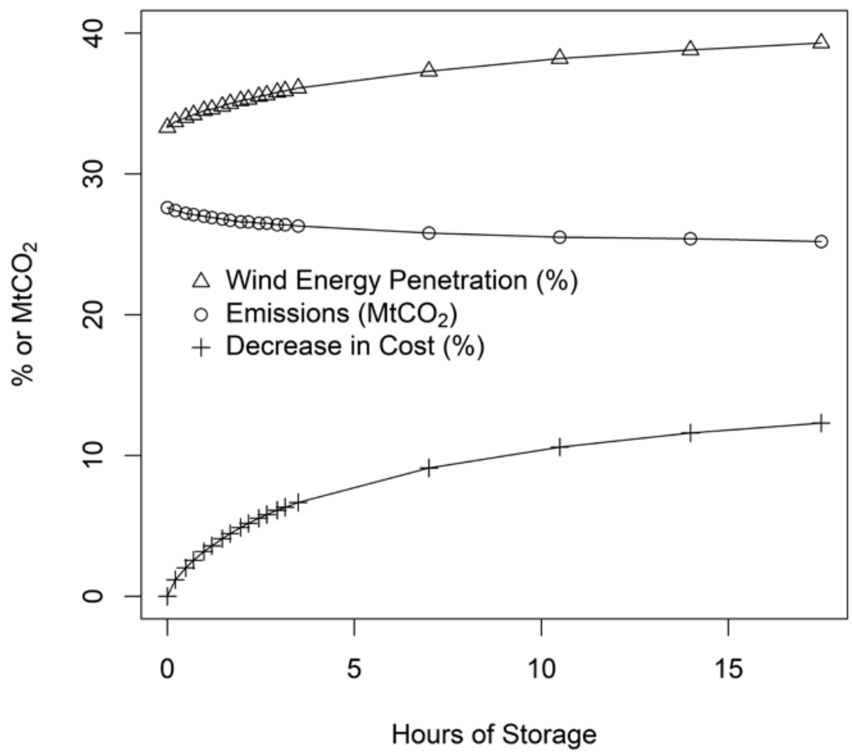


**Figure 4.5: Reduction in operational costs, total emissions and wind energy penetration for 60% wind and a $65/MWh curtailment cost with various levels of storage.**

Unlike the findings of McKenna et al. [98], who found that, under some assumptions, storage could increase system emissions, Figure 4.5 shows a steady decrease in emissions as the storage capacity increases. This is replicated in all cases evaluated and this is likely due to the optimization of the storage operation. While McKenna et al. assume exogenous operation of storage, our model allows for endogenous optimization of the storage operation. We show the results for the 60% renewable energy case with a $65/MWh curtailment cost for the remainder of this section to provide illustrative results.

Figure 4.6 shows the generation over the course of a typical week with 14 GWh of storage in the system with storage power unconstrained while Figure 4.7 shows the same situation but with the storage power constrained to 1.4 GW (0.1 MW/MWh), typical of what would be expected for an average pumped hydro storage system. It can be seen that there is more generation by natural gas turbines in the case where the storage power is constrained indicating that storage might not be able to provide as much of a benefit to the system when it is power constrained. There is also more curtailment in Figure 4.7 as the ability of the storage system to absorb large amounts of wind energy is limited by the power constraint.

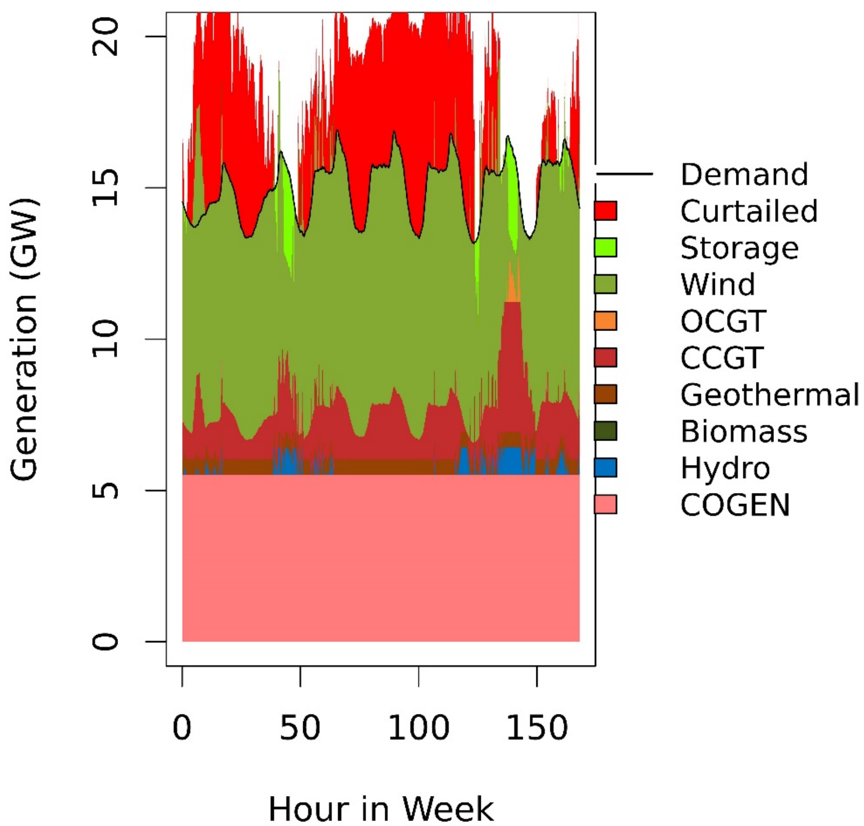


**Figure 4.6: Generation with SG restriction active and 14 GWh of storage but no restriction on storage power (60% renewables, $65 curtailment cost).**

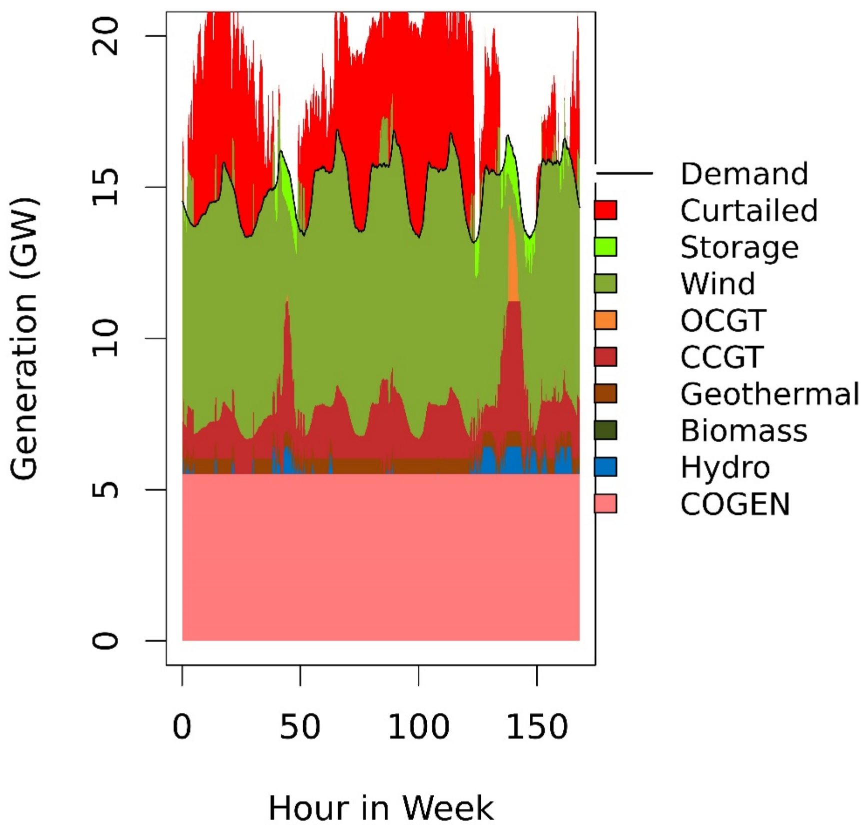


**Figure 4.7: Generation with SG restriction active and 14 GWh of storage and storage power restricted to 0.1 MW/MWh (60% renewables, $65 curtailment cost).**

Another interesting feature of Figure 4.6 and Figure 4.7 is the operation of the storage system. Rather than operating in either a peak shaving/trough filling mode or a wind balancing mode, as assumed by McKenna et al. [98], the storage system operates only occasionally due to the high penetration of wind energy during the week shown. Figure 4.8 shows the same generation per time slice data, but for a lower wind week. In this case, due to a lack of wind in the system, there is only occasional opportunity for the storage system to reduce wind curtailment, and therefore the storage system provides little value during this week. We need to look for a week with an intermediate amount of wind to be able to get significant value from the storage system.

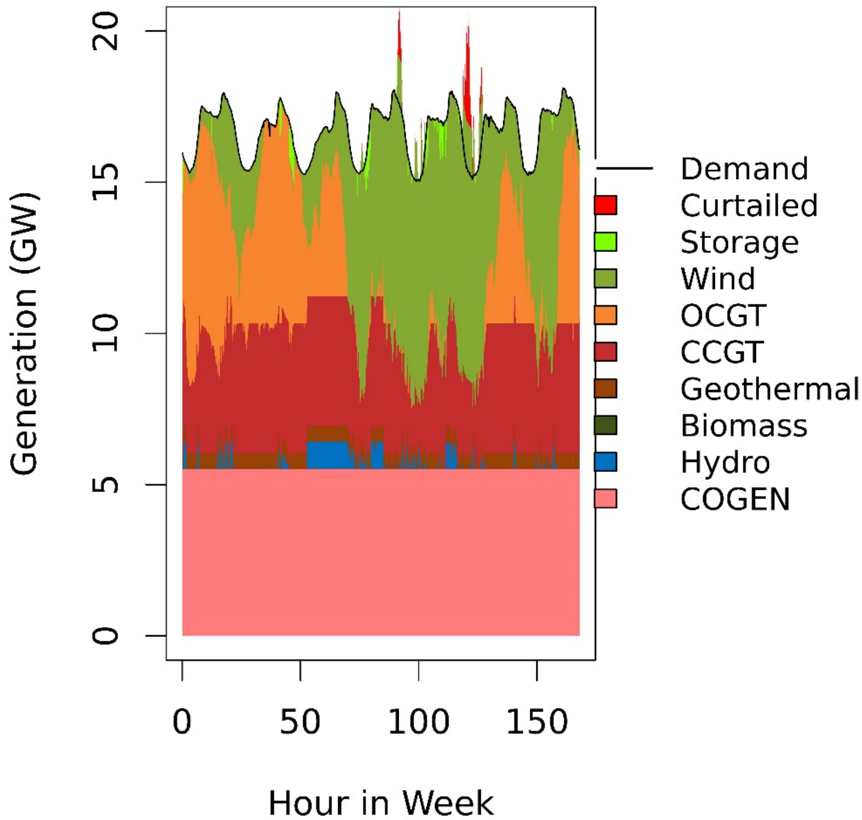


**Figure 4.8: Generation with SG restriction active and 14 GWh of storage and storage power restricted to 0.1 MW/MWh (60% renewables, $65 curtailment cost) for a low wind week.**

Figure 4.9 shows a week where storage is being dispatched. The variation of the wind during this week allows the storage system to charge and discharge numerous times throughout the week, adding significant value. During this week the storage system shows six to seven charge-discharge cycles compared to appoximately one cycle in the low wind week and one to two in the high wind week. Figure 4.9 is also interesting in the way storage is operated. The first two cycles of the storage system seem to operate mainly as demand shifting, but the next few cycles operate in a more wind peak shifting way, even powering load from storage during one of the nighttime load nadirs. The assumptions on storage operation by McKenna et al. [98] will therefore significantly decrease the value they calculate for storage in both economic and emissions reduction terms.

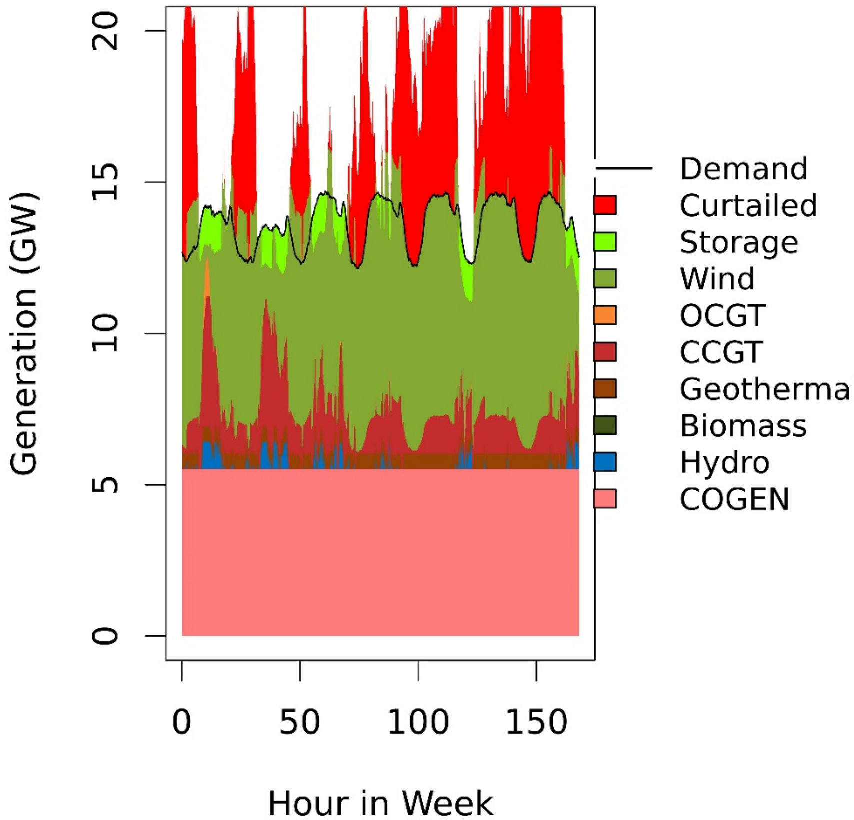


**Figure 4.9: Generation with SG restriction active and 14 GWh of storage and storage power restricted to 0.1 MW/MWh (60% renewables, $65 curtailment cost) for a more variable wind week.**

### *4.4.3 VALUE PROVIDED BY STORAGE*

To illustrate the value that storage provides in the system, and to investigate the impact that synchronous generation requirements have on this value, we calculate the reduced cost to the system with storage installed. The value that storage provides is calculated as:

$$V = C_T^0 - C_T \tag{34}$$

where, $C_T^0$ is the cost without storage and $C_T$ is the reduced cost with a given capacity of storage. We then normalize Equation 34 for the size of the storage system, $S_V$, to get the value per unit of storage capacity, $v$, as:

$$v = \frac{C_T^0 - C_T}{S_V} \tag{35}$$

Equations 34 and 35 are used to calculate the value that a given storage size provides to the system for each combination of storage size and power to capacity ratio of storage.

Figure 4.10 shows the value provided by storage for a system with 60% wind and a $65 curtailment cost for the case where there is no synchronous generation constraint and with the synchronous generation constraint. For this figure storage power is unconstrained. If there is a synchronous generation requirement in the system the value storage can provide is significantly reduced, by nearly half at all levels of storage.

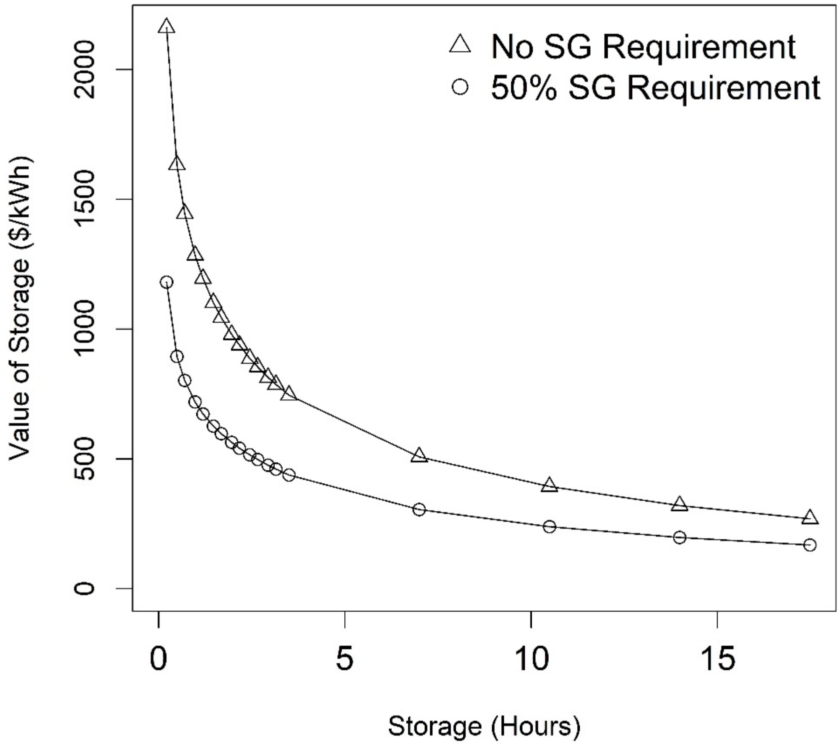


**Figure 4.10: Value provided by storage per unit of storage capacity for nominally 60% renewable energy, $65 curtailment cost with and without a 50% synchronous generation requirement.**

Figure 4.11 shows the value provided by storage with the synchronous generation constraint but, in this case, with and without a constraint on the storage power. We constrain the storage power to 1 MW/MWh, typical of a battery storage system, and to 0.1 MW/MWh, typical of a pumped hydro facility. There is no discernable difference between the value provided by the storage when unconstrained and when constrained to 1 MW/MWh – both provide nearly identical value to the system and show up directly on top of each other in the figure. For pumped hydro, with power constrained to 0.1 MW/MWh, however, the power constraint does impact the value at low installed capacities, indicating that battery storage would be able to provide more valuable service to the grid at smaller installed capacities.

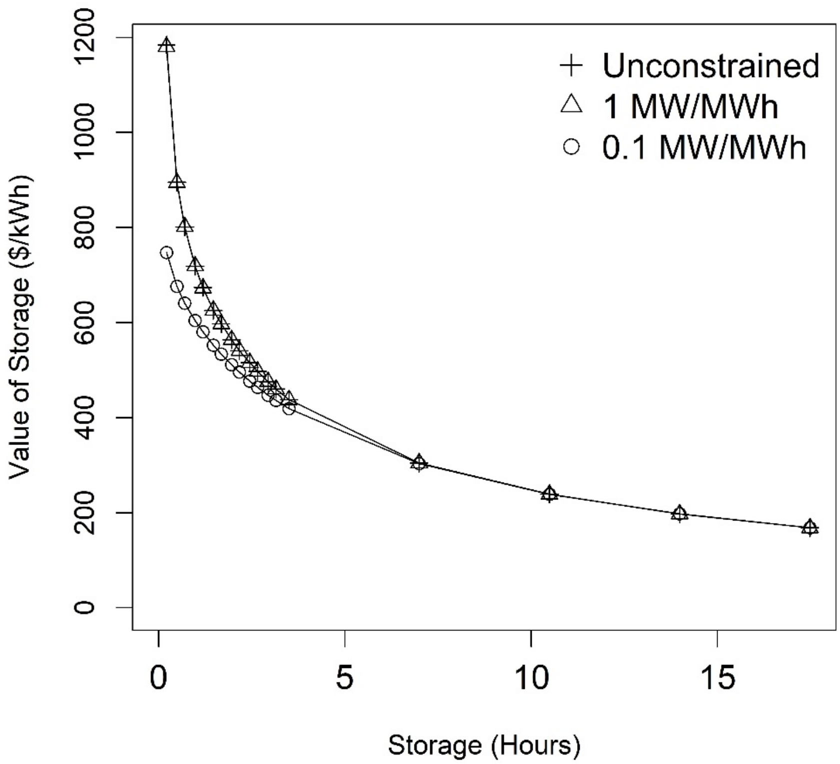


**Figure 4.11: Value provided by storage for 60% renewable energy, $65 curtailment cost with and without a power limit on storage.**

### 4.5 Discussion

The requirement for frequency regulation in the grid has a major impact on the operation of generators and the ability of the system to absorb renewable energy. The amount of curtailed wind power in the grid increases significantly when a synchronous generation constraint is active. This constraint also significantly increases system costs and system $CO_2$ emissions. The specific impact will depend on the system mix and it was observed that in Alberta the cost increase and emissions impact was smaller than that found in other works due to the existence of a large amount of must run cogeneration in the system, which provides a base level of synchronous generation that may not exist in other jurisdictions.

As storage is often seen as a potential technology to reduce curtailment and increase renewable penetration in the grid we evaluated the impact that a synchronous generation requirement has on the ability of storage to reduce curtailment and provide value to the grid. We find that, with a synchronous generation constraint active, the reduction in curtailment and the resulting renewable energy penetration is significantly lower than the amount of available wind power would suggest. We also find that storage does not operate in any pre-defined way such as peak demand shaving or wind shifting but has a variety of operating strategies that cannot be easily classified as there is much variation in the optimal operation of storage. We also find that neither low or high wind weeks utilize the storage system significantly, but that highly variable wind weeks see significant storage operation and cycling, indicating that the storage system is providing system value during these weeks.

Finally, we evaluate the value that a storage system can provide to the system and find that, with a synchronous generation requirement, the value that storage can provide is roughly half the value without a synchronous generation requirement in the system. This indicates that it might be beneficial to find ways that variable renewables can contribute to grid frequency regulation such that storage can provide more value to the system. The impact of limited power input/output from a storage system was also evaluated and it was found that a typical battery power ratio of 1 MW/MWh had a negligible impact on the value that storage provides to the system but that a typical pumped hydro power ratio of 0.1 MW/MWh had an impact, but only at low installed capacities.

## 4.6 Limitations

This study used an optimization model, so is not able to capture any potential market dynamics that would exist in the market based Alberta system which would impact the operation of the storage system, though we expect these impacts to be minimal as storage would likely want to store energy when costs are low and generate when costs are high, which would correspond to optimal operation as modelled. The potential impact of the capacity market being developed for Alberta [198] is also not considered in our model and it is not clear how this would impact the operation of a storage system nor if a storage system would benefit from such a market.

The perfect foresight of the optimization model for the wind regime over the course of a week also over-estimates the value that storage can provide to the system. Wind power is not perfectly predictable over the course of a week, though prediction is getting better and a day ahead prediction of wind power is becoming more accurate. The lack of perfect forecasts means that the operator of a real storage system would have to gamble on the future predictions of wind which may or may not occur. It would be an interesting future modelling exercise to incorporate this type of decision making into an energy systems model to see the impact that this has on operation algorithms for storage, but this is beyond the scope of the current study.

## 4.7 Conclusions

The requirement for synchronous generation for frequency regulation, and the resulting restriction on the instantaneous penetration of variable renewable energy such as wind, has a significant impact on the system. This impact increases costs, decreases the amount of renewable energy used in the system, increases curtailment, and increases emissions. Finding suitable non-fossil fuel generation that can provide effective frequency regulation services to allow high instantaneous variable renewable generation during grid operation will aid in meeting future electricity emissions goals.  This will allow storage and other technologies to add more value to the system.

# 5. SUMMARY, CONTRIBUTIONS AND FUTURE WORK

Achieving internationally agreed upon emissions targets is critical to ensuring that climate impacts of these emissions are minimized. This dissertation presents three studies that address risk of increased emissions in energy systems models, investigates the impact that curtailment costs have on system operation and the value of storage and finally evaluates the impact of synchronous generation constraints on system operation.

In the first study, an assessment is presented of how society can hedge against the risk that these target will be missed, due to uncertainty in the emission levels of key generation technologies, in the context of the Alberta electricity system. We find that a significant build out of wind power is required to hedge against the risk of missing emissions targets. In the second study, the operational implications of curtailment of high penetrations of wind power in the generation mix and the potential contribution of storage and dispatchable loads are assessed. It is found that both technologies provide value to the system. In the third study, a high temporal resolution model is developed that shows that restrictions on the instantaneous penetration of wind energy reduces the ability of storage to provide value to the system.

## 5.1 Contributions

This work demonstrates a need for planners to take into account both the risks associated with a given system plan, how to hedge against it, and also the potential challenges when a system has high penetrations of wind power. Specific contributions that are broadly applicable to energy systems modelling and planning are:

- Policies that encourage early adoption of wind will likely decrease risks of exceeding emissions targets. While Parkinson and Djilali [47] find that both wind and run-of-river would increase to hedge against climate risk, the lack of hydro potential in Alberta means that wind is the main option for hedging risk.
- Allowing nuclear energy in the mix has a lower overall system cost, and a lower overall risk of exceeding emissions, even without a risk premium applied. The social challenges with nuclear, however, may make this option difficult to pursue from a policy perspective.
- Storage and dispatchable loads have the potential to reduce curtailment in the system and thereby lower system costs. The inclusion of curtailment costs increases the value that storage and dispatchable loads can provide by anywhere from 10 to 60%, depending on the amount of wind power and the cost of curtailment.
- The value storage provides to the system is very high for small amounts of installed capacity but declines quickly with increased capacity. The value that dispatchable loads provides varies less with installed capacity.
- The ability of storage to reduce integration costs for VR generation is restricted when the instantaneous penetration of renewable energy in the system is constrained.
- Storage for integration of VR generation does not operate in a pre-defined peak shaving, wind shifting way, but does a combination of both depending on the specific wind resource available in a given week.

In addition to the general system level and modelling insights, a number of additional contributions applicable to the Alberta, Canada system are:

- A 5% risk premium for Alberta starts the build out of wind about 5 years earlier, and the build out of solar around 7 years earlier than without the risk premium. Policies that encourage early build out of wind and/or solar can decrease the emissions risk for the Alberta system.
- Nuclear power in Alberta would essentially eliminate the need for any fossil generation other than the must run co-generation and, as long as enough flexibility was available in the system, wind and nuclear could produce around ¾ of the energy needs of the province, with the balance provided by co-generation and the small amounts of hydro and other generators in the system.
- Storage, at small installed capacities, can provide significant value to the Alberta system. As the installed capacity of the storage system increases the value decreases quickly indicating diminishing returns.
- Dispatchable loads provide consistent value to the Alberta system over a range of installed capacities in contrast to the diminishing returns for storage.
- In conjunction with evaluation of storage and/or dispatchable loads, investing in research on technologies that will allow high instantaneous penetrations of renewable energy in the grid will ensure that any investments in storage can be fully utilized.

In summary, we have implemented a risk hedging framework into the OSeMOSYS energy systems model and used it to evaluate how to reduce the risk of exceeding emissions targets. The large build out of wind required to hedge risk was then considered from a system operation perspective and the impact of curtailment costs and synchronous generation requirements were evaluated. These contributions, and continuing work on refining modelling techniques, will contribute to the building ability of energy systems models to inform policies for meeting global climate challenges.

## 5.2 Future Work

Future work should include incorporating electricity market dynamics into the modelling structure to better represent the Alberta, Canada electricity system. This may become increasingly important as Alberta is implementing a capacity market and it is yet unclear exactly how this market will interact with the existing energy market in the province. Including the potential for trade with other jurisdictions could also expand the applicability of the models developed. Expanding the high temporal resolution model to a mixed integer unit commitment and dispatch model would be a step towards incorporating such market dynamics into the modelling.

Finally, as the results of the long term modelling and the high temporal modelling answer different questions about the same system, it would be beneficial to find a way to hard-link these different temporal structures. This would allow for a single model setup and a single set of data to be used to probe both long term and short term characteristics of a system. Collins et al. [199] note that there are two main methods of integrating short term variations into energy systems models: soft linking short term and long term modelling approaches and incorporating constraints into long term models to attempt to represent some of the challenges. Developing a framework to hard-link across different temporal scales would provide policy makers with a more nuanced understanding of the system.

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## APPENDIX A: OSEMOSYS CODE FOR INCORPORATING RISK

To incorporate risk into OSeMOSYS the following sets, parameters, variables and constraints were added to OSeMOSYS.

### Sets

```
set RANDOMDRAWS;
```

Randomdraws is a sequential set from 1 to N, the number of random draws in the model run.

### Variables

```
var Risk >= 0;
var RiskNUp{n in RANDOMDRAWS} >= 0;
var RiskNDown{n in RANDOMDRAWS} >= 0;
```

Risk is the risk measure, which is comprised of only the upside risk as defined below. Two variables, RiskNUp and RiskNDown are used to allow the model to sum only the upside risk.

### Parameters

```
param BaseEmissionIntensity{t in TECHNOLOGY};
```

Baseline emissions intensity for each technology. This is the deterministic expected average emissions intensity for this technology with no consideration of uncertainty.

```
param EmissionsIntensity{n in RANDOMDRAWS,t in TECHNOLOGY};
```

The emissions intensity for each technology for each random draw. This is used to calculate the upside/downside risk.

```
param OptimalCost;
```

Cost of the 'optimal' system, without any risk hedging considerations.

```
param RiskPremiumFactor;
```

The risk premium factor for the model. How much more we are willing to pay to hedge against the risk.

### Objective

```
minimize risk: Risk;
```

We minimize the risk, which is calculated as the upside risk in constraint EQRiskSum.

### Constraints

```
s.t. EQRiskDraws{n in RANDOMDRAWS}: sum{y in YEAR, t in
TECHNOLOGY, l in TIMESLICE,r in REGION, m in MODE_OF_OPERATION}
(RateOfActivity[r,l,t,m,y] * (BaseEmissionIntensity[t] -
EmissionsIntensity[n,t])) - RiskNUp[n] + RiskNDown[n] = 0;
```

For each random draw, this equation calculates the upside or downside risk for the given technology mix and operational decisions.

```
s.t. EQRiskSum: sum{n in RANDOMDRAWS} RiskNUp[n] = (max{nn in
RANDOMDRAWS} max(nn)) * Risk;
```

This equation sums the upside risk to calculate the overall risk in the system.

```
s.t. Cost: sum{r in REGION, t in TECHNOLOGY, y in YEAR}
(((((sum{yy in YEAR: y-yy < OperationalLife[r,t] && y-yy>=0}
NewCapacity[r,t,yy])+ ResidualCapacity[r,t,y])*FixedCost[r,t,y] +
sum{m in MODE_OF_OPERATION, l in TIMESLICE}
RateOfActivity[r,l,t,m,y]*YearSplit[l,y]*VariableCost[r,t,m,y])/(
(1+DiscountRate[r,t])^(y-min{yy in YEAR}
min(yy)+0.5))+CapitalCost[r,t,y] *
NewCapacity[r,t,y]/((1+DiscountRate[r,t])^(y-min{yy in YEAR}
min(yy)))+DiscountedTechnologyEmissionsPenalty[r,t,y]-
DiscountedSalvageValue[r,t,y]) + sum{s in STORAGE}
(CapitalCostStorage[r,s,y] *
NewStorageCapacity[r,s,y]/((1+DiscountRateStorage[r,s])^(y-min{yy
in YEAR} min(yy)))-CapitalCostStorage[r,s,y] *
NewStorageCapacity[r,s,y]/((1+DiscountRateStorage[r,s])^(y-min{yy
in YEAR} min(yy)))))<= (1 + RiskPremiumFactor) * OptimalCost;
```

We restrict the cost to being less than the optimal cost plus an additional risk premium factor.

## APPENDIX B: OSeMOSYS CODE FOR COSTING CURTAILMENT

To incorporate curtailment costs into OSeMOSYS, the following parameters, variables and constraints were added/modified.

### Parameters

```
param CurtailmentCostPerUnit{r in REGION, t in TECHNOLOGY, y in
YEAR};
```

The Curtailment Cost in $/Energy Unit for each technology.

### Variables

```
var CurtailmentCost{r in REGION, t in TECHNOLOGY, y in YEAR} >=
0;
```

The total yearly cost of curtailment for each generator.

```
var CurtailedEnergy{r in REGION, t in TECHNOLOGY, m in
MODE_OF_OPERATION, l in TIMESLICE, y in YEAR} >= 0;
```

The amount of energy curtailed for each generator in each timeslice.

### Objective Function

```
minimize cost: sum{r in REGION, t in TECHNOLOGY, y in YEAR}
 (((((sum{yy in YEAR: y-yy < OperationalLife[r,t] && y-yy>=0}
 NewCapacity[r,t,yy]) + ResidualCapacity[r,t,y]) *
 FixedCost[r,t,y] + (sum{m in MODE_OF_OPERATION, l in TIMESLICE}
 RateOfActivity[r,l,t,m,y] * YearSplit[l,y] *
 VariableCost[r,t,m,y]) + CurtailmentCost[r,t,y]) /
 ((1+DiscountRate[r,t])^(y-min{yy in YEAR} min(yy)+0.5)) +
 (CapitalCost[r,t,y] * NewCapacity[r,t,y]) /
 ((1+DiscountRate[r,t])^(y-min{yy in YEAR} min(yy))) +
 DiscountedTechnologyEmissionsPenalty[r,t,y] -
 DiscountedSalvageValue[r,t,y]) + sum{s in STORAGE}
 (CapitalCostStorage[r,s,y] * NewStorageCapacity[r,s,y] /
 ((1+DiscountRateStorage[r,s])^(y-min{yy in YEAR} min(yy))) -
 CapitalCostStorage[r,s,y] * NewStorageCapacity[r,s,y] /
 ((1+DiscountRateStorage[r,s])^(y-min{yy in YEAR} min(yy)))));
```

The objective function is updated to add in the curtailment cost to variable and operating costs.

### Constraints

```
s.t. CurtailedEnergy{r in REGION, t in TECHNOLOGY, f in FUEL, l
in TIMESLICE, m in MODE_OF_OPERATION, y in YEAR:
OutputActivityRatio[r,t,f,m,y] <>0}: ((((sum{yy in YEAR: y-yy <
OperationalLife[r,t] && y-yy>=0} NewCapacity[r,t,yy]) +
ResidualCapacity[r,t,y])    * AvailabilityFactor[r,t,y] *
CapacityFactor[r,t,l,y] * CapacityToActivityUnit[r,t] -
(RateOfActivity[r,l,t,m,y])) * CurtailmentCostPerUnit [r,t,y]) =
CurtailedEnergy[r,t,m,l,y];
```

This constraint calculates the curtailed energy per time slice.

```
s.t. CurtailmentCost{r in REGION, t in TECHNOLOGY, y in YEAR:
CurtailmentCostPerUnit[r,t,y]<>0}: sum{m in MODE_OF_OPERATION, l
in TIMESLICE} CurtailedEnergy[r,t,m,l,y] * YearSplit[l,y] =
CurtailmentCost[r, t, y];
```

This constraint calculates the cost of the curtailed energy.

## APPENDIX C: BASE COST PARAMETERS

Cost parameters are listed for the capital, fixed, variable and fuel costs for each technology as at the 2010 base year for the model period. For wind and solar there is an assumed learning curve so the costs decline over time. For coal and natural gas prices are projected to increase over time. The start and end of the model period cost values are provided for these technologies.

**Table C: Base Model Cost Parameters**

| Technology | Capital Cost ($Million/MW) | Fixed Cost ($Million/MW) | Variable Cost ($/MWh) | Fuel Cost ($/MWh) |
|---|---|---|---|---|
| COAL | 3084 | 35.91 | 4.25 | 5.87 – 10.27 |
| COAL + CCS | 4966 | 76.50 | 9.03 | 5.87 – 10.27 |
| CCGT | 972 | 14.6 | 3.11 | 16.64 – 45.15 |
| CCGT with CCS | 1990 | 30.20 | 6.44 | 16.64 – 45.15 |
| SCGT | 642 | 6.69 | 9.85 | 16.64 – 45.15 |
| COGEN | 1203 | 14.60 | 3.11 | 16.64 – 45.15 |
| BIOMASS | 3908 | 100.35 | 0 | Varies |
| GEOTHERMAL | 4144 | 95.00 | 0 | 0 |
| HYDRO | 2789 | 13.42 | 4.25 | 0 |
| NUCLEAR | 5254 | 88.62 | 2.03 | 2.56 |
| WIND | 2102 - 1848 | 37.57 | 0 | 0 |
| SOLAR | 3679 - 1378 | 26.36 | 0 | 0 |