The Effects of CO_2 Abatement Policies on Power System Expansion

by

Conrad Fox
B.Sc.E., Queen's University at Kingston, 2008

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Supervisory Committee

Dr. Andrew Rowe, (Department of Mechanical Engineering)

Supervisor

Dr. Peter Wild, (Department of Mechanical Engineering)

Supervisor

Dr. Curran Crawford, (Department of Mechanical Engineering)

Departmental Member

Abstract

Supervisory Committee

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Human development owes a great debt to cheap plentiful energy. Historically, abundant and energy dense materials such as coal, oil and more recently natural gas, have played an important role in powering our economies. To this day, any study analysing the short-term costs and benefits of energy system expansion, will continue to favour fossil fuels. At the same time, there is increasing concern about the levels of human made greenhouse gasses such as CO_2 (the major by product of burning fossil fuels) and their forecasted effects on the global climate. This thesis investigates the consequences of using political intervention to internalize the cost of future negative effects of anthropogenic CO_2 emissions. More specifically, this thesis investigates the effects of regulatory and market based instruments for curbing CO_2 emissions from electric power systems in terms of both cost and efficacy.

A model is developed to approximate the yearly changes in generation capacity and electricity supply mixture of a power system subject to the constraints of carbon abatement policies. The model proposes a novel approach for incorporating investment in non-dispatchable, intermittent wind generation capacity as a decision variable in the planning process. The model also investigates the effects of the stochastic nature of input parameters through the use of Monte Carlo simulation. To explore many features of this model, the Ontario power system is chosen for a case study because of its diverse portfolio of both generation technologies and political objectives. Five policies are simulated and compared with a 'business-as-usual' base case in which no carbon abatement policy is imposed. No single policy can meet all of the political objectives being investigated; however, some policies are clear winners in terms of specific objectives. Due to the broad scope of this work, the study finds many conclusions, such as:

- Aggressive policies do not always promote heavy investment in intermittent wind generation sources.
- On a $/t$CO_2$ avoided basis, aggressive policies are expensive. Modest policies (very small penalties for CO_2 emissions) are very sensitive to the uncertainties in future fuel prices and load profiles.
- Investment in nuclear capacity is very responsive to the severity of CO_2 penalty.

The study also concludes that the most aggressive policies produce the greatest overall reductions in CO_2 emissions.

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Nomenclature

Acronyms

LDC	Load-Duration Curve
IGCC	Integrated Gasifier Combined Cycle
NGCC	Natural Gas Combined Cycle
PHEV	Plug-in Hybrid Electric Vehicle
MILP	Mixed-Integer Linear Program
LP	Linear Program
NPV	Net Present Value
O&M	Operations and Maintenance
GHG	Greenhouse Gases
AV	Generator Availability
OCGT	Open Cycle Gas Turbine
CCGT	Combined Cycle Gas Turbine
IESO	Independent Electricity System Operator of Ontario
IAM	Integrated Assessment Model
DICE	Dynamic Integrated model of Climate and the Economy

Symbols

C_K	Capacity cost ($/MW_installed-year)
C_F	Amortized fixed cost of generation capacity ($/MW_installed-year)
C_V	Amortized variable cost of generation capacity ($/MWh-year)
C^{INV}	Cost of investment ($/MW capacity)
C^{AOM}	Annual O&M Costs ($/MW installed capacity)
C^{DCM}	Cost of decommissioning ($/MW capacity)
$C^{VOMbase}$	Variable O&M Costs for base load energy ($/MWh produced)
C^{VOMmid}	Variable O&M Costs for mid load energy ($/MWh produced)
$C^{VOMpeak}$	Variable O&M Costs for base load energy ($/MWh produced)
C^{refurb}	Cost of refurbishing a nuclear plant ($/MW refurbished)
$C^{fuelswitch}$	Cost of recommissioning a coal plant to operate using biomass fuel ($/MW recommissioned)
P^{INV}	Integer number indicating minimum technology investment capacity
P^{NP}	Total name plate capacity of technology (MW)
P^{DCM}	Integer number indicating the minimum technology size
E^{base}	Base load energy produced by generator over time horizon (MWh)
E^{mid}	Mid load energy produced by generator over time horizon (MWh)
E^{peak}	Peak load energy produced by generator over time horizon (MWh)
P^{refurb}	Integer number indicating the nuclear capacity refurbished (MW)
$P^{fuelswitch}$	Integer number indicating the coal capacity recommissioned to use biomass fuel (MW)
WE^{base}	The amount of energy 1 MW of installed wind capacity provides to base-load
We^{mid}	The amount of energy 1 MW of installed wind capacity provides to mid-load
We^{peak}	The amount of energy 1 MW of installed wind capacity provides to peak-load
$C_{VOM,i}^{LC}$	The variable O&M cost for generator i, in load category LC ($/MWh)

VMC_i^{LC}	The variable maintenance cost for generator i, in load category LC ($/MWh)
CO2tax	The carbon tax ($/tCO2)
$CO2_i^{LC}$	The carbon intensity of generator ‘i’ providing energy to each load-category (tCO2/MWh)
R_{VOM}	The stochastic component of the variable O&M cost
LF_t	The load forecast for year t
YI_t	The average yearly energy consumption increase
R_{LF}	The stochastic component of the load forecast

1. Background and Motivation

1.1 Human development in a word: Energy

There is a significant link between human development and access to energy. Humans and energy share a long history, from fire that allowed man to cook and stay warm, to the harnessing of streams and rivers to grind grain and eventually produce electricity. Human social development is the result of access to energy. The United Nations acknowledges that access to energy is a necessary precursor *for*, and not a result *of*, development [1]. With this in mind, there should be no surprise that the most developed countries with the largest economies also have the highest energy use per capita. In fact, the developed nations' access to cheap plentiful energy sources like coal, oil and gas has long been touted as the explanation for their wealth and prosperity [1].

1.2 Energy and Carbon Dioxide

There is, however, a complication with energy sources like coal, oil and gas: carbon dioxide emissions. The issue of climate change caused by anthropogenic CO_2 emissions has been widely debated and is at the vanguard of many political contentions in recent years [2]. These debates have prompted research into social, technological and political solutions to the problem. Fossil fuels used for the production of electricity account for nearly one third of anthropogenic CO_2 emissions [3]. Herein lies a problem. We need energy to maintain the current standard of living in wealthy countries and need *far more* energy to raise poorer countries out of poverty [1]. At the same time, fossil-fuels are still cheap and plentiful [1]. It is clear that any analysis that simply weighs immediate costs and benefits will favour fossil fuels [2]. The question is how do we best internalize the future consequences of emitting carbon dioxide in our current system?

1.3 Carbon Abatement Policies

The issue of carbon abatement in electric power systems has gained importance since the signing of the Kyoto protocol in 1997, when 160 nations resolved to reduce CO_2 and other greenhouse gases [2]. The most commonly proposed mechanisms to reduce CO_2 emissions take the form of an economic incentive [4]. These economic incentives can be broadly summarized by the following four instruments [5]:

- Carbon Tax
- Cap-and-trade
- Subsidies
- Regulation

A carbon tax is an instrument that puts a monetary value on every tonne of CO_2 emitted. The underlying theory of the tax is that increasing the cost of running carbon intensive power plants - those that use fossil fuels - will provide incentives to seek alternative technologies. A subsidy is similar to a tax, but instead of penalizing carbon emissions, the subsidy is a direct incentive for low-carbon emitting technologies that could take the form of a feed-in-tariff or price guarantee.

A carbon cap-and-trade system imposes a cap on the aggregate CO_2 emissions and allows the market to determine the price for emissions in the form of carbon credit trading or investments in new technologies. Some economists argue that a cap and trade system would be more efficient than a tax, since the tax could be set at a sub-optimal level [5]. The issues surrounding optimal carbon tax timing will be discussed later in this thesis.

Regulation policies are less market-based and more authoritative since the government directly intervenes with the system. In this thesis, the regulation policy will take the form of targeting a specific generation technology for mandatory decommissioning, i.e. disallowing a particular technology to continue operating in the power system.

The consequences of political intervention on essential infrastructures, such as power systems, are the subject of speculation. There are many studies in the literature that draw implicit conclusions about the effects of policy, based on assumptions about the composition of the infrastructures of the future. This method does not directly target the policy itself, merely infers which policies might be able to achieve some future scenario. One such study, presented in [6], assumes a certain level of wind power, plug-in hybrid electric vehicles and heat storages in the make-up of the power system of Finland in 2035, and draws conclusions about the policies needed to cause this outcome. There are more examples, such as [7] and [8], which also assume certain levels of wind power or hydrogen infrastructure penetration in future energy systems and again infer political strategies. These studies will be more thoroughly analysed in Chapter 2, but they are mentioned here to differentiate the objectives of this thesis.

1.4 Objective

In this work, a model is designed to explicitly model the effects of various policies on the expansion of a power system. A policy is imposed, the model forecasts the optimal expansion of the power system under the political constraint, and the final output is the expected composition of the power system as determined by minimum average cost. This method directly models the effect of the policy to allow explicit conclusions to be drawn.

1.5 Thesis Outline

In this work, a model is developed to investigate the expected impacts of CO_2 abatement policies in terms of installed generation technologies, electricity supply mixtures and emissions rates from an example power system. Chapter 2 introduces the concept of power system planning. With large infrastructures like power systems, the effects of policy will not be evident overnight; they will have a gradual and cumulative impact, so it is important to review the planning and expansion process to understand the underlying mechanisms. Chapter 3 introduces a model that optimizes power system expansion and includes a novel method for incorporating non-dispatchable, intermittent generation sources and the stochastic nature of the input parameters such as fuel costs and load growth. Chapter 4 introduces the Ontario power system and defines many of its important characteristics that will be used for the case study. Chapter 5 describes the calibration and validation of the model and provides a detailed analysis of our ‘business as usual’ (no carbon abatement policy) base case. Chapter 6 highlights the results of the expansion of the Ontario power system under several carbon abatement policies. Chapter 7 presents a detailed comparison of the policies' impacts on the future power system which is used in Chapter 8 to make conclusions and recommendations for further study.

2. Background and Introduction to Power System Planning

The rapid growth of large-scale power systems in the 20th century gave rise to the development of many methods for system expansion planning. By the early 20th century, power systems were becoming an inextricable part of economic growth, furthering the importance of future planning. The traditional method for determining the optimal generation mixture is described in [9] and [10], and outlined in Section 2.1. This method is extended in Section 2.2 to include intermittent generation sources. Section 2.3 reviews modern planning techniques and the state of the art.

2.1 Traditional Power System Planning: Load-Duration and Screening Curves

The first step in this analysis is acquiring load data over a specific period of time. The typical analysis involves one year of load-data at an hourly interval. To make a load-duration curve, the data are organized in descending order, from the hour with the highest to the hour with the lowest demand, with hours/year (8760 hours) on the abscissa.

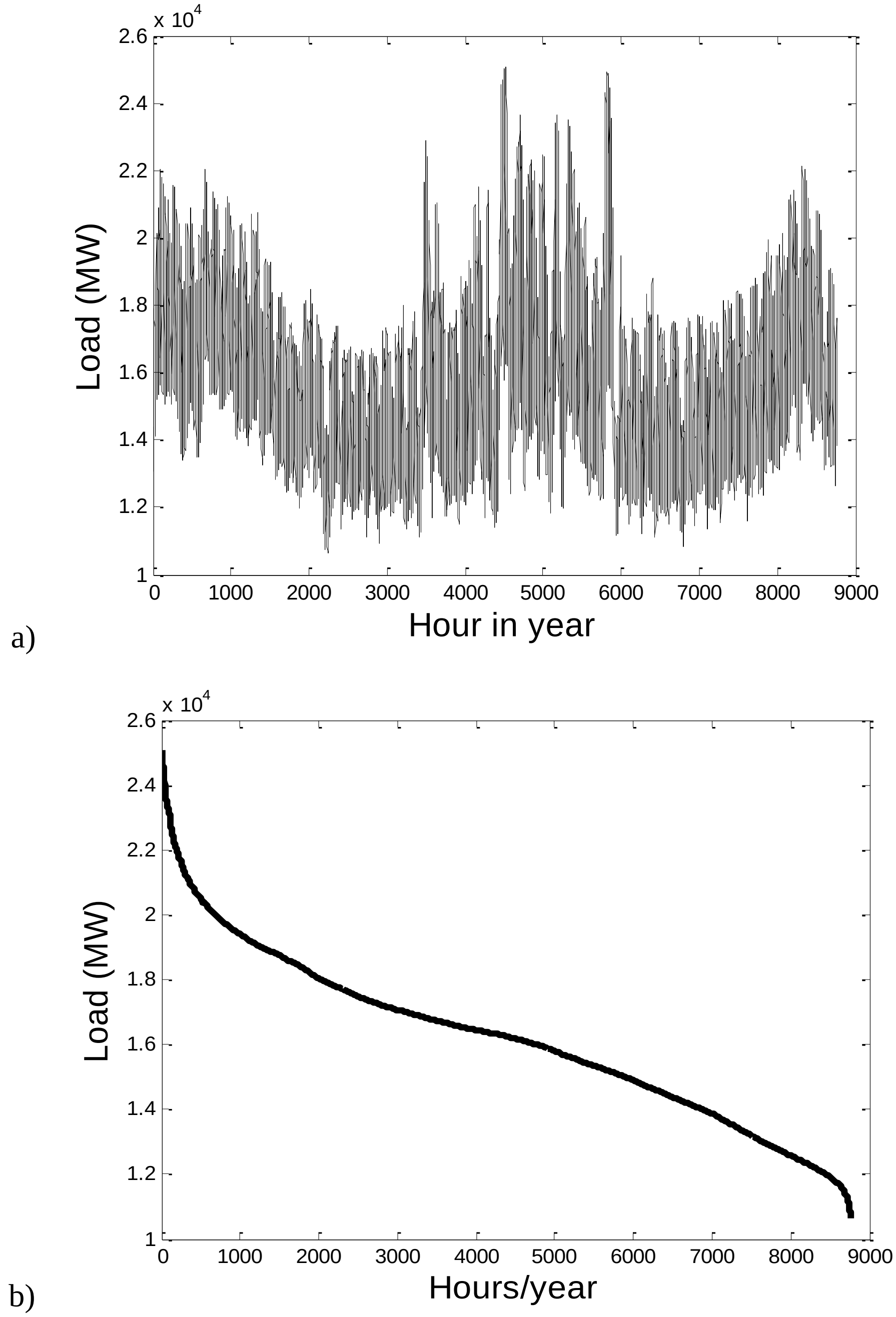


Figure 2-1 – (a) typical yearly load curve (b) the same load-data ordered into a load-duration curve.

The next step is to create screening curves. As summarized in [10], a screening curve plots the average capacity cost of a specific generation technology against capacity factor. The capacity cost is a monetary value that represents the amortized cost of installing a certain level of generation capacity, presented in $/MW_installed-year (amortized). The capacity factor, or utilisation time, represents the fraction of the year that the generator is operating. For example, base-load nuclear plants will operate at almost maximum output for the entire year, giving them high capacity factors. The capacity cost is typically approximated by a linear curve with an intercept that represents the fixed cost (construction cost) and a slope that represents a constant variable cost.

$$C\_K = C\_F + cf * C\_V, \qquad [2.1]$$

Where, C_K, is the sum of fixed costs, C_F, and variable costs, C_V. The latter term is assumed to be a linear function of capacity factor, cf. The fixed cost is the amortized cost of construction over the expected lifetime of the project and the variable cost includes fuel costs and variable O&M costs; all values are in $/MW_installed-year.

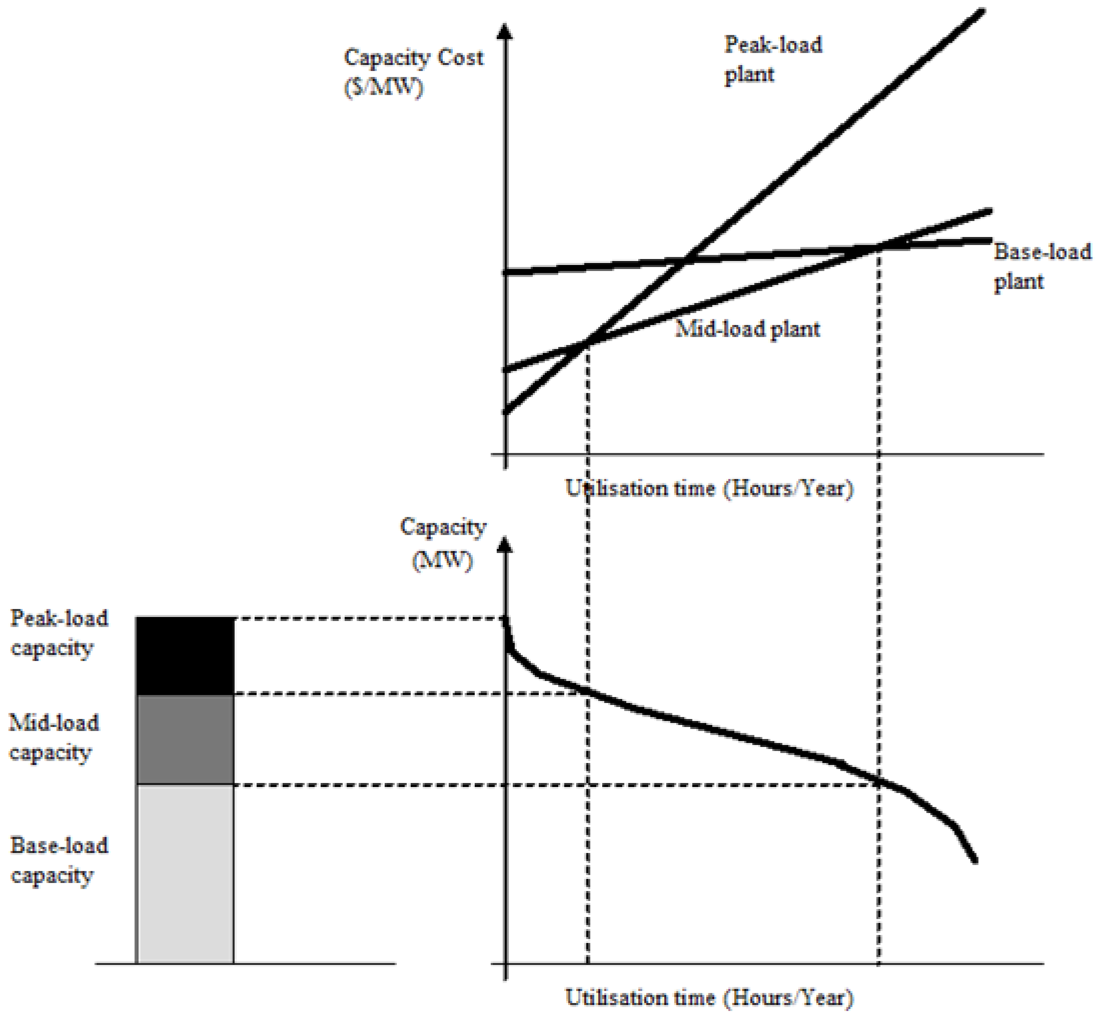


Figure 2-2 - Using screening curves and a load-duration curve to determine optimal installed generation capacities.

Figure 2.2 presents three screening curves: a typical curve for a base-load plant such as coal or nuclear; a mid-load plant such as a combined-cycle gas turbine; and a peak-load plant such as an open-cycle gas turbine. The 'capacity' refers to the amount of capacity each technology should provide as part of the optimal installed generation capacity mixture.

Using the screening curve we see that the base-load plants have high capital costs but low operating cost (largest intercept, smallest slope). To rationalize the large capital cost, the base-load plants have a high utilisation rate (capacity factor) to take advantage of the relatively low operating cost. The peak-load plants have a lower capital cost but much higher operating cost, making a lower capacity factor optimal for this type of generation. The mid-load plants have capital and operating costs somewhere in between those of base and peak-load plants and thus operate at a capacity factor between base and peak-load.

With these two tools, the load-duration curve (henceforth called LDC) and the screening curves, we can determine the optimal mix of generation for a long-term economic equilibrium. The long-term economic equilibrium assumes that the load curve, fuel prices and construction costs are constant for sufficient time that a least-cost equilibrium can be achieved. This essentially means we are assuming the LDC and screening curves are constant. The optimal mix can then be determined graphically as shown above in Figure 2-2. The amount of peak-load capacity can be read from the LDC and corresponds to the capacity factor/utilisation time of the peak-load plant, as determined from the screening curve. Figure 2-2 summarizes the capacity requirements of the optimal generation mix for the stylized example.

2.2 Extending the LDC-Screening curve analysis

In the 1970's, motivated by the oil embargo, there was significant interest in renewable generation sources such as wind and solar [11]. An important area of research emerged in power system planning with non-dispatchable, intermittent generation sources. These techniques started by extending the previous analysis to incorporate the resource specific effects of intermittent resources.

In [12] intermittent generation, like wind power, is modelled as a negative load. This can be done by directly subtracting the amount of wind power generated, from the load curve (Figure 2-1 (a)) at that specific time interval; i.e. subtract all of the wind power produced in hour 1 from the load in hour 1 and continue for all 8760 hours in the year. Doing this will shift the load profile and thus the LDC. This will have implications for the optimal generation mixture using the screening curve method. This is summarized below.

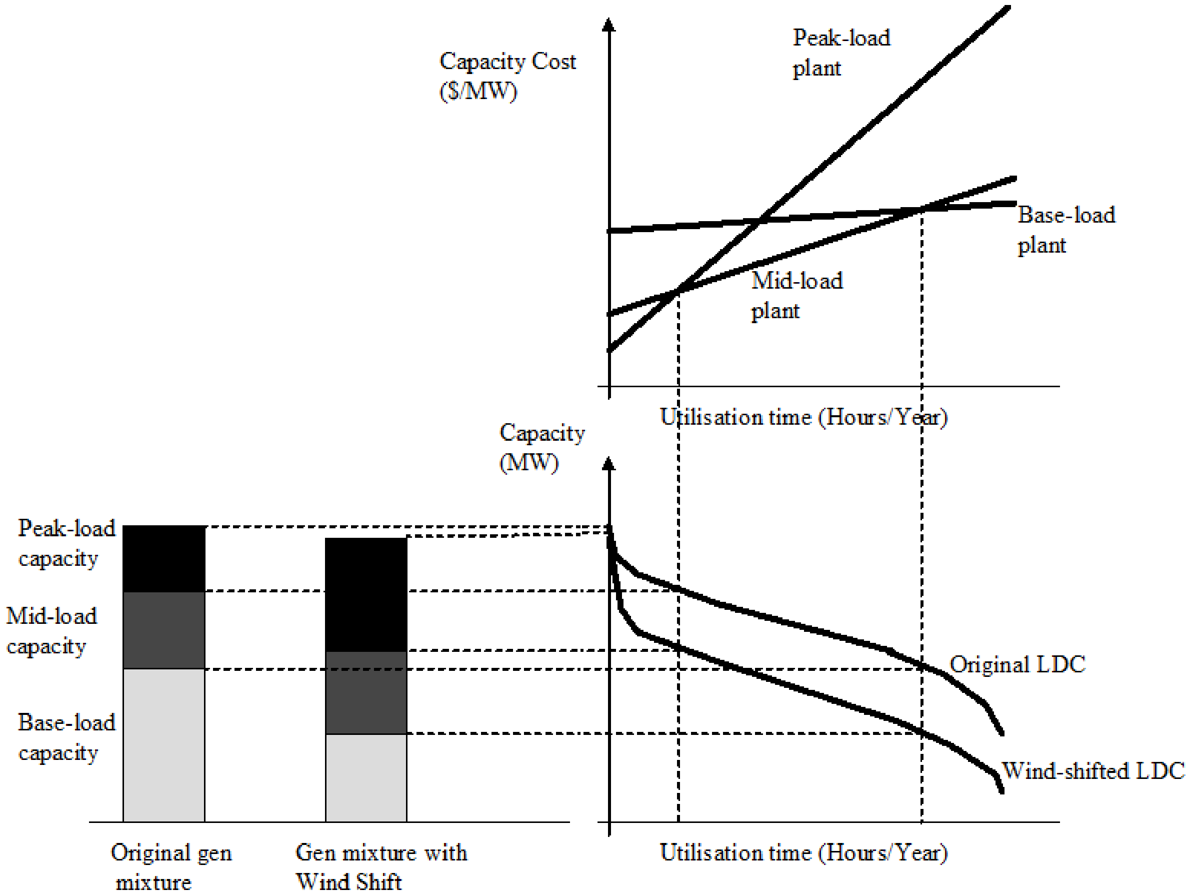


Figure 2-3 - The effects of a wind-shifted LDC on optimal installed capacity.

As expected, the wind-shifted LDC generates a different optimal generation mixture relative to the original LDC. In this example, the wind power increases the peak and mid-load capacity requirements, while decreasing the amount of base-load. In [13] this simple method for assessing the long-term costs and benefits of adding wind generation to a power system is explored. This model uses load-duration curves and screening curves to determine the optimal installed capacity and capacity factors of integrated gasifier combined cycle (IGCC) coal plants and natural gas combined cycle (NGCC) plants in a power system with various levels of wind penetration. This analysis assumes long-term economic equilibrium. This assumption provides a reasonable method for directly comparing the costs imposed by wind power on an ideal power system, but tells us little about how a power system should evolve in a more realistic and uncertain world. Useful information about when generators should be decommissioned or built is not captured, as well as the influence of increasing interties or transmission.

In [13], Kennedy uses a wind-shifted LDC; a load duration curve that has been shifted by the expected hourly wind power output from a resource off the coast of Long Island, NY. This method is an efficient way to capture the effect of a wind farm on the power system and has been used in various works, including [12-14]. It is, however, limited to considering a single wind resource. The optimal long-term generation mix could (and most likely would) include wind power from several resources from different regions; these benefits cannot feasibly be captured using this method. This assumption makes it difficult to determine the optimal, most economically efficient amount of wind power in our system.

2.3 Developments in power planning/state of the art

There are many models that try to address some of the shortcomings of the previous methods mentioned at the end of the previous section. It is important to note that generation expansion planning is a complex task with many inherent uncertainties that lead to many trade-offs in the planning process [15]. There are many commercial modelling tools available that try and capture these uncertainties and provide realistic estimates of optimal power system planning. A good summary of these models can be found in [16]. Two of these models will be briefly reviewed below; Balmorel and a multi-period model from the University of Waterloo.

Ravn et al develop a dynamic partial-equilibrium model for the electricity and combined-heat and power sector in the Baltic Sea region called Balmorel [17]. This model contains high resolution detail about the specific power systems in the Baltic Sea region in terms of generation assets, transmission and interconnection. At the heart of the model is a mixed-integer linear program that can optimize the infrastructure investments given projections of future energy needs, fuel prices and policies. The model can invest (or decommission) generation and transmission capacity at the beginning of each year, and is constrained to ensure that it can supply expected energy needs. It has been used as the backbone for several papers, an example of which is outlined below.

In Kiviluoma et al [6], the Balmorel model is used to assess the integration costs of wind power, plug-in electric vehicles and thermal energy storage. There are many assumptions made about the future power system to estimate the optimal investment strategy for servicing the power needs of Finland in 2035. Most notable, this paper assumes certain levels of wind penetration and PHEV adoption. This provides insight into the structure of the power system that can handle these technologies at the assumed penetration levels. For low and high fuel cost scenarios, with a low and high CO_2 cost (tax), the model suggests optimal investment strategies to service the projected electricity and heat load requirements. Further insight could be gleaned from a higher resolution simulation where the years leading up to 2035 are incorporated and the system is optimized at larger time scales. This would provide insight into the optimal evolution of the power system in terms of when investment/decommission decisions should be enacted.

In [18], Mirzaesmaeeli develops a mixed-integer non-linear program to investigate the optimal power system expansion for the Ontario power system. The proposed model is not as complex as Balmorel since it considers only a single power system and neglects the transmission network. This model uses yearly time steps to optimize both infrastructure costs and expected cost of supplying electricity. The portfolio of generation technologies that can be developed include nuclear, coal and gas; with an option to fit carbon capture and sequestration technologies on the fossil fuel generators. Two case studies are presented; one without restrictions on carbon emissions, and one with a simple emissions cap to conform to the Ontario political goals of 2005. The model does not include renewable generation sources, such as wind and solar, or the ability to retrofit coal plants to run on biomass fuel. The model uses a high-low prediction for load growth over the planning horizon being considered. This does not capture the expected distribution of outcomes (generation mixture, CO_2 emissions, costs) associated with the uncertainty of future fuel prices and load growth.

This Chapter provides background on power system expansion planning. The traditional method for determining the optimal generation mixture is outlined in Section 2.1. This method is extended in Section 2.2 to include intermittent generation sources. Section 2.3 reviews modern planning techniques and the state of the art. These methods are used as the foundation of the model developed in this work. This model is presented in the next chapter.

3. Optimal Power System Investment Model

3.1 Model Overview

This work employs a mixed-integer linear programming (MILP) model to determine the least cost solution to co-optimize generation investments and servicing the expected load profiles. The model makes decisions based on forecasts of future load-profiles, fuel prices and non-dispatchable resource profiles. These forecasts form the constraints of the MILP model that optimizes the generation capacity expansion over the given time horizon; minimizing infrastructure cost and cost of supplying electricity.

The starting conditions are set by the user and should reflect the generation mixture in the base-year of the power system being investigated. The time-step of the MILP is yearly. To model the power system's optimal evolution, the first year is set by the user while the rest of the years in the planning horizon are optimized by the model. A mixed-integer model is needed to capture the minimum investment capacities of the various generation technologies. A Monte Carlo simulation is employed to provide insight into the sensitivity of the power system expansion. Details of the Monte Carlo simulation method are presented in Section 3.2, followed by details of the MILP model in Section 3.3.

3.2 Monte Carlo Simulation

There are several inputs that must be projected (forecasted) before being sent to the optimization model. The stochastic nature of the input parameters consequently propagates through to the output variables. To approximate the expected generation mixture and its associated distribution, a Monte Carlo simulation is performed. This is an effective technique for handling models with uncertain or stochastic inputs. Each iteration of the Monte Carlo simulation takes a realization of the stochastic input parameters, uses them in the MILP model and saves the output. It reiterates this process for several realizations of the input parameters to get a distribution of output values that should reflect the uncertainty in the stochastic inputs.

This results in inputs and outputs being approximated by statistical distributions, as opposed to single values. A flow diagram of the Monte Carlo simulation process follows in Figure 3-1.

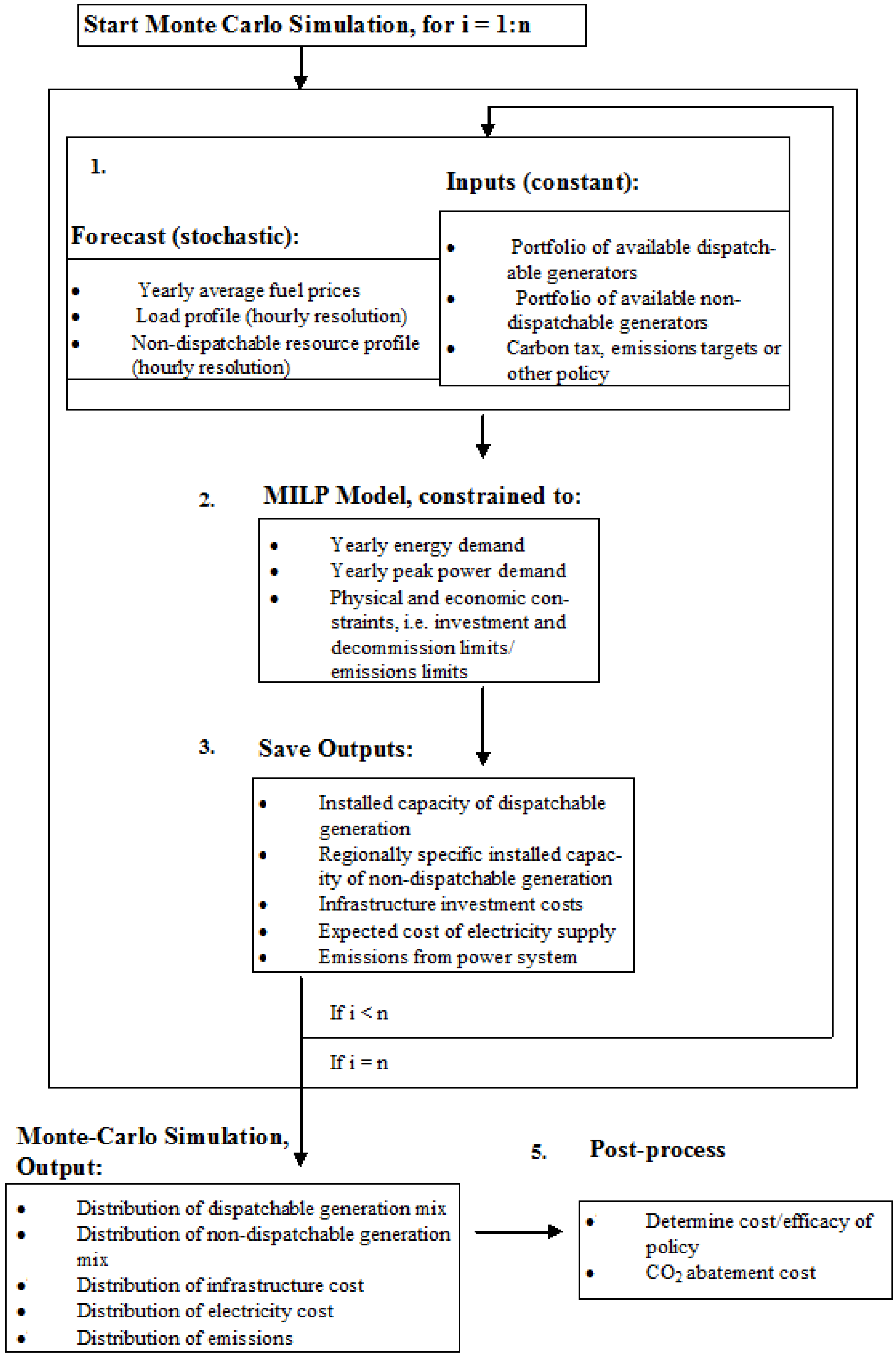


Figure 3-1 - Flow diagram of the Monte Carlo simulation.

3.3 MILP optimization model

Linear programming is a technique for optimizing a linear objective function subject to linear equality and inequality constraints. The problem can be formulated to minimize or maximize the objective function, which could represent a cost or profit function. Algorithms for solving linear programs emerged during the Second World War, most notably for optimizing army expenditures. In 1947 the simplex method was published by George B. Dantzig [19]; an efficient algorithm which is widely used today. The simplex method is at the heart of the ILOG IBM CPLEX 12.1 solver; the solver used in this work. To allow for integer solutions, an algorithm that uses Gomory's fractional cuts is applied in the MILP function of CPLEX [20]. The simplex method is applied in a similar fashion to a traditional LP with continuous variables, but an additional algorithm is implemented to ensure that the solution is optimized with respect to the integer constraints. The CPLEX solver is called from within the MATLAB R2009a environment, which is used to execute the entire simulation.

3.3.1 Objective Function

The objective function is a cost-minimization function: minimizing infrastructure costs and the cost of supplying yearly energy/peak power demands. The yearly time-step inherently limits the number of times that decisions can be made to once per year, for every year in the planning horizon. The objective is simply the sum of six decision variables for each dispatchable generator, three decision variables for non-dispatchable generators and one decision variable each for nuclear refurbishment and coal fuel-switching. Each decision variable is multiplied by its associated cost over the planning horizon.

Objective Function

Minimize:

$$NPVfactor * \sum_t^T \left(\sum_{\boldsymbol{i}}^{\boldsymbol{I}} C_{t,i}^{INV} \cdot P_{t,i}^{INV} + C_{t,i}^{AOM} \cdot P_{t,i}^{NP} + C_{t,i}^{DCM} \cdot P_{t,i}^{DCM} + C_{t,i}^{VOM} \cdot E_{t,i} \right) +$$

$$NPVfactor * \sum_t^T \left(\sum_{t,j}^{J} C_{t,j}^{INV} \cdot P_{t,j}^{INV} + C_{t,j}^{AOM} \cdot P_{t,j}^{NP} + C_{t,j}^{DCM} \cdot P_{t,j}^{DCM} \right) + \qquad [3.1]$$

$$NPVfactor * \sum_t^T C_{t,nuke}^{refurb} \cdot P_{t,nuke}^{refurb} + \sum_t^T C_{t,coal}^{fuelswitch} \cdot P_{t,coal}^{fuelswitch}$$

$$NPVfactor = \frac{1}{(1+d)^t} \qquad [3.2]$$

Where i – dispatchable generators
j – non-dispatchable generators
t – time in years
d – discount rate

And the total energy cost is:

$$C_i^{VOM} \cdot E_i = \sum_i^I C_i^{VOMbase} \cdot E_i^{base} + C_i^{VOMmid} \cdot E_i^{mid} + C_i^{VOMpeak} \cdot E_i^{peak} \qquad [3.3]$$

A detailed description of costs and variables follows in Table 3-1.

Table 3-1 - Summary of cost function and variables in the objective function.

Cost		Decision Variable	
C^{INV}	Cost of investment ($/MW capacity)	P^{INV}	Integer number corresponding to minimum technology investment capacity (e.g. 1 = 500MW Nuclear)
C^{AOM}	Annual O&M Costs ($/MW installed capacity)	P^{NP}	Total name plate capacity installed of technology *i* (or j) at time-step *t* (MW)
C^{DCM}	Cost of decommissioning ($/MW capacity)	P^{DCM}	Integer number corresponding to minimum technology size (e.g. 1 = 500MW Nuclear)
$C^{VOMbase}$	Variable O&M Costs for base load energy (includes Fuel/CO_2 costs) ($/MWh produced)	E^{base}	Base load energy produced by generator over time horizon (MWh)
C^{VOMmid}	Variable O&M Costs for mid load energy (includes Fuel/CO_2 costs) ($/MWh produced)	E^{mid}	Mid load energy produced by generator over time horizon (MWh)
$C^{VOMpeak}$	Variable O&M Costs for base load energy (includes Fuel/CO_2 costs) ($/MWh produced)	E^{peak}	Peak load energy produced by generator over time horizon (MWh)
C^{refurb}	Cost of refurbishing a nuclear plant ($/MW refurbished)	P^{refurb}	Integer number indicating the nuclear capacity refurbished (MW)
$C^{fuelswitch}$	Cost of recommissioning a coal plant to operate using biomass fuel ($/MW recommissioned)	$P^{fuelswitch}$	Integer number indicating the coal capacity recommissioned to use biomass fuel (MW)

The first bracketed term in the objective function represents the infrastructure costs and variable O&M costs for the dispatchable generators. The infrastructure costs are the summation of investment (new builds), yearly O&M and plant decommissioning costs. The energy cost is the variable operating cost of the dispatchable generators. This term captures the cost of fuel, variable O&M and carbon tax (where applicable).

The second bracketed term represents the infrastructure costs for non-dispatchable generators. Similar to the dispatchable generators, the infrastructure costs for non-dispatchable generators are the summation of investment (new builds), yearly O&M and plant decommissioning costs.

The last summation term in the objective function represents the costs associated with refurbishing nuclear generators and fuel switching coal fired plants to use biomass (wood pellets) in their boilers. Once a nuclear plant is refurbished it is assumed to revert to its original operating parameters: i.e. same fixed and variable O&M costs and electricity output capabilities. The fuel-switched coal plant, however, takes on different operating parameters, which will be discussed further in Chapter 4. The 'NPVfactor' before each summation term discounts future years so that the entire cost can be presented as a net present value, in terms of $CAD2010.

The traditional screening curve method uses a linear function to capture the cost of capital and the operating costs associated with a given capacity factor (utilisation time). In this model, the capital cost is captured by the investment cost while the operating costs are separated into three categories: base-load, mid-load and peak-load with an additional cost to capture the yearly O&M. These operating costs reflect the fuel efficiency and associated variable O&M costs with operating at each load category; servicing base, mid or peak-load. This segmenting of the load provides higher resolution detail of the costs incurred by generators, both for investment and operations. This also allows us to incorporate a decommissioning cost; something that cannot be done with simple screening curves and more closely models a realistic system. We now need to quantify the three load-categories in terms of power capacity and energy requirements.

3.3.2 Segmenting the LDC

The load-duration curve can be used to give insight into broad changes in generation requirements of a power system, as demonstrated in Chapter 2. This method will be used to estimate the amount of base, mid and peak capacity and energy requirements; information that we need for the optimization model.

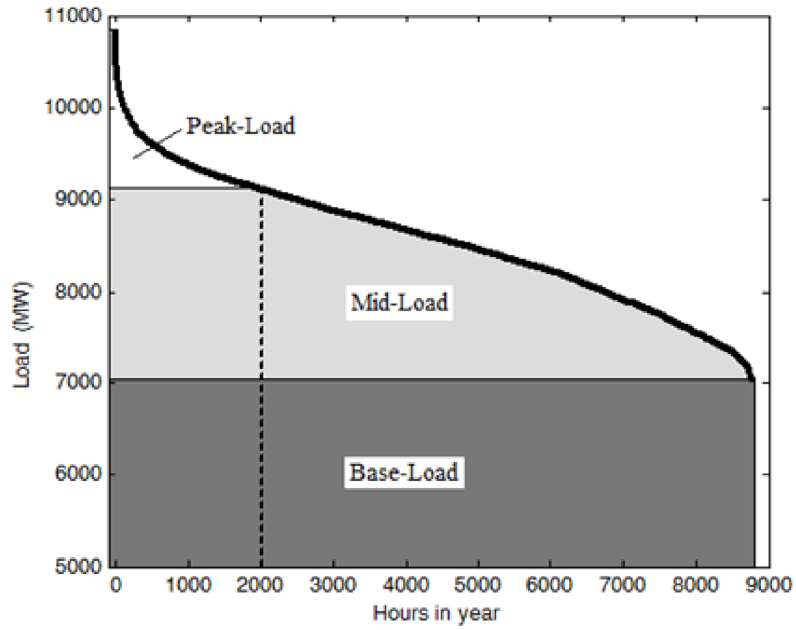


Figure 3-2 - Schematic of segmented load duration curve.

To determine the power capacity and energy requirements for base, mid and peak loads, the LDC is segmented as shown in Figure 3-2. In [21, 22], peak load is defined as the electricity demanded for the first 2000 hours in the LDC, mid-load is from hour 2000 to hour 8760 and base-load is the minimum amount of load that is always demanded throughout the year. The peak load of 2000 hours is the sum of daily peak demand, which occurs for about 5 hours every day. In the example shown in Figure 3-2, the base-load requirement is just over 7000MW (can be read off the y-axis). The mid-load power capacity corresponds to (~9000 - ~7000) 2000MW, and peak is around 1600MW. Using these values as the power requirements of our system will ensure that each load-category can be met.

The energy requirement of each load category is simply the area under the LDC corresponding to that category's power capacity. Peak-load energy requirement is the white area, the mid-load energy requirement is the light gray area and the base-load energy is the dark gray area in Figure 3-2.

3.3.3 Making Wind Power Capacity Investment a Decision Variable

For both dispatchable and non-dispatchable generators, the infrastructure costs can be quantified in the same manner; the sum of the investment (construction) cost, the yearly O&M cost and the decommissioning cost. The difference in how we model these two generator classes shows up in the variable O&M cost. Intuitively, it is relatively easy to quantify dispatchable generators, like coal or gas, as decision variables in our model. For dispatchable generators, the cost for each load category (base, mid and peak) can be captured by the fuel costs and maintenance costs associated with servicing that load. The optimizer can be sent a certain 'availability factor,' a theoretical maximum amount of time the generator can operate during the year, and then perform a simple resource allocation optimization based on the relative costs of the generators to service the load. Wind power, however, can be assumed to have no fuel costs and have all of its variable maintenance costs captured in the yearly O&M cost. We cannot dispatch the wind power like conventional dispatchable generators, so the question arises: how do we account for the amount of energy/power capacity provided by each MW of wind capacity? To answer this, we return to the LDC.

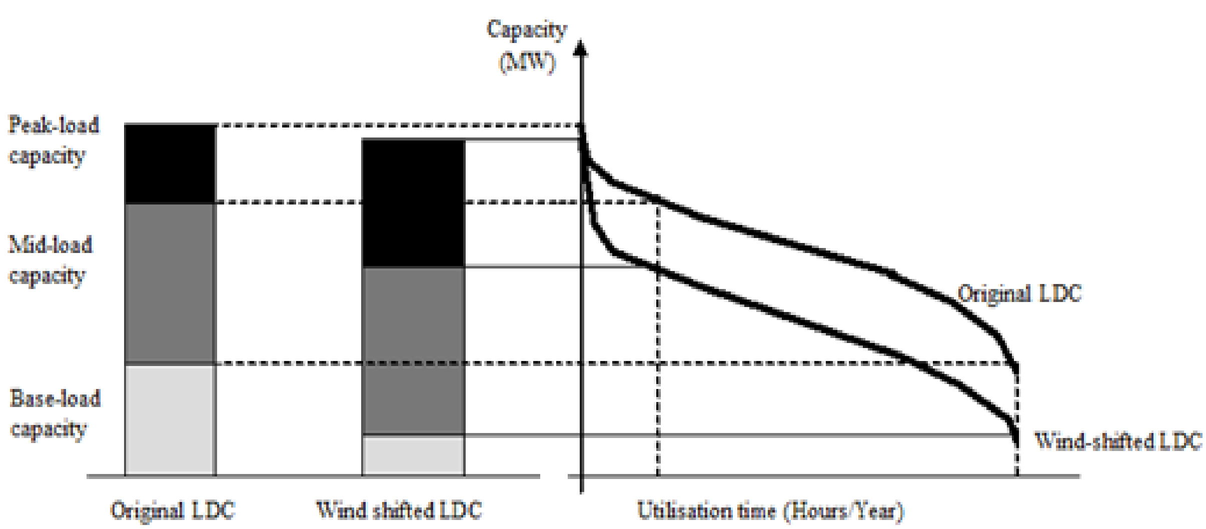


Figure 3-3 - Change in load-categories due to wind power influence.

Figure 3-3 is similar to Figure 2-3 except that instead of using the screening curves to segment the LDC, we are using the definitions of base, mid and peak-load established in the previous section. This method requires forecast load data and forecast wind power output for the year being investigated (forecasting methods will be discussed in Chapter 4). As introduced in Chapter 2, the hourly wind power output is subtracted from the hourly load and then sorted in descending order to produce our wind-shifted LDC. The original LDC and the wind-shifted LDC are both segmented into the base, mid and peak-load energy and power requirements as outlined in the previous section. Now there are two sets of values for each energy and power capacity requirement: one without a wind shift and one with the wind shift. If we take the difference of these two sets of values and normalize them to 1MW, we get a succinct set of values which tells us how 1MW of wind power added at this resource site will affect all three load categories in terms of energy and power capacity requirements. For example, from Figure 3-3 we see that the wind shifted LDC reduces the amount of base-load power capacity, but increases the amount of mid and peak capacity needed. Therefore, each MW of power capacity added at this resource will have a positive base-load value (decreases amount of base-load power needed) and a negative mid and peak-load value (increases the amount of mid and peak-load power needed). For the rest of this work, this will be referred to as the wind farm's 'power credit,' where there is a base, mid and peak-load power credit. Similarly, there will be a base, mid and peak-load energy credit, which is defined as the amount of energy 1MW of wind capacity provides each load category in a specific year. This method has the implied assumption that the relationship between installed wind capacity and power/energy credit is linear. This relationship is not perfectly linear; however, a linear approximation is assumed in this work. An analysis and discussion of this linear assumption can be found in Appendix A.

The defining feature of this method is that it can capture the differences between wind resources based on their effect on each load-category. This allows the model to select the most useful resources to be developed based on the load shape and available wind resources in the power system being investigated.

3.3.4 Optimization Constraints

In this section, the constraints of the optimization model are presented.

Nameplate Capacity Balance:

The first constraint considered is the nameplate capacity balance. The nameplate capacity balance can be thought of as an accounting constraint that updates the level of installed capacity to include the newly built or decommissioned capacity in each time step, as decided by the optimization.

$$\mathbf{P_{t,i}^{NP}} = \mathrm{P}_{\mathbf{t-1,i}}^{\mathbf{NP}} + \mathrm{P}_{\mathrm{t-delay,i}}^{\mathrm{INV}} - \mathrm{P}_{\mathrm{t,i}}^{\mathrm{DCM}} \qquad [3.4]$$

There is a time-delay between when the investment cost is incurred, and when the capacity comes online. This time-delay represents the generator build-time and is captured in the $\mathrm{P}_{\mathrm{t-delay,i}}^{\mathrm{INV}}$ term, where 't-delay' represents the build-time in years. The nameplate installed capacity of each generation technology at any time-step 't' must be equal to the installed capacity at the previous time-step 't-1' plus any new capacity invested at 't-delay', minus any capacity decommissioned at the current step 't.' The constraint as presented applies to all of the generators except nuclear, since its nameplate capacity must also take into account the capacity added after refurbishment. Therefore, the nameplate capacity balance for nuclear generation is as follows.

$$\mathrm{P}_{\mathrm{t,i}}^{\mathrm{NP}} = \mathrm{P}_{\mathrm{t-1,i}}^{\mathrm{NP}} + \mathrm{P}_{\mathrm{t-delay,i}}^{\mathrm{INV}} - \mathrm{P}_{\mathrm{t,i}}^{\mathrm{DCM}} + \mathrm{P}_{\mathrm{t-delay}}^{\mathrm{refurb}} \qquad [3.5]$$

An additional constraint is needed so that the model can only refurbish the capacity that is being decommissioned.

$$\mathrm{P}_{\mathrm{t,nuclear}}^{\mathrm{refurb}} - \mathrm{P}_{\mathrm{t,nuclear}}^{\mathrm{dcm}} \leq 0 \qquad [3.6]$$

This constraint limits the amount of refurbished capacity to that which is decommissioned and forces the refurbishment decision to be made in the same time period. This makes intuitive sense since these decisions are coupled: the decision is whether to decommission the nuclear plant, or decommission *and* refurbish.

The initial nameplate capacity of all the generation technologies is set by the user and should represent the base-year of the study. Information about power capacity that has already been commissioned or is in the process of being constructed within the first few years of the study should also be taken into account, and will be discussed in the Chapter 4.

Energy constraints:

The energy constraints ensure that all of the energy demanded is supplied by the available generators.

$$\sum_t^T \sum_i^I E_{t,i}^{base} + \sum_t^T \sum_j^J (WE_{t,j}^{base} * P_{t,j}^{NP}) = \text{Base load energy demanded} \quad [3.7]$$

$$\sum_t^T \sum_i^I E_{t,i}^{mid} + \sum_t^T \sum_j^J (WE_{t,j}^{mid} * P_{t,j}^{NP}) = \text{Mid load energy demanded} \quad [3.8]$$

$$\sum_t^T \sum_i^I E_{t,i}^{peak} + \sum_t^T \sum_j^J (WE_{t,j}^{peak} * P_{t,j}^{NP}) = \text{Peak load energy demanded} \quad [3.9]$$

The energy supplied by the wind resources is a function of installed capacity, as outlined in the previous section. The ‘WE’ values correspond to the amount of energy 1 MW of installed wind capacity in resource location ‘j’ provides to the respective load segments. The energy demanded and ‘WE’ values in each category are found using the load demand curve method outlined above.

Maximum energy supply constraint for dispatchable generation:

This constraint only applies to dispatchable generators and simply limits the amount of energy each technology can provide to its nameplate capacity multiplied by its availability.

$$\sum_i^I (E_i^{base} + E_i^{mid} + E_i^{peak}) \leq P_i^{NP} * AV_i * HOURS \quad [3.10]$$

Here 'HOURS' represents the number of hours in a simulation; for this work that is 8760hrs (1 year) and AV_i is the availability of the technology (ratio of maximum deliverable energy/(nameplate capacity*HOURS)). For example, nuclear plants can operate very close to their nameplate capacity for almost the entire year, giving them a high AV, while Hydro plants can be limited by water availability and have a lower AV.

Power Capacity Constraints:

These constraints ensure that the sum of the available power capacities of all the generation technologies is greater than or equal to the yearly peak demand (power demanded at hour 1 in the LDC) as determined by the forecasted LDC.

$$\sum_t^T \sum_i^I (P_{t,i}^{NP} * CF_{t.i}^{base}) + \sum_t^T \sum_j^J (P_{t,j}^{NP} * WP_{t.j}^{base}) \geq \text{Base load power capacity} \quad [3.11]$$

$$\sum_t^T \sum_i^I (P_{t,i}^{NP} * CF_{t.i}^{mid}) + \sum_t^T \sum_j^J (P_{t,j}^{NP} * WP_{t.j}^{mid}) \geq \text{Mid load power capacity} \quad [3.12]$$

$$\sum_t^T \sum_i^I (P_{t,i}^{NP} * CF_{t.i}^{peak}) + \sum_t^T \sum_j^J (P_{t,j}^{NP} * WP_{t.j}^{peak}) \geq \text{Peak load power capacity} \quad [3.13]$$

The generator capacity allocation coefficients, e.g. $CF_{t.i}^{base}$, define the fraction of the generators capacity that can be allocated to service a particular load-segment. For example, nuclear plants are mostly used to service base-load, so its $CF_{t.i}^{base}$ coefficient is large relative to its mid and peak coefficient. The capacity allocation coefficients for each technology will be presented in the next chapter.

The 'WP' values correspond to the amount of power 1 MW of installed wind capacity in resource location 'j' would provide to the respective load segments, and is a function of installed wind capacity.

Additional Coal/Biomass Constraints:

The two generation technologies are defined by the previously mentioned objective function and constraints, with additional constraints so that coal plants can be 'fuel-switched' into biomass generators.

$$P_{t,coal}^{fuelswitch} - P_{t,coal}^{dcm} \leq 0 \qquad [3.14]$$

This constraint restricts the model to fuel-switch only as much coal capacity as has been decommissioned. The decision is also constrained to the time period in which the coal plant is decommissioned. If a decision is made to fuel-switch a coal plant, this plant will assume different variable O&M costs associated with using biomass.

3.4 Electricity Trading

Inter-regional electricity trading is standard practice in any interconnected electricity market. The dynamics of electricity trading are market based and are related to the electricity market clearing price differentials between trading regions. To estimate the volume of trades, a model that simulates the electricity market clearing prices for all interconnected regions would have to be developed, at a minimum resolution of hourly time intervals. Such a model is out of the scope of this current work.

In this Chapter the MILP model used to determine the minimum cost of satisfying load growth is presented. The stochastic components, load, fuel cost and wind power output, were discussed and the Monte Carlo simulation method is presented as a means of capturing the uncertainty in input parameters. The next Chapter introduces the case study and presents details of the models used to forecast input parameters.

4. Input Data: Setting-up the Case Study

In this chapter, the data used in the case study is introduced. The power system being studied is that of Ontario, Canada. Ontario has both a diverse generation mixture and a diverse set of policies for curbing carbon dioxide emissions. The broad political landscape and diverse electricity system will allow many features of the proposed model to be explored.

4.1 Forecasted Inputs

As outlined in Chapter 3, there are three categories of forecasted inputs in this model. These inputs are:

- Variable O&M costs for dispatchable generation;
- Future load profiles;
- Hourly wind power output for each region being investigated.

Each input must be forecast in a manner that maintains its underlying temporal profile; to most accurately model how they behave in real-life and thus capture their expected impact on future power system configurations. The method used for each category is explained below.

4.1.1 Dispatchable Generation: Variable O&M costs

The variable O&M costs in this model will be captured by the following equation, in units of $CAD2010/MWh:

$$C_{vom,i}^{LC} = VMC_i^{LC} + FC_i + R_{VOM,i} + CO2_i^{LC} * CO2tax \qquad [4.1]$$

Where, $C_{vom,i}^{LC}$ is the variable O&M cost for generator i, in load category LC ($/MWh)
VMC_i^{LC} is the variable maintenance cost for generator i, in load category LC ($/MWh)
FC_i is the fuel cost for generator i ($/MWh)

$R_{VOM,i}$ is the stochastic component of the fuel cost (unitless)

$CO2_i^{LC}$ is the carbon intensity of generator i, in load category LC (tCO_2/MWh)

$CO2tax$ is the carbon tax (where applicable) ($\$/tCO_2$)

There are four parts to the variable O&M costs; maintenance, fuel, carbon tax and a stochastic component 'R_{VOM}'. The fuel cost increases yearly according to projections found in [23]. The stochastic component is a normally distributed random variable with a mean value of zero and standard deviation found empirically corresponding to the standard deviation of fuel costs over the past 20 years.

For each technology a range of variable maintenance costs was found in the literature. The means of these ranges were used in the simulations. The same method was used to define the carbon intensities of each generator. A range was found and the average value was used for each technology. Table 4-1 summarizes the values used for variable maintenance and carbon intensity.

Table 4-1 – Summary of variable maintenance and carbon intensities of dispatchable generators. **References:** * = [24] + = [25] # = [26] ¥ = [27]

Technology	Variable O&M (excluding fuel) ($CAD2010/MWh)	Carbon Intensity (tCO_2/MWh)
Nuclear	2.04 - 4.03*	0.06#
Pulverized Coal	4.25 - 9.05+	0.863 - 0.961#
CCGT	3.43 - 6.45+	0.421 - 0.577#
OCGT	14.7+	0.605 - 0.751#
Hydro	5 - 15+	0#
Biomass	4.25 - 9.05+	0.075¥
Wind	0	0

The carbon intensities for coal, combined cycle gas turbine (CCGT) and open- cycle gas turbine (OCGT) generators are dominated by the amount of CO_2 released when burning the fuel. The carbon intensity for nuclear power and biomass is based on the amount of carbon associated with the extraction and refinement process of the fuels. For nuclear this is an average value where the refinement and enrichment is assumed to be done with coal power to give an upper estimate of the carbon intensity. Ontario operates CANDU reactors which use unenriched uranium. The carbon intensity of this fuel should be slightly lower than the one presented since the most energy intensive part of nuclear fuel processing is the enrichment. The value as presented is kept to provide a conservative estimate of nuclear power's carbon intensity.

The carbon dioxide associated with the biomass is also an average, taking into account drying, pelletizing and transportation. Note that the 'carbon neutrality' assumption of biomass is being employed here. This assumption asserts that all of the carbon dioxide released during the burning of the fuel is recaptured by the trees and plants from where it came.

The carbon dioxide emissions associated with the construction of the generators is not taken into account. The emissions associated with generator construction are produced in the materials manufacturing (concrete and steel), materials transportation and construction machinery. The proposed policies are all directly related to power system emissions and do not attempt to regulate the emissions associated with all industries previously mentioned that are involved in the construction of generation technologies. For this reason, these emissions are not considered in this work.

The fuel costs were taken from projections made by the United States government based Energy Information Administration (EIA). The EIA projected coal and gas costs to 2035 for the average large-scale coal plant and average CCGT [23]. In [23], the heat rates associated with the average CCGT and OCGT power plant is used to determine the future projections of their respective fuel costs.

Forecast nuclear fuel costs were found in [28]. Since uranium is so energy dense, a 100% increase in the per-pound price only results in an increase of a few dollars on a $/MWh basis. This results in the nuclear fuel costs being very flat into the future.

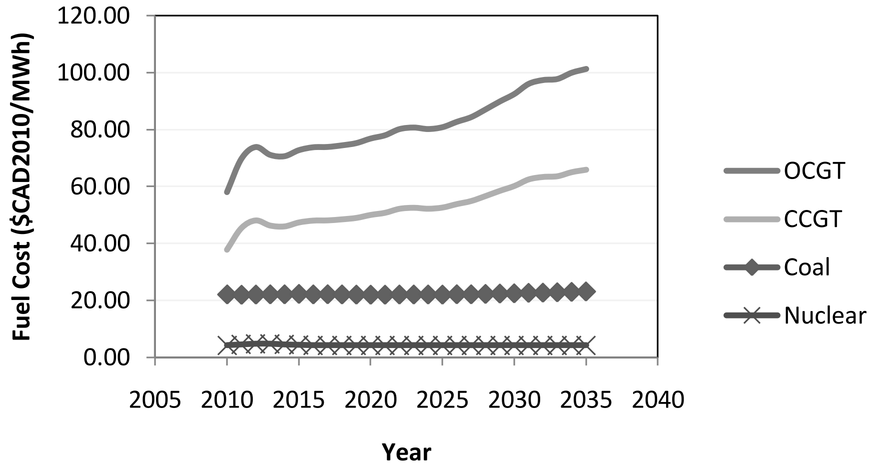


Figure 4-1 – Forecast fuel prices; coal and gas prices are from EIA [23], nuclear from [28].

The variable cost of hydro power is considered constant since it is not subject to fuel cost increases or influenced by a carbon tax. The variable cost is based entirely on operations and maintenance costs due to mechanical wear on the generation equipment.

The technology for using wood pellets to generate electricity is still in its infancy, as such there are few readily available market tools or resources to predict fuel costs. In [27], the cost of energy for the wood pellets is $8.2/GJ and the assumed heat rate of a converted coal plant is 11.3 MJ/kWh. This is equivalent to a fuel cost of 92.66$/MWh; this cost will be kept constant throughout the simulations. It is likely that if demand for wood pellets increased significantly, economies of scale could reduce this fuel cost, but at the current time there is not enough information to suggest any such trend. A stochastic variable is added to the variable O&M costs to complete the equation as presented in equation 4.1. The following plots present one realization of the forecast variable O&M costs described by equation 4.1.

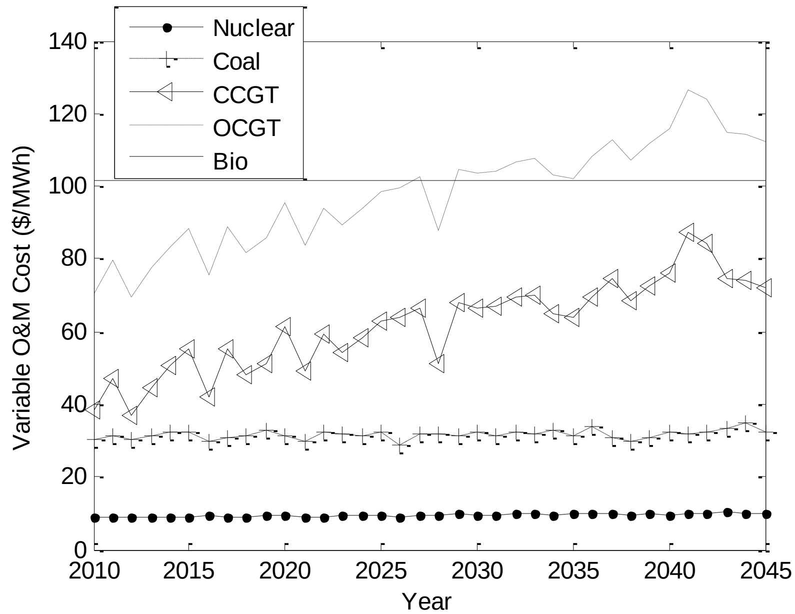


Figure 4-2 – One realization of mid-load variable O&M cost projections without any carbon tax.

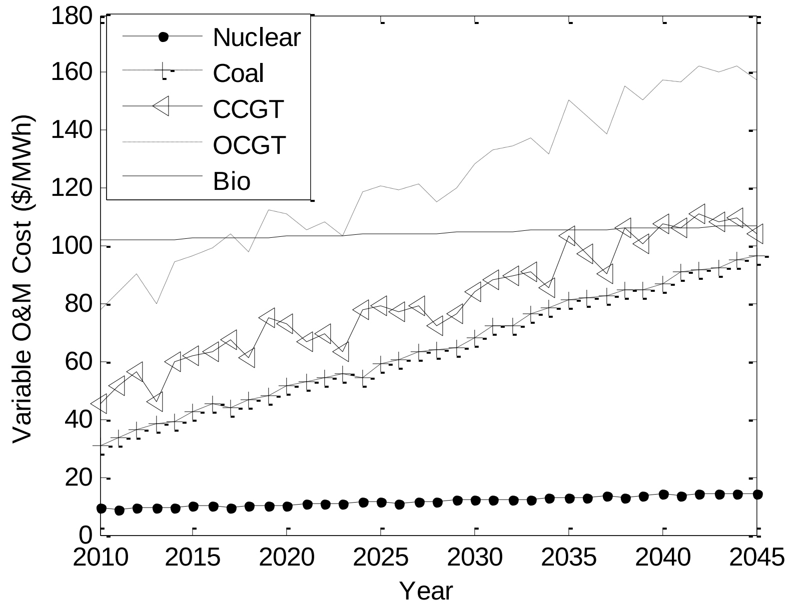


Figure 4-3 – One realization of mid-load variable O&M cost projections with a simple carbon tax that increases linearly by \$2/tCO2 per year, starting in 2010.

Figures 4-2 and 4-3 show one realization of the mid-load variable O&M projections, including fuel costs, for all of the dispatchable generators except hydro. Figure 4-3 highlights the impact of a carbon tax on the cost of running a coal plant relative to natural gas. The effect of a carbon tax on nuclear power and biomass is many times smaller than on fossil fuel generators, as expected. The economics of biomass improve greatly with higher carbon taxes.

4.1.3 Forecasting Load Profiles

As seen in Chapter 2, the shape of the load-duration curve influences the energy allocation and the optimal generation expansion. In any power system, the shape of the LDC can change significantly from year-to-year, but the average energy consumption growth rate for Ontario is estimated to be increase by 3% per year [29].

To generate the forecast LDCs, the hourly internal Ontario load data from 2010 is used as the base, with a normally distributed random variable added to each hour.

$$\mathrm{LF_t} = \mathrm{Load2010} + \mathrm{YI_t} + \mathrm{R_{LF}} \qquad [4.4]$$

Where, LF_t is the load forecast for year t

Load2010 is the observed load data in Ontario for 2010

YI_t is the average yearly energy consumption increase

R_{LF} is the stochastic component of the load forecast

YI_t is simply a 3% increase to the average energy demand of the previous year. R_{LF} has a mean of zero, but has a standard deviation that is proportional to the average yearly power demand; as this increases each year, so does the standard deviation. This trend was determined by analyzing several years of load-data and results in a 0.125 increase in the standard deviation for every 1MW increase in the average power demand. This analysis can be found in Appendix B.

The following plot shows one realization of LDC projections for 2015 and 2025, with the LDC for 2010 included for reference. These curves are made using the model defined in equation 4.4.

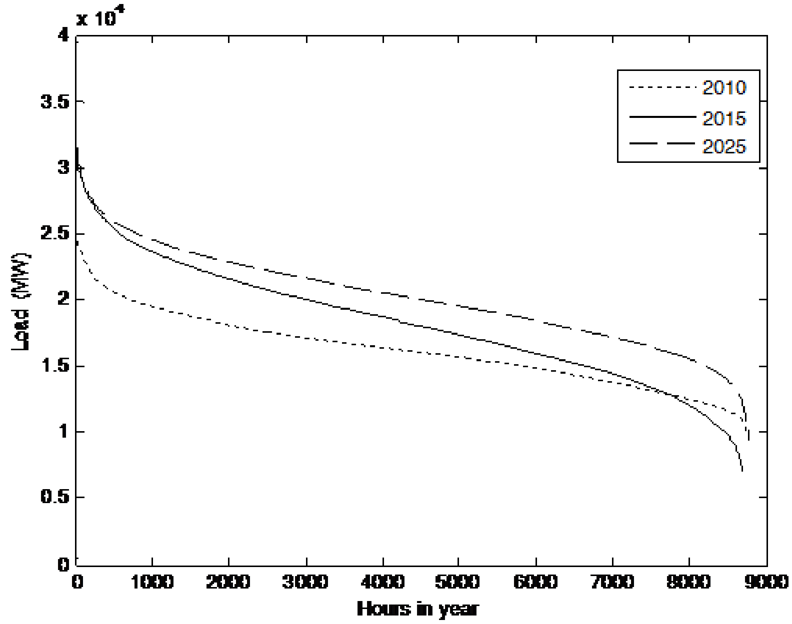


Figure 4-4 – Forecast Ontario LDC curves for 2015 and 2025, with 2010 for reference.

Some years in this simulation have load-duration curves with a steep slope, which results in a greater peak and mid-load requirement, while others have a flatter slope, indicating a base-load dominated curve. To gain more insight into the validity of these simulated LDCs, the annual energy consumption and peak power demand is compared with forecasts found in the literature.

The yearly energy demand increase was compared with forecasts done by the Government of Ontario in [29], and appears to be in agreement.

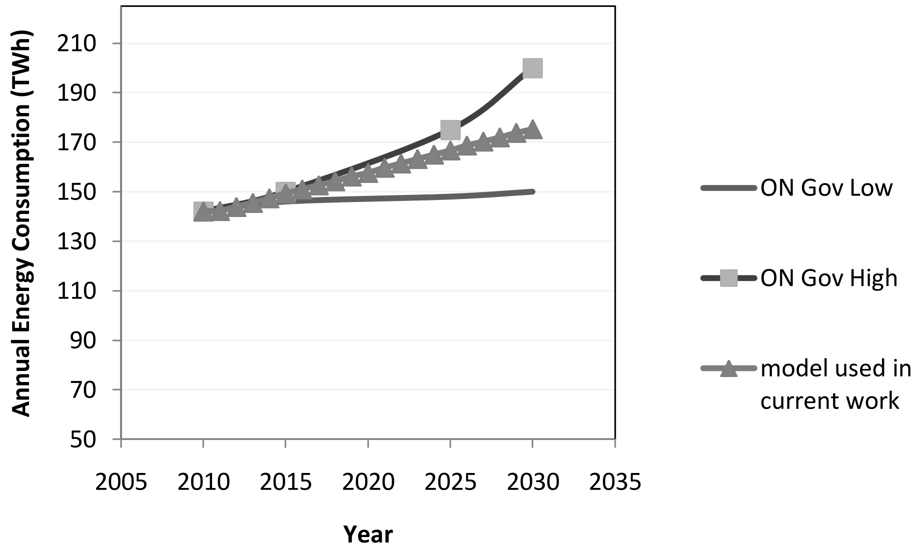


Figure 4-5 – Annual energy consumption forecasts; high and low estimates from the government of Ontario are compared with a typical profile of the simulation method being used in this work.

The simulated data shown in Figure 4-5 are the yearly total energy consumed for one realization of the load forecast algorithm (curve labelled ‘model used in current work’). This curve sits within the high and low estimates proposed by the Government of Ontario in [29], suggesting an acceptable prediction.

The next plot shows the comparison between the forecasted peak power demand from this work with that of two sources found in the literature. The two sources are from a paper presented to Ontario Power Authority by Navigant Consulting [30], and another by Chui et al. [31] from the University of Waterloo.

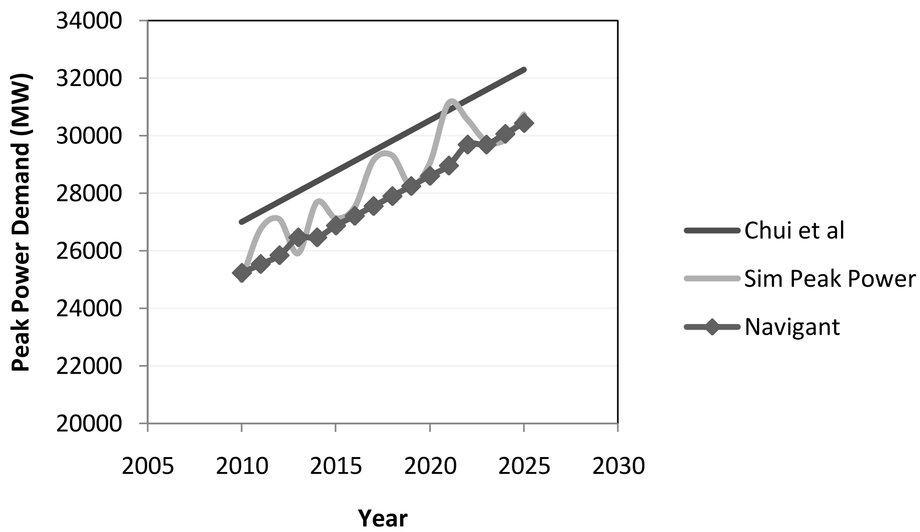


Figure 4-6 – Peak power demand forecasts; Chui et al, Navigant Consulting compared with typical peak power curve from simulation method being used in this work.

The peak power projections from this simulation fluctuate within the bounds set by the forecasts found in the literature and suggest that this model has validity. When considering the number of forecasts required for this simulation (which is the number of iterations of the Monte Carlo simulation times the number of years in the time horizon) speed is a significant factor. This close agreement with literature forecasts, and the speed at which the forecasting method runs make it an appropriate choice for this simulation.

4.1.4 Forecasting Wind Power Profiles

There are currently over 15 wind farm sites in Ontario, each with site specific power output profiles. These wind farms also range in size from less than 1 MW to over 200MW. To include investment in wind power capacity in the decision making process, information about the wind sites is needed. Hourly wind power output data were gathered for eight wind farms in Ontario, from the IESO (independent Electricity System Operator of Ontario). To simplify the model, these eight wind farms were put into four ‘wind zones,’ regions that the model sees as a single resource site. It is assumed that the power output characteristics of each wind zone apply to all wind capacity in that zone. More simply, every MW of installed wind capacity in its specific wind zone will provide the same amount of annual energy. This is done so that the optimizer can calculate each wind zone's output characteristics and then decide in which zone to invest.

Figure 4-7 presents the location of the four wind zones being studied in this work.

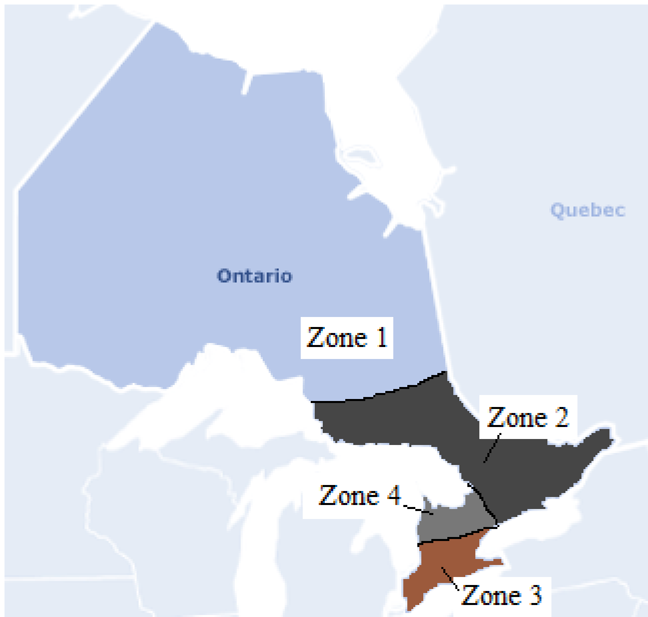


Figure 4-7 – Location of the four wind zones in Ontario.

Table 4-2 – Summary of wind farms currently in each wind zone.

Wind Farm Name	Location	Wind Zone
Prince Farm	Sault Ste. Marie	1
Wolfe Island EcoPower Centre	Wolfe Island	2
Port Alma Wind Farm	Port Alma	3
Erie Shores Wind	Port Burwell	3
Kingsbridge Wind	Kincardine	4
Ontario Wind Power	Kincardine	4
Amaranth/Melancthon	Shelburne	4
Ripley Wind Power	Ripley	4

Currently, zones 1 and 2 host single wind farms of about 200MW of installed capacity, while zones 3 and 4 are comprised of several wind farms. If we used the aggregate output from the farms in zones 3 and 4, the wind power fluctuations would be somewhat smoothed since the output would be from farms over a larger area than the single farms in zones 1 and 2. Therefore, the largest farm in each of zones 3 and 4 was chosen as the representative wind power profile for that region.

There are many methods available in the literature for simulating wind resources and wind farm power output data. Some employ auto-regressive moving-average (ARMA) models, as presented in [32], while others employ somewhat simpler methods which involve removing all periodic shape data from the time series and approximating the stochastic component with a probability distribution function, as presented in [33]. The method in MacCormack [33] starts by subtracting the yearly mean from the wind output time series to produce a first set of residuals. The next step is to remove the seasonal mean, then monthly and daily to produce a final set of residuals that represents the stochastic component. A probability distribution function is approximated and then used to reproduce this stochastic component using a random number generator, and then the daily, monthly and yearly mean is added back to produce a simulated yearly wind farm output. This method is employed in the current work and is described in detail in [33]. The following plot shows a typical simulation for 100 hours.

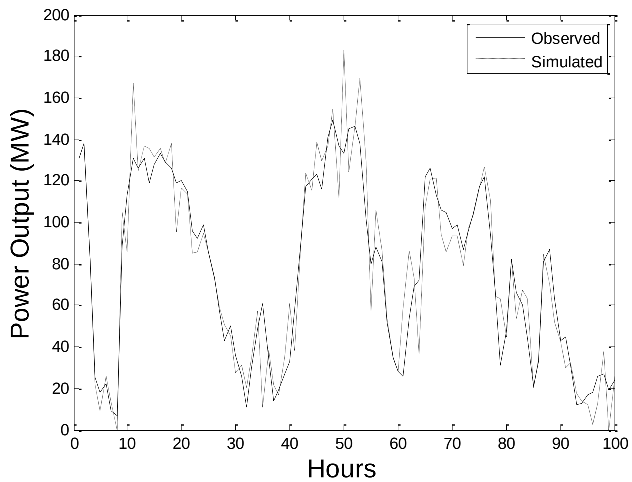
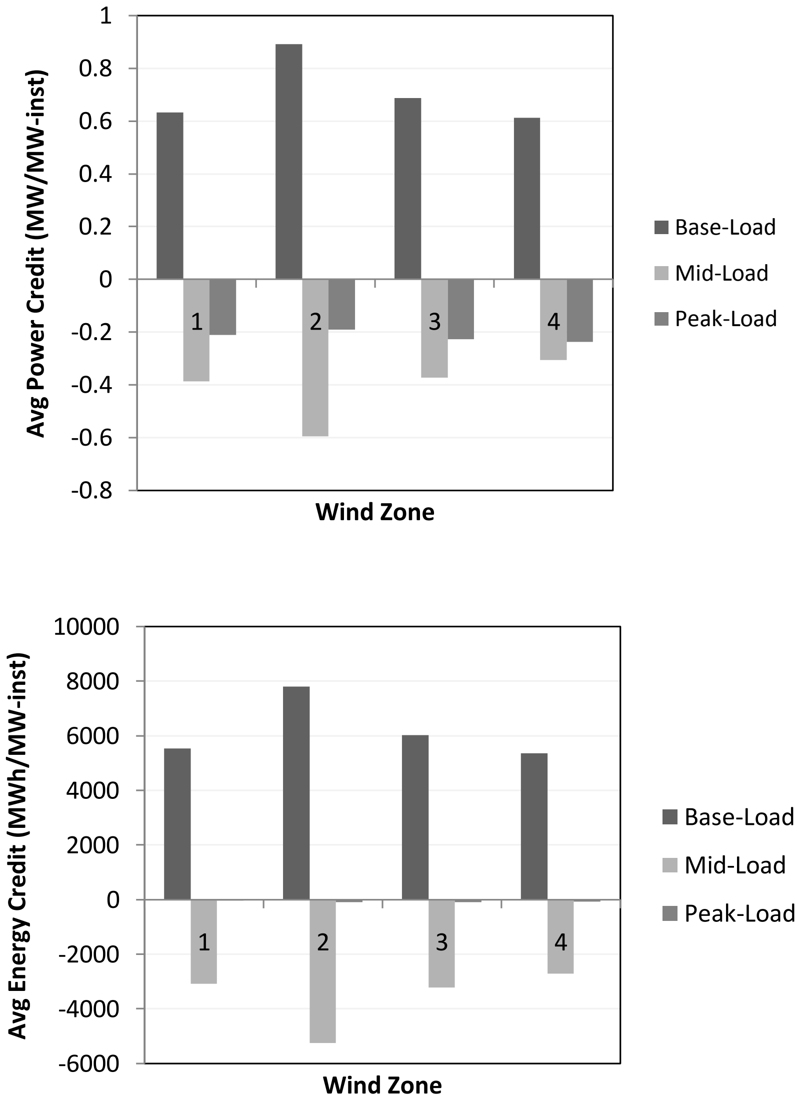


Figure 4-8 – Observed and simulated hourly wind power output data from zone 1 for 100 hours.

The final goal of our wind resource simulation is to define its ‘power credit’ and ‘energy credit;’ the amount of power and energy each MW of installed wind capacity will provide the grid in a given year. As outlined in Chapter 3, the hourly wind power output is subtracted from the hourly load data; therefore, the hour in which the wind blows is important in the decision making process. In Figure 4-8, the general shape of the wind output is maintained, but the peaks and valleys can shift; changing the resources’ effect on the load-duration curve each year, and thus its effect on power and energy credits.

In each year the wind zones will have a different power and energy credit since both the load and wind power output profile for each of those years is changing. To estimate the expected performance of each wind zone, the following plots present the power and energy credits for each zone averaged from 1000 simulations. This average is an estimate of the expected long-term performance of each wind zone.



a)

b)

Figure 4-9 - Expected long-term performance of each wind zone in terms of a) power credit and b) energy credit.

From Figure 4-9 a) and b) we can see that wind zone 2 supplies the most base-load power capacity and energy to our system than any other wind zone. However, it also demands the most mid-load power and energy from other generators to compensate. Conversely, wind zone 4 produces the least amount of base-load relative to the other wind zones, but also demands the least amount of mid-load compensation. It will be interesting to see which wind zones are most often selected by the optimizer, and thus have the most favourable mixture of power/energy credits.

4.2 Defining Generators: Investment, Decommission and Performance

There are many financial and performance based factors to take into consideration when planning new generation capacity for a power system. When estimating the investment cost of a new power plant, the construction cost, maintenance and fuel costs must all be included but can vary from site to site because of issues such as access to transmission and ease of transporting materials/fuel. Moreover, the performance of each power plant of a given technology may also vary. Much like the variable O&M costs and emissions intensity values presented earlier in Chapter 4, investment costs and performance metrics used in this work are averages taken from power plants currently operating in Ontario, as well as estimates from the EIA. The following tables summarize the investment costs and performance metrics for the power plants considered in this work.

Table 4-3 – Generator investment cost.

References: **1** = [18] **2** = [34] **3** = [25] **4** = [27] **5** = [29]

Technology	Availability (AV)	Construction Time (years)	Overnight Capital Cost (CAD2010/kW)
Nuclear	0.90[1]	7.00[1]	3037.23[1]
Nuclear Refurb	0.90[1]	2.00[2]	1400.00[2]
Coal	0.75[1]	4.00[3]	1777.00[1]
CCGT	0.85[1]	3.00[1]	965.40[3]
OCGT	0.30[3]	2.00[3]	694.79[3]
Hydro	0.60[1]	4.00[3]	2076.00[3]
Biomass (converted coal)	0.75[1]	2.00[4]	640.00[4]
Wind	(determined by LDC method)	3.00[3]	2438.00[3]

Table 4-4 – Generator fixed O&M, decommission costs and build limits.
References: **1** = [18] **2** = [34] **3** = [25] **4** = [27] **5** = [29]

Technology	Fixed O&M (CAD2010/kW)	Decommission Cost (CAD2010/kW)	Maximum New Build Capacity (MW)
Nuclear	112.84[1]	1299.73[1]	inf
Nuclear Refurb	112.84[1]	1299.73[1]	limited to nuclear decommission
Coal	29.67[3]	426.60[3]	inf
CCGT	17.76[3]	96.54[3]	inf
OCGT	16.72[3]	69.48[3]	inf
Hydro	40.83[1]	307.00[3]	1000.00[5]
Biomass (converted coal)	29.67[3]	426.60[3]	limited to coal decommission
Wind	28.07[3]	243.80[3]	12000 (3000 per wind zone)

Table 4-3 and Table 4-4 summarize the input data used to make investment/decommission decisions in this model. Since little information about the performance of biomass converted coal plants exists, the biomass converted coal is assumed to have the same fixed O&M and decommission cost of existing coal plants. For the base case, the maximum new build capacity for new nuclear, coal, CCGT or OCGT is unconstrained, hence the 'inf' in Table 4-3. Nuclear refurbishment is constrained to only the nuclear capacity that is scheduled to be decommissioned. Similarly, biomass converted coal is constrained to coal capacity that is decommissioned. The maximum hydro capacity available is limited to 1000MW as this is the amount of future hydro capacity that is conceivably developable in Ontario, as presented in [29]. Each wind zone is limited to 3000MW of total capacity. Each wind zone covers a large area, which could conceivably host 3000MW of wind capacity. This allows the model to develop up to 12 000MW of wind power, distributed evenly among the four wind zones. Although it is unlikely that 3000MW of wind capacity distributed within a single region would retain the same output characteristics, this can act as a proxy for the development of wind sites not considered in this work. The total potential wind capacity in Ontario far exceeds 12000MW. This assumption implies that the first 12000MW developed should have a large enough regional diversity that the aggregate would have similar output characteristics as the 4 wind zones being considered.

The generator capacity allocation coefficients quantify the amount of capacity each generator provides to each load-segment (base, mid and peak). For example, Ontario runs its nuclear reactors so that 70% of their power services base-load requirements, and 30% for mid-load [35]. This results in a 'base-load capacity factor' of 0.7, 'mid-load capacity factor' of 0.3 and 'peak-load capacity factor' of zero. These coefficients tell the model that if 1 unit of nuclear power is built, it can provide up to 70% of its capacity for base-load and 30% for mid-load. These coefficients were found for all of the generators in this study, and are summarized below.

Table 4-5 – Summary of generator capacity allocation coefficients.
References: **1 =** [35] **2 =** [18] **3 =** [25]

Technology	Base-load Capacity Factor	Mid-load Capacity Factor	Peak-load Capacity Factor
Nuclear	0.7[1]	0.3[1]	0[1]
Nuclear Refurb	0.7[1]	0.3[1]	0[1]
Coal	0.5[2]	0.4[2]	0.1[2]
CCGT	0.1[1]	0.5[1]	0.4[1]
OCGT	0[3]	0[3]	1[3]
Hydro	0.4[2]	0.3[2]	0.3[2]
Biomass (converted coal)	0.5[2]	0.4[2]	0.1[2]

The OCGT capacity allocation coefficients were determined by the assumption presented in [25] that they are used exclusively as peaking plants.

4.3 Policy Constraints

In this section the method used to incorporate the proposed policies is outlined.

4.3.1 Carbon Tax

As presented in Section 4.1.1, the equation that defines variable O&M cost for each dispatchable generator already has a carbon tax component.

$$C_{vom,i}^{LC} = VMC_i^{LC} + FC_i + R_{VOM} + CO2_i^{LC} * CO2tax \qquad [4.1]$$

The carbon tax can change each year, so that an increasing (or decreasing) carbon tax can be imposed on the system. The carbon tax profiles will be discussed further in Chapter 5.

4.3.2 Carbon Cap

To impose a cap on the model we need to add another constraint to the optimization.

$$\sum_i^I CO2_i^{LC} \cdot (E_i^{base} + E_i^{mid} + E_i^{peak}) \leq CO2cap_t \qquad [4.5]$$

Where $CO2_i^{LC}$ is the carbon intensity of generator i, in load category LC
$CO2cap_t$ is the user defined emissions cap for year t

This constraint allows the user to specify the carbon cap for each year. The carbon cap profile can be varied (e.g. from a modest cap to very aggressive) over time. The carbon cap profile and its effect on the power system evolution will be analysed in detail in Chapter 6.

4.3.3 Discount Rate

In a cost-benefit analysis that uses the net-present value as a metric for comparison, the discount rate is an important factor. The discount rate is a measure of the time preference of consumption; the higher the discount rate the more current consumption is weighted. In [36], the social discount rate for climate change is discussed, and a range of 3-6% is proposed. For this work, a discount rate of 5% is chosen. This relatively high discount rate will weight current consumption higher than future consumption, and thus act to lessen the future costs of carbon dioxide emissions. This will produce conservative estimates of the cost of CO_2 abatement since it will appear expensive to make the necessary changes to the current power system to meet the political targets.

4.4 Planning Horizon

4.4.1 Planning horizon: short vs. long-term investment strategies

The planning horizon is an important parameter in this model since it influences the generation investment strategy and, consequently, the electricity supply mixture. To illustrate this point, consider how the model would weigh the costs and benefits of investing in nuclear or coal capacity to service base-load energy needs. The investment costs associated with nuclear capacity are high, but the variable operating costs are low and projected to be relatively stable (as seen in Figure 4-2 and Figure 4-3). Consider a case in which all nuclear or coal capacity brought online will be used at maximum output capacity (thereby maximizing the return on both investments). The net present value of investments in coal and nuclear capacity are plotted in Figure 4-10 as a function of the planning time horizon

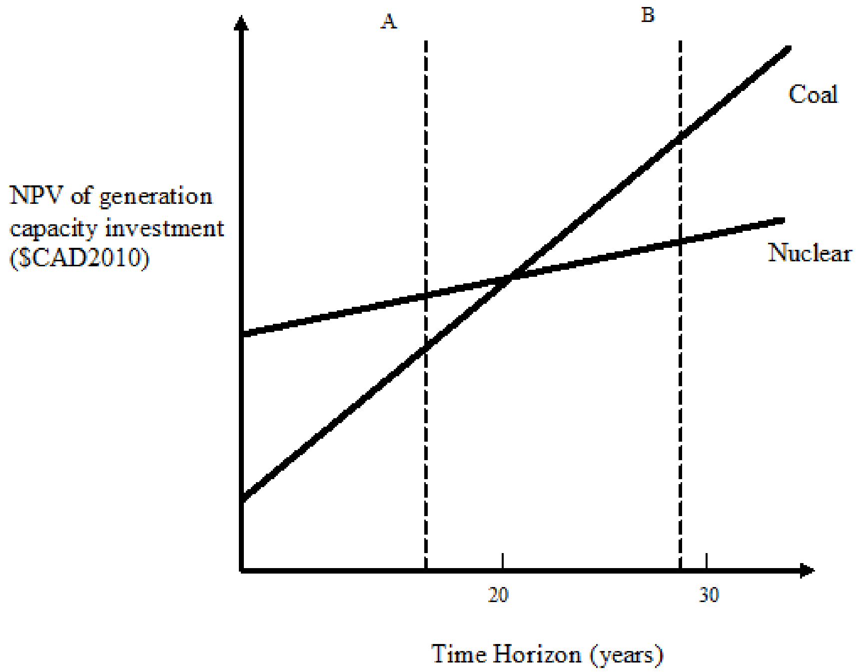


Figure 4-10 – Schematic of stylized example illustrating the effect of planning horizon length.

The y-intercept represents the investment cost (build cost) for these technologies; nuclear is more expensive to build relative to coal. The slope represents the yearly variable O&M costs (mostly fuel); the slope for coal is greater than nuclear in this example. If we used time horizon **A** then the model would invest in coal capacity to service the base-load, while if we chose time horizon **B**, the model would invest in nuclear. With time horizon **A,** the model does not have enough time to realize the operational benefits (cheaper long-term energy) of nuclear capacity relative to coal.

4.4.2 Time Horizon

The model interprets the end of the time horizon as the end of all time. This brings us back to the problem presented in the previous section, namely, generation capacity with high investment costs and low operating costs will be unattractive near the end of the time horizon. This is because an investment in a nuclear plant to come online four years before the end point has only four years in which its relative utility (as a provider of cheap energy) can be realized, which will not be enough time to rationalize the investment cost.

To address this problem, the simulation is carried out over a longer time horizon than will be analysed and the unwanted years of data are discarded. In this case study, the expansion of the Ontario power system is analysed starting in 2010 and ending in 2030. To avoid the previously mentioned complications, each simulation will optimize from 2010 to 2050, and the data after 2030 will be discarded. This should provide insight into the long-term optimum generation mixture and how it changes under the influence of different policies without being affected by the previously mentioned problems arising from sub-optimal time horizon selection.

In this Chapter, the Ontario power system is presented along with the stochastic models for forecasting input parameters. Each policy is discussed and their respective constraints on the model are presented. This Chapter also provides a rationale for the selection of discount rate and the planning time horizon. The next chapter defines the 'business-as-usual' base case which will be used to compare each policy in Chapters 7 and 8.

5. Calibration and Base Case

5.1 Defining the base case: Ontario's power system

To assess the impacts of a given policy on the power system expansion, we first need a base case. This base case, as with every scenario in this study, starts in 2010; defining the starting point as the generation mixture in Ontario at the end of that year. Table 5-1 summarizes the Ontario generation fleet as of December 2010.

Table 5-1 – Summary of installed capacity in Ontario at the end of 2010
Reference: all table data was found in [37].

Technology	Installed capacity in 2010 (MW)
Nuclear	11446
Coal	4484
CCGT	8997
OCGT	500
Hydro	7924
Wind Zone 1	187
Wind Zone 2	191
Wind Zone 3	196
Wind Zone 4	472

In Chapter 3, the concept of a time-delay, with respect to when the investment in new capacity occurs and when the capacity comes online, was introduced. Each generation technology has an associated build-time and cannot come online immediately. This prevents the model from adding capacity for the first few years of the simulation since any investments made in year 1 (2011) will not be able to come online for a few years (refer to the Chapter 4 for generator build-times). Of course the Ontario Power Authority (the governing body that oversees the reliability of the Ontario power system) performs ongoing planning exercises and has several projects in various stages of development. These projects will be added exogenously into the model based on their expected start dates and are summarized in Table 5-2.

Table 5-2 – Summary of large-scale capacity coming online in Ontario
Reference: all table data was found in [38].

Technology	Capacity to be installed (MW)	Expected date in service
Nuclear	1500	2012
Wind	620	2012
CCGT	700	2013
Wind	145	2013

Some of this new capacity, especially wind power, will be available part-way through 2011 and 2012 but this model can only integrate new capacity at the beginning of each year. Therefore, this capacity is assumed to all come online at the start of 2012 and 2013 respectively. As well as this scheduled capacity increase, the aging fleet of Ontario nuclear reactors are scheduled to be decommissioned/refurbished between 2011-2018. To account for this, mandatory decommissioning of capacity will be imposed on the system by manipulating the lower bounds of the nuclear decommission variable in the model, and the decision whether to refurbish or leave the capacity decommissioned will be made by the optimizer.

Table 5-3 – Scheduled nuclear capacity decommissioning
Reference: all table data was found in [29].

Nuclear capacity being decommissioned (MW)	Year
1000	2011
1500	2012
1000	2015
1000	2016
1500	2018

It should be noted that these capacity values are approximate so that they can fit with our integer capacity constraints in the model; namely that nuclear can only be decommissioned/built in blocks of 500MW.

5.2 Case Study 1: Calibration and validation of the model

5.2.1 Energy Output by Generator Type

The only information that we can use to calibrate this model pertains to the base year of 2010. The installed capacity published by the IESO has already been enforced on the model, but how does the model allocate the energy output by generator type?

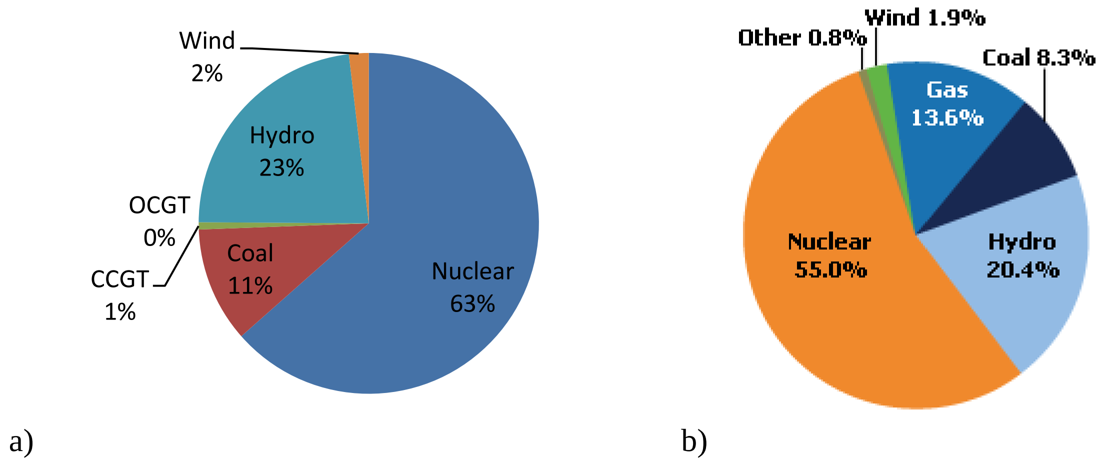
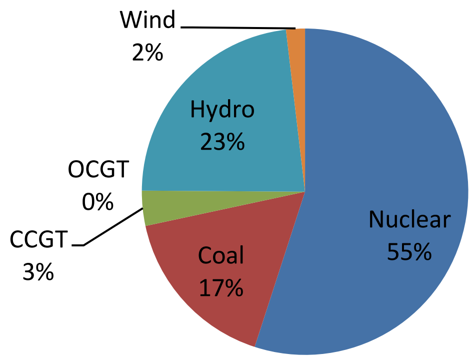


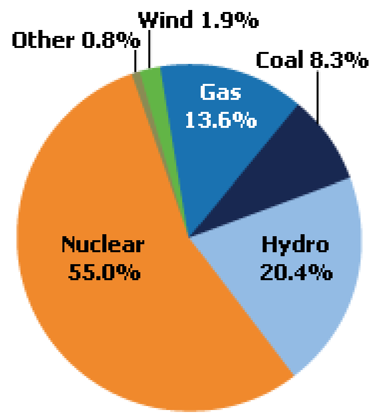
Figure 5-1 – a) Energy output by generator type from model for the base year, 2010 b) energy output by generator type for 2010, from IESO [37].

There is a discrepancy between the optimal generation allocation decided by the model, shown in Figure 5-1 a) and the actual observed energy output in 2010 shown in Figure 5-1 b). Energy produced by wind generation differs by 0.1% and hydro by about 2.6%. The energy provided by wind is in close agreement. The difference in the hydro allocation can be attributed to the fact that the availability factor for hydro (presented in chapter 4) is an average number. The amount of hydro available each year will differ based on climatic factors, such as spring freshet and precipitation. Therefore, hydro's availability factor will also differ each year. This relatively small discrepancy should average out since we are using an average availability factor. Some years actual hydro output will be larger than that predicted by this model, and some years it will be smaller. The discrepancy of 2.6% between simulated hydro output and actual hydro output is within the range proposed by EIA in [25] .

The most obvious problem with these figures is with the allocation of nuclear energy. As presented in the Chapter 4, nuclear generation has an availability of 0.9, meaning that it can output at 90% capacity for the entire year (or output at 100% for 90% of the year). Since nuclear power plants have low variable operating costs, the optimizer dispatches all available nuclear energy. The yearly energy allocation in this model is seen as a single value for each load-segment (each year has an amount of base, mid and peak energy that needs to be provided) so it cannot take into consideration operational constraints like ramp-rates or transmission congestion. In reality these operational constraints will limit the output of nuclear generators so that they cannot output at 90% capacity for the entire year, hence we get this discrepancy in supplied electricity from nuclear plants. To account for this a new value for availability factor can be used. This 'effective' availability factor internalizes the operational constraints such as ramp rates and transmission congestion. Through trial and error, an effective availability of 0.78 for nuclear power results in an energy allocation in close agreement with the real Ontario electric energy output for 2010. Note that the calibrated availability factor for nuclear power of 0.78 is used for the rest of the analysis presented in this work.



a)



b)

Figure 5-2 – a) Calibrated energy output by generator type from model for the base year, 2010 b) Energy output by generator type for 2010, from IESO [37].

The nuclear output is now in agreement, but an issue persists with the fossil-fuel energy allocation. The total amount of gas and coal generation presented in Figure 5-2 a) and Figure 5-2 b) differ by about 1.9%. The reason why the model is using more coal than gas is simply because coal is cheaper (for fuel price projections refer to Chapter 4). Since 2006, Ontario has mandated the phasing out of coal generation [29]. Given that CCGT and coal plants have similar operating parameters, the Ontario government has been dispatching gas preferentially to coal since 2006; this explains the discrepancy of coal output in the two figures.

5.2.2 Electricity Cost and Emissions

The annual CO_2 emissions, as determined by the model for 2010, are compared with the yearly emissions published by the Government of Ontario [37] in the following table.

Table 5-4 – Annual CO_2 emissions in 2010; data from [37].

Source	Annual power system CO_2 emissions (Mt CO_2)
Government of Ontario	21
Modelled	24.9

From Table 5-4, the model predicted higher CO_2 emissions from electricity production than published by the Government of Ontario. The actual power system operation in 2010 was subject to a mandated phase-out of coal power in the production of electricity in Ontario [39]. Since this constraint is not imposed on the model, a greater proportion of coal power is used and thus greater emissions are predicted.

5.3 Base Case Simulation

5.3.1 Power System Capacity, 2010-2030

With increasing peak-demand and yearly energy requirements, the power system will need to expand in terms of installed capacity and energy output. At the same time, the power system has to manage the decommissioning of aging nuclear capacity and the integration of new wind, gas and nuclear power. With no restrictions on the amount of coal, gas, wind and nuclear capacity that can be developed and a social discount rate of 5%, the model predicts the optimal power system expansion as follows:

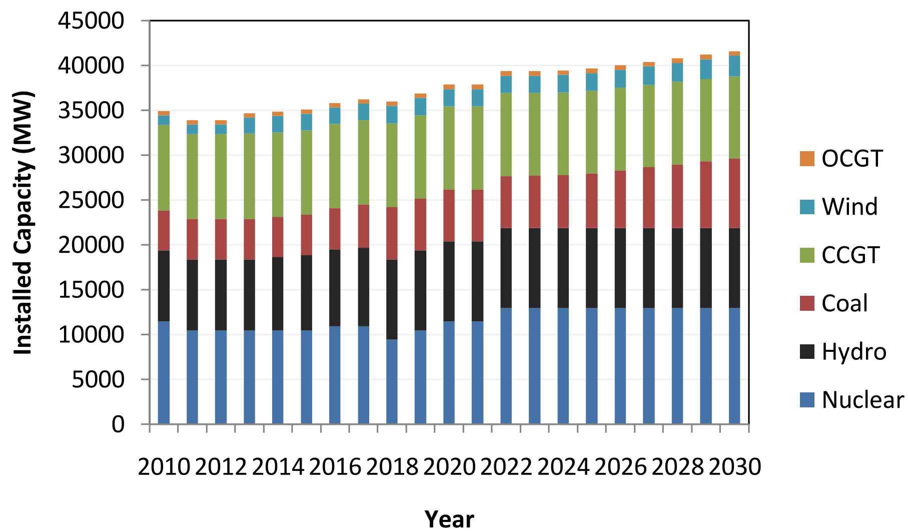
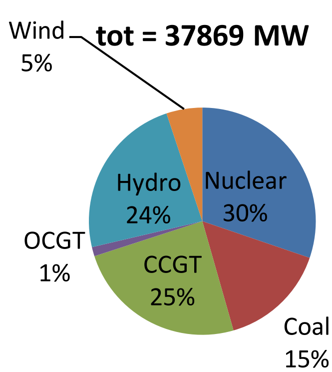
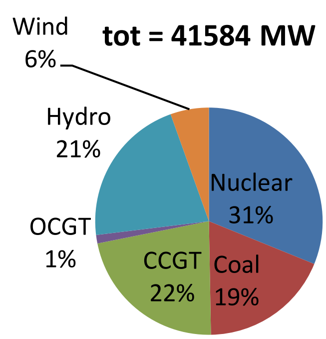


Figure 5-3 – Average installed generation capacity from 2010-2030 in base case scenario.

Figure 5-3 is a summary of the investments in generation capacity for the entire time horizon in the base case simulation. The data in Figure 5-3 are averages of the 1000 runs done in the Monte Carlo simulation. Note that in the years between 2010 and 2020 there are large blocks of nuclear capacity being decommissioned and refurbished. To gain insight into the generation mix, it makes more sense to zoom-in on specific years.



a)



b)

Figure 5-4 – Detailed view of installed generation capacity; a) installed capacity in 2020 and b) installed capacity in 2030.

From Figure 5-4 a) and b), the percentage of nuclear capacity maintains a 30% penetration level. The model decides to refurbish all nuclear capacity that is scheduled to be decommissioned, but does not invest in any new capacity (1500 MW of new nuclear capacity comes online in 2012, refer to Table 5-2). In 2013 700 MW of new CCGT capacity comes online as previously scheduled, but the model elects to decommission almost 1000 MW by the end of the planning horizon. This suggests that without any carbon policy it works out cheapest to substitute coal power for gas. The biggest investments are in coal, wind and hydro. The following table outlines the new investment/decommissioned capacity recommended by the model; this excludes the scheduled new capacity coming online from 2011 to 2013 as outlined in Table 5-2.

Table 5-5 - Summary of investment and decommissioning of capacity over time horizon.

New investment/decommission capacity (MW)	
Nuclear	0
Coal	3228
CCGT	-987
OCGT	-1.65
Hydro	997
Wind	484
Biomass	0

From Table 5-5, it is cheapest to decommission almost 1000 MW of CCGT, and replace it with hydro. The model also invests heavily in coal and wind power to help service the base-load requirements. It may appear as though the model is not satisfying the integer investment limits discussed in previous chapters, but since this is a Monte Carlo simulation these values have been averaged from 1000 data points. It is interesting to note that wind power is competitive, even in the base case without any emissions constraints.

5.3.2 Electricity Supply Mix, 2010-2030

The electricity supply mix will have the most direct correlation with overall power system emissions. The following plot summarizes the mixture of technologies used to satisfying the predicted energy needs.

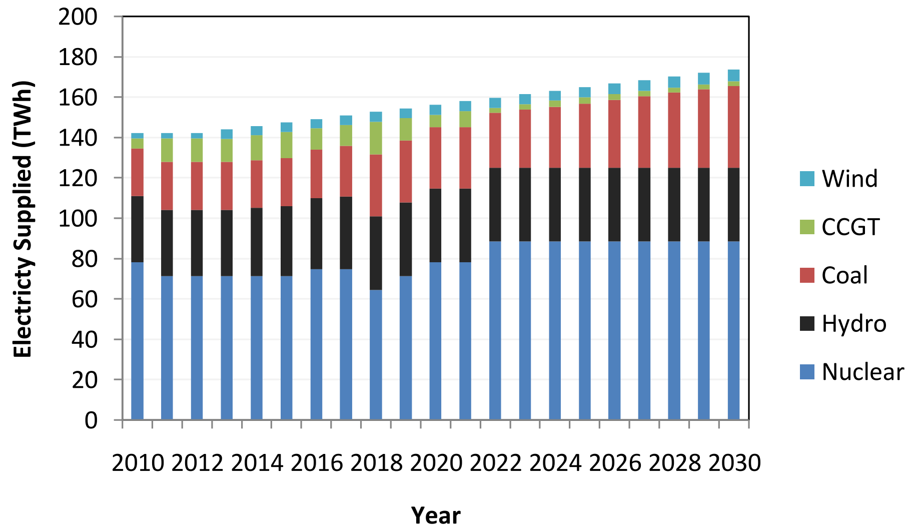


Figure 5-5 – Electricity supply mix by generator type over planning horizon.

The general dispatch strategy that can be gleaned from Figure 5-5 is that the system runs as much nuclear, hydro and coal as it possibly can. This is done because these technologies have the lowest variable operating costs (marginal cost). All available wind energy is dispatched (it is treated as a negative load, refer to Chapter 2) while CCGT capacity is used to service the rest of the energy needs. CCGT is the marginal generation technology. In years when there is a drop in base-load capacity (2018; because of nuclear decommissioning) the CCGT plays a larger role in the energy mix. To gain insight, the energy supply for specific years is presented below.

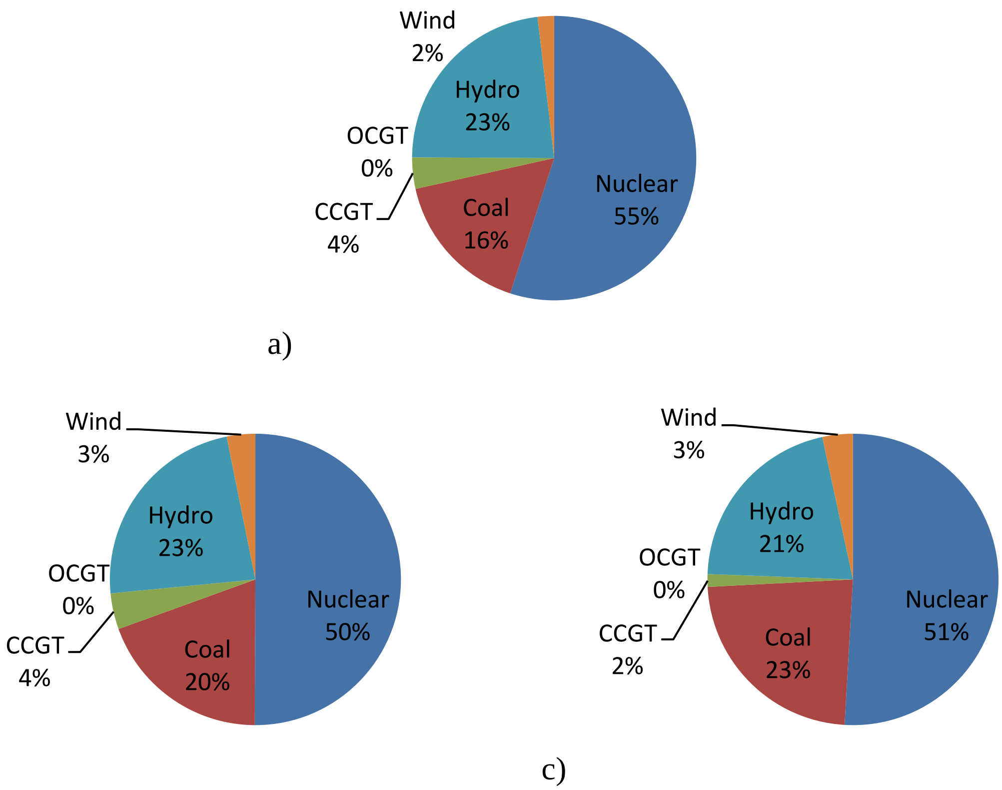


Figure 5-6 – Detailed view of electricity supply mix by generator type; a) energy supply in 2010, b) energy supply in 2020 and b) energy supply in 2030.

The general trend in Figure 5-6 a)-c) is that nuclear power is providing less electricity while the system shifts towards coal generation. There is a decrease in hydro on a percentage basis because of the physical limits in our model: there was only 1000MW of hydro capacity available to be developed. There is a small increase in wind which results in 3% of total energy in 2030. This suggests that wind power is economical in our base case at an energy penetration of 3%. With this shift towards coal power we would expect an increase in emissions.

5.3.3 Emissions Analysis

As observed in the previous section, without any policy constraint, the amount of coal derived electricity increases over the time horizon. It is expected, of course, that this will increase GHG emissions.

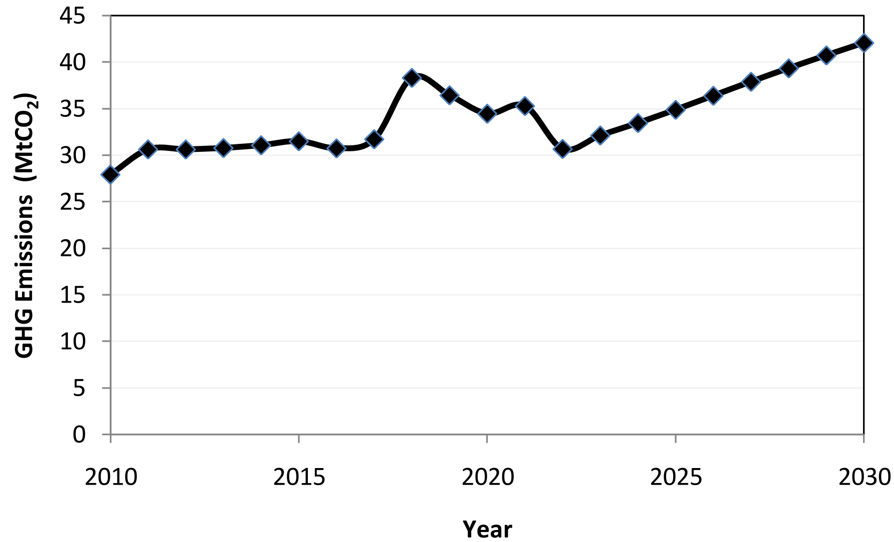


Figure 5-7 – Average GHG emissions profile for base case scenario.

The general trend in Figure 5-7 is that annual GHG emissions increase by almost 20Mt CO_2 by the year 2030. The roughness in the curve is due to the scheduled nuclear decommissioning and new nuclear coming online. It is interesting to note that the largest yearly fluctuations in GHG emissions are directly related to installed nuclear capacity. After 2023 the emissions increase steadily due to increased coal derived electricity being dispatched.

In Figure 5-7, each point on the curve represents the mean of a distribution of GHG emissions associated with the power system operation in that year. These distributions will be further analysed in Chapter 7. For now, it is important to note that there is an expected increasing trend of GHG emissions associated with our base case scenario that could result in 42Mt of CO_2 being released in 2030.

5.3.4 Cost

There are two categories of costs in this simulation: costs associated with infrastructure and costs associated with servicing load (producing electricity). As outlined in Chapters 3 and 4, the infrastructure costs are the sum of new-builds, decommissioned plants and yearly fixed O&M. The average cost of infrastructure over the time horizon for our base case is 41.497billion

($CAD2010). This is just the average, the underlying distribution of which is shown in the following figure.

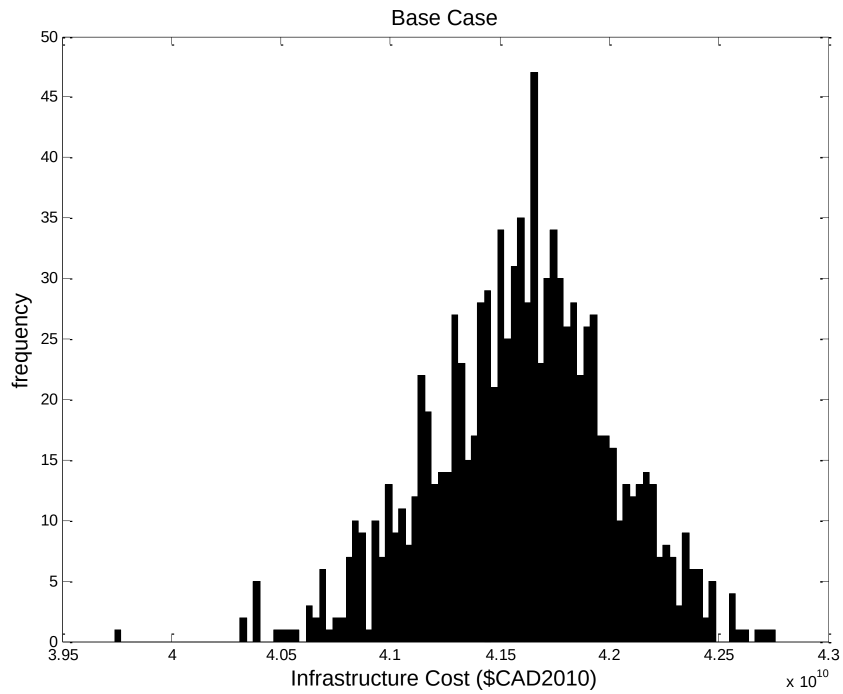


Figure 5-8 – Distribution of infrastructure costs for base case.

The overall infrastructure cost ranges between 39.74 – 42.7 billion $ ($CAD2010); this range will be an important parameter when comparing policies in upcoming chapters.

The cost of supplying electricity also changes yearly, based on the available generation capacity and the generation mixture used to service the load. An important metric that takes both infrastructure costs and cost of supplying electricity into account is the *levelized electricity cost*. The levelized electricity cost is the value of the objective function (or all of the costs) divided by all of the electricity produced over the time horizon. This metric will also be important when comparing policies in Chapter 7, and is presented below for the base case scenario.

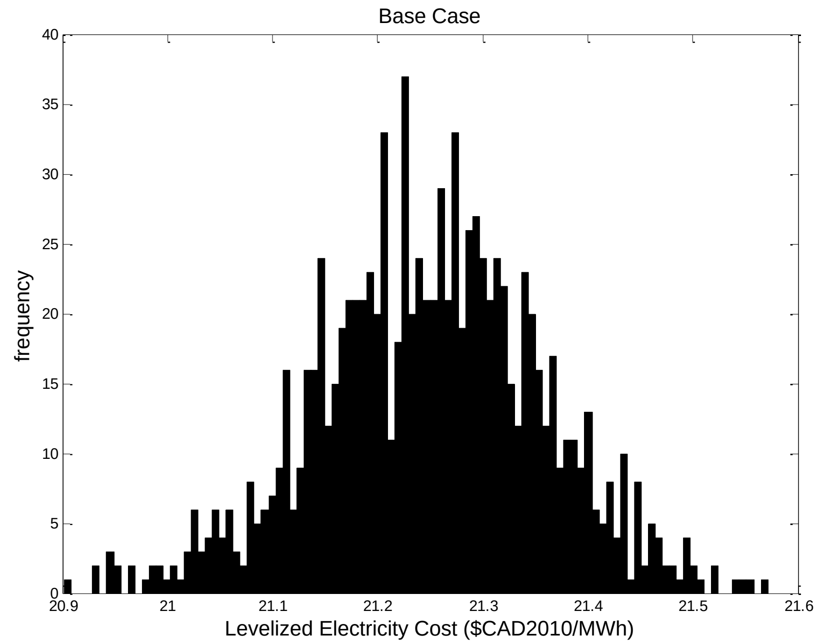


Figure 5-9 – Distribution of levelized electricity cost for the base case.

The levelized cost distribution in Figure 5-9 is balanced, with large chunks missing due to the large integer investment constraints. If the investments were continuous variables, this distribution would be much smoother. For the base case, the average levelized cost is 21.25 $CAD2010/MWh, and ranges from 20.9-21.57 $CAD2010/MWh.

With the base case power expansion established in this chapter, Chapter 6 will simulate and analyse the effects of the carbon abatement policies.

6. Simulating the Effects of Carbon Abatement Policies on Power System Expansion

6.1 Introduction to Carbon Policies being studied

There are three types of policy interventions analysed in this chapter. The first is a 'carbon cap,' where the aggregate yearly CO_2 emissions from all generation technologies conform to an imposed target. How such a policy could be implemented in practice is not obvious, but this policy can double as a measuring stick to assess how efficiently the other policies can reach these targets.

The second policy involves the mandatory decommissioning of coal fired generation by the end of 2014. This is a direct regulation policy. The third policy is a market instrument in the form of a carbon tax. This policy directly charges each technology a $/t$CO_2$ value for emissions associated with their electricity production.

6.2 Carbon Cap: Simulation and Analysis

As outlined in Chapter 4, the carbon cap is simply a constraint on the aggregate CO_2 emissions associated with electricity production. The cap that is imposed is a step function to represent Ontario's goal of achieving yearly power system emissions that are 6% below those of 1990, by the year 2014 and 15% below 1990 levels by 2020 [39]. In year 2014, the cap will be set to 25.38 MtCO_2/year (6% below the emissions in 1990) and to 22.95 MtCO_2/year by 2020. The cap of 22.95 MtCO_2/year cap will be imposed for the rest of the simulation (until 2030). As seen in Chapter 4, this cap will be an upper limit; the model can emit less than or equal to the imposed cap.

6.2.1 Power System Capacity, Carbon Cap Scenario

This scenario has the same increasing power/energy requirements of the base case, but now the model must satisfy the political emission targets.

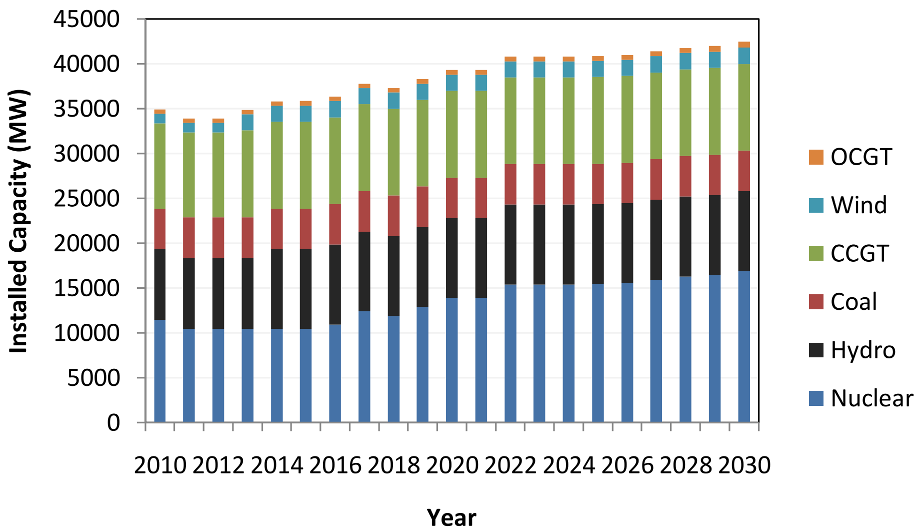


Figure 6-1 – Average installed capacity in the emissions capped scenario.

The power system expansion profile in Figure 6-1 represents the average installed capacity from the 1000 data points for each year. There is a noticeable increase in nuclear and wind power capacity with a slight decrease in CCGT.

Table 6-1 presents a summary the investment/decommission decisions made by the model over the entire planning horizon. All values exclude the previously scheduled capacity to come online in the years 2011 to 2013 (refer to Table 5-2).

Table 6-1 – Summary of capacity investment/decommission decisions for emissions cap scenario.

	New Investment/Decommission Capacity (MW)
Nuclear	3939
Coal	0
CCGT	-525
OCGT	163
Hydro	1000
Wind	24
Biomass	0

On average, all available hydro power is developed (1000MW) and almost 4000 MW of nuclear capacity is brought online. There is a small investment in wind power of 24 MW (on top of the 750 MW already scheduled to come online by 2013). Most interesting to note is that the optimal solution chooses to keep all coal power online and decommission about 500 MW of CCGT. It appears as though it is still more favourable to have coal generation instead of gas, but the effect of the emissions constraint is more noticeable in the electricity supply mixture presented below.

6.2.2 Electricity Supply Mix, Carbon Cap Scenario

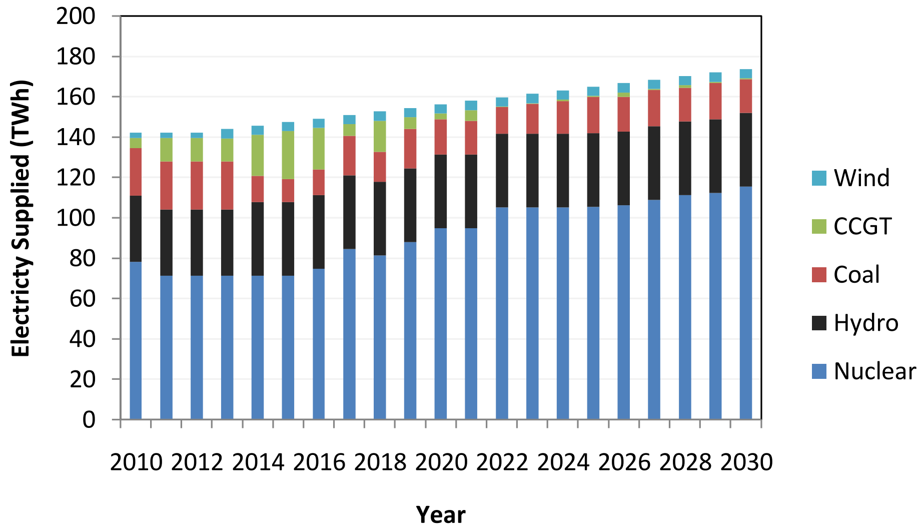


Figure 6-2 – Electricity supply mix by generator type over planning horizon for emissions cap scenario.

From Figure 6-2 the dispatch scheme is similar to the base case; all available nuclear, hydro and wind power is dispatched while the fossil-fuel generators are used to make up the difference. CCGT is still the marginal generator but plays a slightly larger role in the years with nuclear refurbishment to ensure that the emissions constraints are met. Once the refurbished and new nuclear capacity comes online, coal produces as much as it can under the emissions constraint with CCGT playing a very small role in the electricity supply of 2022-2030. Nuclear generation takes on a much larger role in the electricity supply and is used to meet most of the future energy needs. The currently installed coal capacity is used as much as it can within the emissions constraint and CCGT is on the margin. Just as in our base case, wind power is used to service about 3% of energy needs, again suggesting that perhaps this is the economic wind energy penetration level for this scenario.

6.2.3 Emissions Analysis, Carbon Cap Scenario

Since the CO_2 emissions in this simulation are directly constrained, they should predictably be as close to the political targets as possible.

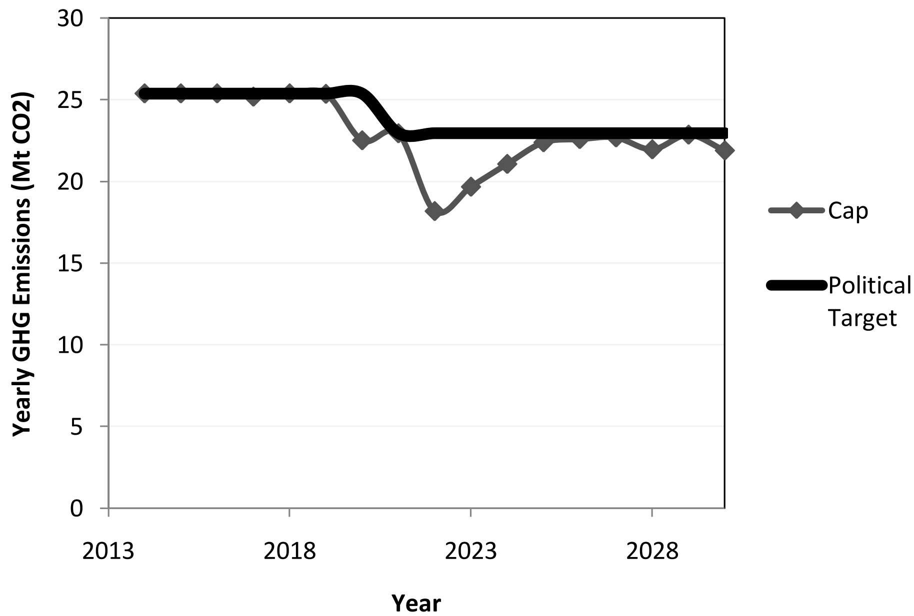


Figure 6-3 – Average GHG emissions profile for emissions capped scenario.

As expected, the emissions shown in Figure 6-3 stay as close to the political targets. The years in which the emissions are noticeably lower than the political emissions targets, such as in 2022, are due to a large amount of nuclear capacity coming online. Since it is most economic to dispatch as much nuclear energy as possible there is a dip in CO_2 emissions. The emissions level slowly rises as energy requirements increase, until the emissions constraint is hit once again (around 2025).

6.2.4 Cost, Carbon Cap Scenario

The average infrastructure costs are 50.2bil ($CAD2010), higher than the base case since there is a relatively large investment in nuclear capacity. The infrastructure costs range from 49.1 – 50.9bil ($CAD2010); as depicted by the following plot of the underlying distribution.

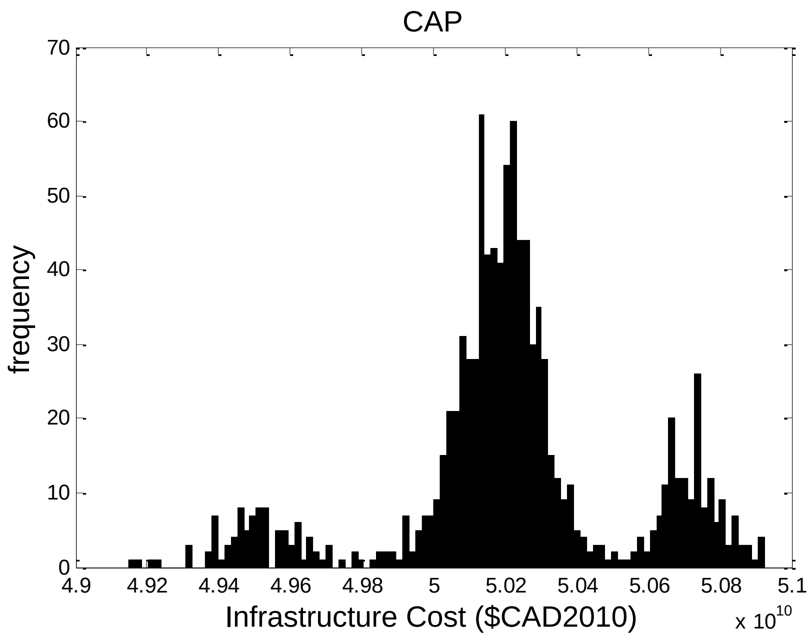


Figure 6-4 – Distribution of infrastructure costs for emissions capped scenario.

This distribution in Figure 6-4 has three distinct hills. These hills arise because of the large cost associated with investing in nuclear capacity and the fact that these investments are constrained to large integer blocks of capacity.

The levelized electricity cost incorporates both the infrastructure costs and cost of supplying electricity. A power system with a greater proportion of nuclear capacity will be able to dispatch more low-cost nuclear energy than one that invests in less nuclear capacity. The following plot captures the distribution of the levelized electricity cost.

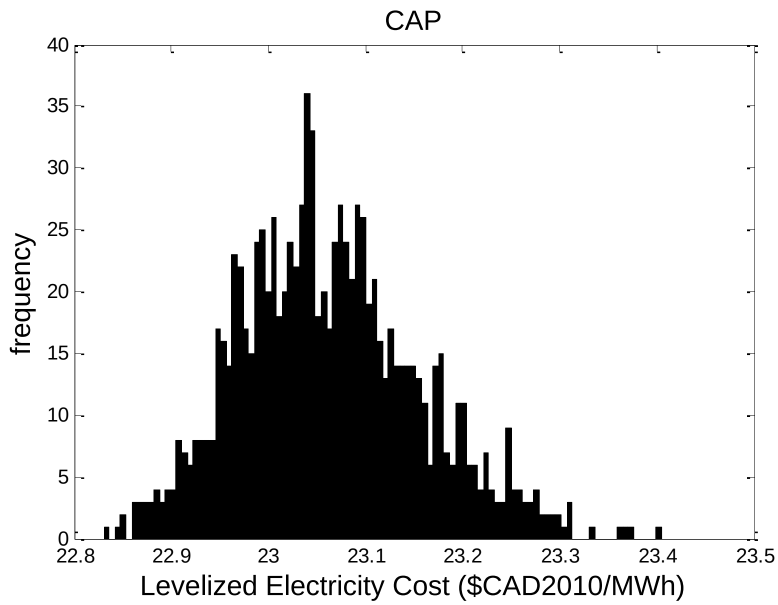


Figure 6-5 – Distribution of levelized electricity cost for the emissions capped scenario.

The distribution of levelized electricity cost in Figure 6-5 internalizes the cost of investing in nuclear capacity and the benefit of cheaper nuclear derived electricity to produce a much more even distribution. The average levelized electricity cost is 23.06 $CAD2010/MWh with a range of 22.83 – 23.40 $CAD2010/MWh. These emissions, costs and their associated distributions will be analysed in further detail in Chapter 7.

6.3 Regulation: Mandatory Coal Decommissioning by 2014

The mandatory coal decommissioning policy (CDCM) has already been written into Ontario law and appears in the Ontario Long-Term Energy Plan [29]. To incorporate this policy, we need to add a new constraint.

$$\sum_{t=1}^{t=5} P_{t,coal}^{dcm} = Initial\ Coal\ Capacity\ in\ 2010 \qquad [6.1]$$

This constraint ensures that the sum of coal's decommissioning variable, $P_{t,coal}^{dcm}$, from 2010-2014 is equal to the initial coal capacity; that is, all of the initial coal capacity must be decommissioned by the end of 2014.

6.3.1 Power System Capacity, Coal Decommissioning Scenario

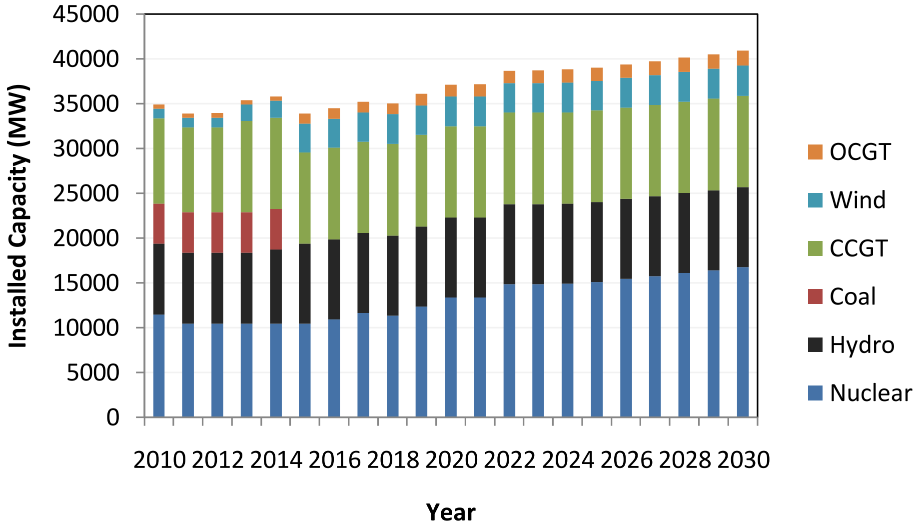


Figure 6-6 – Average installed capacity in the mandatory coal decommissioning scenario.

Despite being able to decommission the coal capacity in any year from 2011 to 2014, the least cost solution in Figure 6-6 keeps it all online until the end of 2014. The deficit is supplanted with nuclear, hydro, wind and the previously scheduled CCGT capacity, starting in 2015.

Table 6-2 – Summary of capacity investment/decommission decisions for the decommissioning coal scenario.

	New Investment/Decommission Capacity (MW)
Nuclear	3811
Coal	-4500
CCGT	0
OCGT	1171
Hydro	1000
Wind	1556
Biomass	3.3

All available hydro capacity is developed, along with about 3800MW of nuclear capacity. There is also a significant investment in wind power. The increase in wind power necessitates greater mid-load and peak-load capacity to compensate. The mid-load capacity is serviced by hydro and CCGT while investments of 1171 MW of OCGT are needed to ensure that peak-load power demand can be met.

6.3.2 Electricity Supply Mix, Coal Decommissioning Scenario

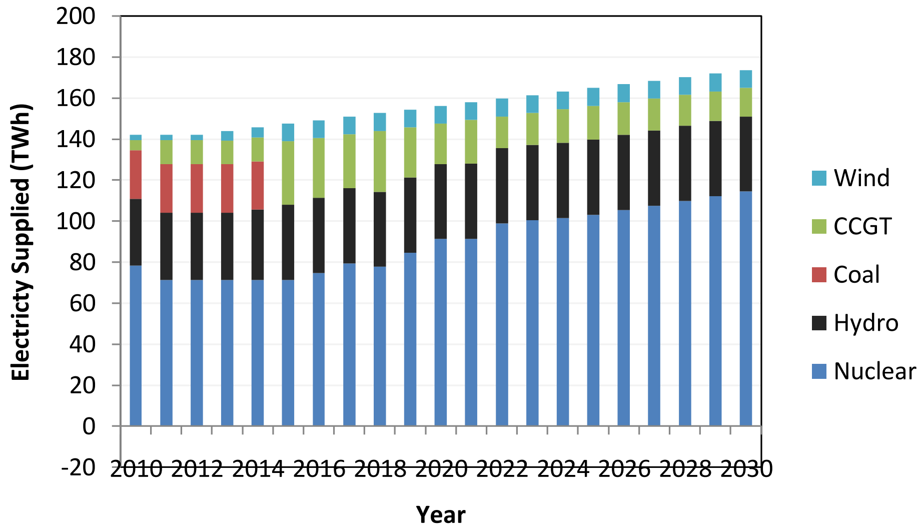


Figure 6-7 – Electricity supply mix by generator type over planning horizon for mandatory coal decommission scenario.

For the first five years in Figure 6-7 the model dispatches the generators in almost the same manner as in our base case. The immediate drop in coal capacity at the end of 2014 is compensated by gas derived electricity in the CCGTs, energy form the new hydro capacity and from new wind capacity. The expensive CCGT energy is slowly replaced by nuclear derived electricity as new capacity continues to come online throughout the simulation. The decrease in coal derived electricity will have obvious emissions implications.

6.3.3 Emissions Analysis, Coal Decommissioning Scenario

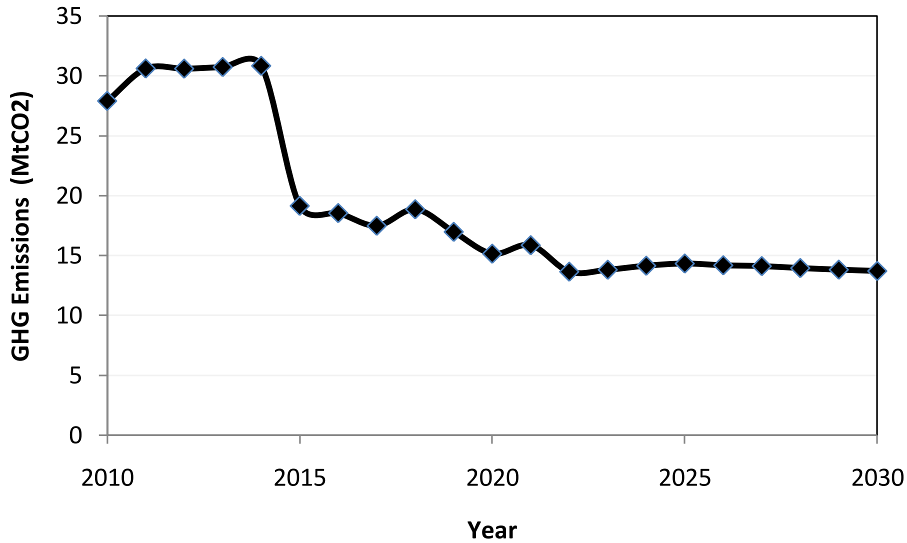


Figure 6-8 – Average GHG emissions profile for mandatory coal decommissioning scenario.

As expected there is a sharp decrease in GHG emissions once the coal capacity is decommissioned in Figure 6-8. There continues to be a more gradual decrease until about 2022, as the nuclear energy is replacing gas fired generation. This profile appears to follow the political targets of the emissions cap scenario quite closely; this will be investigated further in Chapter 7.

6.3.4 Cost, Coal Decommissioning Scenario

The infrastructure cost will absorb the mandatory coal decommissioning and then have to make-up for this deficit by purchasing new power capacity in other technologies; mostly nuclear. This makes the average infrastructure costs 51.8bil ($CAD2010). The distribution of these costs follows.

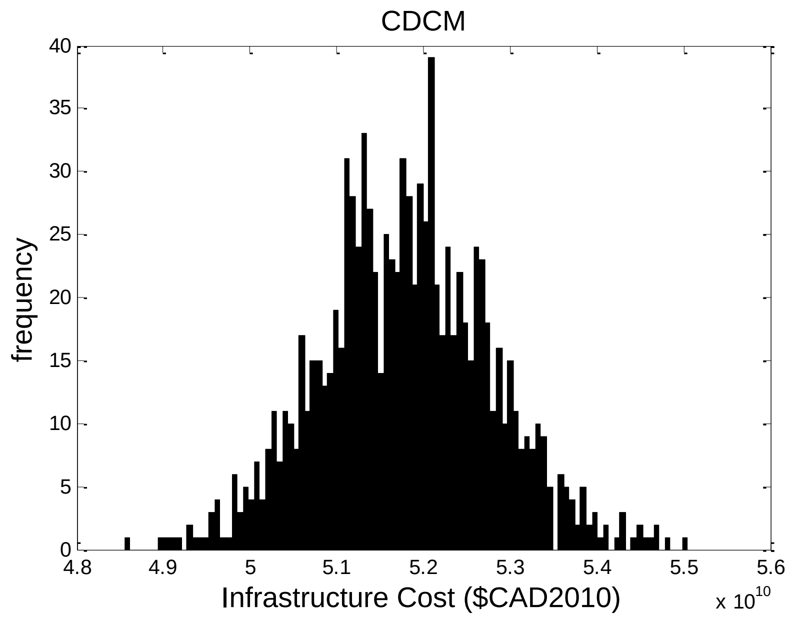


Figure 6-9 – Distribution of infrastructure costs for the mandatory coal decommission scenario.

The infrastructure costs in Figure 6-9 range from 48.5 – 55bil ($CAD2010), suggesting that the optimal path forward is very sensitive to the uncertainties in the future fuel prices and load growth scenarios. This uncertainty will affect the levelized electricity cost; as evidenced by the following plot.

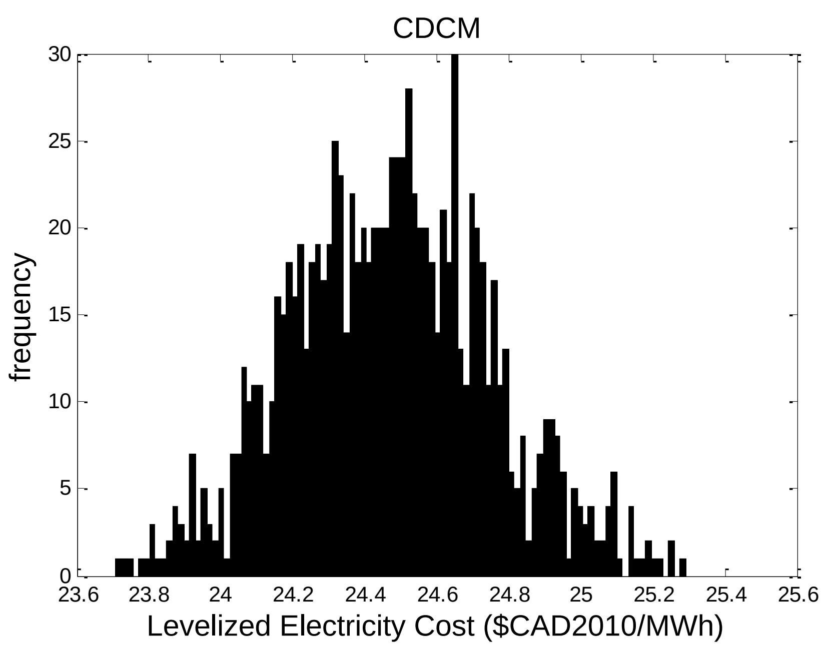


Figure 6-10 – Distribution of levelized electricity cost for the mandatory coal decommission scenario.

As expected, the range of the levelized electricity cost in Figure 6-10 is also wide, ranging from 23.7 – 25.3 $CAD2010/MWh, suggesting that this policy is very sensitive to future prices, load-growth and wind resource scenarios. However, the average levelized electricity cost is comparable to the emissions capped scenario at 24.47 $CAD2010/MWh.

6.4 Market Instrument: Carbon Tax

As outlined in Chapter 4, the carbon tax is a cost applied to the variable O&M of each generation technology based on their respective carbon intensities. Hydro and wind are assumed to have a carbon intensity of zero, and therefore their operating costs are not affected by a carbon tax. The notion of optimal timing and aggressiveness of a carbon tax was most notably proposed and analysed by Nordhaus et al. in [40]. Many of these tax profiles were generated by an integrated assessment model (IAM) that seeks to balance costs and benefits of taking action on climate change. The carbon tax is directly related to the assumed damage function associated with increased greenhouse gas levels in these models. In [4], several damage functions are analysed and optimal carbon tax profiles are generated from an IAM model called DICE (Dynamic Integrated model of Climate and the Economy). Monte Carlo simulations are performed varying key parameters in the damage functions to produce a distribution of the optimal carbon tax profile. The carbon tax profile suggested by Nordhaus [40] and two profiles suggested by Roughgarden [4] will be analysed in this work and are summarized in the following table.

Table 6-3 – Summary of Carbon Taxes from Roughgarden et al, direct excerpt from [4] **.**

Source of data	Optimal Carbon Tax ($/ton C)		
	1995	2055	2105
DICE	5.24	15.04	21.73
Median	22.85	51.72	66.98
Mean	40.42	84.10	109.73
"Surprise"	193.29	383.39	517.09

Note: "Surprise" values are 95th percentile results. Explicitly including low probability, high consequence outcomes alerts policy makers to consider strategic hedging options to reduce the risk of experiencing catastrophic outlier events.

The source data labelled 'DICE' is from the Nordhaus study in [40] while the median, mean and "surprise" data are results from the Monte Carlo simulation performed by Roughgarden et al. in [4]. For this thesis, the DICE, Mean and "Surprise" data in Table 6-3 will be used as the investigated carbon tax profiles. The DICE data will be referred to as "NH" (Nordhaus), the "Mean" data will be "RGM" (Roughgarden – Mean) and the "Surprise" data will be "RGE" (Roughgarden – Extreme.) The data in the previous table was used to construct simple linear carbon tax profiles over the time horizon being investigated. The carbon tax starts in year 2011 (since there were no carbon taxes in 2010).

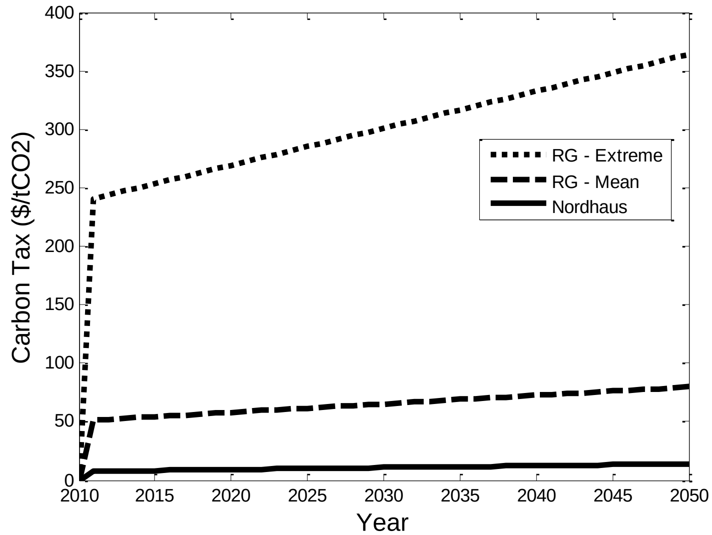
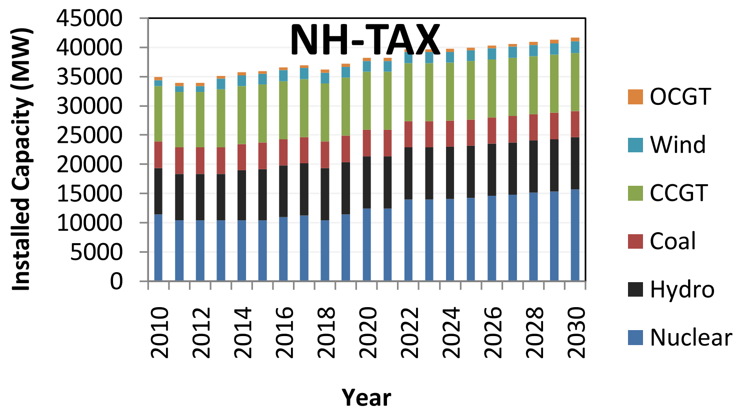


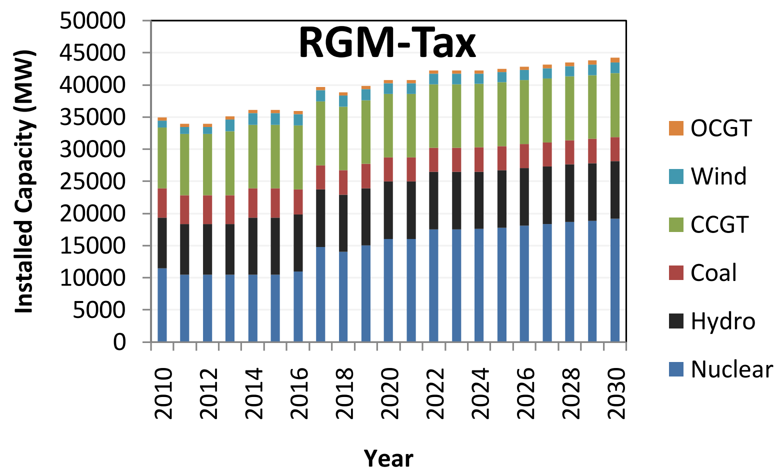
Figure 6-11 – Profiles of the carbon taxes being investigated in this work.

In Figure 6-11 the relative magnitudes of each carbon tax is apparent. The Nordhaus tax is far smaller in terms of both $/t$CO_2$ and yearly tax increase, than those proposed by Roughgarden. The aggressive taxes have the potential to provoke a feedback effect, wherein the greater cost for energy (resulting from the large tax) results in less demand. In this work there is the assumption that these effects are captured in the load growth models.

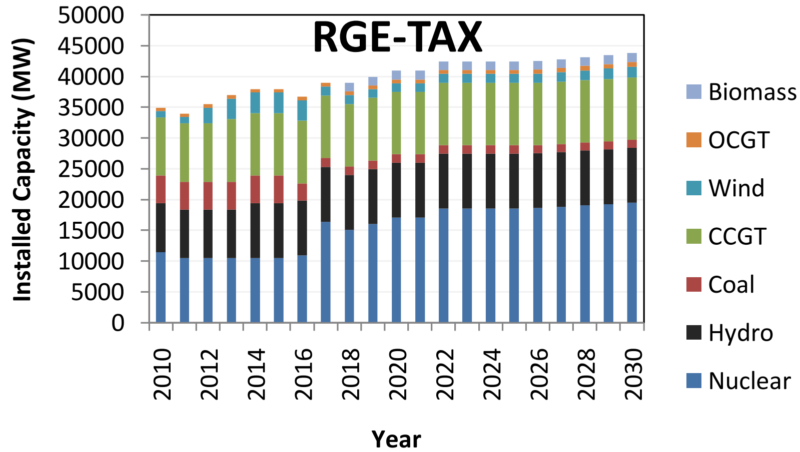
6.4.1 Power System Capacity, Carbon Tax Scenario



a)



b)



c)

Figure 6-12 – Average installed capacity for each carbon tax policy scenario. a) NH-tax b) RGM-tax c) RGE-tax.

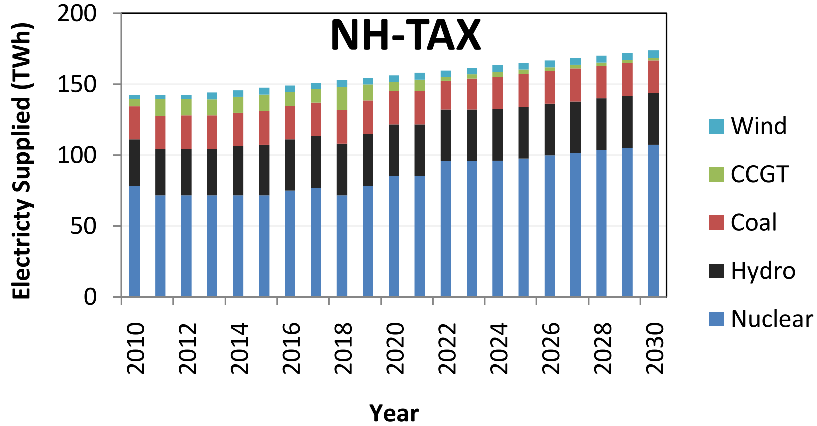
The three carbon tax scenarios have similar effects on the optimal capacity mixture in the power system expansion. These effects become more apparent as the carbon tax aggressiveness increases. As the severity of the tax increases so does the amount of nuclear capacity and the level of decommissioned coal capacity. It appears as though under each tax scenario most of the CCGT capacity is kept online.

Table 6-4 – Summary of capacity investment/decommission in all three tax scenarios over the planning horizon.

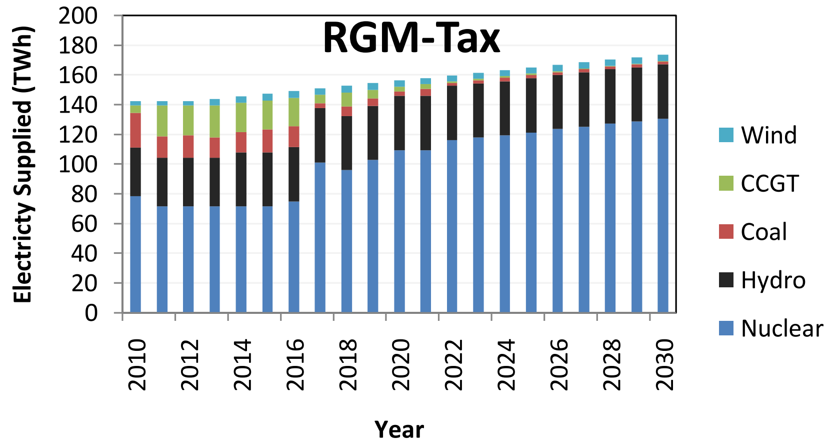
NH-TAX New Investments/Decommission (MW)		RGM-TAX New Investments/Decommission (MW)		RGE-TAX New Investments/Decommission (MW)	
Nuclear	2724	**Nuclear**	6245	**Nuclear**	6546
Coal	0	**Coal**	-724	**Coal**	-3237
CCGT	-241	**CCGT**	-298	**CCGT**	-57
OCGT	89	**OCGT**	186	**OCGT**	301
Hydro	1000	**Hydro**	1000	**Hydro**	1000
Wind	208	**Wind**	-63	**Wind**	-55
Biomass	0	**Biomass**	0	**Biomass**	1450

From Table 6-4, every level of taxation promotes all hydro resources to be developed. There is also a clear relation between severity of the tax and the level of installed nuclear and OCGT capacity. Interestingly, as the tax severity increases, the level of investment in wind power decreases. The NH-tax promotes the highest investment in wind power of all taxes being investigated; but even this is only a modest amount of around 208 MW. RGE-tax, the most aggressive climate policy investigated in this thesis, is the only simulation where there is any investment in biomass fired generation. The carbon tax directly affects the variable O&M costs of generating electricity, so we would expect that the model dispatches the least carbon-intense generators; this is analysed in the next section.

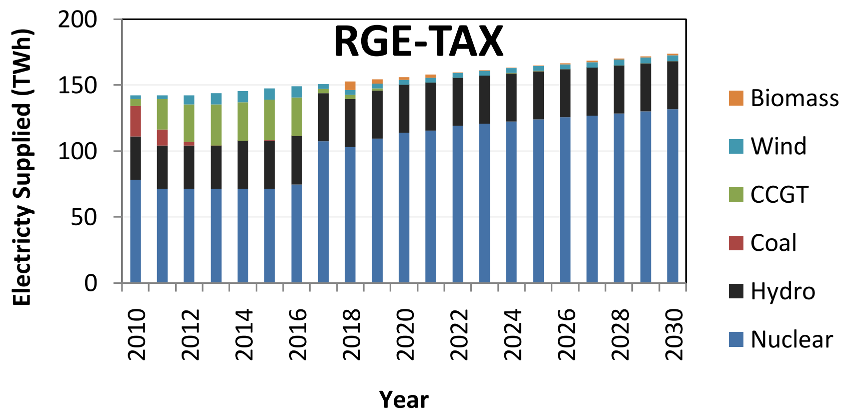
6.4.2 Electricity Supply Mix, Carbon Tax Scenario



a)



b)



c)

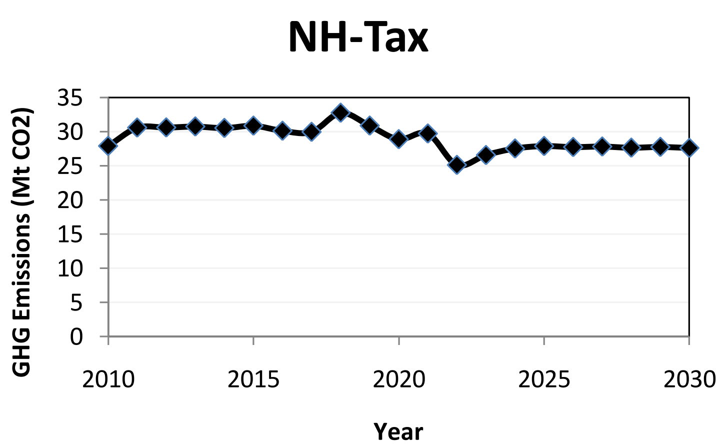
Figure 6-13 – Electricity supply by generator type for all three carbon tax scenarios; a) NH-tax b) RGM-tax c) RGE-tax.

From Figure 6-13 a), the NH-tax appears to dispatch all available nuclear, hydro, wind and coal in almost the same manner as in the base case. The CCGT is again the marginal generator; this tax promotes investment in nuclear power to supplant coal, but does not significantly change the electricity supply mixture.

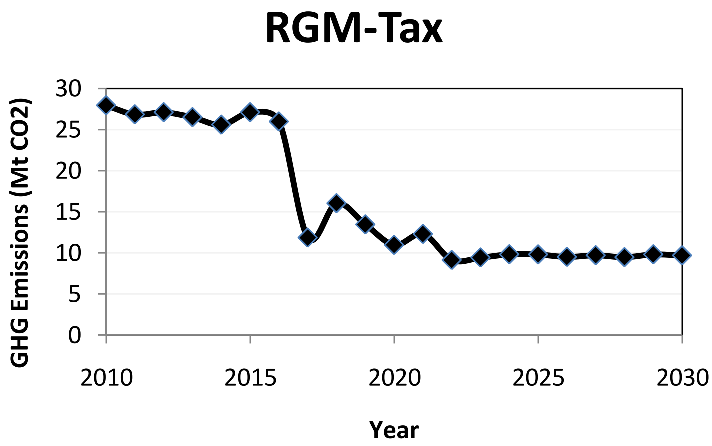
From Figure 6-13 b), the RGM-tax promotes a dispatch schedule that replaces almost all coal electricity with nuclear. Again, CCGT is mostly used to fill in the gaps (marginal generator), especially during years with nuclear refurbishment. There still persists a small amount of electricity derived from fossil-fuels, but far less than the NH-tax.

From Figure 6-13 c), the RGE-tax changes the dispatch to almost entirely fossil-fuel free by 2020 (very small amount of CCGT derived electricity persists). The penalty for CO_2 emissions is so severe that it makes sense for the model to develop biomass generation to come online in 2018 so that it can service the load and make up for the dip in nuclear capacity (there is 1500MW of nuclear being decommissioned/refurbished in 2018). The Biomass derived electricity slowly decreases as more nuclear capacity comes online.

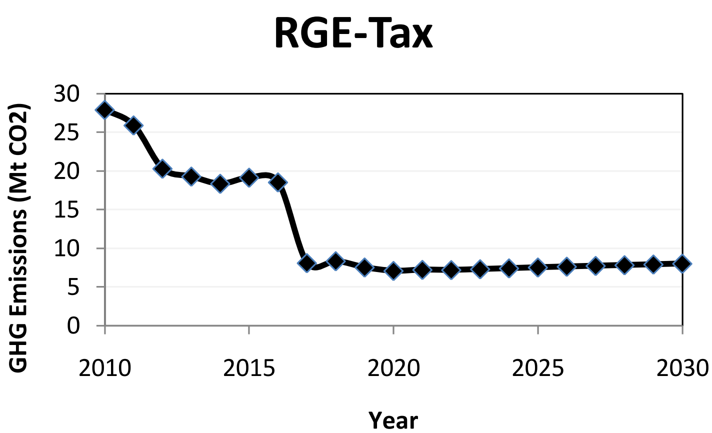
6.4.3 Emissions Analysis, Carbon Tax Scenario



a)



b)



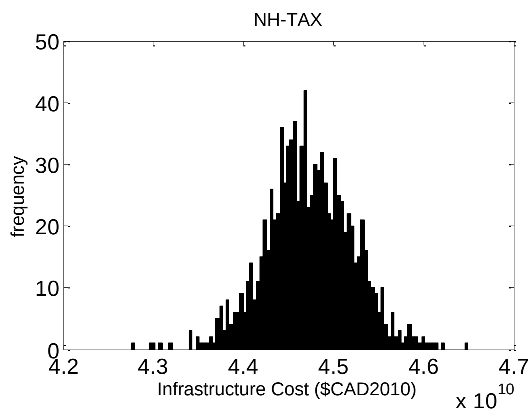
c)

Figure 6-14 – Average GHG profiles for the all three carbon tax scenarios; a) NH-tax b) RGM-tax c) RGE-tax.

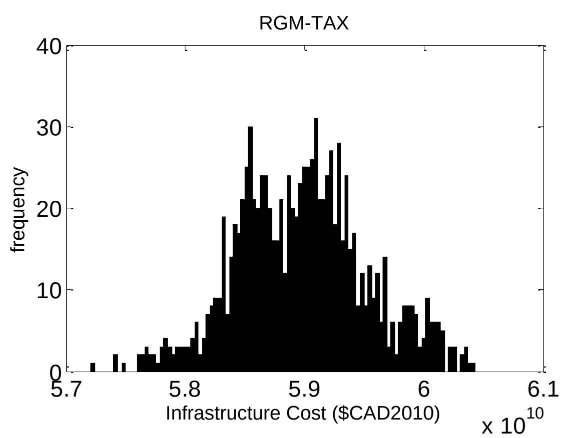
As expected, the yearly GHG output in Figure 6-14 a)-c) decreases as the carbon tax severity increases. As expected, the higher the severity of the tax, the lower the yearly emissions output. The RGE stabilizes to the lowest emissions rate of all the tax scenarios at about 7.5 $MtCO_2$/year in 2017, RGM stabilizes around 9.8 $MtCO_2$/yr in 2021 and the NH tax around 28 $MtCO_2$/yr in 2022. This result is intuitive; the most aggressive carbon taxes promote the greatest emissions reductions.

6.4.4 Cost, Carbon Tax Scenario

The more aggressive the carbon tax, the more the model invests in nuclear power. Nuclear investment will increase the infrastructure costs but should also decrease the cost of supplying electricity. This section will analyse both infrastructure costs and electricity costs, starting with the infrastructure costs.



a)



b)

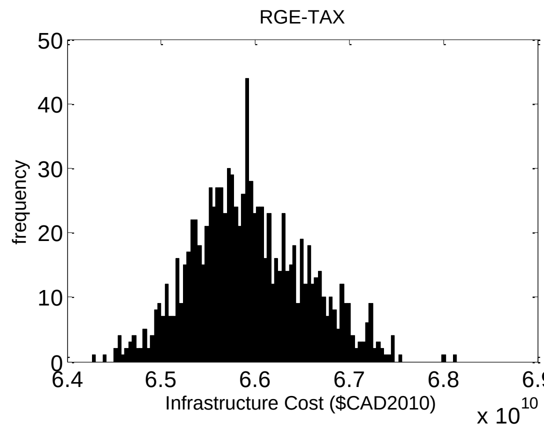
c) 

Figure 6-15 – Distribution of infrastructure costs associated with each carbon tax a) NH-tax b) RGM-tax c) RGE-tax

Table 6-5 – Summary of costs for carbon tax scenarios.

Carbon Tax	**Average Infrastructure Cost (bil$CAD2010)**	**Range of Infrastructure Cost (bil$CAD2010)**	**Average Levelized Electricity Cost ($CAD2010/MWh)**	**Range of Levelized Electricity Cost ($CAD2010/MWh)**
NH	45	42.8 - 46.5	22.78	22.3 – 23.1
RGM	59	57.2 - 60.4	28.75	28.2 – 29.1
RGE	66	64.3 - 68.1	39.96	39.4 - 40.5

As expected, the RGE incurs the highest infrastructure costs, RGM the second highest and NH the lowest. From Figure 6-15 a)-c), there are no obvious relationships between carbon tax severity and the distribution of the infrastructure costs, and all taxes result in an infrastructure cost range (max-min) of around 3.75$bil.

The levelized cost includes the cost of supplying electricity; intuitively as the amount of nuclear capacity increases the cost of supplying electricity decreases, so we might expect that this would compensate for the increase in infrastructure costs. However, it is clear from the levelized cost numbers in Table 6-5 that the cheaper electricity from greater nuclear capacity does not help compensate for the infrastructure costs. The average NH infrastructure costs are about 68% of those for the RGE scenario, while the average NH levelized electricity cost is about 57% of that for the RGE. This suggests that the cost of supplying electricity increases the cost gap between the two policies. The taxes in the RGE scenario are so severe that even the minor emissions associated with nuclear energy have a large impact on the overall cost of supplying electricity.

As presented, the more aggressive the carbon tax, the greater the reduction in emissions and the greater the cost on the power system. If your objective is cheap carbon emissions abatement, it is not immediately apparent which policy is the best; this will be analysed in detail in Chapter 7.

7. Comparing Policies

In this chapter, each scenario will be compared. The first area of comparison will look at the installed capacity and energy supply mixtures under each policy. This will lead into a more detailed analysis of the wind power investments encouraged by each policy. Section 7.2 will analyse the expected power system costs under each policy and compare the emissions. Section 7.3 will tie together the emissions and cost estimates by introducing the carbon abatement cost metric which normalizes all scenarios to the base case to allow for direct comparison between policies.

7.1 Comparison of Installed Capacity and Electricity Supply Mixture

As presented in Chapter 6, the more aggressive carbon policies tend towards higher investments in nuclear power. In this section we will directly compare the differences in capacity and electricity supply mixture resulting from each policy.

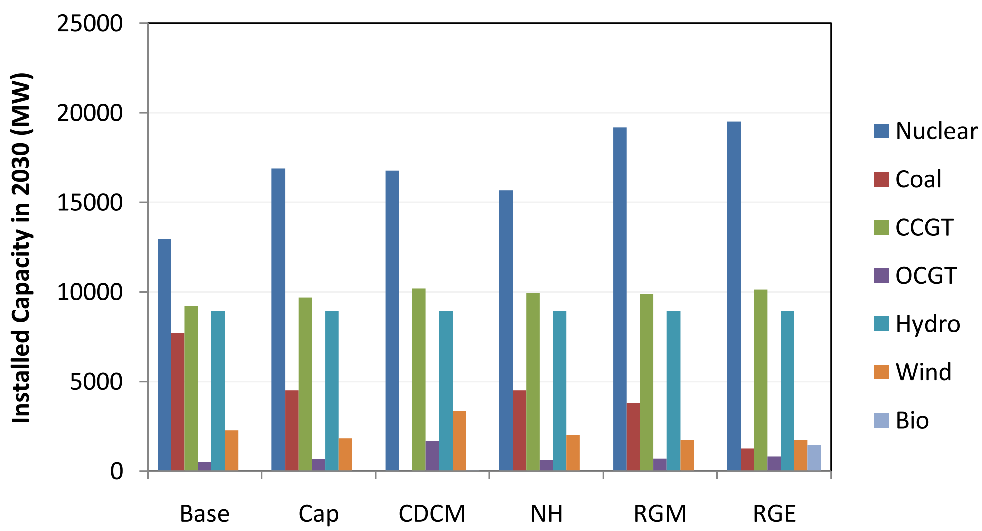


Figure 7-1 – Installed Capacity in 2030 for each policy scenario.

In Figure 7-1, the level of installed hydro capacity is similar for each policy; it has a low operating cost and is very flexible, so it is almost always fully developed. The base case clearly has the highest installed coal capacity, leading to the intuitive conclusion that any emissions abatement policy requires the reduction of coal capacity. Less obvious is the fact that the base case has the second highest installed wind capacity; second to the mandatory coal decommissioning policy. This will be further investigated in the next section. Any policy intervention results in greater installed nuclear capacity; with the most aggressive policy (RGE-Tax) having the highest installed nuclear capacity. It's clear that each scenario promotes a different generation mixture, but it also has an influence on the total installed capacity of 2030; as evidenced by the following plot.

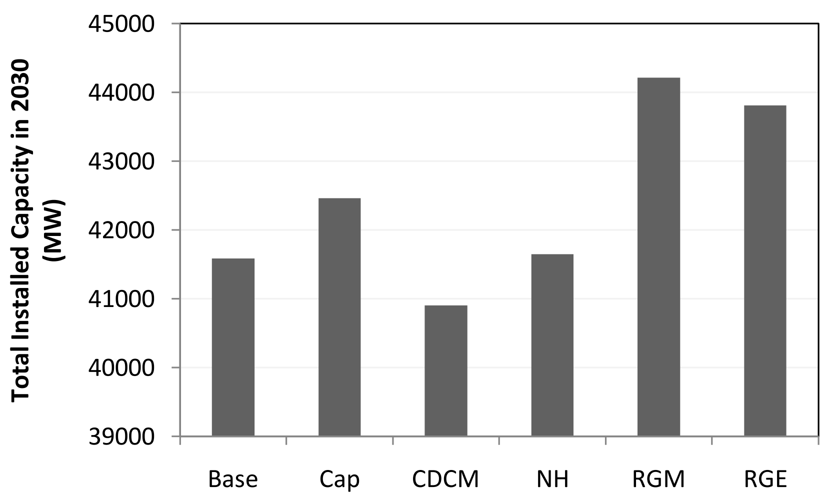


Figure 7-2 – Total installed capacity in 2030 for each policy scenario.

In Figure 7-2, the total installed capacity is different for each scenario without any obvious trend; each scenario has specific reasons for their respective installed capacities. From Chapter 5, the base case mostly invests in new coal capacity to service growing energy requirements, using all initial nuclear assets to their maximum and investing in just enough coal, wind and OCGT capacity to meet the growing power/energy requirements of the future. The CCGT capacity is kept online to service years without enough base capacity (years with nuclear refurbishment).

The emissions capped scenario expands in such a way that it can hit all power/energy requirements and the emissions constraints, but does not elect to decommission any coal. The coal capacity is kept online to ensure power capacity requirements are met, but does not use it to provide much energy, resulting in a relatively large amount of capacity online in 2030.

In the decommissioning coal scenario, all of the coal capacity is taken offline and the model simply meets all of the new capacity requirements in the cheapest manner possible. There is very little 'dead-wood' in this scenario, meaning that the system is using most of the generators close to their maximum output, and consequently has the lowest overall installed capacity of these scenarios.

Each tax scenario has its own particular reasons for their respective installed capacities at 2030, without any obvious trend with each other. For the NH-tax, it is cheaper to run coal and take the emissions penalty than invest in expensive nuclear; this keeps the total installed capacity levels down. For the RGM-tax it only makes sense to run a bit of coal and supplement all of the base-load needs with nuclear. In this case, the model invests quite heavily in nuclear but elects to keep all of the coal online; this is why it has the highest installed capacity in 2030. The RGE-tax elects to decommission almost all of the coal, and replaces it with about 1500MW of biomass fired generation. This makes its final installed capacity in 2030 slightly lower than the RGM-tax. To gain further insight, the following plot highlights the differences in energy dispatch in 2030 for each scenario.

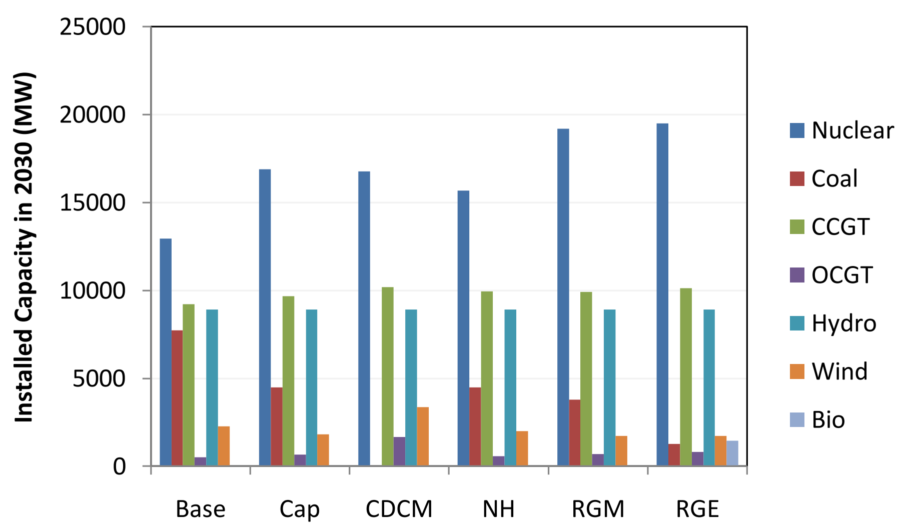


Figure 7-3 – Electricity supply mix in 2030 by generator type for each policy scenario.

Remembering that the Cap scenario is the least-cost solution to hitting the emissions targets as outlined in [39], in Figure 7-3 it appears as though the closest matches in terms of energy mix are the coal decommissioning scenario and the NH-tax scenario. The coal decommissioning scenario appears to replace all coal generated electricity with CCGT and wind energy, and maintains a similar level of nuclear output as the capped scenario. The NH-tax scenario outputs slightly more coal derived electricity and less nuclear than the capped scenario. The most obvious trend from Figure 7-3 is that the more aggressive the emissions policy, the greater the nuclear output. In terms of incentive for wind energy, it is not immediately apparent why the more aggressive emissions abatement policies do not encourage greater wind penetration.

7.2 Analysis of Wind Power Investment

The model was limited to 3000 MW of wind capacity that could be added to each of the four wind zones, allowing a maximum of 12000MW of total developable capacity. The greatest investment in wind power occurs under the coal decommissioning scenario with about 3300MW total wind capacity in 2030. This is still far from the upper limit of available wind capacity. The implication being that based on this model, any aggressive move towards wind power capacity will likely shift the power system further away from the least-cost solution. From the previous section, it also appears that wind power is more attractive in power systems with relatively high levels of mid-load capacity available; systems with mostly base-load capacity cannot absorb as much wind power. To elaborate on that point, the following plots are presented.

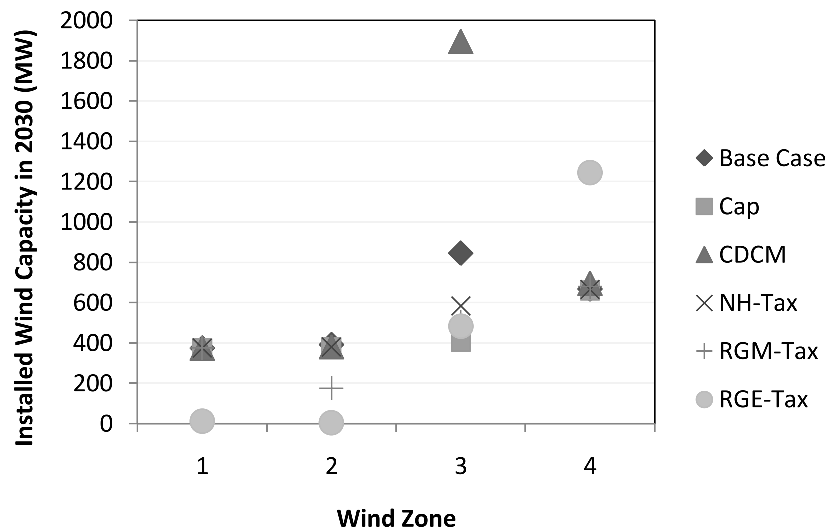


Figure 7-4 – Installed wind capacity in each wind zone by policy scenario.

In Figure 7-4, wind zone 3 is the clear favourite for the base case and for the coal decommissioning scenario, while wind zone 4 is the winner for the RGE-Tax. To explain this it helps to review Figure 4-9 from chapter 4.

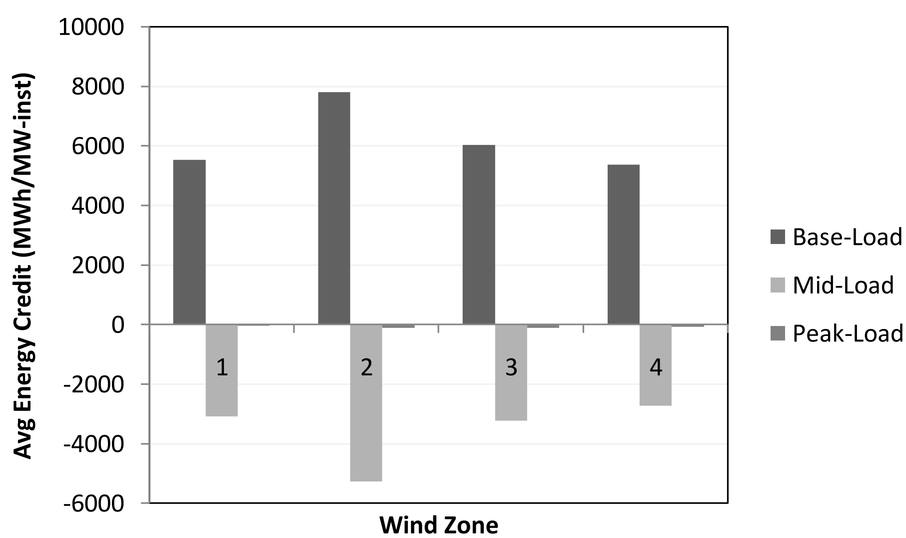


Figure 4-9 - Expected long-term performance of each wind zone in terms of a**) power credit and b) energy credit** credit

From Figure 4-9, wind zone 3 provides the second largest amount of firm base-load energy, while not requiring as much mid/peak-load compensation as wind zone 2. Wind zone 4 provides the smallest amount of firm base-load energy but also requires the least amount of mid/peak-load compensation. In the base case and coal decommissioning scenario, using fossil fuel fired mid-load energy is not too expensive to compensate for large investments in wind zone 3. The RGE-tax is penalized so heavily for any emissions that it can only rationalize using the hydro assets to compensate for the wind power; consequently it only invests modestly in the wind zone that requires the least amount of compensation: wind zone 4. This last point is counter-intuitive; larger emissions penalties result in less wind power investment. This is true for this study of the Ontario power system, however, if we were looking at a hydro dominated system, one which could compensate for wind without being subject to large CO_2 penalties such as that in British Columbia, this point might not hold true.

7.3 Final Cost Estimates and Emissions

7.3.1 Cost Estimates

In Chapter 6, the infrastructure and levelized cost of the power system expansion under each policy was different, in both magnitude and range of uncertainty. The following plots summarize and compare the infrastructure and levelized costs

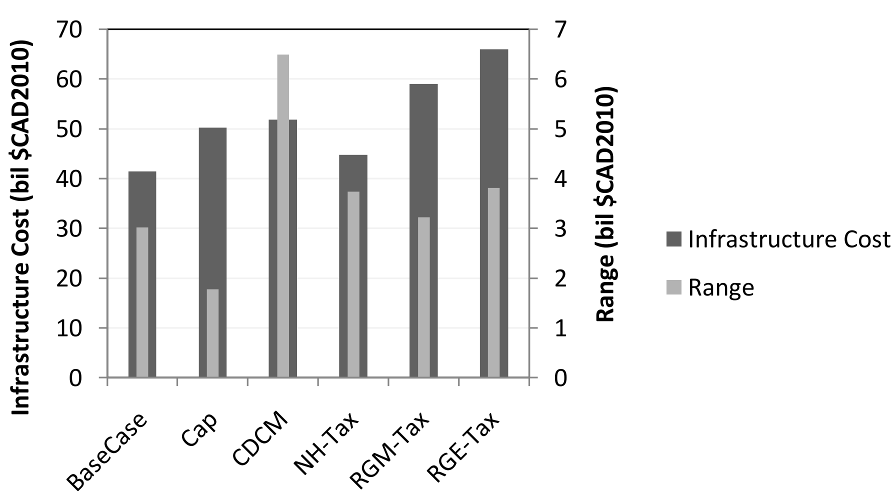


Figure 7-5 – Comparison of infrastructure costs for each policy scenario.

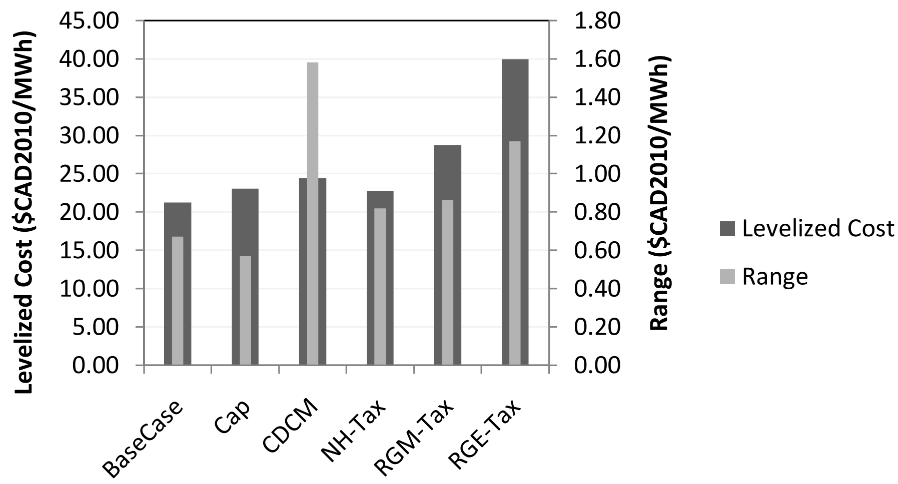


Figure 7-6 – Comparison of levelized electricity cost for each policy scenario.

The dark bars in Figure 7-5 and Figure 7-6 represent the average cost for each policy scenario, while the light bars represent the range (the difference between the maximum and minimum cost in the distribution resulting from the Monte Carlo simulation). The average infrastructure and levelized electricity costs follow the same trend, with the base case being the cheapest and RGE-Tax being the most expensive.

The emissions capped scenario and the NH-tax impose similar costs, with the infrastructure costs of NH-tax being about $5bil cheaper, and the levelized electricity cost 28¢ cheaper than the emissions cap scenario. However, the range of costs (uncertainty) in the NH-tax scenario is greater than that in the emissions cap scenario. The worst case scenario, if NH-tax incurred its most expensive costs, it would still have cheaper infrastructure costs than the emissions capped scenario, but a slightly higher levelized electricity cost.

The coal decommissioning scenario has only slightly higher infrastructure and levelized electricity costs than the emissions capped scenario, however, this scenario does have the highest range of costs. In the most favourable conditions (lower end of the range) the CDCM scenario is cheaper than the average cost of the emissions cap.

The next step in rationalizing these policies will be to look at the emissions they avoid.

7.3.2 Emissions Estimates

In Chapter 6 the yearly GHG output profiles for each policy were presented, but did not do any comparison between policies. The next plot will show the differences in yearly emissions output by policy scenario, and compare them to the political targets outlined in [39].

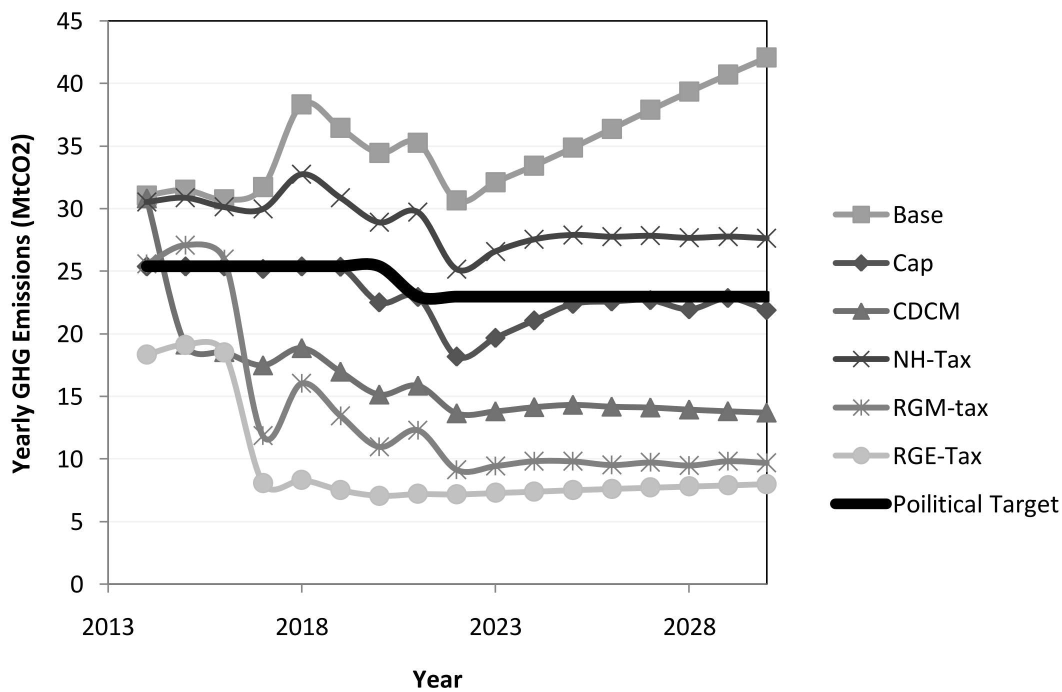


Figure 7-7 – Average yearly GHG emissions by policy type with political targets highlighted.

In Figure 7-7 the yearly emissions profiles for each policy is presented, starting the same year as the political targets, 2014. The only policy that strictly meets the political targets, other than the emissions capped scenario, is the RGE-tax. The RGE-tax maintains an expected GHG emission output far lower than the proposed political targets. However, the coal decommissioning and RGM-tax scenarios are close to meeting the political targets.

The CDCM only misses the emissions target in 2014, since the policy does not enforce coal decommissioning until the end of 2014. To ensure that the political emissions target is met, the coal decommissioning policy could be enforced a year earlier, i.e. all coal capacity must be decommissioned by the end of 2013.

The RGM-tax is slightly above the political target emissions level until 2017, when it quickly dips to a level below the target. This scenario could easily be manipulated to hit the emissions targets by simply altering the generator dispatch from 2014-2016; but this would of course increase the cost of supplying electricity in these years. The base case and NH-tax scenario do not come close to achieving the political targets in any year.

Each policy has a different yearly emissions profile, and will thus produce different total amounts of GHG emissions from 2010-2030. A plot summarizing the expected total GHG output and its associated range follows.

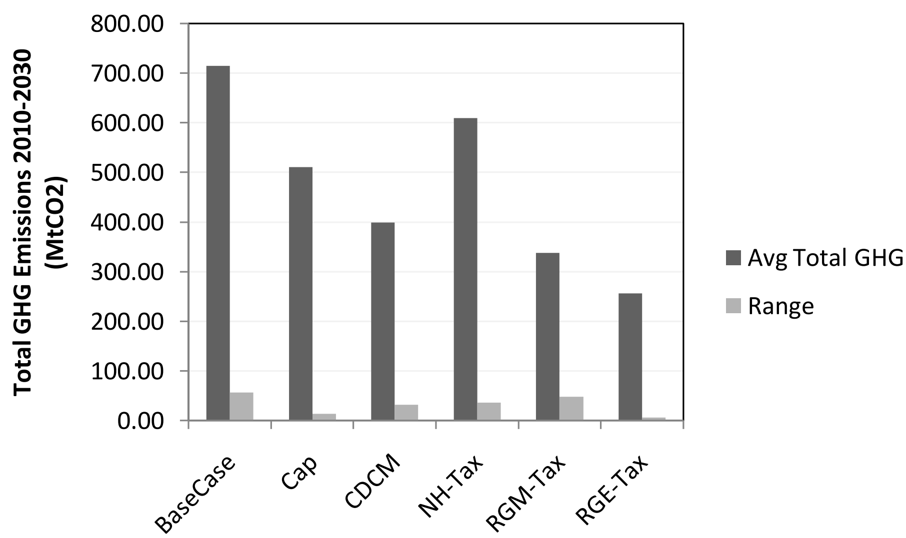


Figure 7-8 – Total GHGs emitted over the planning horizon for each policy scenario.

In Figure 7-8, every policy intervention results in lower GHG emissions than the base case, but only the CDCM, RGM-tax and RGE-tax outperform the emissions cap scenario in terms of total GHGs emitted. The range (difference between maximum and minimum value) for the base case is the largest for all scenarios; since the base case does not limit emissions in any way it is open to a wider spectrum of generation technologies that form its distribution of least-cost solutions, which in turn creates a wider range of possible GHG emissions. As expected, with increasing aggressiveness of carbon taxation, there is a decrease in total GHGs emissions. With the differences in amount of carbon dioxide emitted and total costs we need to introduce a new metric to help quantify the efficacy of these policies.

7.4 Carbon Dioxide Abatement Cost and Policy Efficacy

7.4.1 Carbon Dioxide Abatement Cost

A common metric used to assess the efficacy of emissions policies is the carbon dioxide abatement cost. This metric will normalize the cost of removing CO_2 emissions from the power system operation on a dollar per tonne of CO_2 avoided basis. Summarized in equation form:

$$CO_2\ Abatement\ Cost = \frac{TotalCost_{withpolicy} - TotalCost_{basecase}}{TotalEmissions_{basecase} - TotalEmissions_{withpolicy}} = \frac{\$}{tCO_2} \qquad [7.1]$$

The carbon dioxide abatement cost was calculated for each policy and are presented in the following plot.

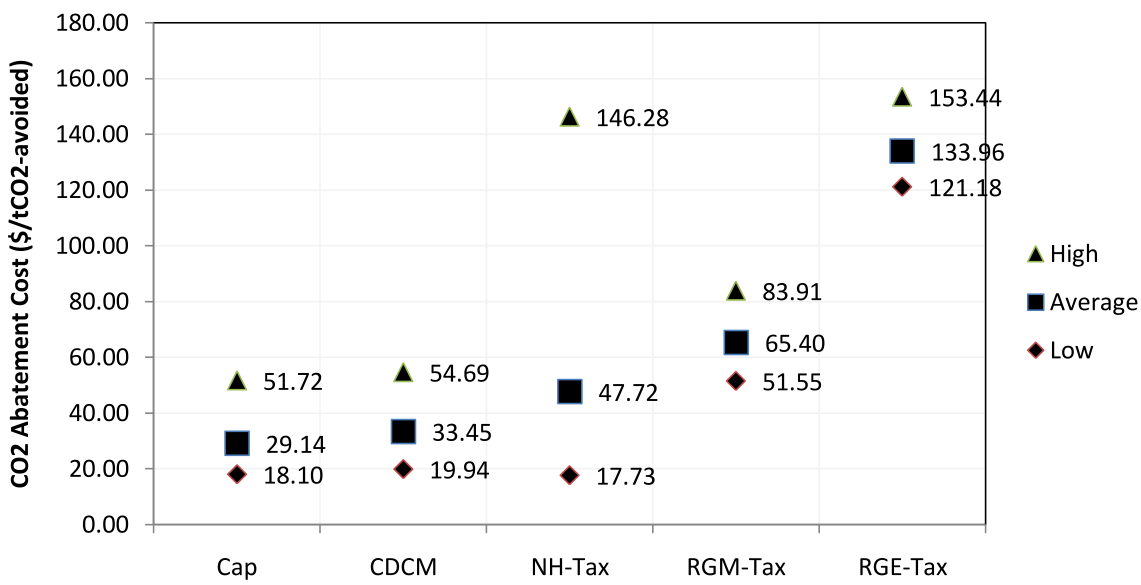


Figure 7-9 – Carbon dioxide abatement cost for each policy scenarios.

The large squares in Figure 7-9 are the average carbon abatement costs for each policy. This uses the mean values of all costs and all expected GHG emissions. The diamonds are the lowest estimate of the carbon abatement cost for each policy; using the lowest estimates of costs and GHG emissions for the policy and compare those to the largest estimates of costs and GHG emissions of the base case. The triangles are the highest estimate of carbon abatement cost; using the highest estimates of costs and GHG emissions for the policy and comparing those to the lowest estimates of costs and GHG emissions of the base case.

Looking just at the averages, the emissions capped scenario has the lowest abatement cost with the coal decommissioning scenario relatively close behind. The average abatement cost for the tax scenarios increases rapidly with the aggressiveness of the tax.

The most striking feature of this plot is the high-low range of the carbon abatement cost for the NH-tax. As we saw in the previous section, the NH-tax does not avoid a significant amount of emissions. On average it avoids a modest amount of emissions for a relatively small price increase, hence the average abatement cost of 47.72$/t$CO_2$, but the high-low range shows the extreme sensitivity of this metric. In situations where the costs incurred because of the NH-tax are large relative to the base case you get a large cost spike; although the opposite produces the cheapest carbon abatement cost. This highlights the uncertainty or riskiness in employing a modest carbon tax. The modest carbon tax has a small impact on the overall cost (relative to other policies in this thesis), but also has a very small impact in terms of GHG emissions reductions; it is this close trade-off that makes the NH-tax very sensitive. The sensitive range is essentially highlighting the fact that you could be paying a small amount extra for a very modest reduction in GHG emissions or you could be paying quite a bit extra for the same modest reduction in GHG emissions. All other policies have a high-low abatement cost spread in the range of 32-35$/t$CO_2$, while the NH-tax's spread is 129$/t$CO_2$.

7.4.2 Summary of Policy Efficacy

As with any policy, there are several objectives that need to be optimized. For this study, if you asked an environmentalist the objective might be to minimize overall GHG emissions from the power system. An economist might argue that any restrictions on the power system will drive up prices and make business uncompetitive in that region, so if any policy must be imposed it should be the cheapest. The policy maker has to take these conflicting objectives into consideration when making a policy. Table 7-1 presents a summary of the important metrics from this study that a policy maker could use to make an informed decision. It should be noted that the carbon dioxide abatement costs associated with the various policies presented in Table 7-1 may not be directly comparable. For example, the abatement cost associated with the carbon tax includes the cost of the tax, whereas the abatement cost associated with the cap includes no such cost.

Table 7-1 – Summary of efficacy metrics by policy scenario.

Metric	Cap	CDCM	NH-Tax	RGM-Tax	RGE-Tax
Mean Levelized Electricity Cost ($/MWh)	23.06	24.47	**22.78**	28.75	39.96
Max-Min Range	**0.57**	1.58	0.82	0.86	1.17
Total Installed Wind Capacity in 2030 (MW)	1820	**3352**	2004	1733	1741
Mean Total GHG Emissions Avoided (MtCO2)	204	316.3	105.3	376.8	**458.8**
Does Policy Meet Political Targets (as outlined in [38])?	Yes	No; only misses targets in year 2014	No	No; only misses targets in 2014-2016	Yes
Mean Carbon Dioxide Abatement Cost ($/t$CO_2$-avoided)	**29.14**	33.45	47.72	65.4	133.9
Max-Min ($/t$CO_2$)	**51.7 - 18**	54.7 - 19.9	146.3 - 17.7	83.9 - 51.5	153.4 - 121.1

The ‘best’ policy is heavily dependent on our main objective. From Table 7-1, the RGE-Tax provides the greatest reduction in GHG emissions, but is also the most expensive policy. On a levelized cost basis, the NH-tax policy is the cheapest, however when we look at the total GHGs avoided, the abatement cost and its sensitivity, it does not appear so favourable. If our objective is to simply hit the political targets outlined in [39], the emissions cap scenario is the cheapest way to do that; on a levelized cost basis and on a carbon abatement cost basis. Conclusions and recommendations will be made in the Chapter 8, based on the information presented in this chapter.

8. Conclusions and Recommendations

To make an absolute conclusion about the best policy in this project would inherently be imposing a bias on the most important objective. With this in mind, conclusions will be made about the policies that satisfy several broad objectives and merit further investigation as the foundation of plausible carbon abatement policies. A brief discussion about the transaction costs, or how these policies could be implemented, will follow and may further refine in the readers mind the best policy. Section 8.2 in this chapter will discuss limitations of this model and recommendations for future work.

8.1 Important Conclusions

In this section, the most important conclusions are presented, and their relative importance is discussed. It does not make sense to define the best policies purely on a cost basis. The cheapest policies are always going to be those that most closely resemble the base case, or the case without any additional constraints imposed. For this case study, there are four main objectives that should be considered when rationalizing these policies. The most obvious is the specific political targets mandated by the province of Ontario. The next objective is the total CO_2 avoided and the CO_2 abatement cost. The levelized electricity cost is closely related to the CO_2 abatement cost, and should also be considered. Finally there may be other factors such as a political interest in a specific generation technology that should be taken into account.

Broad conclusions about capacity investments can be made for hydro, since every scenario developed all (or almost all) available capacity. It should also be noted that every scenario refurbished all of the nuclear units that were scheduled for decommissioning and that only the most aggressive carbon tax policy promoted investment in fuel-switched coal plants to biomass. Lastly, as we saw in Figure 7-9, the modest NH-tax scenario has a wide distribution of expected carbon abatement cost, suggesting that modest carbon taxes have the greatest inherent risk in terms of efficacy.

8.1.1 Hitting the Political Targets

The carbon emissions cap and RGE-tax scenarios explicitly satisfy the political emissions targets as set out in [39]. The coal decommissioning and RGM-tax come close and could satisfy the emissions targets by making small adjustments to the electricity supply in the first few years of this study (this would of course affect the cost of supplying electricity). The base case and the NH-tax do not come close to satisfying the emissions targets.

8.1.2 Total GHG emissions, Carbon Abatement Cost and Levelized Cost

The most aggressive policy in this case study, RGE-tax, resulted in the greatest GHG emissions reductions. If the objective is the greatest reduction in GHG emissions, then the RGE-tax is the best policy; however, every political decision must (should) consider the costs. If we consider at the total GHG emissions, carbon abatement and levelized costs all at the same time, we get a clearer picture of which policies are worth investigating further.

Table 8-1 – Summary of emissions and cost metrics.

Policy	**Levelized Cost ($/MWh)**	**Carbon Abatement Cost ($/tCO2)**	**Total GHGs avoided (MtCO2)**
Emissions Cap	23.06	29.14	204.07
Coal Decommission	24.47	33.45	316.31
RGM-Tax	28.75	65.4	376.79
RGE-Tax	39.96	133.96	458.86

The three policies in Table 8-1 are highlighted since they are the only ones that can conceivably meet the government of Ontario's emissions targets. If the most important objective is to satisfy the political targets, then the carbon emission cap scenario is the winner, however it is not obvious how it could be implemented (this will be discussed further in the next section). If the goal is to avoid a greater amount of carbon emissions (while coming close to satisfying the yearly political emissions targets), the coal decommissioning scenario looks promising; however it does not guarantee future success beyond the planning horizon since it does not regulate carbon emissions from other fossil fuels, such as natural gas. Of the two Roughgarden-tax scenarios, the RGM is cheaper but results in about 82 Mt of CO_2 more than the RGE. Both of these tax scenarios cost more than the emissions cap and coal decommissioning scenarios.

8.1.3 Political Interests

Wind turbines have been adopted as symbols of a shift towards 'sustainable energy.' As such, it may be an important political objective to increase their presence in the generation mixture.

Table 8-2 – Installed wind capacity in 2030 by policy scenario.

Policy	Cap	CDCM	RGM-Tax	RGE-Tax
Installed Wind Capacity in 2030 (MW)	1820	3352	1733	1741

The emissions cap and both tax scenarios result in a similar level of wind power penetration. The coal decommissioning scenario has almost double the amount of wind capacity in 2030 as the other policies, making this the most attractive if installed wind capacity is an important political objective.

8.1.4 Policies for Further Investigation

The decommissioning coal scenario can meet all political objectives relatively effectively in terms of cost and emissions savings. Since this policy has already been written into law, the next step would be to work towards ensuring the necessary capacity investments, as outlined in Chapter 6, can be made to meet the least-cost path forward. The issue of ensuring emissions reductions after 2030 should also be considered, since this scenario offers no direct constraints on future emissions.

A tax scenario could meet all political objectives, but can be more costly than the decommissioning coal policy. However, from the analysis in this thesis, modest carbon taxes result in only modest emissions savings and can end up being very expensive (refer to Chapter 7). Further investigation into the optimal timing and aggressiveness of the tax should be conducted. The tax scenario could also be combined with the decommissioning coal policy to ensure long-term emission reductions.

The emissions capped scenario is the cheapest and most direct way to achieve the political objectives outlined by the Ontario government; however it is not obvious how this could be implemented in practice. Depending on the market structure, an efficient cap-and-trade system might be able to mimic the results found in this work.

8.2 Implementing the Policies; Further Discussion and Caveats

It is worth reiterating how each policy achieves emissions reductions to further refine how they might be implemented. The emission cap scenario is conceptually easy to understand; it simply limits the amount of CO_2 that can be emitted by the entire system and lets the model decide the cheapest possible way to meet all other requirements. If a perfectly efficient market system could be implemented that capped emissions output and allowed generators to trade emissions credits, in theory this market would act like the MILP model in this work. The coal generators would buy emissions credits that allow it to produce electricity up to the point that it is no longer economic; the combined cost of variable O&M and carbon credits would be exactly equal to the benefit of producing one more unit of electricity. Each generator would now have a different economic output level, which would change the generator technology investment incentives and result in a generation mix similar to that found in this work. The cost of implementing this policy, in terms of setting up a market and enforcing the emissions caps, would not be trivial and would have to be investigated further before any final decision to continue with this policy.

The regulation policy, mandatory decommissioning of coal generators, directly penalizes the most carbon intensive generators in the power system. As we saw, this policy reduces GHG emissions over the planning horizon investigated. The complication with this policy is in the distribution of wealth; the coal plants being decommissioned would need to be compensated for foregoing all future electricity production. This cost would have to be considered when doing a thorough analysis of this policy.

The carbon tax policy directly impacts the cost of producing electricity, penalizing generators by an amount proportional to their carbon intensity. The increase in cost associated with generating electricity from carbon intensive fuels is apparent in this work; it is directly added to the variable O&M costs. The higher cost of doing business will promote investment in cheaper, less carbon intensive generation technologies. Interestingly, since high taxes disincentivize the use of fossil-fuels, including gas generation, this limits the amount of economically available mid-load energy and constrains the amount of economically viable wind power capacity. This could be a clear indication that under such a policy there would be an opportunity for new less carbon intensive mid-load capacity technologies. Again, the cost of monitoring carbon emissions and enforcing tax payments would have to be considered in the final analysis.

8.3 Extending the Model; Recommendations and Future Work

There are inherently many assumptions made when trying to model something as large and relatively vague as the effects of carbon policies on power system expansion. Improvements on this model will be presented below, along with the reason for simplifying assumptions made in this work.

- **Larger portfolio of generation technologies**: This project only considers investing in the technologies as outlined in chapter 3. The results may change if other generation technologies were included, such as solar, offshore wind or next generation nuclear and natural gas plants. The generation portfolio was limited to technologies foreseeably available for large-scale power production over the planning horizon.

- **Carbon Tax and Carbon Cap Profiles**: This project investigated previously optimized carbon tax profiles and a carbon emissions cap as proposed by the government of Ontario. The carbon taxes all took the form of a linear function; a more efficient carbon tax may assume some other type of profile, such as quadratic or exponential.
- **Different Power Systems**: This work only considers the Ontario power system as our case study. The results would change based on the specifics of the power system being investigated. Factors like expected load growth, installed generation in the base year and regionally specific renewable resources have significant influence on the cost and efficacy of carbon dioxide abatement policies.
- **Sensitivity to Discount Rate**: This work assumed a social discount rate of 5%. There are many differing opinions as to the correct discount rate, so the sensitivity should be analysed. However, considering the amount of time and analysis required for this study using only a single discount rate, this would be a considerable undertaking.
- **Benefits of Regional Diversity in Wind Power**: This model directly compares wind zones based on their expected effect on the power system. It does not, however, internalize the possible benefits of two compensating wind farms; wind farms whose output combined is much smoother together than individually. This would make the current model non-linear and would be difficult to incorporate but would add another layer of realism to the analysis.
- **Electricity Trading:** The current model determines the least cost solution to satisfying electricity demand and does not estimate market clearing prices. Future work could include this information, along with the market clearing prices of interconnected regions to estimate the volume of electricity trades and their associated CO_2 emissions.
- **Lifecycle Analysis:** The emissions associated with plant construction could be incorporated to make this more of a lifecycle analysis. This work does not consider the emissions associated with construction, but rather focuses on the operation of the power system, and not a lifecycle analysis.

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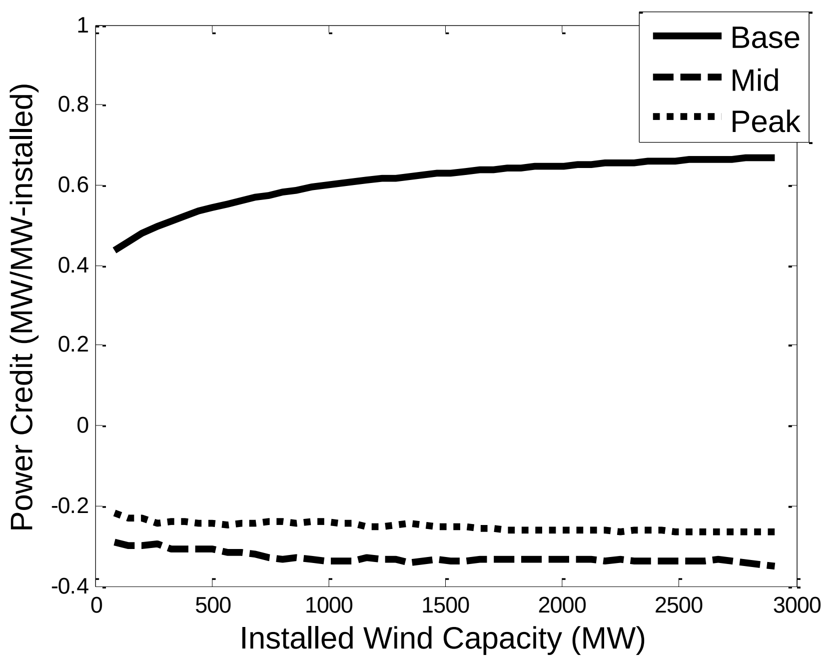
Appendix

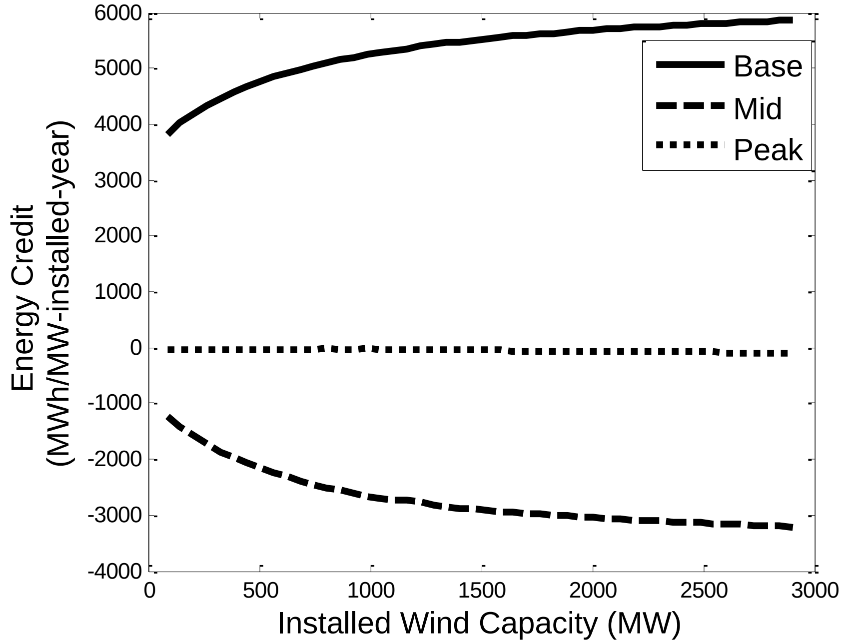
A Installed wind capacity and power/energy credits

This section analyses the linearity assumption between installed wind capacity and power/energy credits.

The relationship between power/energy credit and installed wind capacity are shown below for wind zone 4. These plots are based on the observed wind power output and observed load data in Ontario for 2010.



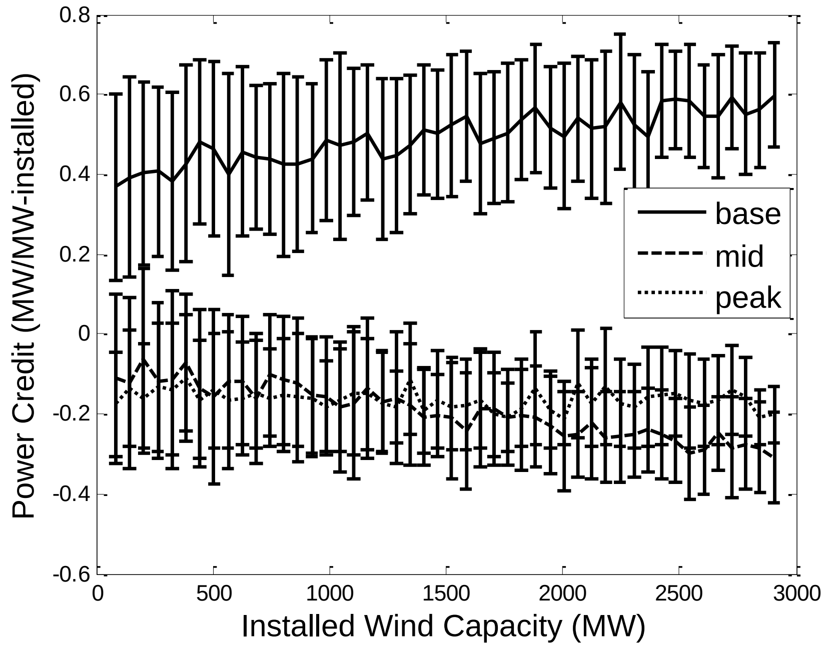
a)



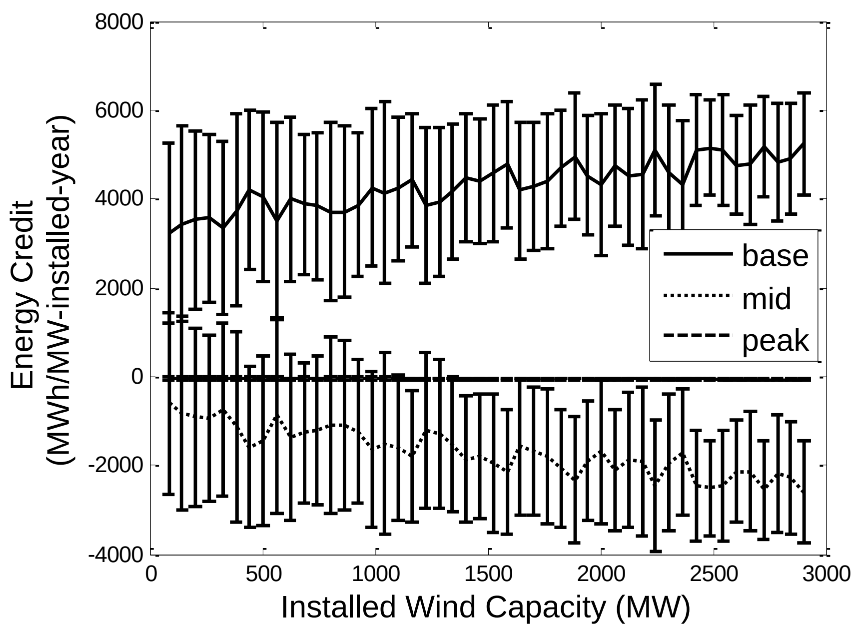
b)

Figure A-1 – a) Power credit for wind zone 4 using 2010 data; b) Energy credit for wind zone 4 using 2010 data

The relationships presented in Figure A-1 show a non-linear increase in base power/energy credit with increasing installed wind capacity. Similarly, mid-load energy credit shows a decreasing energy credit with increasing installed wind capacity. These curves were generated using real data from 2010. The work presented in this thesis generates thousands of forecasts of both wind output and load data, which changes the shape of these curves. The following plots illustrate this point.



a)



b)

Figure A-2 – a) Average power credit for wind zone 4 with standard deviation b) Average energy credit for wind zone 4 with standard deviation

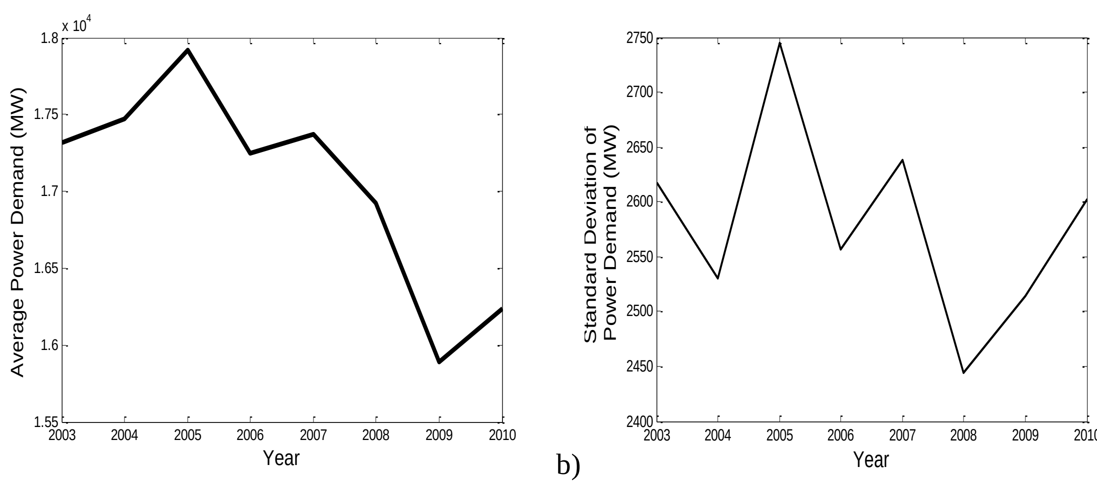
Figure A-2 a) and b) presents the average power and energy credits for wind zone 4 from 1000 realizations of forecasted wind output and load data with error bars of one standard deviation. The stochastic component of the forecast smoothes the non-linearity in Figure A-1. This is the basis for the linearity assumption of power/energy credit to installed wind capacity.

B Stochastic load-forecast model

In this section, the method used to determine the stochastic component of the load-forecast model is presented. The following equation defines this model.

$$LoadForecast_t = Load2010 + YearlyIncrease_t + RandomNoise \quad \text{[B1]}$$

In Chapter 4, it was noted that there is an average yearly energy consumption increase of about 3% [29], which is captured by the 'YearlyIncrease' variable in equation B1. The 'RandomNoise' variable is the stochastic component of the model. This is a normally distributed random variable, with mean of zero and a standard deviation which is proportional to the yearly average power demand. To understand the motivation for the non-constant standard deviation of the random variable, consider the following plots.



a) b)

Figure B-1 – a) Yearly average power demand b) Yearly standard deviation of power demand

There is a relationship between Figure B-1 a) and b). These plots depict a general trend suggesting that as the average yearly power demand increases, so too does the standard deviation of power demand. To present this more clearly, a plot of standard deviation vs. average power demand follows.

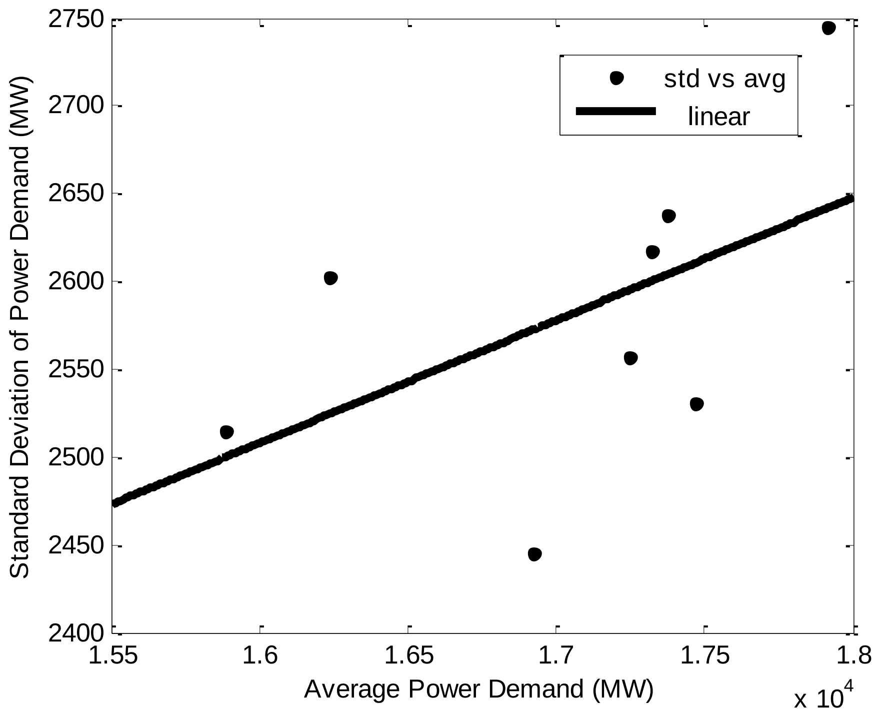


Figure B-2 – Relationship between standard deviation and yearly average power demand

A linear model was fit to the average power demand and standard deviation data and is presented in Figure B-2. The slope of this linear fit was found to be 0.125; meaning that for every MW increase in average power demand the standard deviation increases by 0.125. This value of 0.125 is used as the yearly increase in standard deviation of the random variable in the load forecasting model.