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Prices, reliability of supply and large scale wind generation in electricity markets

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Prices, Reliability of Supply and Large Scale Wind Generation in Electricity Markets

by

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Abstract

This thesis focuses on anticipating electricity prices, reliability of supply, and emissions in deregulated energy-only markets in the medium and long term considering both the large-scale integration of wind generation and other inflexible generation and the strategic behavior of other flexible generators. The first part of this thesis evaluates the effects of large-scale wind powered generation on the fixed cost recovery of existing conventional generators and the ability of existing conventional generators to profit from economically withholding energy. The anticipated impact on reliability of supply and prices in the medium term is also evaluated. In the second part of the thesis, a general model of long term equilibrium that allows for generation additions and retirements is developed and applied to determine the distribution of electricity prices and reliability of supply at equilibrium assuming competitive, inflexible, and strategic generator behaviors. The third part of the thesis applies Probabilistic Neural Networks (PNN) to model complex individual generator behaviors. The PNN are integrated in simulations of existing markets to anticipate prices, the likely entry of new generation, reliability of supply, and emissions in the medium term.

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Dedication

This thesis is dedicated to my mother and the memory of my father whose love and guidance have shaped my life

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Nomenclature

Indices:

i	Level of aggregate demand, period, data point, capacity level
j	Level of aggregate generating capacity, cluster, sample of input data
k	Previous periods in ARMA models, simulation periods in LOLE, capacity outage

Parameters and Variables:

a_k	Weighting coefficient in ARMA models on previous input k
b_j	Weighting coefficient in ARMA models on previous output j
c_i	Cost weighting associated with incorrect classification of x as class i
C_j	Level of aggregate generating capacity j, cluster mean j
d	Dimension of inputs in PNN model
D	Avg. in-service time per occasion of demand, period length in LOLE, LOLP
D_j	Residual demand level j of l demand levels
$e(t)$	Zero mean normally distributed white noise applied to ARMA models
$e(t-k)$	Zero mean normally distributed white noise at previous period k
E	Total energy demanded over period of study
E_k	Energy not supplied associated with capacity outage E_k
F_n	Fixed costs of generator n
h_i	Apriori probability that x is chosen from class i
k	No. of cluster means, no. of generators available, no. of generator offer blocks
L_i	Level of aggregate demand i
n	No. of capacity outage levels, no. of data points, no. of generators
n	Dispatched/available capacity of dominant supplier

n_a	No. of non strategic base load generators
n_b	No. of non strategic mid load generators
n_c	No. of non strategic peaking generators
n_d	No. of strategic base load generators
n_i	No. of input vector data samples associated with class i
N	No. of time periods, no. of simulation periods, no. of levels of capacity
N_0	No. of components that can fail that are tested
$N_s(t)$	No. of tested components surviving at time t
0_k	Aggregate capacity outage k
p	Probability of availability of individual generator in binomial
p_k	Probability of capacity outage 0_k
p_{D_j}	Probability of demand level D_j
p_{Q_i}	Probability of supply capacity level Q_i
P	Probability operator
P_{avail}	Probability of availability
$P_{unavail}$	Probability of unavailability
P_i	Offer price of energy block i
P_s	Probability of starting failure in 4 state Markov model
P_0	Probability of residing in state 0 in 4 state Markov model
P_1	Probability of residing in state 1 in 4 state Markov model
P_2	Probability of residing in state 2 in 4 state Markov model
P_3	Probability of residing in state 3 in 4 state Markov model
$P(n)$	Price at step n
$P(n-1)$	Price at step n-1
q	Probability of unavailability of individual generator binomial expansion
Q_i	Capacity level i

$Q_{a,i}$	Available capacity level i of from all generators type a
$Q_{b,i}$	Available capacity level i of from all generators type b
$Q_{c,i}$	Available capacity level i of from all generators type c
$Q_{d,i}$	Available capacity level i of from all generators type d
$Q_{n,i}$	Average dispatch of generator n as fraction of avail. capacity when prices $= P_i$
$R_{n,i}$	Availability of generator n when prices equal P_i
s	Time increment s
t	Time or time period
T	Average reserve shutdown time between periods of need in 4 state Markov model
T_i	No. hours/year where prices equal P_i
V_n	Variable costs of generator n
x_{ij}	Input sample vector j associated with class i in PNN
X	Random variable X
Δt	Duration of time step
λ	Failure rate
μ	Repair rate
σ_i	User defined smoothing parameter in PNN

Abbreviations:

AESO	Alberta Electric System Operator
AR	Auto-Regressive model
AR(2)	Auto-Regressive model with 2 autoregressive terms
AR(4)	Auto-Regressive model with 4 autoregressive terms
ARMA	Auto-Regressive and Moving Average model
ARMA(3,2)	ARMA model with 3 autoregressive and 2 moving average terms

Avg.	Average
CC Gas	Combined Cycle Gas generators
CF	Capacity Factor
CO2	Carbon dioxide
CSF	Conjectured Supply Function
EIR	Energy Index of Reliability
Elect.	Electricity
Emiss.	Emission intensity (tonnes/MWh)
FC	Annual Fixed Costs of a unit of capacity of a peaking generator
Fix Cost	Fixed Cost
Gen.	Generation
Gj	Gigajoule
GHG	Greenhouse gas
GWh	Gigawatt-hour
Hrs	Hours
Inflex.	Inflexible
IPP	Independent Power Producer
LF	Load Factor
LOEE	Loss of Energy Expectation
LOEP	Loss of Energy Probability
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
MAPE	Mean Average Percent Error
MC	Marginal Cost
MCP	Market Clearing Price
MW	Megawatt

MWh	Megawatt-hour
Mt	Megatonnes
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NERC	North American Electric Reliability Corporation
No.	Number
Observ.	Observed
O+M	Operating and Maintenance
PC	Price Cap
pdf	Probability density function
Pk Dem.	Peak Demand
PNN	Probabilistic Neural Network
SC Coal	Supercritical Coal fired generators
SFE	Supply Function Equilibrium
Var. Cost	Variable Cost
VoLL	Value of Lost Load
Wind	Wind generators
Yr	Year

Functions:

$E(x)$	Expected value of x
$f(t)$	Failure density function of t
$f(x)$	Probability density function of random variable x
$f_i(x)$	Estimated probability density function of random variable x for class i
H	No. of hours per year prices set by price cap

${}_nC_k$	No. of combinations of k out of n
$p_i(x)$	Probability that x is part of class i
P_k	Probability of k of n units being available in binomial expansion
$Q(t)$	Probability of component failure in time t
R	Objective function to be minimized in K means algorithm
R_{ij}	Output of node j associated with class i in pattern layer of PNN
$R(t)$	Reliability of a component as a function of time
T	Transpose operator
$y(t)$	Output of AR or ARMA model at time t
$\lambda(t)$	Failure rate or instantaneous hazard rate as function of t

Chapter 1

Introduction

1.1 Overview

In deregulated electricity markets, electricity prices, reliability of supply, and generation development are no longer centrally planned but emerge from the interplay between market participants whose behavior is influenced by physical operating constraints, changing cost structures, transmission tariffs, uncertainty in supply and demand, the design of the market, and market rules [3]. Challenges in these markets are anticipating future electricity prices [4,5], reliability of supply [6–10] and the coordination of regulated (and centrally planned) transmission expansion with deregulated (and market driven) generator development [11–14].

Accurate forecasts of electricity prices and reliability of supply must consider the behavior of suppliers in the context of the market design and market rules. Uncertain hourly variation in demand and supply and the inability to economically store electrical energy gives rise to changing opportunities for suppliers and loads with differing sizes, cost structures, operational constraints, and objectives to profitably modify their behavior [15–29]. The behavior of participants can significantly impact prices, investment in new generation, the need for transmission expansion, and the long term reliability of supply [15].

Anticipating future prices, generation additions, and reliability of supply are important to planning the efficient expansion of the electric system because both transmission and generation investments are non portable, long lived assets with high capital costs which have long lead times for approval and construction [2].

The focus of this thesis is anticipating medium and long term electricity prices and reliability of supply in deregulated energy-only electricity markets considering both the large scale integration of wind generation and other inflexible generation and the strategic behavior of other flexible generators. Three areas of interest are investigated. First, the effects of the large-scale integration of wind powered generation in energy-only electricity markets on the fixed cost recovery of existing conventional generators and the ability of existing conventional generators to profit from economically withholding energy is evaluated. In the second part of the thesis, a general model of long term equilibrium in energy-only electricity markets that allows for generation additions and retirements is developed and applied to determine the distribution of electricity prices and reliability of supply at equilibrium assuming competitive, inflexible, and strategic generator behaviors. In the third part of the thesis, Probabilistic Neural Networks (PNN) are applied to modelling complex individual generator behaviors which are integrated in simulations of existing energy-only markets to anticipate prices, the likely entry of new generation, reliability of supply, and emissions in the medium term.

1.2 Literature Review

1.2.1 Review of Previous Work on Modelling Wind Generation

To study the potential impact of the large-scale integration of wind generation on prices and reliability of supply, realistic long term time series of future wind generation at individual sites as well as for the system as a whole are required [30–36].

Previous publications have proposed methods to simulate time series of hourly wind generation. In systems with existing wind generation, future time series of wind generation have been modelled by simply scaling historical outputs [37]. This approach will not anticipate how future wind generation scenarios will affect the overall volatility of wind generation output.

To model wind generation at future sites that capture the mean, variance, and autocorrelation of observed wind speeds over time, time series of wind speeds at individual sites have often been modelled. [30–36,38,39]. In [30,34–36,38,39] the resulting time series sequence is applied to a wind turbine generation model to create a time series of an individual generator power output.

In [38], the hourly mean wind speed and standard deviation for every hour of the year at a particular site are specified and sequences of hourly wind speeds are simulated by randomly selecting values from a normal distribution with the specified mean and standard deviation. In this study, it was not shown that this approach could capture the significant auto-correlation of wind speeds that have been observed [30–33].

In [30], a Weibull distribution function is used with an Auto-Regressive model (AR) that relates the current wind speed to the wind speed in the previous hour. This is combined with 24 estimated diurnal cycle factors per month. A method is also described to model the output from an array of wind generators where the time space correlation of wind speed between sites is specified. However, the correlation is assumed to be the same between all sites. In this study the model also understated the higher order auto-correlation.

AR models with terms corresponding to time lags of one hour and 24 hours were developed in [31]. These models require extensive site specific historical data to derive values of the mean wind speed and standard deviation in wind speed for each hour of the year.

In [32], the use of an Auto Regressive (AR) model where the wind speed at time t is dependent on the wind speed in the previous two time periods (AR(2)) was investigated to model wind speed at a single site. Seasonal variation was captured by dividing the yearly data into twelve one month series and creating twelve AR(2) models. Diurnal variations were not captured by this model.

In [33], the wind speed at a site is modelled using an Auto-Regressive and Moving Average (ARMA) model where the wind speed at time t is related to a moving average of previous inputs modelled as noise and a weighted sum of previous wind speeds corrupted by noise. In [33], the hourly mean and standard deviation in wind speed for each hour of the year were extracted from a thirty seven year database of wind speed. Higher order AR models which dispense with moving average inputs of noise were considered as substitute for the ARMA models. ARMA(3,2) models, which consider the wind speed at time t to be related to a moving average of the past two input values modelled as noise and a weighted average of the past three wind speed measurements were developed. Substitute AR(4) models which consider wind speed in the past four time periods were also developed using one year of wind speed data. However, the AR(4) models did not capture seasonal and diurnal variations.

In [34], time series of the generation output for two disparate wind generation facilities were modelled and the correlation between the two facilities was assumed. Studies of generating capacity adequacy with time series models of two and three wind generation sites with uncorrelated outputs are presented in [35], where significant differences in adequacy were found if the wind generation is modelled as a single site.

In [36], time series of the generation output for two wind generation sites were modelled and the correlation between them varied. A trial and error process was proposed to generate correlated time series outputs between the two wind generation sites. Such a process may be onerous when correlations between many sites must be modelled.

In [39], a technique is presented to synthesize time series of hourly wind speed at one site by adjusting hourly data from another site. Adjustments are made to reflect differences in generator hub height as well as mean wind speed. This method avoids the need to use ARMA models but relies on the similarity of wind regimes at two different sites.

In [40], a time series of the overall wind power generated by all wind generation facilities in a region is modelled based on the observed characteristics of existing generation.

In [41], a common ARMA model is developed that can be applied to multiple wind generation sites provided the annual mean wind speed and standard deviation in hourly wind speeds are known.

In [42], a time series model is derived that avoids the need for historical wind speed data and for generator wind turbine models and instead relies on modelling future wind generation facilities based on analysis of the historical MW outputs from existing wind generators. The model captures the annual average output, regular seasonal and diurnal variations, uncertainty in output from hour to hour, and correlations between outputs of different plants.

1.2.2 Review of Previous Work on Impact of Adding Large Amounts of Wind Generation to Existing Power Systems

Some previous works have looked at the impact of adding large amounts of wind generation to existing power systems. These papers primarily focus on the impact on the wind generators. In [43], the impact of adding wind generation to a model of the existing German power system was investigated. The study looked at the amount of wind generation that could be profitably deployed from the perspective of a wind generator. Among other things, this study showed that the large-scale introduction of wind generation into the German power system could result in significantly lower electricity prices and reduced probabilities of load interruption. In their study, the authors assumed perfectly competitive behavior of dispatchable conventional generators.

In [44], the value of adding wind generation to power systems in terms of possible reductions in the overall cost of supply was evaluated. Wind generation was considered to be one of several types of generation available to meet the demand. It was shown that the value of wind generation could be calculated from the average system marginal cost, the capacity factor of the wind generator, and the covariance between the hourly power output from the wind generation and the hourly system marginal cost. The total costs of generation were compared for cost minimizing generation mixes including and excluding wind generation. To add value, wind generation must be able to economically displace other generation types. If it cannot, wind generation would be excluded from a cost minimizing mix of generation types to serve the load and any addition of wind generation would only serve to increase total generation cost.

With the assumptions made in [44], the addition of wind generation reduced overall cost and acted to change the cost minimizing generation mix by displacing base loaded generation in favor of mid load or intermediate generation. In this case, much of the value of wind generation came from avoiding the fixed costs of other generation types that were displaced. However, when wind generation is added to existing systems these savings may not be fully realized. Total costs may rise if the costs arising from the addition of wind generation are not offset by cost savings from retirement of existing generators. Aside from changes in total generation costs, the addition of wind generation in deregulated markets may have significant distributional impacts in the medium term on the cost of energy to loads and the revenue received by existing non-wind generators.

In [45], the relationship between wind power generation and electricity prices in a simulated market environment was investigated. The authors used historical data from the Austrian and German power systems to create a stylized model of a power system. The authors' simulations indicated that assumptions around the share of load served by wind generation, the supply curve from other generators, the variance of the wind power generation, and the correlation between the wind power generation and demand all significantly affect the revenues and hence the market value of wind generators.

Like in [43], the analysis in [45] also found that the introduction of wind generation tends to lower electricity prices. In [45], the authors also found that the average revenues per MWh achieved by wind generators are lower than that achieved by conventional base load generators. Further, they found that market value of incremental additions of wind generation decreases with increasing levels of wind generation.

Adding wind generation can impact both prices and reliability of supply. The reliability of supply relates to the adequacy of installed generating capacity to meet demand in all hours. As shown in [43–45], the impact of adding wind generation on electricity prices and on reliability of supply is influenced by the capacity and mix of generation types supplying the demand prior to the introduction of wind. To remove the effects of assuming an existing system that is under supplied, over supplied or has a suboptimal mix of generation types to minimize the cost of supply, a system where the capacities and mix of generation types to serve the load are optimized to minimize the cost of supply was chosen as a starting point for the analysis in Chapter 3 of this thesis.

1.2.3 Review of Previous Work on the Cost Minimizing Mix of Generator Types to Meet a Given Load

Previous papers have dealt with the general problem of determining the cost minimizing mix of generator types to meet a given load [5, 46, 47]. Early papers assume a context of a single utility that is seeking to minimize the cost of generation needed to supply the load. As an example, in [46] the authors proposed a method that extended the classical screening curves approach to incorporate capacity constraints on existing units. In [47], the authors looked at determining the cost minimizing generation mix with the inclusion of some Independent Power Producers (IPPs) and constraints on emissions. Price duration curves, which arise in deregulated markets, were not considered in these papers.

In [5], generation expansion in a deregulated market was examined. The installed generation in Queensland, Australia was compared to a cost minimizing portfolio of base, intermediate, and peaking plant to meet the load with the conclusion that, in the case studied, the deregulated market has led to too much base load plant being installed relative to peaking plant. Simulations show this leads to lower prices in the short run, but that the lower prices may fail to facilitate the entry of peaking plant leading to price spikes and a deterioration in reliability.

1.2.4 Review of Previous Work on Generator Responses to Uncertainty in Demand

Because wind generators have low variable costs and unpredictable outputs, they often operate as price takers and this introduces a significant source of uncertainty in the residual demand seen by other generators. This uncertainty in residual demand may affect the ability of in merit dispatchable conventional generators to profitably withhold supplies under different supply conditions.

Several papers have been written on electricity supply curve responses to demand with uncertainty [4, 17–21, 23, 48]. These papers show that multiple market equilibriums may exist and determining these equilibrium points may be challenging. In general, in the face of uncertainty, suppliers are to varying degrees able to extract prices above the marginal cost that would be expected in a fully competitive market.

In [17], it was argued that with uncertainty in demand, firms will not compete on the basis of quantity or price alone but will offer supply functions of quantity and price that optimize their outcome given a residual demand. Without uncertainty in demand, there is a multiplicity of Nash equilibrium in such supply functions. However, with uncertainty in demand, a unique Nash equilibrium emerges.

In [18], a model was constructed of an electricity market with a limited number of suppliers who can offer a single bid each and model demand as either certain or as being one of three discrete demand outcomes with fixed probabilities. The authors found Nash equilibrium values of electricity market prices and showed that the outcome may not reflect marginal cost offers by suppliers.

In [19], a computer simulation was used to evaluate the performance of competitive markets for electric power. They found that price volatility increases if uncertainty in demand is present and suppliers are paid standby costs regardless of whether the supplier is dispatched.

A work in [20] considered bidding strategies of multi-plant producers as well as uncertainty in demand and costs. The authors' results showed that producers who may set prices were incented to bid shade (i.e. offer at prices just below their next competitor).

In [21], a multi-agent system was employed to model a wholesale electricity market with six equally sized suppliers with different variable costs and demand equal to the combined capacity of five of the suppliers. Agents for each firm submitted price and quantity offers to maximize profits based on estimates of the residual demand curve for each supplier. In their model, firms that began as price takers learned to be speculators and suppliers exhibited greater withholding when there was less uncertainty in demand.

The work reported in [23] examined the impact of uncertainty of demand on incentives for generators to exert market power through tacitly colluding with the conclusion that the probability of submitting a high bid by generators is increased as demand increases (and the likelihood that a generator will have market power increases) and as the probability that other generators will submit a high bid.

In [48], the authors considered electricity prices that emerge when the suppliers are assumed to offer energy at marginal cost and when suppliers offer quantities based on a Cournot model. As would be expected, this model showed market prices were higher when offers were based on the Cournot model.

The work in [4] considered uncertainty in both supplier availability and in demand and computed the market prices that resulted from Bertrand, Cournot, and Supply Function Equilibrium models. As might be expected, prices increased as the number of competitors decreased.

1.2.5 Review of Previous Work on Generator Behaviors, Electricity Prices and Reliability of Supply in Energy-Only Markets

In the long term, it has often been assumed that electricity prices would be reflective of a competitive market. In these models, it is assumed generators offer energy at marginal cost and, over time, will just recover all fixed and variable costs [6,49]. In energy-only markets, fixed costs are recovered when generators are dispatched and market prices exceed the individual generators marginal cost.

In competitive markets without capacity payments, the recovery of supplier's fixed costs is related to the reliability of supply [6]. The reliability of supply relates to the adequacy of installed generating capacity to meet demand in all hours. Measures of reliability of supply include Loss Of Load Expectation (LOLE) and Loss Of Load Probability (LOLP) which measure the expected number of hours over a period such as a year when available generation will be insufficient to serve the demand and Loss Of Energy Expectation (LOEE) and Loss Of Energy Probability (LOEP) which measure the expected energy not served per year in total and as a percentage of total energy demanded [50]. Of these measures, LOLP relates to the recovery of suppliers fixed costs in competitive markets.

With price caps, and the fixed and marginal costs and availability of peaking generators that are commonly encountered, the LOLP necessary for peaking generators to fully recover their fixed costs is much higher than the LOLP standards previously applied by regulated utilities [8] (one day in ten years or 2.4 hours/year is given in [9, 10]). This has led to the concern that the emergent reliability of supply in energy-only markets may be inadequate [8, 9].

However, electricity prices in markets have often been observed to be significantly above marginal cost [16]. To better explain energy-only electricity markets, some analysts have proposed that electricity prices are better described by an oligopoly model of Cournot [6] competition where suppliers compete on the basis of volumes rather than price [4, 28]. In this model, suppliers assume that the volume offered by others is fixed and then adjust the volume they offer to maximize their profit on the residual demand. Prices are set by the intersection of the total volume offered with the demand curve. In these models, equilibrium prices reflect a mark-up from marginal cost and are higher than those predicted by a perfectly competitive market. However, the reliance on the demand curve to set prices in Cournot models is problematic in electricity markets because short term demand is widely regarded as being largely inelastic and unresponsive to price [6,15]. As a result, even with a relatively large number of suppliers and reasonable estimates of elasticity of demand, price estimates based on the Cournot model are generally higher than what has been observed [16].

Another model that has been put forward is the Supply Function Equilibrium (SFE) model [17]. This model argues that with uncertainty in demand, firms will not compete on the basis of quantity or price alone, but will offer supply functions of quantity and price that optimize their outcome given a residual demand. Without uncertainty in demand, there is a multiplicity of Nash equilibria in such supply functions. However, with uncertainty in demand, a unique Nash equilibrium emerges when a symmetric oligopoly is considered [17]. At equilibrium, the prices predicted by the SFE model are generally above those predicted by a perfectly competitive market. In practice SFE models have been difficult to implement for large systems with a significant number of generators with limited capacity [27]. A difficulty with SFE models is that the supply functions are assumed to be smooth and continuously differentiable [51]. In electricity markets, this is usually not the case. Instead, suppliers make offers in blocks of price and quantity which create step supply functions.

In [51], step supply functions are considered and it was shown that the SFE equilibria found when assuming a continuously differentiable supply function cannot be generalized to a step supply model. It was also shown that pure strategy equilibria may not exist when considering a step supply model.

In [27], Conjectured Supply Functions (CSF) are used to model electricity prices. These are based on the premise that suppliers conjecture that an increase in their supply will elicit a response from others. Individual suppliers hold conjectures or beliefs that influence their offers. This approach is limited in that the conjectures held by firms are arbitrary and may not reflect the actual response. Secondly, it is implausible to assume that suppliers will continue to hold conjectures that are inconsistent with observed outcomes over multiple periods.

In [18], the authors construct a model of an electricity market with a limited number of suppliers who can offer a single bid each and model demand as either certain or as being one of three discrete demand outcomes with fixed probabilities. They find that the equilibrium values of electricity market prices may not reflect marginal cost offers by suppliers, that there may be multiple Nash equilibrium solutions, and the equilibrium clearing price may not be unique.

In [24], Nash equilibria are found for markets characterized by step supply functions assuming a single shot game. In this case, it was shown that if suppliers follow pure strategies, multiple Nash equilibria can exist. It was also shown that situations exist where suppliers can improve their profit from gaming as opposed to acting competitively. However, in these same situations, profits can be even higher to an individual supplier if other suppliers game while it does not game. In these situations, the expected market outcome is ambiguous. In these cases, the genco may not maximize its profits by adopting a strategy to always game or to always not game. If a genco chooses to always game, it forgoes the possibility of higher profits that would occur if it did not game and another genco were to game. If the generator chooses to always not game, it runs the risk of no genco choosing to game and profits being lower than they could have been if it had chosen to game. To maximize profits a mixed strategy where the genco chooses to game or not in a given period or instance with a certain probability could be adopted. In these instances gencos cannot know with certainty what competing gencos will do.

In other research, efforts have been made to anticipate prices using market simulations to evolve offer strategies of participants. In [52], genetic algorithms are used. The advantages of this approach are that the simulations can reflect observed market outcomes, but the results may not always reflect equilibrium strategies. Further, in the case where multiple equilibrium strategies may exist, the simulation may not reveal all alternative outcomes.

In general, studies of equilibrium prices have assumed a single shot game with a common objective function to maximize profit to individual generators. However, since electricity markets are repeated games, some suppliers may learn to tacitly collude [23] if by doing so their profitability can be improved. Further, the behavior of participants may be influenced by their obligations to supply [6]. If present, these features can be expected to influence future prices.

In the long run, prices that are higher than competitive levels should lead to entry of new generation and downward pressure on prices. Some work has been done on long term equilibrium prices considering the possible strategic and/or collusive behavior of participants when entry or new generation capacity or exit of existing generation capacity is considered [3, 53–56].

In [53], the authors consider a generation expansion process where decisions on new generation additions at a single point in time are made with a modified Cournot model. It is assumed that each players expansion plans are known to other players. In this simulation, strategic behavior in the operation of the generators is not considered. All players are assumed to offer all capacity at marginal cost. The decision for expansion is to decide on the quantity of new capacity to be added.

In [54], the authors simulate both the operations and expansion problem using Cournot models. In these studies, the hourly demands are assumed to be represented by a set of shifting demand curves, each with the same slope but differing intercept values. Because the Cournot model assumes an elastic demand curve, load is price responsive and there are no periods when customers are involuntarily interrupted. Hence there is no loss of load probability and traditional calculations of reliability of supply are no longer possible or relevant.

In [55], an agent based model is used to anticipate operational outcomes and generation expansion. The agents are not assumed to know other agents bidding strategies. Instead, each agent relies on conjectural variation based bidding strategies and incorporate a learning capability. An assumption is made with regard to the expansion plans of others. Based on this, the individual generator formulates its optimal expansion plans. It is indicated in the paper that LOLP values are calculated but the values are not given and the change in LOLP during expansion is not discussed. This approach relies heavily on conjectured responses of others that may or may not reflect actual outcomes.

In [56], a model of the long term dynamics of electricity markets is developed. In this model, the market development is assumed to follow a causal loop where current spot prices influence expectations for future prices which in turn affects expectations for future profitability and drives investment decisions leading to capacity additions and retirements. The resulting installed capacity and demand then determine prices and the loop repeats. The model assumes time delays between investment decisions and new capacity additions. Investment decisions are assumed to be follow a logistic function of the current profitability outlook. In this model, markets are assumed to be competitive with all generation offering all available energy at marginal cost. Strategic behavior of participants and its effect on price is not considered. The model predicts long term cyclic outcomes for generation capacity in relation to demand and hence cyclic variations in reliability of supply. A general deterioration in reliability of supply over time is also predicted. However, the cyclicality of the capacity and the decline in reliability over time are dependent on the assumptions made for model parameters and of investors reaction to prices in forming their investment decisions.

1.3 Research Objectives and Motivations

In deregulated power systems, anticipating future system development is important to system planners and policy makers. This thesis concerns anticipating prices, reliability of supply, and emissions in energy-only markets in the medium and long term considering both the large-scale integration of wind generation and other inflexible generation and the strategic behavior of other flexible generators.

1.3.1 The Medium and Long Term Impacts of Wind Generation on Load and Conventional Suppliers

Around the world, interest in wind generation is increasing. The American Wind Association reported that globally over 27,000 MW of new wind generation capacity was added in 2008. This was 36% more than in 2007 and represented a 28.8% increase in capacity in one year [57]. In some cases, the additions contemplated can be large in relation to the existing load. In Alberta, Canada, interest has been shown in connecting over 5500 MW [58] of new wind generation to a system with a peak demand in 2011 of 10226 MW [59]. In cases such as this, the addition of large amounts of wind generation will affect the shape of the residual demand served by dispatchable conventional generators and will likely result in an increasing discrepancy between the mix of generation that minimizes the cost of serving the demand and the mix represented by the existing generation. Wind generation is also characterized by uncertainty. This uncertainty will be reflected in the residual demand seen by other generators and may motivate changes in the behavior of dispatchable conventional generators.

Chapter 3 of this thesis examines the effects of large-scale integration of wind powered electricity generation in a deregulated energy-only market on medium term electricity prices, reliability of supply, the ability of a dispatchable conventional supplier to exercise market power, and the fixed cost recovery of dispatchable conventional suppliers. In this analysis, medium term refers to the time frame following the introduction of wind generation, but before structural changes to the capacity and mix of generation technologies can be affected. Unlike [43, 45] the work focuses on the market impact of the large-scale integration of wind generation operating in a deregulated market on load and dispatchable conventional generation rather than on the wind generation itself. The impacts on the load dealt with are the effect on prices and effect on reliability of supply.

A contribution of the work in Chapter 3 of this thesis is an evaluation of the changes in the opportunities for a dispatchable conventional generator, acting strategically in an energy-only market, to exercise market power by economically withholding supplies following the introduction of wind generation. Another contribution is an analysis of the effect of wind generation, in an energy-only market, on the fixed cost recovery of dispatchable conventional suppliers.

1.3.2 The Effect of Wind Generation and Strategic Behavior on Long Term Market Equilibrium Prices, Reliability and Emissions

Anticipating the long term equilibrium behavior of generators in deregulated power systems is important to anticipate future system reliability, emissions, and electricity price characteristics. In general, equilibrium models of electricity markets are varied and complex [60]. Most models are concerned with short term equilibrium and do not consider additions or retirements of generation. Long term equilibrium is complicated by the prospects for the large-scale integration of inflexible generation such as wind.

Chapter 4 of this thesis examines the effects the integration of wind powered electricity generation and other inflexible generation in a deregulated energy-only market on long term equilibrium electricity prices, reliability of supply, and emissions. In this chapter, long term refers to equilibrium states where any structural changes to the capacity and mix of generation technologies have been realized. A long term equilibrium model that considers additions or retirements of generation is developed. Consideration is given for a market with competitive generators, inflexible generators, and a strategic generator.

The proposed model differs significantly from other models of equilibrium and long term development. It neither assumes a Cournot game for the generation expansion process [53, 54] nor the operation of the market [4, 28] and importantly there is no dependence on demand response to set prices. Unlike the Supply Function Equilibrium (SFE) model [17], the proposed model allows for generator offers that are made in discontinuous steps. Unlike the Conjectured Supply Function (CSF) model [27] the proposed model is not reliant on conjectured responses of others. Finally, unlike [56] the proposed model is not reliant on a detailed model of the long term dynamics of electricity markets.

A contribution of the work in Chapter 4 is demonstrating that under assumptions of competitive or inflexible behavior by suppliers, long term equilibrium electricity price duration curves and reliability of supply associated with a traditional cost minimizing mix of generation [6] are independent of the load shape, or the amount or production pattern of inflexible generation such as wind generation on the system.

A second contribution is showing how consideration of a strategic supplier provides an explanatory mechanism of market operation that can lead to large improvements in expected reliability of supply, a radical change in the generation mix, and a large change in expected emissions.

1.3.3 Anticipating Prices, Reliability, and Emissions in the Medium Term

Forecasts of future prices and reliability of supply have often assumed perfectly competitive behavior [6, 49]. However, it has been observed that market prices have often not been reflective of competitive markets [15, 16]. Prices that are both below and above reasonable expectations of suppliers marginal costs are commonly observed. These can be caused by operational constraints (minimum loading levels, generator ramp rate limitations, transmission constraints or out-of-market reliability dispatches), tariff structures, scarcity, differing objectives, or strategic and/or collusive behavior of participants. Prices and dispatch affect individual generator cost recovery [6] and the investment in new generation capacity of different types. The installed type and amount of generation capacity in relation to demand governs the resultant reliability of supply to loads [50]. While a significant amount of work has been done with regard to modelling short term electricity prices from strategic behavior, [15–29] relatively little has been done on modelling the impact of participant behaviors on mid term prices, generation investment, and reliability of supply [55].

Chapter 5 proposes a method to model generator behaviors and anticipate electricity prices, entry of new generation, reliability of supply, and emissions in existing deregulated energy-only power markets over the medium term time frame associated with the build cycle for new generation. The proposed method differs from [55] in that existing generator behaviors are modelled on observed behavior and not based on conjectures of others' bidding strategies and no assumptions are made on generator expansion plans. Unlike [56], existing participants are not assumed to offer all capability at marginal cost and anticipated generation expansion is not dependant on a model of the investment process. Unlike [53, 54] generator expansion is not considered to be a Cournot game.

A contribution of the work in Chapter 5 is the application of Probabilistic Neural Networks (PNN) to the modelling of the observed behaviors of individual generators. A second contribution is development of a method that combines generator behavioral models in a market simulation to anticipate price signals for new generation to enter the market, the extent of entry of new generation, and the impact on prices, reliability of supply, and emissions in the medium term.

1.4 Structure of the Thesis

Chapter 2: Since this thesis deals in part with impacts of wind generation, a background discussion on modelling wind generation is given. Background information is also given on reliability of supply and indices used to measure it, the derivation of a general reliability function for components that can fail, representation of generator availability using Markov models, evaluating reliability of supply using Monte Carlo simulations, and expectations for reliability of supply in competitive energy-only markets. Finally, background information on K-means clustering techniques and Probabilistic Neural Networks (PNN) used in creating the behavioral models of generators proposed in Chapter 5 is discussed.

Chapter 3: The effects of large-scale integration of wind powered generation in energy-only markets on dispatchable conventional generation in the medium and long term are examined in this chapter. The impacts on prices, the profitability of conventional generators, and reliability of supply are considered. A focus is given to the impact of wind generation on the ability of dispatchable conventional suppliers to profit from economically withholding energy.

Chapter 4: In this chapter, long term electricity prices, reliability of supply, and emissions in markets with competitive and inflexible generators and with a dominant low cost strategic supplier are evaluated using an equilibrium model based on the premise that at equilibrium all generators neither take a loss or make a profit.

Chapter 5: Chapter 5 deals with the expectations in the medium term for electricity prices, entry of new generation, reliability of supply, and emissions in existing energy-only markets.

Chapter 6: This chapter summarizes the main contributions and conclusions of this thesis.

Chapter 2

Background Review

2.1 Introduction

In this thesis, several methods and techniques are used to model wind generation, evaluate reliability of supply, and to model generator behaviors.

In this chapter, background information is given on the modeling of wind generation using ARMA models [30,34–36,38,39,42], reliability of supply, the derivation of a general reliability function [50], Markov processes and their application to modeling generator unavailability as a stochastic process [50, 61], and the use of Monte Carlo methods in combination with Markov models in evaluating Loss Of Load Probability (LOLP) as a measure of reliability of supply [61]. Background information is also presented on K-means clustering techniques [62] and Probabilistic Neural Networks (PNN) [63] that are used in models of generator behavior proposed in Chapter 5 of this thesis.

2.2 Modeling Wind Generation

This thesis concerns itself with the impact in the medium and long term of the large-scale integration of wind generation and other inflexible generation on prices, reliability of supply, and emissions.

The modeling of wind generation is not a claimed contribution of this thesis. However, to evaluate the impact of wind generation, a model of wind generation is required that accurately depicts key attributes on a system-wide aggregate basis. The need to capture the salient features in models of wind generation and the availability of historical data motivates the type of analysis that is needed.

Previous works have sought to model the MW output from future wind generators by creating models of wind speed based on historical wind speed data and then applying the sequential models of wind speed to a generator wind turbine model [30, 34–36, 38, 39]. In this thesis, a chronological time series model of wind generation as described in [42] with an expected annual average output, regular seasonal and diurnal variations, and uncertainty in output from hour to hour is used. The model used avoids the need for historical wind speed data and for generator wind turbine models. Instead, it relies on modeling future wind generation facilities based on analysis of the historical MW outputs from existing wind generators.

The wind model used in this thesis filters the annual mean value as well as seasonal and diurnal variations from the data prior to further analysis. In the case of wind speed and power output from wind generators, the residual time series $y(t)$ typically exhibits an autocorrelation that decays over several hours [30–33]. To model this, Auto-Regressive and Moving Average (ARMA) models of the form shown in Equation (2.1) are often used. [31–36]:

$$y(t) = \sum_{j=1}^{n} b_j y(t-j) + e(t) + \sum_{k=1}^{n} a_k e(t-k), \quad t = 1, 2, \ldots, N \tag{2.1}$$

The ARMA model (2.1) reduces to an Auto-Regressive (AR) model if the coefficients a_k in the second summation term are set to zero. If the residual time series $y(t)$ is known, appropriate ARMA models can be readily determined using established system identification techniques and tools [33, 64, 65]. As found in [42], for wind generation in Alberta, $y(t)$ can be modelled as an AR(1) model with coefficient $b = 0.967$ and the variance of the noise $e(t)$ equal to 0.012 expressed as a per unit of installed wind capacity.

When modeling several wind facilities on a power system it is necessary to consider how the output of the each facility is correlated to the outputs of all other wind facilities modelled on the system [30, 34, 36]. In general, the volatility in the output of aggregate wind generation is reduced as the correlation between outputs at individual wind facilities is reduced. As described in [42], the benefits of reduced volatility in the aggregate output of all wind generators are largely realized with the first ten facilities installed. For systems with several existing wind facilities, such as Alberta, the volatility of total wind generation in relation to the installed capacity is not expected to vary significantly as new wind generation facilities are added.

2.3 Reliability of supply

Anticipating the reliability of supply of existing power systems in the medium and long term is a goal of this thesis.

Reliability of supply is often related to concerns with the adequacy and security of generation and other supplies. Adequacy addresses whether there are sufficient resources to meet the demand and satisfy operational constraints. Security relates to the ability of the system to respond to disturbances on the system [61]. In this thesis, the reliability of supply relates to the adequacy of installed generating capacity to meet demand in all hours.

The requirements for generating capacity are usually evaluated over both short term and long term time frames. Over the short term, the requirements for generating capacity to respond to unanticipated generator outages or derates and errors in forecast hourly load are usually governed by codified operating standards. A static evaluation of the reliability of supply relates the adequacy of installed generation capacity to meet forecast demand over longer terms.

In general, the installed type and amount of generation capacity in relation to demand governs the resultant reliability of supply to loads [50] and the installed capacity must exceed anticipated peak demand because demand may exceed forecast and generators and other supplies may be unavailable due to planned maintenance outages as well as forced and other unplanned maintenance outages [61].

Various indices have been developed to measure the reliability of supply. These include Reserve Margin, Loss Of Load Expectation (LOLE) and Loss Of Load Probability (LOLP), Loss Of Energy Expectation (LOEE) and Loss Of Energy Probability (LOEP), and an Energy Index of Reliability (EIR) [50, 61]. Many of these indices relate to each other. Each is now discussed.

2.3.1 Reserve Margin

A traditional practice has been to measure adequacy by the percentage of installed capacity over annual peak demand. Intermittent resources such as wind and solar generation are commonly excluded from the calculation [66]. This has commonly been called the Reserve Margin (2.2). While popular, this measure has many shortcomings because it treats all generating capacity included in the calculation equally. However, the adequacy of the installed generating capacity to meet the load varies significantly depending on the size, type, availability, and maintenance requirements of different generators in the system. The Reserve Margin is also a poor measure of the ability of installed generation to serve demand in other hours than the peak demand hour [50].

$$\text{Reserve Margin} = \frac{\text{Installed Capacity (MW)} - \text{Annual Peak Demand(MW)}}{\text{Annual Peak Demand(MW)}} \text{ x } 100\% \tag{2.2}$$

2.3.2 Loss of Load Expectation and Loss of Load Probability

Widely used measures of reliability of supply are Loss Of Load Expectation (LOLE) and Loss Of Load Probability (LOLP). The basic method for evaluating the reliability of supply is to compare the hourly demand to the level of available generation and other supplies such as imports. Because generators are subject to random failures, there is a probability in any time period that one or more generators will be unavailable. If the size of each generator and the probability it will be available are known, a table can be created which calculates the probability that different possible levels of aggregate generating capacity C_j will be available [50]. The reliability of supply is evaluated by a numerical convolution of the load distribution and the available capacity distribution that compares the demand in each period L_i to the levels of available capacity C_j specified by the capacity table [50] [61]. When the available capacity falls short of the demand, some demand is not served. The frequency of unserved demand is weighted by its probability of occurrence P and the result is summed for all periods over some period k as shown in (2.3). The result is a measure of the expected Loss Of Load Expectation (LOLE) expressed in hours. When expressed as a fraction over the period it becomes the Loss Of Load Probability (LOLP) as shown in (2.4) [50]. When LOLE is evaluated over a year and LOLP is expressed in hours/year the values become the same.

$$\text{LOLE}_k = \sum_{i=1}^{k} P\left(\sum_{j=1}^{n} C_j < L_i\right) \tag{2.3}$$

where P is the probability operator.

$$\text{LOLP} = \frac{\text{LOLE}_k}{\text{Period}_k} \tag{2.4}$$

2.3.3 Loss of Energy Expectation and Loss of Energy Probability

The LOLE and LOLP calculations do not measure the energy that was not supplied when generation and other supplies were insufficient to meet the demand. The Loss Of Energy Expectation (LOEE) measures the expected energy not supplied in a period. The Loss Of Energy Probability (LOEP) measures the energy not supplied divided by the total energy demanded. If a capacity outage O_k with probability p_k results in the remaining generating capacity being less than the load for t_k hours over the period, then the energy not supplied E_k associated with capacity outage O_k is the sum of the demand that is greater than the available capacity after outage O_k for all hours in the period. If the product of E_k and the probability p_k is summed over all capacity outages k, the result is the Loss Of Energy Expectation (LOEE) expressed in units of energy as shown in (2.5). If the LOEE is divided by the total energy demanded over the period E, the result is the Loss Of Energy Probability (LOEP) as shown in (2.6). [50]

$$\text{LOEE} = \sum_{k=1}^{n} E_k . p_k \tag{2.5}$$

$$\text{LOEP} = \sum_{k=1}^{n} \frac{E_k . p_k}{E} \tag{2.6}$$

2.3.4 Energy Index of Reliability

LOEP is usually a very small number. Typical values are under 1%. In the case of Alberta, the AESO has estimated LOEE over a two year period in the range of 44 MWh to 1567 MWh [66]. Over a one year period, the estimated LOEE would range from 22 MWh to 783.5 MWh. The total annual energy load in Alberta has ranged from 69,914 GWh in 2009 to 73,602 GWh in 2011. This indicates an expected LOEP of between 0.0000224 and 0.000000299. Subtracting the LOEP from one yields a measure of reliability of supply termed the Energy Index of Reliability (EIR) (2.7). In the case of Alberta, the EIR would be between 0.9999776 and 0.999999701.

$$\text{EIR} = 1 - \text{LOEP} \tag{2.7}$$

2.3.5 General Reliability Function

To develop models to evaluate the reliability of supply, a general discussion of the reliability of components that can fail is needed.

A general derivation of the reliability of a component that can fail over time is given in [50]. In this derivation, a number of identical components N_0 is tested. $N_s(t)$ = Number surviving at time t and $N_f(t)$= Number failed at time t. The reliability as a function of time is then given as,

$$R(t) = \frac{N_s(t)}{N_0} = 1 - \frac{N_f(t)}{N_0} \tag{2.8}$$

and,

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = -\frac{1}{N_0}.\frac{\mathrm{d}N_f(t)}{\mathrm{d}t} \tag{2.9}$$

The failure density function $f(t)$ is,

$$f(t) = \frac{1}{N_0}\frac{\mathrm{d}N_f(t)}{\mathrm{d}t} \tag{2.10}$$

so,

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = -f(t) \tag{2.11}$$

If $\lambda(t)$ is the instantaneous hazard rate,

$$\lambda(t) = \frac{\mathrm{d}N_f(t)}{\mathrm{d}t}\frac{1}{N_s(t)} \tag{2.12}$$

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{-\mathrm{d}R(t)}{R(t)\mathrm{d}t} \tag{2.13}$$

so,

$$\int_0^t f(t)\mathrm{d}t = \int_1^{R(t)} -\mathrm{d}R(t) = 1 - R(t) \tag{2.14}$$

since,

$$\lambda(t) = \frac{-\mathrm{d}R(t)}{R(t)\mathrm{d}t} \tag{2.15}$$

$$\int_0^t \lambda(t)\mathrm{d}t = -\int_1^{R(t)} \frac{\mathrm{d}R(t)}{R(t)} \tag{2.16}$$

and,

$$R(t) = e^{-\int_0^t \lambda(t)\mathrm{d}t} \tag{2.17}$$

As noted in [50], this derivation makes no assumptions regarding the form of the failure function.

If the failure rate λ is constant over the time period t then,

$$R(t) = e^{-\lambda t} \tag{2.18}$$

therefore the probability of a failure in time t is,

$$Q(t) = 1 - e^{-\lambda t} \tag{2.19}$$

and the failure density function is given as,

$$f(t) = \frac{-\mathrm{d}R(t)}{\mathrm{d}t} = \lambda e^{-\lambda t} \tag{2.20}$$

This shows that with the assumption that the failure rate λ is constant over time, the reliability of a component over time is an exponentially distributed random variable. This is an important result for evaluating the reliability of a component. The assumption of a constant failure rate may not be valid for new components where problems are being remedied and failure rates are falling as they are rectified. The assumption of a constant failure rate may also not be valid for aged components that are wearing out and failure rates are increasing over time. However, it is commonly assumed that for power system components the failure rates remain constant over their economically useful lives [50].

An important feature of exponentially distributed random variables is that they are memoryless. To be memoryless,

$$P\{X > s+t|X > t\} = P\{X > s\} \tag{2.21}$$

For exponentially distributed random variables,

$$P\{X > s\} = e^{-\lambda s} \tag{2.22}$$

$$P\{X > t\} = e^{-\lambda t} \tag{2.23}$$

$$P\{X > s+t\} = e^{-\lambda(s+t)} = e^{-\lambda s}e^{-\lambda t} = P\{X > s\} P\{X > t\} \tag{2.24}$$

So, exponentially distributed random variables are memoryless.

Another important result is derived below. Since,

$$Q(t) = 1 - e^{-\lambda t} \tag{2.25}$$

A Taylor series expansion yields,

$$Q(t) = 1 - [1 - \lambda t + \frac{(-\lambda t)^2}{2!} + \frac{(-\lambda t)^3}{3!} + ...] \tag{2.26}$$

$$Q(t) = \lambda t - \frac{(-\lambda t)^2}{2!} + \frac{(-\lambda t)^3}{3!} + ... \tag{2.27}$$

If $\lambda t << 1$ then $Q(t) \approx \lambda t$ and $R(t) = 1 - \lambda t$.

This shows that if a device is observed to be operating, then the probability it will fail in the next time period t is closely approximated by λt provided $\lambda t << 1$.

Finally, since the probability that a component will survive in time t is an exponentially distributed random variable, the expected or Mean Time to Failure (MTTF) can be found. The expected value of a continuous random variable x with probability density function $f(x)$ is given by,

$$E(x) = \int_0^\infty x f(x)\mathrm{d}x \tag{2.28}$$

For a device that can fail the expected or Mean Time to Failure (MTTF) can be calculated as,

$$E(t) = \int_0^\infty \lambda t e^{-\lambda t}\mathrm{d}t \tag{2.29}$$

This can be integrated by parts.

$$\int u\mathrm{d}v = uv - \int v\mathrm{d}u \tag{2.30}$$

where,

$$u = t \tag{2.31}$$

$$\mathrm{d}v = \lambda e^{-\lambda t}\mathrm{d}t \tag{2.32}$$

then,

$$\int_0^\infty \lambda t e^{-\lambda t}\mathrm{d}t = \left[-te^{-\lambda t}\right]_0^\infty - \int_0^\infty -e^{-\lambda t}\mathrm{d}t \tag{2.33}$$

and,

$$E(t) = MTTF = \frac{1}{\lambda} \tag{2.34}$$

Similarly, for components that can be repaired, if the probability that a component that has failed will not be repaired in time t is an exponentially distributed random variable with repair rate μ, then the Mean Time to Repair (MTTR) is $\frac{1}{\mu}$.

2.4 Markov Models of Generator Availability

Markov processes have often been used to model generator availability over time [50, 61].

Markov processes are stochastic processes that map random variables over time to a set of states. Transitions between states in Markov processes are random events. The probability of transitioning from one state to another at some time t in the future is governed by transition rates that are constant over a time period. Markov processes can be used to determine over time the probability that the system will exist in each of the modelled states. A key feature of Markov processes is that the probability of transitioning from the current state to another state is independent of how the process arrived at the current state. This is often described as memoryless.

Generator failures are commonly assumed to be random events that occur over time. If the failure rate remains constant over time and without repair, generator availability can be modelled as an exponentially distributed random variable where the probability of failure over a time step is constant and is memoryless.

Likewise, the probability a failed or derated generator will not be repaired over time can be treated as an exponentially distributed random variable with the probability of repair over a time step is constant and memoryless.

Since both the availability and unavailability of a generator can be treated as exponentially distributed random variables that are memoryless, the availability of a generator over time can be modelled as a Markov process where generators are in one of a set of states at time t.

Markov processes can be either continuous or discrete time processes [50]. However,

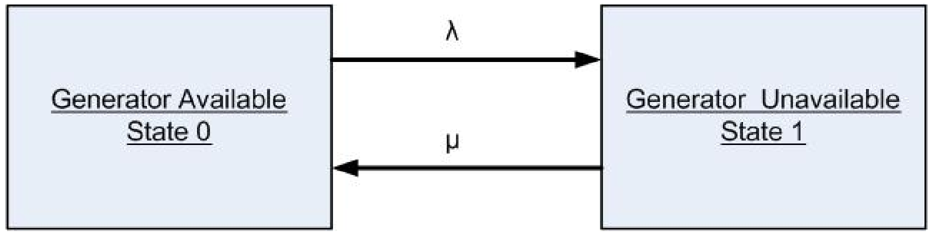

Figure 2.1: Two state Markov model of generator availability

generator availability over time is normally modelled as a discrete time Markov process with a finite set of states. In the simplest example, a generator can be modelled in one of two states, available or unavailable as shown in Figure 2.1. As shown in Section 2.3.5, if the failure rate λ is constant over an interval t and $\lambda t << 1$, the probability that a generator that is currently available will fail over time t into the future is simply given by λt. It follows that the probability that a generator that is currently available will remain available over time t is $1 - \lambda t$. Similarly, for a generator that is currently unavailable, if the repair rate μ is constant over an interval t and $\mu t << 1$, the probability that a generator will be repaired over time t is given by μt and the probability that the generator will remain unavailable over time t is $1 - \mu t$

If discrete time steps Δt are considered, the probability that a generator that is currently available will fail in the next time step is $\lambda \Delta t$ and the probability that a generator that has failed will be repaired in the next time step is $\mu \Delta t$.

If the state a generator is in at time t is known, then the probability of being in the observed state at time t is 1 and the probability of being in other states at time t is 0. The probability that the generator will be in each state after n time steps is then given by,

$$\begin{bmatrix} P_{avail}(t_n) & P_{unavail}(t_n) \end{bmatrix} = \begin{bmatrix} P_{avail}(t) & P_{unavail}(t) \end{bmatrix} \begin{bmatrix} 1 - \lambda \Delta t & \lambda \Delta t \\ \mu \Delta t & 1 - \mu \Delta t \end{bmatrix}^n \tag{2.35}$$

For the two state model, a limiting or steady state probability of finding a generator in the distant future in the available or unavailable state can easily be calculated if $\mu\Delta t$ and $\lambda\Delta t$ are known. At steady state, the probabilities of being in each state do not change over successive time steps. If $\Delta t = 1$ and both $\mu t << 1$ and $\lambda t << 1$ then,

$$P_{avail}\lambda - P_{unavail}\mu = 0 \tag{2.36}$$

Since the generator can only be available or unavailable, the sum of the probability of being available and the probability of being unavailable equals one.

$$P_{avail} + P_{unavail} = 1 \tag{2.37}$$

Therefore,

$$P_{avail}\lambda = (1 - P_{avail})\,\mu \tag{2.38}$$

$$P_{avail}(\lambda + \mu) = \mu \tag{2.39}$$

$$P_{avail} = \frac{\mu}{\lambda + \mu} \tag{2.40}$$

similarly,

$$P_{unavail} = \frac{\lambda}{\lambda + \mu} \tag{2.41}$$

In simulation studies, often the limiting or steady state probability that the generator will be available is estimated and the goal is to calculate μ and λ.

For base load generators, the Mean Time To Repair (MTTR) measured in hours can be estimated from the average duration that a unit is observed to be unavailable. The repair rate μ is then the reciprocal of the MTTR.

$$\mu = \frac{1}{MTTR} \tag{2.42}$$

If the steady state availability and Mean Time To Repair (MTTR) are assumed or known, the failure rate λ and repair rate μ can be calculated.

Since at steady state,

$$P_{avail} = \frac{\mu}{\lambda + \mu} \tag{2.43}$$

and,

$$P_{unavail} = \frac{\lambda}{\lambda + \mu} \tag{2.44}$$

then,

$$\lambda = \frac{\mu P_{unavail}}{P_{avail}} \tag{2.45}$$

In many studies, two state models such as shown in Figure 2.1 are used and are considered adequate. As an example, two state models are considered adequate for modelling the availability of base load units [61]

For some studies, more complex models of generator availability that incorporate additional states are used. A four state model shown in Figure 2.2 is proposed in [61] for modelling generators that are not base loaded. The four state model adds available but not needed and unavailable but not needed states to the two state model. The model also adds a number of possible transitions between states. In this model, T is the average reserve shutdown time between periods of need, D is the average in-service time per occasion of demand and P_s is the probability of starting failure. In particular, the possibility that a generator that is available but not needed fails when called upon is modelled separately with a different failure rate than a failure of a generator that is operating at the time of failure.

Also, this model is able to represent generators that are available but not operating as not available to fail.

Like the two state model, the four state model can be modelled as a Markov process and the steady state probabilities of residing in each state can be derived from the transition rates. These are given in [61] as,

$$P_0 = \frac{\mu T \left[D\lambda + 1 + D\left(\mu + 1/T\right)\right]}{A} \tag{2.46}$$

where,

$$A = (D\lambda + P_s)\left[(\mu T + 1) + \left(\mu + \frac{1}{T}\right) D\right] + \left[(1 - P_s) + D\left(\mu + \frac{1}{T}\right)\right]\left(\mu\left(T + D\right)\right) \tag{2.47}$$

$$P_1 = \frac{D\lambda + P_s}{A} \tag{2.48}$$

$$P_2 = \frac{D\mu\left(1 - P_s + \mu D + D/T\right)}{A} \tag{2.49}$$

$$P_3 = \frac{D\left(\mu + 1/T\right)\left(D\lambda + P_s\right)}{A} \tag{2.50}$$

Four state models are not used in this thesis because they are not well suited to market simulations. In the four state model, generator transitions between the available when needed and available when not needed states as well as transitions between the unavailable when needed and unavailable when not needed states are treated as random rather than market driven events.

To recognize the differences in the probability of base load and non base load generators being available when called upon, the availabilities that are assumed for non base loaded generators are chosen in part to reflect that these plants are often not in use and in these

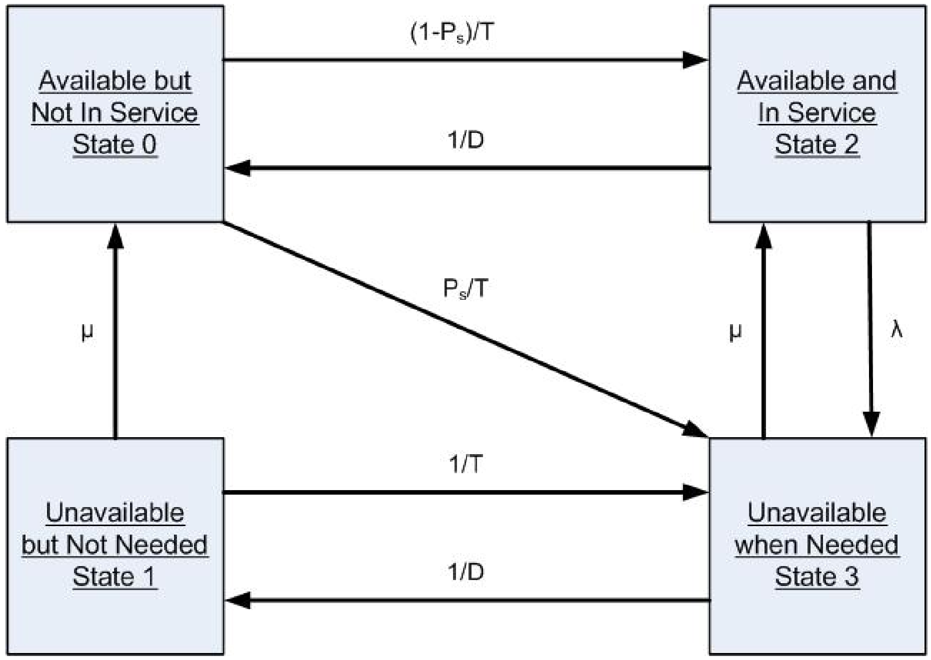

Figure 2.2: Four state Markov model of generator availability

periods the probability of failure is very small. It is assumed that all equipment de-rates and forced, unplanned and planned outages are captured in the assumed availability. Failures of generators are assumed to be independent.

2.4.1 Sample Functions of Hourly Generator Availability

Markov models of generator availability can be used to create sample functions of the hourly availability of each generator. A sample function of the hourly availability of each generator is one realization of the ensemble of possible realizations of hourly availabilities for all generators that could occur.

Assuming each generator is represented by a two state Markov model, sample functions of the hourly availability of each generator can be created as follows. An initial state for each generator is assumed. A random number between zero and one with a uniform distribution is then created for each generator. If the initial state of the generator is available, the random number is compared to the probability of failure $\lambda\Delta t$. If the random number is less than or equal the probability of failure, the generator becomes unavailable in the following time period. If the initial state of the generator is unavailable, the random number is compared to the probability of repair $\mu\Delta t$. If the random number is less than or equal the probability of repair, the generator becomes available in the following time period. In subsequent periods, new random numbers are created for each generator and the process is repeated. The process is repeated for each hour over the period of interest. This creates a single hourly scenario of generator availability for all generators over the period of interest.

The process is illustrated in (2.51) - (2.55) for a hypothetical system with three generators over fifteen time periods. For illustration $\Delta t = 1$ and failure rates of 0.05, 0.1, and 0.15 failures per hour and repair rates of 0.12, 0.14 and 0.16 repairs per time period are assumed. (These are not realistic values and are used to illustrate the process only) In (2.51) and (2.55) the available state is represented with a 1 and the unavailable state with a 0.

$$\text{Initial states } = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix} \tag{2.51}$$

$$\text{Failure rates } \lambda = \begin{bmatrix} 0.05 & 0.1 & 0.15 \end{bmatrix} \tag{2.52}$$

$$\text{Repair rates } \mu = \begin{bmatrix} 0.12 & 0.14 & 0.16 \end{bmatrix} \tag{2.53}$$

$$\text{Gen. Capacity (MW) } = \begin{bmatrix} 450 & 250 & 100 \end{bmatrix}^T \tag{2.54}$$

$$\text{Rand. No.s (0,1)} = \begin{bmatrix} 0.27 & 0.66 & 0.14 \\ 0.27 & 0.66 & 0.18 \\ 0.36 & 0.04 & 0.30 \\ 0.72 & 0.16 & 0.51 \\ 0.90 & 0.02 & 0.41 \\ 0.13 & 0.51 & 0.54 \\ 0.57 & 0.83 & 0.70 \\ 0.72 & 0.25 & 0.08 \\ 0.63 & 0.00 & 0.16 \\ 0.86 & 0.38 & 0.86 \\ 0.31 & 0.70 & 0.66 \\ 0.37 & 0.06 & 0.17 \\ 0.18 & 0.08 & 0.42 \\ 0.04 & 0.66 & 0.67 \\ 0.44 & 0.38 & 0.95 \end{bmatrix} \text{Avail.} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \tag{2.55}$$

2.5 Monte Carlo Simulations to Estimate Reliability of Supply

Monte Carlo methods are algorithms that rely on repeated random sampling to simulate inputs to processes. In general, a domain of possible inputs is defined, input values are randomly generated from a probability distribution over the domain of possible inputs, and then a deterministic calculation is performed on the inputs. The results over many input values are then aggregated.

Monte Carlo methods can be used with stochastic processes to create multiple sample functions or realizations of the stochastic process from the ensemble of possible realizations. Each of these sample functions is an input to a deterministic calculation of an output. After many sample functions have been evaluated, the mean values and distribution of outcomes can be estimated.

As described in the previous section, Markov models can be used to create sample functions of hourly generator availability. Each sample function is a single realizations of the ensemble of possible realizations. To evaluate the reliability of supply for each sample function, the available generation capacity at each time step is summed and compared to the system demand in that time step. When the available capacity falls short of the demand, some demand is not served and a loss of load is flagged. For each sample function of hourly generator availability, the number of hours where generation is inadequate to meet the demand is noted. Simulations are run k times with different sample functions of hourly generator availability until the average number of hours when generation is inadequate to meet load converges. The average number over all simulations of the number of hours when generation is inadequate to meet load forms an estimate of the expected Loss Of Load Expectation (LOLE). When LOLE is expressed as a ratio over the period considered, it becomes (LOLP).

The method for evaluating LOLE and LOLP is illustrated in (2.56) - (2.58) for the single sample function of hourly generator availability shown in (2.55). In (2.57), a period with a shortfall of capacity to meet load is flagged with a 1. Periods where the available capacity is sufficient to meet the demand are flagged with a 0.

$$\text{Availability Capacity } t_{i1} \text{ (MW)} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 450 \\ 250 \\ 100 \end{bmatrix} = \begin{bmatrix} 450 \\ 450 \\ 700 \\ 700 \\ 450 \\ 450 \\ 450 \\ 550 \\ 800 \\ 800 \\ 800 \\ 550 \\ 800 \\ 350 \\ 350 \end{bmatrix} \tag{2.56}$$

$$\text{Hourly Load } t_i \text{ (MW)} = \begin{bmatrix} 379 \\ 284 \\ 200 \\ 308 \\ 374 \\ 98 \\ 382 \\ 624 \\ 142 \\ 529 \\ 110 \\ 538 \\ 704 \\ 696 \\ 492 \end{bmatrix} \text{Avail. Capacity } t_i < \text{Hourly Load } t_i = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \tag{2.57}$$

In this example, the period D is fifteen hours and only one sample function is shown so $k = 1$ and $N = 1$. The LOLE for this is three hours. Since it is over a fifteen hour period, the LOLP is 3 hours per fifteen hour period.

$$\text{LOLP (hours/}D) = \frac{1}{N}\sum_{k=1}^{N}\sum_{i=1}^{D}(\text{Avail. Capacity } t_{ik} < \text{Hourly Load } t_{ik}) = 3 \tag{2.58}$$

Monte Carlo methods are a flexible means to simulate stochastic processes. These methods can provide estimates of both the expected values and the distributions of outcomes. The main limitations are the possibility of long computing times and that Monte Carlo methods can only provide estimates rather than exact values of mean values and distributions of outcomes.

2.6 Electricity Prices and Long Term Reliability of Supply

In competitive markets where generators are assumed to offer all available MW capacity at marginal cost and where there are no capacity payments or markets (energy-only markets), LOLP expressed in hours per year is related to the recovery of generator's fixed costs [6]. Fixed costs are recovered when generators are dispatched and market prices exceed the individual generators marginal cost. In competitive markets, peaking generators which are used for short periods to meet peak demands depend entirely on periods of scarcity when prices rise to the price cap for fixed cost recovery. The number of hours each year of prices at the price cap (LOLP) that are necessary for peaking generators to fully recover fixed costs can be calculated as [6],

$$\text{LOLP} = \frac{\text{Annual Fixed Cost/MW}}{\text{(Price Cap-MC)(Availability of Peaking Gen.)}} \tag{2.59}$$

where MC is the marginal cost of a peaking generator.

It is common for regulators to set price caps at levels that limit potential abuse of market power [6]. With price caps, the assumption of competitive behavior, and the fixed and marginal costs and availability of peaking generators that are commonly encountered, the LOLP necessary for peaking generators to fully recover their fixed costs is in the range of 65 + hours/year [8] and is much higher than the LOLP standards previously applied by regulated utilities (one day in ten years or 2.4 hours/year is given in [9, 10]). This has led to the concern that the emergent reliability of supply in competitive energy-only markets may be inadequate [8, 9].

2.7 K-means Clustering of Generator Outputs

Models of generator behavior are developed in Chapter 5 of this thesis that relate observed market parameters including price to the MW output of individual generators. These models are simplified if the number of discrete generator output levels considered can be reduced by finding output level clusters. K-means clustering is a common method to reduce a set of n observations to k different clusters so within each cluster the sum of squares of the distances from each point to the cluster mean is minimized [62]. The algorithm seeks to minimize the objective function in (2.60).

$$R = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - C_j \right\|^2 \tag{2.60}$$

where C_j is the mean of cluster j and $x_i^{(j)}$ is data point i of n points associated with cluster j. The algorithm is implemented by initially selecting k points as trial cluster means. Each data point is assigned to the closest cluster mean. Once all data points have been assigned, the means of the data points assigned to each cluster are recalculated. The process is repeated by reassigning each data point to the nearest updated cluster mean and recalculating the cluster mean values until there is no further change in the assignment of data points to cluster means.

K-means clustering is a widely used algorithm. Its simplicity and ease of application are its strengths. It is well suited to problems where clusters of observed values are roughly spherically or elliptically distributed around the means and the objective function is convex. Its weakness is that in non convex situations, the final K-means may differ based on the initial estimates used. In this thesis, this concern is addressed because for each generator, clusters of generator output levels are found over a single dimensional range of possible output levels. As well, initial estimates of cluster means are chosen to be evenly distributed between the observed minimum and maximum generator outputs. The K-means algorithm always results in k clusters even if the underlying observations suggest a greater or lesser number is appropriate. In this thesis, this concern is addressed by constraining clusters to represent a minimum number of observations.

2.8 Probabilistic Neural Networks (PNN)

In Chapter 5 of this thesis, PNN are proposed to model individual generator behaviors in response to observed market parameters. PNN were first proposed in [63]. PNN have previously been applied in power systems to fault diagnosis and differential protection in power transformers [67,68], prediction of wind generation [69], and power system security and vulnerability assessments [70, 71].

PNN are generally applied to the problem of classifying multivariate input data into a number of different classes i. PNN classify input data by applying Bayes optimal decision rule shown in (2.61).

$$\text{x is part of class i if } h_i c_i f_i(x) > h_j c_j f_j(x) \text{for } i \neq j \tag{2.61}$$

where $f_i(x)$ is the probability density function (pdf) of x for class i, h_i is the apriori probability that x is chosen from i, and c_i is a cost weighting associated with incorrectly classifying x as i.

The PNN assign apriori probabilities based on the relative number of examples in the training set associated with each class. In the case where there are an equal number of examples in the training set associated with each class and there is no reason the losses associated with making an incorrect decision for each class differ, h_i and c_i can be assigned values of one. In this case, a sample x is classified as part of class i if the pdf of variable x associated with i evaluated at the sample x is greater than the pdf of the variable x associated with any other class j evaluated at the sample x.

PNN operate by first using examples of known associations between input data x and classes i to estimate the probability density function of the input data for each class of output. The PNN then uses the estimates of the probability density functions learned from the training examples to classify new data to output classes i using Bayes optimal decision rule shown in (2.61).

PNN estimate the pdf of inputs x associated with each class i by averaging gaussian radial basis functions centered on the examples of data with known associations to an output class. As indicated in [63], this estimator will approach the underlying pdf of x associated with class i provided the pdf is smooth and continuous. The pdf estimator is implemented as shown in Equation 2.62.

$$f_i\left(x\right) = \frac{1}{\left(2\pi\right)^{d/2} {\sigma_i}^d n_i} \sum_{s=1}^{n_i} e^{\left(\frac{-\left(x-x_{ij}\right)^T\left(x-x_{ij}\right)}{2{\sigma_i}^2}\right)} \tag{2.62}$$

where x_{ij} is the j^{th} sample of data associated with class i, n_i is the number of input vector data samples associated with class i, d is the length of the input vector, and σ_i is a user defined factor that defines the smoothing applied to the estimated pdf.

The PNN is implemented as a four layer feedforward network as shown in Figure 2.3. The first layer distributes data from a vector of input data to the nodes in the second layer. The second layer is the pattern layer. This layer contains one node for each of the known associations between input data vectors and output classes that the network is trained on. The nodes in this layer contain the estimation of the pdf of x associated with each class i. The nodes in the pattern layer are divided into groups associated with each of the i classes. When presented with an input x, each node in the pattern layer computes an output using Equation 2.63.

$$R_{ij} = \frac{1}{\left(2\pi\right)^{d/2} {\sigma_i}^d} e^{\left(\frac{-\left(x-x_{ij}\right)^T\left(x-x_{ij}\right)}{2{\sigma_i}^2}\right)} \tag{2.63}$$

The third summation layer has one node for each class and determines the maximum likelihood that the input x is classified as i by averaging the outputs of pattern nodes associated with each class.

$$p_i\left(x\right) = \frac{1}{n_i} \sum_{j=1}^{n_i} R_{ij} \tag{2.64}$$

The fourth layer is the decision layer, where the input data vector is classified to the class associated with the node from the summation layer with the largest output.

PNN are attractive because they offer several advantages over other classifiers. Unlike conventional neural networks, PNN are based on a statistical foundation and as the training samples increase the PNN approach Bayes optimal classifications [63]. The training of PNN is achieved by incorporating training examples into the network directly and this avoids the often lengthy training requirements of conventional neural networks [63]. By adjusting a single smoothing parameter σ, PNN allow the decision surfaces to be as complex as necessary. Further, as new training samples are introduced, the smoothing parameter can easily be adjusted without need for retraining. PNN are also attractive because they are tolerant of infrequent erroneous samples. At the same time, PNN can function with sparse training sets. Finally, PNN can easily adapt to changing circumstances and overwrite old patterns with new patterns as new training samples become available. The main drawbacks of PNN are that each training sample adds a node to the network so network size scales with the size of the training set. Computation time can become lengthy as the network size increases. Finally, the ability of PNN to correctly classify outputs is reliant on differences in the pdf of the input parameters associated with each class of output.

2.9 Emissions

Generally, total system emissions are estimated by summing the product of annual energy production in MWh by generator and the emission intensity in tonnes/MWh associated with each generator.

2.10 Summary

In this chapter, background material related to the methods and techniques utilized in this thesis was presented. A general discussion on modelling wind generation using ARMA

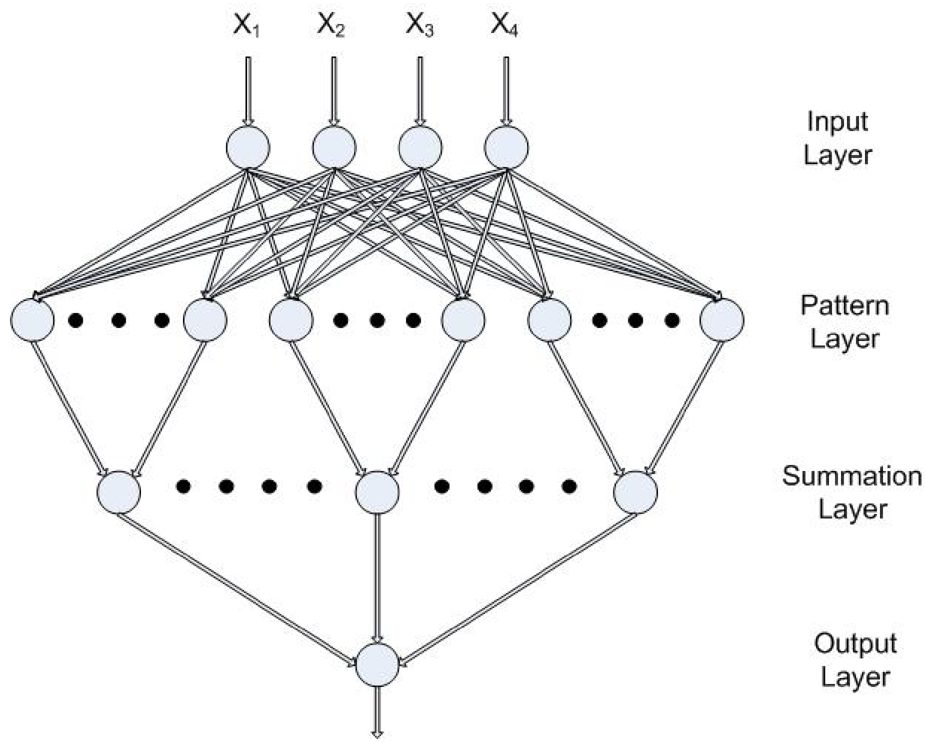

Figure 2.3: Probabilistic neural network

models was given. Reliability of supply was discussed and a general reliability function for components that can fail was derived. Markov processes and their application to model generator unavailability was presented. The use of Monte Carlo simulations in conjunction with Markov models of generator unavailability to evaluate LOLP as a measure of reliability of supply was also described. Background information on K-means clustering techniques and Probabilistic Neural Networks used in the behavioral models proposed in Chapter 5 of this thesis was also presented.

Chapter 3

Short and Medium Term Impacts on Price, Reliability and Dispatchable Conventional Suppliers of Large-Scale Integration of Wind Generation

3.1 Introduction

In this chapter, the market impact of the large-scale integration of wind generation operating in a deregulated energy-only market on load and dispatchable conventional generation is analyzed. The impacts on the load dealt with are the effect on prices and effect on reliability of supply.

Rather than modeling the generation mix of a specific system as a starting point, the system prior to the integration of wind generation is modeled as a cost minimizing mix of base load, mid load and peaking generation. In this case, all generators are initially neither making profits nor taking losses. The cost minimizing mix of generation can be found using traditional screening curves and adjusting installed capacity for availability and generator sizes [6]. This was done to model the impact of wind generation on a system that is initially neither oversupplied or undersupplied by any type of generation. The effects of wind generation on load and dispatchable conventional generation in the medium and long terms before structural changes to the capacity and mix of generation technologies can be affected is examined.

An energy-only market with multiple competitive suppliers with sufficient overall installed capacity that individual suppliers compete based on Bertrand pricing (where suppliers compete on price) rather than a Cournot model (where suppliers compete on volumes) is considered. Multiple strategic suppliers are not explicitly considered, but it is expected that cooperation or collusion among suppliers would be similar in effect to increasing the size of a single strategic supplier. Rather than considering bidding strategies of producers who may set prices, the focus is on bidding strategies of a low marginal cost producer who does not normally set prices.

Unlike [43,45], this chapter focuses on the market impact of the large-scale integration of wind generation operating in a deregulated market on load and dispatchable conventional generation rather than on the wind generation itself.

A contribution of the work in this chapter is an evaluation of the changes in the opportunities for a dispatchable conventional generator, acting strategically in an energy-only market, to exercise market power by economically withholding supplies following the introduction of wind generation. Another contribution is an analysis of the effect of wind generation in an energy-only market on the fixed cost recovery of dispatchable conventional suppliers.

The rest of this chapter is organized as follows. Section 3.2 describes the methodology and modeling used in this chapter. Section 3.3 describes the simulation studies and the effects of different amounts of installed wind generation on electricity prices, reliability of supply, revenues and costs of dispatchable conventional generators and the strategic behavior of a dominant supplier modeled as a single large low marginal cost generator. Possible responses of the market and/or regulator to the large-scale integration of wind generation are considered. Finally, Section 3.4 provides summary and conclusions.

3.2 Methodology and Modeling

To study the short and medium term impacts on price, reliability, and dispatchable conventional suppliers of the large-scale integration of wind generation, a system model was created that includes hourly dispatch models of wind generation, load and resultant residual demand, a probabilistic model of dispatchable conventional generator availability, a model of an energy-only market with a price cap, and a model of generator costs and dispatch behavior. The system model was used to perform a number of simulations which were used to evaluate the overall reliability of supply, the ability of a dominant supplier acting strategically to profitably withhold supplies, and the revenues and costs for each generator type at different levels of wind generation penetration.

The methodology and modeling can be summarized as follows:

Step 1) Using historical data, hourly time series models were created of different levels of aggregate wind generation over a year that capture seasonal and diurnal regularities, correlations in outputs between wind facilities, and the uncertainty in output from one time period to the next. The methodology and model used is fully described in [42].

Step 2) Residual demand curves were then created for varying penetrations of wind generation by subtracting the hourly time series of various wind generation scenarios created in Step 1 from an hourly time series model of demand. The residuals are sorted from highest to lowest to create a set of residual demand duration curves for different levels of wind generation. The residual demand duration curves are then reduced to 100 points spaced equally over the year.

Step 3) A supply model was created comprised of a specified number of generators of different types and availabilities. For each generation type, assumed fixed costs, marginal costs, and availabilities were assigned. The binomial expansion is used in order to compute the probability distribution of the available generation capacity at any instant.

Step 4) The reliability of supply was then assessed by comparing the possible levels of supply to demand and calculating the expected frequency of supply shortfalls per year.

Step 5) A model of an energy-only electricity market was created and assumptions were made for the price cap and demand elasticity.

Step 6) The supply, demand, and market models were then combined into a production and market simulation program capable of calculating electricity prices, optimal offer volumes for a dominant supplier that seeks to maximize profit, and the production, revenues, and costs for all generators over the course of a year.

Step 7) Finally, the production and market simulation program was used to run simulations with different levels of wind generation.

3.2.1 Wind Generation Model

Because wind generators have low variable costs and unpredictable outputs, they often operate as price takers and can be modeled as modifiers to the residual demand seen by other suppliers [44, 45]. In this chapter, wind generation is assumed to operate as a price taker and is modeled as described in [42] with an expected annual average output, regular seasonal and diurnal variations, and uncertainty in output from hour to hour. The uncertainty in the wind output is modeled as zero-mean normally distributed noise with a specified variance consistent with the differences between modelled and observed MW output of wind generators given in [42]. To simulate the uncertainty faced by a dispatchable supplier who must make an offer ahead of delivery, the variance in the noise was chosen to represent the uncertainty in the forecast hourly output of wind generation over a two hour window.

The method used to model the wind can be generally applied. For illustrative purposes, the annual mean values, regular seasonal and diurnal variations and variance in the wind output in this chapter are reflective of wind generation in Alberta as specified in [42].

3.2.2 Effect of Wind Generation on Residual Demand

Typically, the output from a wind generator displays a low capacity factor [44]. In the case of Alberta, wind generators have an expected average output of 35% of installed wind capacity [42]. In general, if the output from wind generators is poorly correlated to load, the Load Factor (LF) or average load divided by peak load of the residual demand that must be met by dispatchable conventional generators will fall as wind generation is added to the system. In this chapter, to maintain consistency with the model of wind generation, a demand profile is derived from historical 2006 hourly load on the Alberta system [59]. Choice of another year would not significantly alter the results of this analysis because the load factor and shape of the load duration curve in Alberta have remained stable over several years [59]. Using this as an example, the effect of increasing installed wind capacity from 0% of peak annual demand to 80% of peak annual demand is shown in the load duration curves in Figure 3.1.

3.2.3 Supply Model

To meet the demand, it is assumed that other than wind generators, there are fifty generators that are each fully dispatchable over their entire capability. The dispatchable conventional generators are assumed to be comprised of peaking, mid load, and base load generators. The fixed costs in $/MW/Yr and marginal cost in $/MWh assumed for each generator type are shown in Table 3.1. Marginal costs were chosen to be reasonable approximations to gas fired and coal fired generation fuel costs. The fixed costs were chosen so that, ignoring availability, peaking capacity would be required to meet the load approximately one third of the time, mid load capacity would be required two thirds of the time, and base load

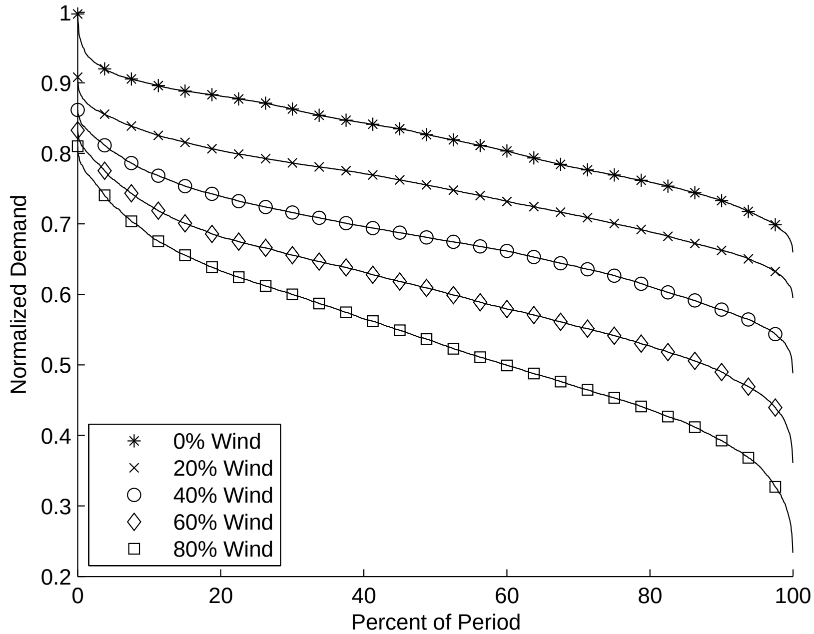

Figure 3.1: Effect of penetration of wind generation on residual demand.

capacity would be required all of the time. These numbers are not necessarily indicative of current costs. The fixed costs in \$/MW/Yr and marginal cost in \$/MWh for each generator type were not calculated directly from assumptions of investment costs, discount rates, and amortization periods. Once availability is considered, the percent of time each type of generator is required to meet load varies from these initial assumptions.

An optimal generation mix, before adding any wind generation, to meet the demand profile derived from historical 2006 hourly load on the Alberta system was determined by finding the installed capacity of each generation type that minimizes the total cost of supply over a year given the fixed costs, variable costs, and availability for each generator type and with a given a price cap and subject to the constraint that annual revenues just equal costs for all generators. The optimal mix used as a starting point is given in Table 3.2. The dispatchable conventional generators have a combined capability that exceeds the annual hourly peak residual demand.

The relative numbers of peaking, mid load and base load generators were then chosen so

Table 3.1: Assumed fixed costs in \$/MW/Yr and marginal cost in \$/MWh of each generator type

	Annual Fixed Costs (\$/MW/Yr)	Marginal Costs (\$/MWh)
Base Load	\$262,800.00	\$15.00
Mid Load	\$175,200.00	\$30.00
Peaking	\$43,800.00	\$75.00

Table 3.2: Installed dispatchable capacity of each generator type

	Capacity (% of Pk Dem.)	No. Units	Unit Size (% of Pk Dem.)
Base Load	82.2	39	2.16
Mid Load	11.7	4	2.91
Peaking	16.3	7	2.32

that the individual generator sizes in the generation mix prior to any wind additions would be approximately the same. This avoids disproportionate impacts on available capacity due to outages of generators of different sizes. This resulted in seven peaking generators, four mid load generators, and thirty-nine base load generators.

To investigate the effect of large-scale integration of wind generation on the market power of dispatchable conventional generators, one base load generator is assumed to be a dominant supplier [72] who strategically varies its offer volumes to maximize profits. The incentives for withholding supply are similar but not identical for all generator types in that all generators that are dispatched face similar prospects for increased profits from increases in price. Withholding by a dominant base load supplier is the most interesting, since the base load supplier has opportunities to withhold, in this model, to boost prices to the mid load marginal cost, or to the peaking marginal cost, or to the price cap. Peaking plants can only boost prices to the cap, which will be profitable for them, but is a less complex and less interesting analysis. The remaining suppliers are assumed to act as fringe suppliers and always offer their full output at marginal cost. The dominant supplier has the same fixed costs in \$/MW/Yr and marginal cost in \$/MWh as other base load generators, but is treated as a separate generator type whose capacity may differ from that of other base load generators.

Base load generators are assumed to be available to serve load in any given hour with a probability of 90% [73] and unavailable to serve load with a probability of 10%. Mid load and peaking generators are assumed to be available to serve load in any given hour with a probability of 95% and unavailable to serve load with a probability of 5%.

The availability of each generator is modelled with a two state model to have the simplest model possible to illuminate the key point in the analysis. For base load units, a two state model is appropriate [61].

A more complex four state model [61] that adds available but not needed and unavailable but not needed states to the two state model was considered. The four state model also adds a number of possible transitions between states. In particular, the possibility that a generator that is available but not needed fails when called upon can be modeled with a different failure rate than a failure of a generator that is operating at the time of failure. Also, this model is able to represent generators that are available but not operating as not available to fail. However, the four state model is not well suited to incorporate into a market simulation because transitions between available when needed and available when not needed as well as transitions between unavailable when needed and unavailable when not needed are treated as random rather than market driven events.

In choosing a two state model for this analysis, a 95% availability for mid load and peaking generators was assumed in part to reflect that these plants are often not in use and in these periods the probability of failure is very small. It is assumed that all equipment derates and forced, unplanned and planned outages are captured in the assumed availability. Failures of suppliers are assumed to be independent.

By assuming that all generators of a single type are the same size and all have the same probability of availability, it is possible to calculate a table of probabilities of available capacity for each generator type using a binomial expansion [50],

$$P_k = {}_nC_k p^k q^{(n-k)} \tag{3.1}$$

where P_k is the probability of k of n units being available, ${}_nC_k$ is the number of combinations of k out of n generators of a certain type, p is the probability of availability for an individual generator, q is the probability of unavailability for an individual generator, and n is the number of equally sized units.

If all generators of a specific type are the same size, the generation capacity available from each type of generation is defined by the number of available generators multiplied by the generator capacity of an individual generator. At any one time, the possible number of generators available from each generation type ranges from 0 to n. This defines $n+1$ possible capacity levels for each generation type. The total capacity available from all types of generation is given by the sum of the capacity available from each generation type. The total number of different combinations of available capacity from all generation types, denoted here by N, can be written as:

$$N = (n_a + 1)(n_b + 1)(n_c + 1)(n_d + 1) \tag{3.2}$$

where n_a is the number of non-strategic base load generators, n_b is the number of mid load generators, n_c is the number of peaking generators, and n_d is the number of strategic base load generators $(n_d = 1)$. If each of the possible levels of capacity is indexed by i, the capacity level Q_i can be defined as:

$$Q_i = Q_{a,i} + Q_{b,i} + Q_{c,i} + Q_{d,i} \tag{3.3}$$

where Q_i is the available capacity of all dispatchable conventional generators at level i, $Q_{a,i}$ is the available capacity of non-strategic base load generators at level i, $Q_{b,i}$ is the available capacity of mid load generators at level i, $Q_{c,i}$ is the available capacity of peaking generators at level i, and $Q_{d,i}$ is the available capacity of the strategic base load generator at level i. For each Q_i there is an associated probability p_i of occurrence.

Seven peaking, four mid load, and thirty-nine base load generators were assumed. One of the base load generators is a dominant supplier which can have a different capacity than the other thirty-eight base load generators. This leads to eight possible levels of peaking generator capacity, five possible levels of mid load generator capacity, thirty nine possible levels of base load generator capacity, and two levels of dominant supplier capability. The total number of possible levels of capacity available to serve load is given by the product of these possible capacity levels, or N=$8 \times 5 \times 39 \times 2 = 3120$ levels. If the generators were all different in size, the number of different possible levels of capacity available to serve load rises to 2^n. In this chapter, a total of fifty conventional generators were assumed. Consideration of all 2^{50} possible levels of capacity available to serve load would not be practical. Larger numbers of generators of differing sizes and availabilities could be considered using alternate techniques such as the recursive calculation of a capacity outage probability table [50] that limits the possible levels of capacity available by disregarding capacity outages with very low probabilities of occurrence.

3.2.4 Energy-Only Electricity Market Model

To examine the effects of introducing large amounts of wind generation on electricity prices, the amount of long-term generation capacity other than wind and the behavior of a dominant supplier, a model of an energy-only electricity market is used in which price in each hour is set by the intersection of supply and demand. This type of market has been well described by others such as [6]. Demand is assumed to be inelastic up until a price cap of $1000/MWh. The demand is assumed to vary each hour throughout the year and is normalized so the demand in the peak hour is set to one. The effects on capacity and/or operating reserve markets are not considered and are beyond the scope of this analysis.

3.2.5 Optimal Offer from the Dominant Supplier

To assess the effect of adding wind generation on the ability of a dominant supplier to profitably withhold supply, each of the possible scenarios of generating capacity available to supply load is paired with a demand level. To model the demand, the system load duration curve is equally divided into one hundred demand intervals. For each of the different demand intervals, the uncertainty in the wind generation output is modeled by adding to the expected residual demand zero-mean normally distributed noise with a specified variance that is dependent on the installed wind capacity. The variance in the noise assumed in this chapter is reflective of the variance in aggregate wind generation output in Alberta as specified in [42]. This allows modeling each demand interval as a random variable. Finally, one hundred equally probable demand level observations for each of the demand intervals are generated.

In the model developed for this analysis, generation is dispatched to meet demand on the basis of marginal cost with the lowest cost generation being dispatched first. The market clearing price is set by the marginal cost of the most expensive generator dispatched to meet the demand. If there is insufficient generation to meet demand, the market clearing price is set by the price cap. The supply curve is not smooth and is not continuously differentiable. The expected profit of the dominant supplier in a given period is:

$$E\{Profit_d\} = \sum_{j=1}^{l}\sum_{i=1}^{N}(MCP(Q_i, D_j, MC, n, PC) - MC_d)Q_{(d,i)}np_{(Q_i)}p_{(D_j)} \qquad (3.4)$$

where PC is the market price cap, MC is the array of marginal costs of all generator types,$\{MC_a, MC_b, MC_c, MC_d\}$, D_j is the residual demand level j of l equally probable demand levels in one period, N is the number of levels of capacity available from all conventional generators, n is the fraction of available capacity from the dominant supplier that is dispatched, $p_{(Q_i)}$ is the probability of supply capacity level $Q_{(i)}$, $p_{(D_j)}$ is the probability of demand level D_j, and MCP is the market clearing price as a function of Q_i,D_j,MC,n, and PC. Appendix A provides a fuller explanation of (3.4). The goal of the dominant supplier is to maximize profit by varying the level of withholding.

$$\text{Maximize Expected Profit} = \max_{n \in \Re} \{E\{Profit_d\} \mid 0 < n < 1\} \tag{3.5}$$

In the model developed in this chapter, it is assumed that in each demand interval the dominant player knows both the current and future overall demand and the current availability Q_i of all dispatchable conventional supply prior to making its offer. For each level of available capacity Q_i, different levels of withholding by the dominant supplier are iteratively evaluated over all probabilistic demand levels. The level of withholding that maximizes the expected profit of the dominant supplier given the uncertain residual demand is chosen and the resultant electricity prices, revenues, expenses, and profit of the dominant supplier along with the probability of occurrence are calculated. The market clearing price in each discrete time interval of the residual load duration curve is calculated as the probability weighted sum of possible price outcomes. Therefore, both the uncertainty in the residual load demand arising from wind generation and availability of conventional units is incorporated into the market clearing price. The process is repeated for all possible starting levels of capacity Q_i from dispatchable conventional generators.

The optimal offer volume for the dominant supplier is determined by maximizing its expected profit. If the dominant supplier is unavailable, its available capacity, offer volume, revenues, and profits are all zero. If the dominant supplier is available, the ratio of the optimal offer volume to the dominant supplier's available capacity is determined for each of the possible starting levels of supply Q_i and residual demand levels D_j. The results are weighted by the probability of occurrence and summed to determine a final ratio of the offered capacity to available capacity of the dominant supplier. A ratio of one indicates that the dominant supplier has no opportunity to withhold supplies to boost prices. Ratios less than one indicate increasing opportunities for the dominant supplier to raise prices by withholding supplies.

3.3 Simulation Studies and Modeling of Large-Scale Wind Integration

The wind, demand, supply, reliability, market, generator costing models, and assumptions described in the previous Section were used to perform several simulations. These simulations were aimed at investigating the medium term and long term impacts of large-scale integration of wind generation on electricity prices, reliability of supply, the profitability of competitive dispatchable conventional base load, mid load and peaking generators, and the ability of dispatchable conventional suppliers of differing sizes to profit from economically withholding capacity. Based on these simulations, possible responses of the market and/or the regulator to the large-scale integration of wind generation are considered.

In this analysis, medium term refers to the time frame following the introduction of wind generation, but before structural changes to the capacity and mix of generation technologies can be affected. Long term impacts consider possible responses of the market and/or regulator to the integration of wind generation that affect the generation capacity and mix of technologies available to serve load and expectations for reliability of supply.

3.3.1 Medium Term Impacts

3.3.1.1 Effect on Electricity Prices

The simulations show that simply adding wind generation to the model results in reduced electricity prices as penetration levels increase. This is not unexpected as adding wind generation to an existing system acts to increase supply without an accompanying increase in demand. As additional wind generation is added, prices are less frequently at the price cap and more frequently set by the marginal cost of mid load and base load generators. This can be seen in Figure 3.2. These results are directionally consistent with the outcome of the simulations performed by [43] and [45].

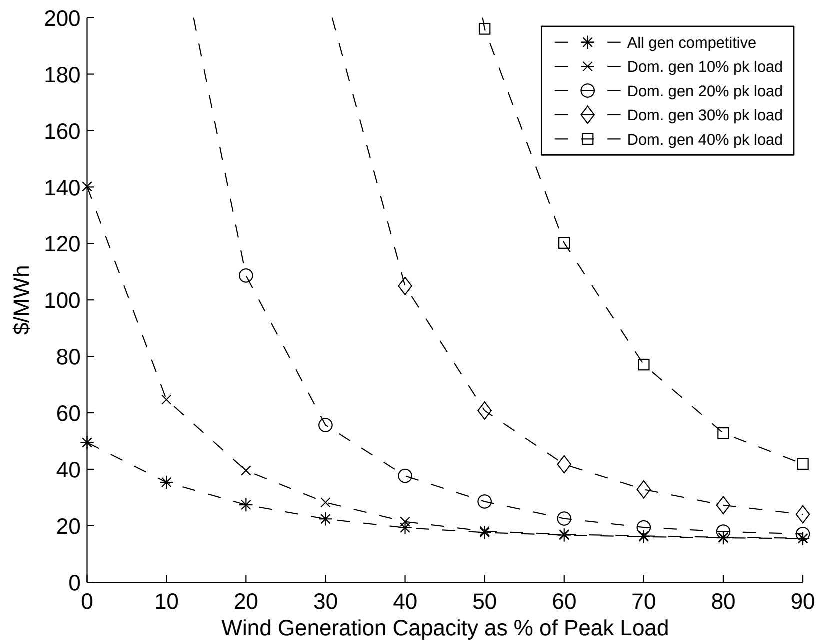

Figure 3.2: Average electricity prices for increasing levels of wind generation penetration with constant amount of dispatchable generation.

3.3.1.2 Effect on Reliability of Supply

The reliability of supply is evaluated by a numerical convolution of the load distribution and the available capacity distribution that compares the demand in each period to the levels of available capacity specified by the previously described capacity table in the supply model [50] [61]. When the available capacity falls short of the demand, some demand is not served. The frequency of unserved demand is weighted by its probability of occurrence and the result is summed for all periods over a year. The result is a measure of the expected Loss Of Load Probability (LOLP) [50] and is expressed in hours/year.

The distribution of generator sizes as well as their availabilities will affect the Loss Of Load Probability (LOLP) calculation. However, there is no standard distribution of generator sizes in power systems. If a system is dominated by a few large generators, their availability will have a pronounced impact on LOLP. By assuming all generators were similar in size, the possibility any one generator or group of generators having a disproportionate impact on the LOLP calculation due to their relative size is avoided. The intent is to have the simplest model possible to illuminate the key point in the analysis.

The uncertainty in the residual load arising from the integration of wind power generation is captured in the LOLP calculation through the residual demand duration curve seen by other generators. Multiple chronological representations of alternate outcomes for wind generation and residual demand were generated and then sorted into one residual demand duration curve that is sampled at equally spaced intervals to represent demand and wind generation over a year. This captures both the variations in loads between intervals and the uncertainty in wind generator outputs.

In the simulations performed, adding wind generation while holding the installed capacity of dispatchable conventional suppliers constant also results in an increasing reliability of supply. This is also not unexpected. Adding supply without an increase in demand naturally leads to fewer hours when the total supply is inadequate to meet the demand. Hence, the reliability of supply increases as shown in Figure 3.3. Again, these results are directionally consistent with the outcome of the simulations performed by [43].

3.3.1.3 Effect on Ability of a Dominant Supplier to Profit by Economic Withholding

Adding wind generation reduces residual demand, limiting opportunities for a dominant supplier to profitably restrict supply. However, the addition of wind generation also introduces uncertainty in the residual demand. The dominant supplier no longer knows with certainty whether withholding supplies will cause prices to rise or not. If the dominant supplier withholds supplies and prices do not rise, profit is lost on the supply that was withheld. However, offering all capacity at marginal cost may forgo an opportunity for greater profit from higher prices. The dominant supplier must choose one value to offer in advance and cannot change its offer when the actual demand is realized.

When increasing levels of wind generation are added to an existing system, the simulations show the total energy withheld by the dominant supplier to maximize profits initially

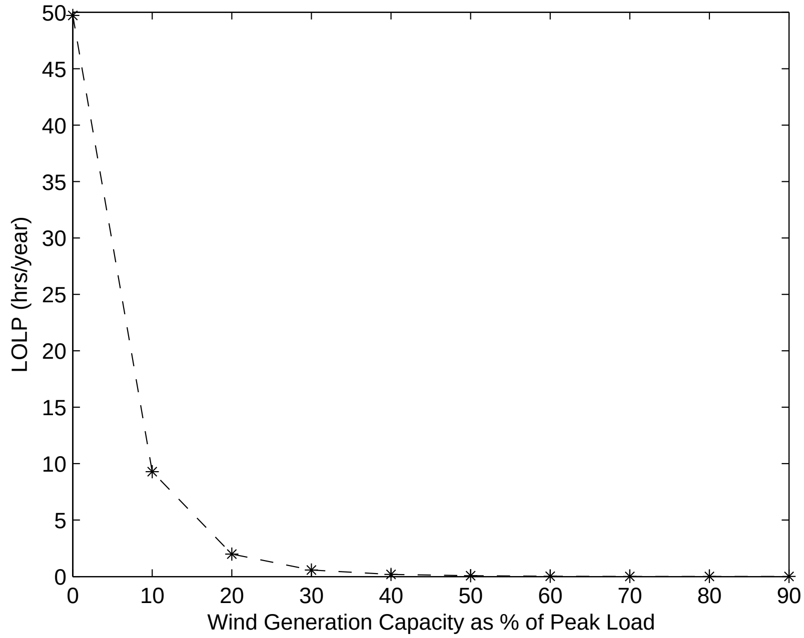

Figure 3.3: LOLP in hours per year for increasing levels of wind generation penetration with constant amount of dispatchable generation.

increases, reaches a maximum when installed wind generation is approximately 40% of peak load, and then decreases as opportunities to speculate on uncertain demand are offset by increased energy supplies from the additional wind generation. This is illustrated in Figure 3.4 which shows how the ratio of capacity offered to available capacity for a dominant supplier with a capacity equal to 10% of the peak load changes as the level of wind generation added increases.

In [21], it was reported when uncertainty was present, suppliers did not withhold capacity but became speculators with regard to the price at which they offered their capacity. The results shown in Figure 3.4 are not inconsistent with the findings of [21]. Offering capacity at high prices can be seen as economic rather than physical withholding. As wind generation is added to the system, there are two countervailing effects. There is the effect of uncertainty that [21] observe, leading to more withholding by the dominant supplier; and there is also the effect of more wind energy supplied to the market. This has the effect of reducing the residual demand leading to less withholding.

As shown in Figure 3.4, with no wind generation added, a dominant supplier with a capacity equal to 10% of the peak load would find it profitable to restrict its dispatch on average to approximately 78% of available capacity. This indicates that even relatively small players have significant opportunities to influence prices. When wind generation with capacity equal to 40% of the peak load is added, this same firm would offer on average about 63 % of its available capacity.

As might be expected, if the total generation capacity is restricted, the ability of the dominant supplier to influence prices is enhanced. Cases were examined where the reliability of supply expressed by LOLP was held constant at the level of the no wind generation case. This was done by reducing the conventional peaking generation capacity as the penetration of wind generation increased. In these cases, the ability of the dominant supplier to influence prices follows a similar pattern but is higher at all levels of wind generation. Figure 3.4 illustrates both the case where wind generation is added to a system while maintaining the dispatchable capacity constant and the case where dispatchable supplies are restricted to hold the reliability of supply constant.

3.3.1.4 Effect on Cost Minimizing Mix of Generation Technologies to Meet Load

As shown in Figure 3.1, the integration of increasing amounts of wind generation has the effect of reducing the load factor of the residual load seen by the dispatchable conventional suppliers. An outcome of the falling residual load factor is that the mix of generation types that is optimal in terms of minimizing the cost of serving the load will change. In the medium term, the prospects for the large-scale integration of wind generation suggest that the load factor of the residual demand may fall faster than the rate at which existing generating plant is retired and new plant is built and the resulting generation mix will not be optimal. In this case, the system will generally be left with relatively more base load plant and less peaking plant than is optimal. The suboptimal generation mix will manifest

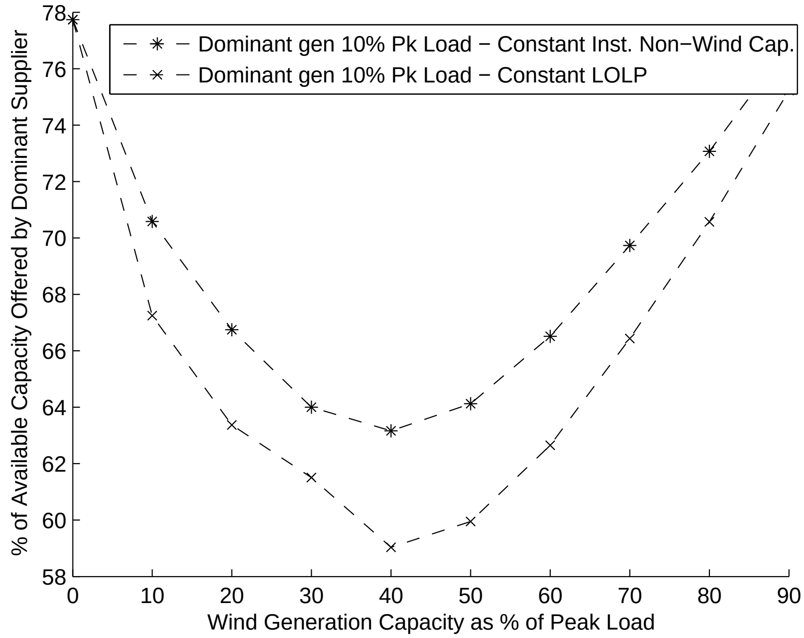

Figure 3.4: Ratio of capacity offered to available capacity for the dominant supplier changes as the level of wind generation added increases.

itself in the divergence in average costs and average revenues for different generator types. With a suboptimal mix of generation types, prices and costs will not be equal for all types of generation.

3.3.1.5 Effect on Capacity Factor of Dispatchable Capacity

While adding wind generation to the system may reduce prices and increase reliability in the medium term, it also results in less supply from the dispatchable generation installed on the system. For many suppliers, the average dispatch level as a percentage of installed capacity or Capacity Factor (CF) will decrease. If the installed dispatchable conventional generation capacity is held constant, the impact on the CF of the non-strategic generation as wind penetration levels increase is shown in Figure 3.5. In relation to the CF without any wind generation, the peaking generators suffer the greatest relative decline in CF as wind generation is added. In the no wind case, the CF for the mid merit generators and peaking generators are 0.581 and 0.108. With wind capacity added equal to 30% of the peak load,

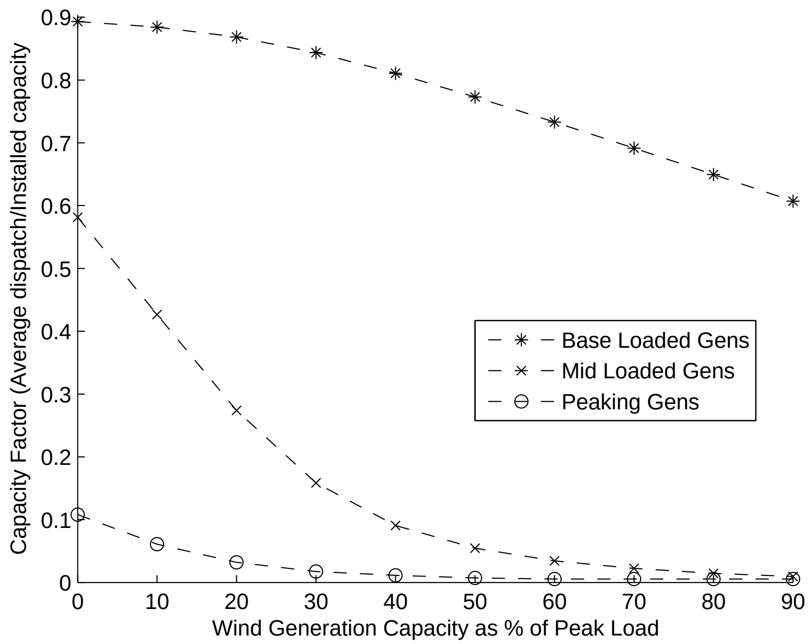

Figure 3.5: Capacity factor of the non-strategic dispatchable generation as wind penetration levels increase.

the CF fall to 0.159 and 0.017 respectively. This represents a 72.7% decline in CF of mid merit generators and an 83.9% decline in CF of peaking generators.

3.3.1.6 Effect on Average Revenues and Costs of Dispatchable Conventional Generators

If generator costs are modeled assuming a fixed cost per MW/year of installed capacity and a marginal cost per MWh, it can be readily seen that average costs rise as the capacity factor falls. Figure 3.6 illustrates the average revenues and average costs of a peaking generator in the scenario where wind generation is added to an existing system with no reductions in the capability of existing dispatchable suppliers. This shows that the average costs of the competitive dispatchable generators exceed average prices realized at all levels of penetration of wind generation above zero. Mid load and base load generators show a lesser but similar divergence between average costs per MWh and average revenues per MWh as the wind generation capacity as a percentage of peak load increases.

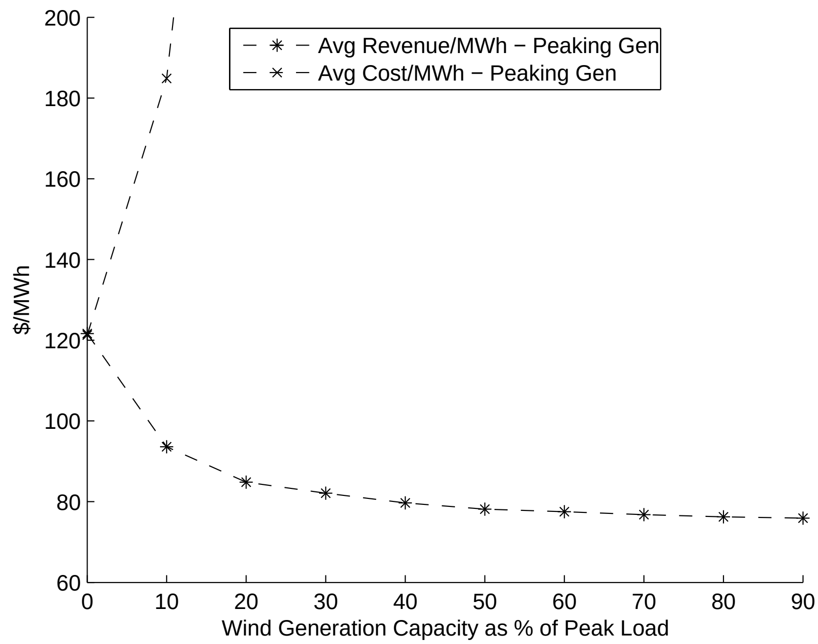

Figure 3.6: Average prices and costs for competitive peaking generators as a function of installed wind capacity.

3.3.2 Long Term Impacts (Market Response)

3.3.2.1 Early Removal of Peaking Generation from Market

Since a generator who offers its output at marginal cost (as assumed in this model) will at least recover marginal costs whenever it is dispatched, the discrepancy between average costs and average revenues shown in Figure 3.6 is caused by a failure to fully recover fixed costs. A failure to recover fixed costs that are unavoidable will not necessarily result in generators removing their capacity from the market. However, some of the generators' fixed costs, such as salaries and some maintenance, can reasonably be expected to be avoided by removing the generator from service. Generators whose revenues fall below that necessary to cover at least the avoidable fixed costs will be mothballed or closed. If the avoidable costs as a percentage of total fixed costs for peaking plants are similar to or higher than mid load and base load generators, then the peaking generators will be closed or mothballed first when reliability increases and the frequency of prices at the price cap decreases. Mid

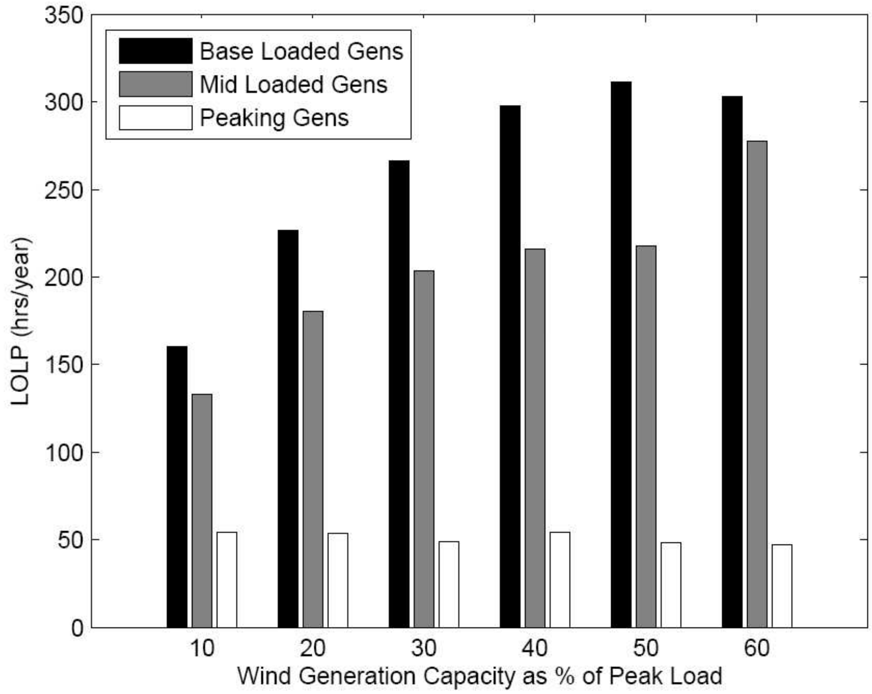

Figure 3.7: LOLP necessary for each of the three generator types to fully recover their fixed costs at increasing levels of wind generation penetration.

load and base load generators will continue to be able to make a contribution to fixed costs when prices are at the marginal cost of the peaking plants.

3.3.2.2 Changes in Reliability of Supply

In the long term, the prices realized by generators must at least equal their average cost or new supplies will not be built. In this case, if load grows and/or older generation is retired, the number of hours that supplies will be inadequate to meet the load will increase. LOLP is a measure of the expected number of hours per year during which available supplies fall short of total demand. In these hours, electricity prices can rise to the price cap. With the price cap and generator fixed and marginal costs assumed in this chapter, the level of LOLP necessary for each of the three generator types to fully recover their fixed costs at increasing levels of wind generation penetration is shown in Figure 3.7.

If the installed capacity of dispatchable conventional peaking generators is reduced as wind generation is added such that the LOLP is held constant at the level prior to the addition of wind generation, the remaining peaking generators will fully recover their fixed costs for all levels of wind penetration. However, the same is not true for mid load or base load generators who can recover their fixed costs from both inframarginal rents (when prices are set by suppliers with higher marginal costs) and periods of scarcity when prices are at the price cap. As shown in Figure 3.7, as the wind generation capacity is increased from 10% to 50% of peak load, the LOLP needed to achieve fixed cost recovery of mid load generators increases from 113 hours to 218 hours a year. For base load generators, the increase in LOLP is even greater, rising from 160 hours a year to 311 hours a year. This represents a 600% increase in the number of hours a year when there would be insufficient generating capacity to meet the total demand for load plus operating reserves. A deterioration in LOLP to the level necessary for mid load and base load generators to fully recover fixed costs would result in large profits for peaking generators. This is because the number of hours when prices are at the price cap would be far more than what is necessary for peaking generators to recover their fixed costs. Thus in the long term, entry of new or mothballed peaking plants will act to limit LOLP and mid load and base load generators will exit. This completes the mechanism by which structural changes to the generation mix will likely be affected in the long term.

3.3.2.3 Changes in the Size of the Dominant Supplier

If the size of the dominant supplier increases, more opportunities will present to profitably support prices by withholding supplies. Thus, a market response to declining prices from increasing amounts of wind generation may be an increase in the size of dominant suppliers, possibly through mergers. If the capacity of dispatchable conventional peaking generators is held constant, Figure 3.8 shows that the size of the dominant supplier necessary for mid load and base load generators to fully recover fixed costs, in this model, would rise from 8% to 32% of the peak load as wind generation capacity is increased from 10% to 60% of peak load. At higher levels of wind penetration, the size of the dominant supplier required

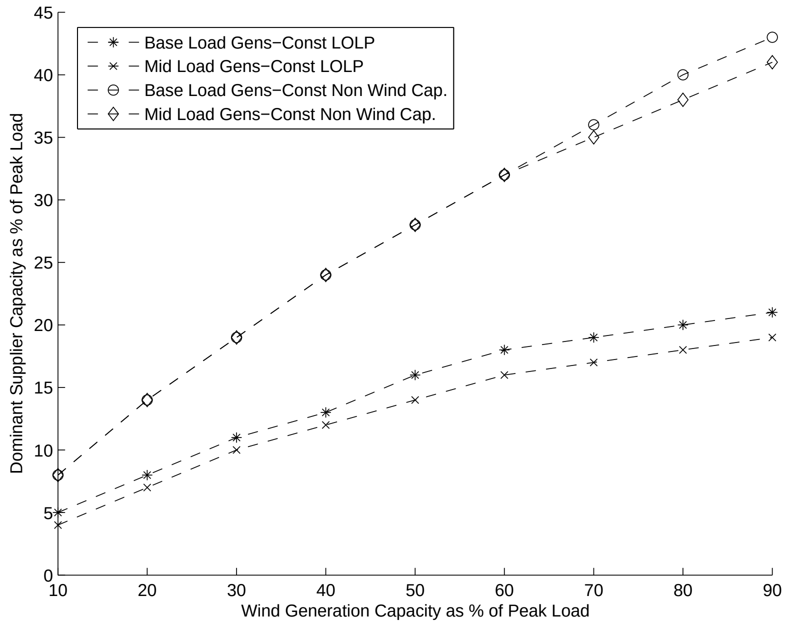

Figure 3.8: Dominant supplier capacity as a percentage of peak load needed to fully recover fixed costs as the level of installed wind generation increases.

to achieve fixed cost recovery is even higher. Also shown on Figure 3.8 is the scenario where the capacity of existing peaking generators is reduced so as to maintain a constant LOLP as wind generation is added. In this case, the size of the dominant supplier necessary for mid load and base load generators to fully recover fixed costs is significantly reduced to between 4% and 18% of peak load. For a system with a 10000 MW peak load, the size of the dominant supplier would be between 400 MW and 1800 MW, which could easily be equal to the capacity of a single generator or a single plant or the portfolio of supplies held by a single supplier.

3.3.3 Long Term Impacts (Regulatory Response)

3.3.3.1 Changes in the Price Cap

Peaking generators that are competing with each other depend entirely on periods of scarcity when prices rise to the price cap for fixed cost recovery [6]. In [6], it is shown that in a fully competitive market, the number of hours each year of prices at the price cap that is necessary for peaking generators to fully recovery fixed costs assuming 100% generator availability is,

$$H = \frac{FC}{PC\text{-}MC} \tag{3.6}$$

where H is the number of hours per year when prices are set by the price cap, FC is the annual fixed costs of a unit of capacity of a peaking generator, PC is the price cap in \$/MWh and MC is the marginal costs of a unit of energy production from a peaking generator.

In order to recover fixed costs during periods when prices are at the price cap, generators must be available for dispatch. To account for generator unavailability, the number of hours H in Equation (3.6) must be adjusted by dividing the H in Equation (3.6) by the peaking generator availability. When expressed in hours per year, this is the LOLP that is necessary in a fully competitive market for peaking generators to fully recover their fixed costs.

As shown in Figure 3.3, the introduction of wind generation while holding the capacity of other dispatchable conventional generation constant has the effect of increasing the reliability of supply by lowering the LOLP. Increasing the price cap enables generators to fully recover fixed costs with fewer hours of prices at the price cap and a lower LOLP. The link between the price cap and the LOLP necessary for peaking generators to recover fixed costs means that raising the price cap also signals a shift in the long term expectation for reliability of supply. While raising the price cap facilitates improved future reliability, it is generally thought that price caps should not be set above the value of increased reliability to the load or Value of Lost Load (VoLL) [6]. In practice, the VoLL in electricity markets is difficult to determine and price caps are often set at levels well below estimated values of VoLL [6]. Raising the price cap to the level necessary for full fixed cost recovery for peaking generators will aid, but not fully recover the fixed costs of mid load and base load generators. Figure 3.9 shows the price cap necessary for peaking generators to fully recover fixed costs as wind generation capacity as a percentage of peak load is increased from 0% to 30%.

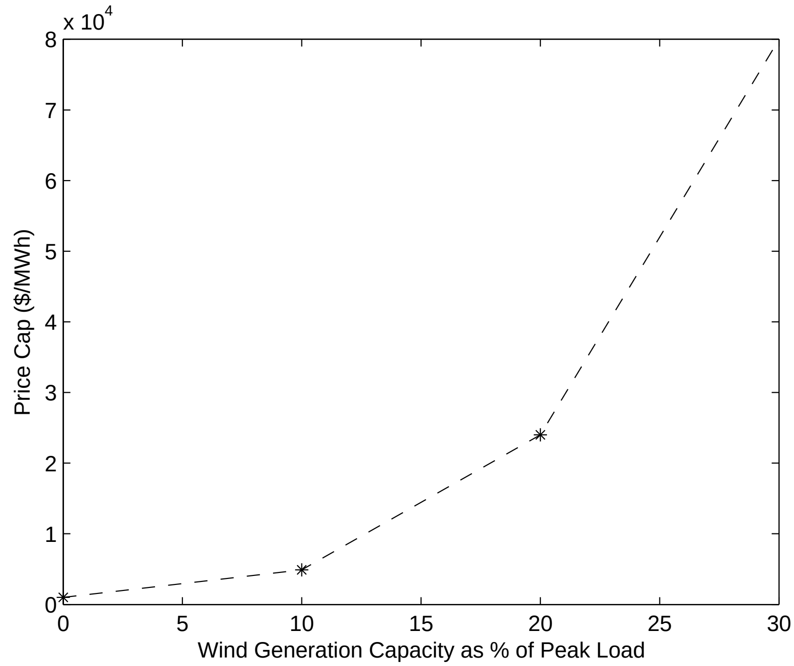

Figure 3.9: Price cap to maintain fixed cost recovery of peaking generators.

3.3.3.2 Capacity Payments

The regulator could attempt to remedy a lack of fixed cost recovery through some form of capacity payments. Alternatively, capacity and or reserve markets could provide another avenue by which suppliers could affect some fixed cost recovery. However, these have not been considered and are beyond the scope of this analysis.

3.4 Summary

In this chapter, the effects of large-scale integration of wind powered electricity generation in a deregulated energy-only market on loads and dispatchable conventional suppliers were examined. A system model was created that includes time series models of wind generation, load and resultant residual demand, a non-chronological duration curve of the resultant residual demand, a probabilistic model of dispatchable conventional generator availability, a model of an energy-only market with a price cap, and a model of generator costs and dispatch behavior. A number of simulations were performed to evaluate the effect on electricity prices, overall reliability of supply, the ability of a dominant supplier acting strategically to profitably withhold supplies, and the revenues and costs of dispatchable conventional suppliers at different levels of wind generation penetration.

It was shown that in the medium term, increased penetration of wind generation can lead to lower electricity prices and increased reliability of supply. However, this is a transient phenomenon. Adding wind generation to the system also results in less supply from the dispatchable conventional generation installed on the system. Because generators have fixed as well as variable costs, average costs of production increase as their capacity factor declines. In the long term, prices must at least equal the average cost of production or sufficient dispatchable supplies will not be built and reliability of supply will deteriorate. In the very long term, the deterioration in reliability can be addressed by a structural re-optimization of the generation mix.

It was also concluded that at low to moderate levels of wind generation, the uncertainty in wind generation output and the consequent residual demand increases the ability of dispatchable conventional generators to profitably withhold energy. As the size of the dominant supplier relative to the peak demand increases, more opportunities will present to profitably withhold supplies. This creates a possible market response whereby prices may be supported or rise without a deterioration in reliability.

The results of this analysis indicate that raising the price cap as the installed wind generation capacity increases is an action the regulator may take to aid in fixed cost recovery of dispatchable conventional generators and provide an economic signal that is consistent with a shift in the generation makeup toward a cost minimizing mix of technologies (i.e. a shift from base load to peaking generators) and a higher reliability of supply following the large-scale integration of wind.

Chapter 4

Long Term Market Equilibrium Model with Strategic, Competitive and Inflexible Wind Generation

4.1 Introduction

Anticipating the long term equilibrium behavior of generators in deregulated power systems is important to anticipate future system reliability, emissions, and electricity price characteristics. In general, equilibrium models of electricity markets are varied and complex [60]. Most models are concerned with short term equilibrium and do not consider additions or retirements of generation. Long term equilibrium is complicated by the prospects for the large scale integration of inflexible generation such as wind.

In this chapter, a general model of long term equilibrium in energy-only electricity markets is developed that allows for generation additions and retirements. Equilibrium electricity prices and reliability of supply are analytically found for markets where all participants behave competitively and for markets with a mix of inflexible supplies and competitive generators. Equilibrium states for markets with a mix of competitive and inflexible generation and a low cost strategic supplier are estimated.

The proposed model differs significantly from other models of equilibrium and long term development. It neither assumes a Cournot game for the generation expansion process [53, 54] nor the operation of the market [4, 28] and importantly there is no dependence on demand response to set prices. Unlike the Supply Function Equilibrium (SFE) model [17], the proposed model allows for generator offers that are made in discontinuous steps. Unlike the Conjectured Supply Function (CSF) model [27] the proposed model is not reliant on conjectured responses of others. Finally, unlike [56] the proposed model is not reliant on a detailed model of the long term dynamics of electricity markets.

A contribution of the work in this chapter is demonstrating that under assumptions of competitive or inflexible behavior by suppliers, long term equilibrium electricity price duration curves and reliability of supply associated with a traditional cost minimizing mix of generation [6] are independent of the load shape, or the amount or production pattern of inflexible generation such as wind generation on the system.

A second contribution is showing how consideration of a strategic supplier provides an explanatory mechanism of market operation that can lead to large improvements in expected reliability of supply, a radical change in the generation mix and a large change in expected emissions.

The rest of this chapter is organized as follows. Section 4.2 develops a general model of long term equilibrium in energy-only electricity markets that allows for generation additions and retirements is developed. The model is then applied with different assumptions regarding generator behaviors. The distribution of electricity prices and reliability of supply at equilibrium are analytically found for fully competitive markets with and without inflexible generation. In Section 4.3, a method to determine long term equilibrium in markets with a mix of competitive and inflexible generators and a low cost strategic supplier is proposed and illustrated. Finally, Section 4.4 summarizes this chapter.

4.2 Long Term Equilibrium

To consider the impact of the integration of wind generation and other inflexible generators on the long term equilibrium prices, reliability of supply, and emissions, a general equilibrium model for energy-only electricity markets is proposed based on the notion that at equilibrium all generators must, over a period of time such as a year, recover all costs and neither make a profit nor take a loss. Profits above costs provide signals for investment in additional generation. Losses signal the need to retire generation. Generator costs can be divided into fixed costs expressed in \$/MW/year and variable costs expressed in \$/MWh. The recovery of fixed costs from energy sales occurs when electricity prices P_i exceed a generator's variable costs. At equilibrium, fixed cost recovery must equal fixed costs for all generators n (4.1).

$$F_n = \sum_{i=1}^{k} (P_i \,-\, V_n)\; T_i \, R_{n,i} \, Q_{n,i} \tag{4.1}$$

such that $0 \leq T_i \leq 8760$, $0 \leq R_{n,i} \leq 1$, $0 \leq Q_{n,i} \leq 1$ and the sum of T_i from i = 0 to k is equal to 8760.

Where

$F_n =$ Fixed costs of generator n,

$V_n =$ Variable costs of generator n, with $V_n < V_{n+1}$,

$P_i =$ Offer price of energy block i,

$T_i =$ No. of hours per year where prices are equal to P_i,

$R_{n,i} =$ Availability of generator n when prices are equal to P_i,

$Q_{n,i} =$ Average dispatch of generator n as a fraction of available capacity when price is equal to P_i and,

$k =$ No. of generator offer blocks in the market with P_k = market price cap.

4.2.1 Fully Competitive Markets

For a fully competitive market, all flexible generators n offer all available capacity at marginal cost V_n. Then, $Q_{n,i} = 1$ for all $n < i$ and 0 for all $n > i$. For $n = i$, there is no contribution to fixed cost recovery because $P_i - V_n = 0$. If F_n, P_i, V_n, $R_{n,i}$ and $Q_{n,i}$ are known then all T_i can be found and,

$$Average\ price = \sum_{i=1}^{k} \frac{T_i P_i}{8760} \tag{4.2}$$

$$Percentage\ of\ time\ prices\ at\ P_i = \frac{T_i}{8760} \tag{4.3}$$

In a fully competitive market, price = price cap P_k when available generation is less than the demand and some load is not served. Thus, in fully competitive markets, the number of hours when the price equals the price cap is equal to the Loss Of Load Probability (LOLP) expressed in hours per year and is equal to T_k.

As shown in (4.1), consistent with familiar generation screening curve analysis [6], it is found that if flexible generators are assumed to behave competitively, and with no transmission constraints, a fixed set of generator types and costs, availability and a fixed market price cap, that the long term time weighted equilibrium electricity prices and reliability of supply are constant and independent of the level or shape of the load throughout the year.

4.2.2 Equilibrium with a Mix of Competitive and Inflexible Generators

In many markets, production from some suppliers is unresponsive to price. Wind generation is an example of this. Such generation can be characterized as inflexible and treated as a modifier to load where the residual demand seen by other suppliers is the demand net of the inflexible supply. If the remaining flexible suppliers behave competitively, the finding in the previous Section 4.2.1 for a competitive market indicates the long term time weighted average electricity price, distribution of electricity prices, and LOLP remain constant and are unaffected by either the amount of inflexible generation such as wind generation or its pattern of production.

4.2.3 Equilibrium with a Strategic Generator Combined with a Mix of Competitive and Inflexible Generators

Changes in available supply and demand give rise to varying opportunities for individual generators or groups of generators to profit from economically withholding a portion of their available capacity. This analysis explores the long term equilibrium that arises in the case where the generator or generators with the lowest variable costs are assumed to act as a dominant supplier [72] which strategically allocates all available capacity between offers at V_n and the price cap P_k to maximize profits. Other generators are assumed to be either inflexible and netted against the demand, or fully competitive and offering all available capacity at their marginal cost V_n.

In this case, the strategic generator or generators n do not offer all available capacity at marginal cost V_n and $Q_{n,i}$ is not equal to one for all $n < i$. For competitive generators to fully recover costs, the number of hours at each price point $P_i > V_n$ must remain the same as in a competitive market. At equilibrium, average prices are higher because the period when prices P_i are equal to the competitive supplier with the lowest marginal cost V_n is increased.

By withholding capacity at opportune times, the dominant supplier can increase its profits and increase prices. The increased profitability of suppliers is met with additions to capacity until all generators neither profit nor take a loss. The additional capacity supported by the strategic behavior of a dominant supplier improves the LOLP by reducing the number of hours each year when available capacity is less than load. In this case, the installed generation capacity and mix of generation types at equilibrium are not independent of the level and shape of load.

4.3 Application to a System with Strategic Coal Generation, Competitive Combined Cycle Gas Generation and Inflexible Wind Generation

In this section, an energy-only market with supercritical coal fired generators, combined cycle gas fired generators, and wind powered generators is assumed. The fixed costs in \$/MW/Yr, marginal cost in \$/MWh and CO2 emissions in t/MWh assumed for each generator type are shown in Table 4.1 [1]. The market price cap is assumed to be \$1000/MWh. The load is assumed to have an annual peak value of 10000 MW. The load shape and pattern of wind generation are modeled on data from the Alberta, Canada system [42]. All non-wind generators are assumed to have an availability of 95%. It is assumed that operating reserves are part of the total demand and providers are compensated at the opportunity cost of not providing energy. A Monte Carlo simulation of available generation capacity is matched to an hourly model of demand based on generator offer prices. The production, revenues, costs, and CO2 emissions for each generator as well as the number of hours when available generation capacity is less than demand are summed over a year. Generators that are profitable have their capacity increased by a small increment and generators that incur losses have their capacity reduced by a small increment. The process is repeated until all generators are neither making a profit nor taking a loss. The process is repeated for several different hourly patterns of generator availability.

The market equilibrium was estimated for three scenarios. Scenario A assumes all generators behave competitively and there is no wind generation. Scenario B adds wind generation with all other generators behaving competitively. Scenario C differs from Scenario B by assuming all coal fired generators are acting as a dominant supplier that strategically apportions its available capacity to offer prices at its marginal cost and the price cap. The average electricity prices and LOLP for each scenario are shown in Table 4.2. Table 4.3 gives the generation mix and CO2 emissions for the different scenarios.

The process used for finding the equilibrium was chosen to mimic a market response to profits and losses. By definition, the end state when all generators are neither making a profit nor taking a loss is an equilibrium as no generation can profitably be added. For Scenario A and B, the result is the cost minimizing mix to meet the residual demand that is consistent with classical screening curves analysis [6]. In Scenario C, an equilibrium exists when the strategic supplier is also the lowest marginal cost supplier who faces no competition from other suppliers with similar costs. If a generator attempts to profit by withholding capability, any increase in price will always create an opportunity for a dispatchable competitor with the same costs to improve profitability by entering the market or increasing its output if not fully dispatched.

In these simulations, the strategic supplier can only offer at marginal cost or just under the price cap. All price supports arise from economic withholding. All withheld energy is priced at just below the price cap. Because of this, prices can rise to just under the price cap without load interruptions.

The assumption of a single low cost strategic supplier that does not face competition from competitors with similar costs is not unreasonable. Table 4.3 shows at the equilibrium that was found the capacity of the strategic supplier in Scenario C is comparable in size to a large generating unit or two medium sized generators.

The solution method used changes generation capacity in small increments because large increments can lead to oscillatory additions followed by retirements as the generation mix is adjusted and progresses towards equilibrium. When initial conditions allow the dominant supplier to profit from strategic behavior, it is incented to increase capacity. However, strategic behavior that supports price above the marginal cost of the next highest competitive supplier also incents generators with higher marginal costs to increase capacity. The entry of higher marginal cost competitive new generation eventually leads to situations where the dominant supplier must reduce in size to maintain profitability. As shown in Table 4.3, at the equilibrium that was found the capacity of the dominant supplier in Scenario C is significantly lower than in Scenarios A or B.

The price duration curves for the Scenarios A and B and for Scenario C are shown in Figure 4.1. The reduced size of the dominant supplier in Scenario C means prices are now set by generators with higher marginal costs during all hours. This provides price supports to the dominant supplier. In Scenarios A and B, prices during some hours were set by the marginal cost of the low cost producer. In these hours, the low marginal cost generator is not recovering any fixed costs.

In competitive markets whenever prices are at the price cap the low cost producer would be expected to produce at full available capacity. A dominant supplier profits by withholding to raise prices. However, this means the average dispatch level of the dominant supplier when prices are at or just below the price cap will be less than the full available capacity. For competitive generators other than the dominant supplier to fully recover costs, the number of hours at each price point $P_i > V_n$ must remain the same as in a competitive market. Withholding by the dominant supplier means a reduction in expected revenues in relation to its available capacity when prices are at or near the price cap. Since at equilibrium, the dominant supplier must just recover all fixed costs, the reduction in revenues is offset by an increase in the hours when prices are set by the marginal costs of the least cost competitive generator.

Consideration of a strategic supplier leads to an increase in total generation capacity as shown in Figure 4.2. Total generation capacity in Scenario A is 10265 MW. In Scenario B, the addition of wind generation results in an overall increase in total generation capacity to 10334 MW but 131 MW of this is wind generation. The total capacity from coal and gas generation decreases slightly to 10203 MW. The addition of a strategic supplier increases total capacity to 11001 MW and also increases the total capacity from coal and gas generation to 10631 MW.

If a generator or group of the lowest marginal cost generators are assumed to act strategically in concert, the equilibrium electricity prices are higher than a fully competitive market, but the level of LOLP is dramatically reduced. In Scenario B, where all generators are assumed to act competitively, the anticipated LOLP is 176.2 hours per year. Consideration of a low cost dominant supplier leads to a large reduction in LOLP to 33 hours per year.

A significant finding is that consideration of a strategic supplier can lead to a structural change in the generation mix and, in the case analyzed, a large reduction in anticipated

Table 4.1: Generation costs by technology [1]

Gen. Type	Fix Cost ($/MW/yr)	Var. Cost ($/MWh)	Emiss.(t/MWh)
SC Coal	$370,723	$24	0.9
CC Gas	$157,680	$58	0.37
Wind	$272,874	-$18	0

Table 4.2: Average electricity prices and no. of hours/year when available generation is less than load

Scenario	Avg. Elect. Price	No. of Hrs Gen. less than Load
A	$71.02	176.2
B	$71.02	176.2
C	$76.95	33

Table 4.3: Generation mix and emissions under different Scenarios

Scenario	MW SC Coal	MW CC Gas	MW Wind	Mt/year CO2
A	8088	2177	0	60.8
B	8010	2193	131	60.4
C	677	9954	370	28.6

emissions. The coal generation capacity has dropped by 92%, from 8010 MW in Scenario B where competitive behaviour was assumed for all generators, to 677 MW in Scenario C where a low cost strategic supplier is assumed. As well, CO2 emissions have dropped by 53%, from 60.4 Megatonnes per year to 28.6 Megatonnes per year.

4.4 Summary

In this chapter, a general model of long term equilibrium in energy-only electricity markets was proposed and applied with different assumptions with regard to generator behaviors. It was found that if flexible generators are assumed to behave competitively, with no transmission constraints, a fixed set of generator costs, availability, and a fixed market price cap, that the long term equilibrium electricity prices and reliability of supply are constant and independent of the level or shape of the load, or the amount or dispatch of inflexible generation on the system.

It was also found that consideration of a strategic supplier provides an explanatory

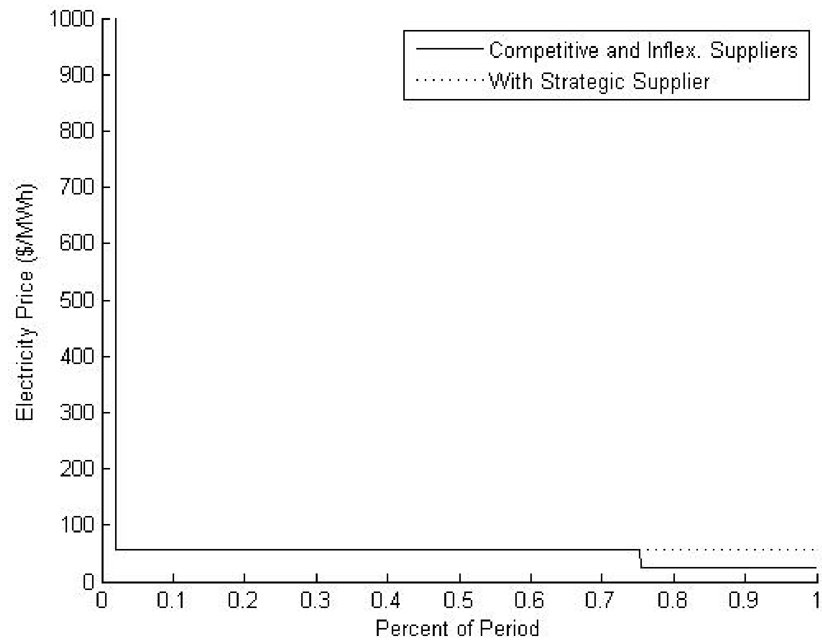

Figure 4.1: Electricity price duration curve with competitive and inflexible suppliers and with a strategic supplier

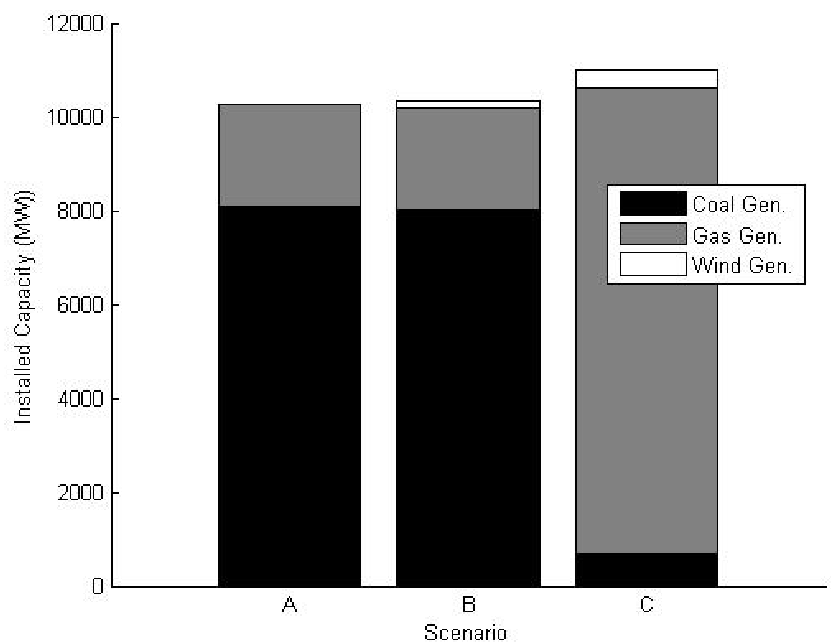

Figure 4.2: Installed generation capacity with competitive and inflexible generation and with a strategic supplier

mechanism of market operation that can lead to large improvements in expected reliability of supply, a radical change in the generation mix, and a large change in expected emissions. The resulting generation mix, reliability, and emissions are not necessarily optimal in the sense of the lowest possible cost.

Chapter 5

Anticipating Prices, Reliability and Emissions in Energy-Only Markets in the Medium Term [1]

5.1 Introduction

The third research objective in this thesis, anticipating electricity prices and reliability of supply in existing energy-only markets over the medium term, is investigated in this chapter. An estimate of the impact on emissions emerges as part of this analysis and is also discussed.

To plan for transmission system expansion and to anticipate future reliability of supply, there is a need to anticipate generation development over the medium term time frame associated with the build cycle for new generation. Questions of interest are both what type of generation is likely to be built and how much generation is likely to be built.

Prices in deregulated electricity markets often reflect strategic behavior of suppliers and differ from would be expected in a perfectly competitive market [15, 16]. This can affect expectations for investment and reliability of supply over the medium term. In deregulated markets, prices provide signals to generators for new investment. For new generation to enter, prices after entry must be sufficient for the generator to recover all costs. Generator costs can be divided into fixed costs expressed in \$/MW/year and variable costs expressed in \$/MWh. The recovery of fixed costs from energy sales occurs when electricity prices exceed a generator's variable costs [6].

If competitive behavior is assumed for all participants in future markets, all generators

[1] Based on the findings of this chapter, a paper is in preparation to be submitted to *the IEEE Transactions on Power Systems*

would offer all available capacity at marginal cost [6, 49]. In this case, the marginal cost of the last generator dispatched sets the electricity price. Prices reflect either the marginal cost of the generator on the margin or the market price cap if generation is inadequate to meet the load.

However, observed prices are often above the marginal cost of any generator but below the price cap [59]. Since prices below the price cap are normally set by generator offers [74], this is indicative of strategic behavior by some generators. Prices above the marginal cost of any generator but below the price cap provide for the recovery of fixed costs by generators that would not be anticipated if competitive behavior of all participants was assumed.

Since the adequacy of fixed cost recovery provides a signal for investment in new capacity, anticipating new generation additions in the medium term requires market models that reflect the observed behavior of generators and can anticipate generation at prices other than marginal cost but below price cap.

A method for modelling generator behaviors, anticipating electricity prices and reliability of supply in the medium term time frame associated with the build cycle for new generation is proposed in this chapter. The anticipated impact on emissions that emerges as part of this analysis is also presented. The proposed method differs from [55] in that existing generator behaviors are modeled on observed behavior and not based on conjectures of others' bidding strategies and no assumptions are made on generator expansion plans. Unlike [56], existing participants are not assumed to offer all capability at marginal cost and anticipated generation expansion is not dependant on a model of the investment process. Unlike [53, 54] generator expansion is not considered to be a Cournot game.

The remaining parts of this chapter are organized as follows. In Section 5.2, electricity markets that are not in long term equilibrium are discussed with reference to generator behaviors, electricity prices, and entry and exit of generation from the market. In Section

5.3, the proposed method for anticipating prices, reliability of supply, and emissions in the medium term is presented. The proposed method is illustrated by an application to the Alberta system in Section 5.4. Conclusions and summary are presented in Section 5.5 of this chapter.

5.2 Electricity Markets that are Not in Long Term Equilibrium

Existing power systems are exposed to continually changing environments in terms of generation costs, average load and load profile, generator additions and retirements, and ensuing changes to the mix of generation technologies available to serve the load. A consequence is that it is unlikely the state of existing electricity markets will match a long term equilibrium state in terms of the types of generation and capacity of generation mix, electricity prices or reliability of supply.

5.2.1 Generator Behaviors

Generators in deregulated electricity markets can be expected to act strategically to maximize profits in the short term. As a result, the dispatch of generators can be expected to vary as changes in available supply and demand give rise to varying opportunities for individual generators or groups of generators to profit from economically withholding a portion of their available capacity. Further, generators with similar technologies and costs but which are managed as part of different generation portfolios or which have different contractual obligations may exhibit different dispatch behaviors [29].

Differences in the behavior of coal fired generators can be readily observed in the Alberta market. Figure 5.1 graphs the hourly MW outputs over a year of two coal generators where the hourly MW outputs for each generator have been arranged in descending order from highest to lowest [59]. For comparison, the hours of zero output have been removed and the outputs of each generator have been normalized so that an output of 1.0 represents

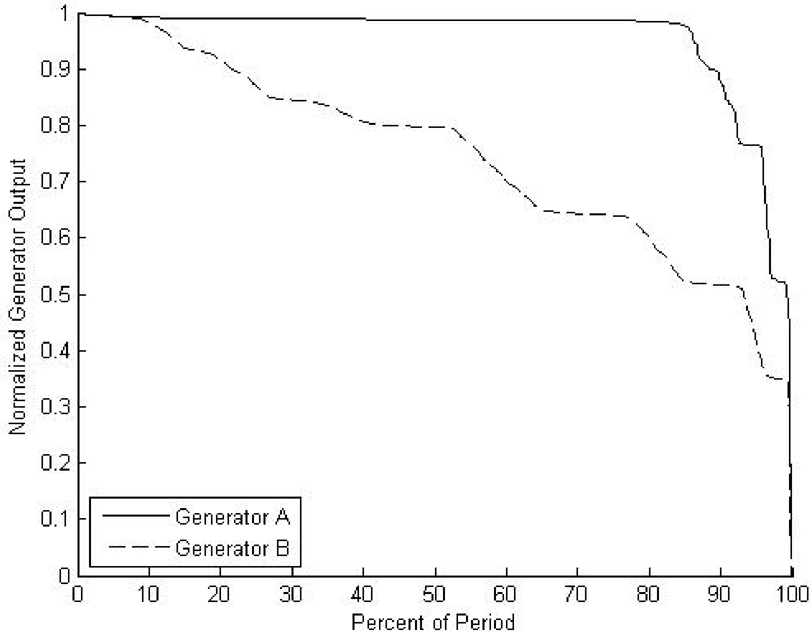

Figure 5.1: Annual generation duration curves for two coal generators in Alberta

the generator output at full capacity. A cursory examination indicates significant differences in how the coal fired units are dispatched. Generator A produces at close to full output during all hours, which is consistent with competitive behavior. In contrast, Generator B operates at significantly reduced output for much of the year, consistent with a greater degree of strategic behavior. Because both generators are coal fired units, they can be expected to have marginal costs that are similar (but not necessarily the same) and below market price during most hours of the year. Coal fired units have long start up times, minimum stable levels of operation, and low fuel costs and hence low marginal costs of production. In fully competitive markets, these generators would be expected to be base loaded and run at maximum output any time prices were above their marginal costs. When prices fall below marginal costs, the same generators would be expected to decrease output to minimum stable levels of generation. However, some generators have been observed to run at maximum capability even when electricity prices are very low. In Alberta, historical information on generator offers shows that several thousand MW of capacity is routinely

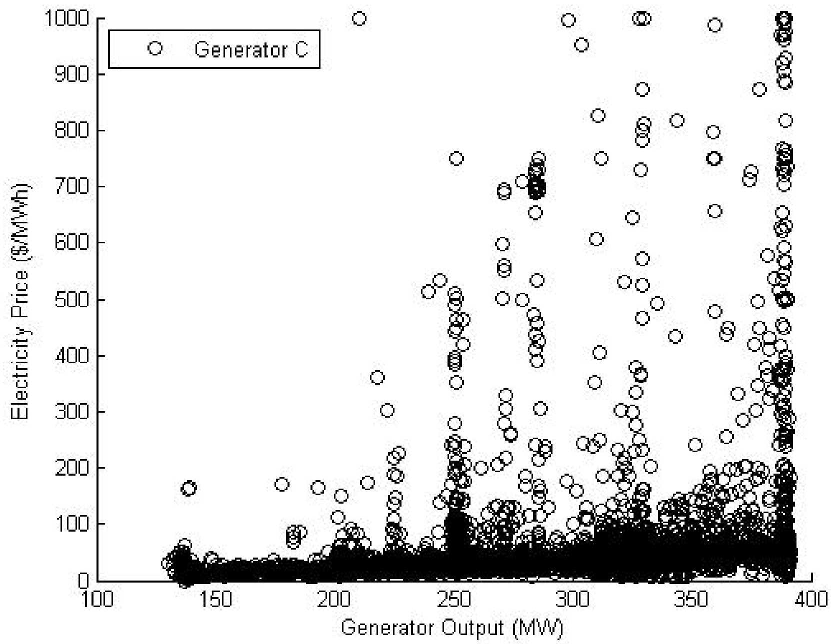

Figure 5.2: Scatter plot of electricity price and a coal generator output in Alberta

offered into the market at $0/MWh [75]. In other instances, when prices are very high, some coal generators have been observed to run significantly below capacity. A scatter graph of the output of one Alberta coal generator against observed prices over the period September 1, 2009 to August 31, 2010, shown in Figure 5.2, illustrates that existing generator output is not adequately modeled by simple relationships to price and availability.

5.2.2 Observed Electricity Prices

Under the assumption of fully competitive behavior, prices are always reflective of either the marginal costs of the generator on the margin or the price cap when all load cannot be served. However, prices in actual markets are often observed to be above the marginal costs of any generator on the system but below the price cap [16, 18]. Such prices arise from strategic offer behavior of generators.

Figure 5.3 shows the electricity prices in Alberta from September 1, 2009 to August

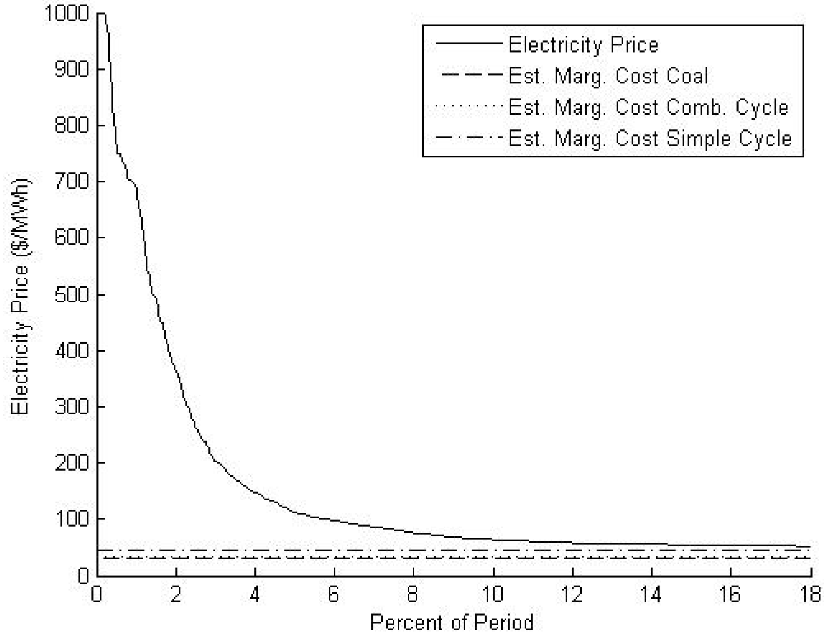

Figure 5.3: Electricity price duration curve in Alberta for highest priced 18% of hours of the study period. The legend indicates the electricity price duration curve, estimated marginal cost of coal generators, the estimated marginal cost of combined cycle generators, and estimated marginal cost of simple cycle gas generators.

31, 2010 sorted from highest to lowest for the highest priced 18% of all hours. Figure 5.4 shows the prices for the lowest priced 35% of all hours [59]. On both figures, the marginal costs of new coal fired generators, combined cycle generators, and simple cycle generators estimated from publically available data provided by the Alberta Electric System Operator are also shown [2]. It can be seen that prices both below and above the estimated range of new generator marginal costs occur and are not uncommon. Data on the marginal costs of existing generators is not publically available. However, it is prices in relation to the marginal cost of new generation that provide signals for new investment.

5.2.3 Price Signals for Generation

In general, profits provide signals for new generator investment and losses could result in generator retirements. Because markets are seldom in equilibrium, prices and profits

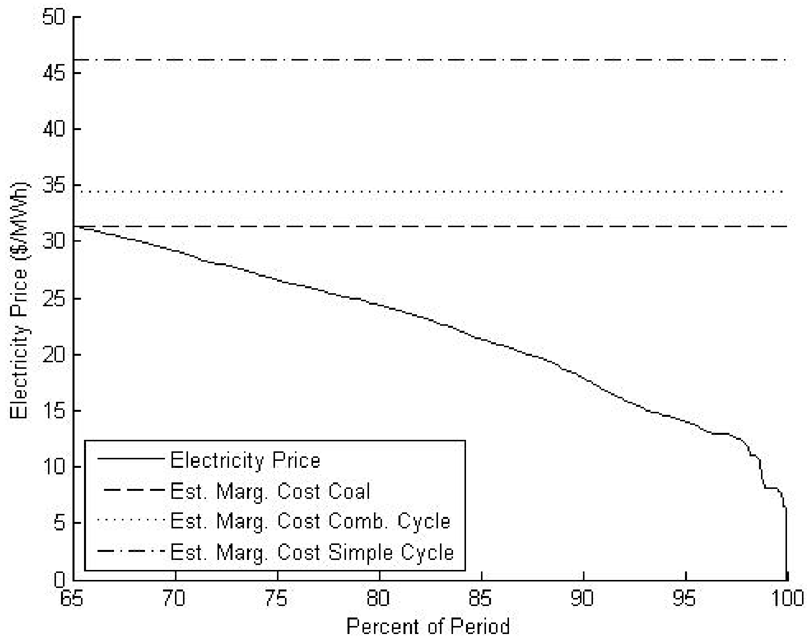

Figure 5.4: Electricity price duration curve in Alberta for lowest priced 35% of hours of the study period. The legend indicates the electricity price duration curve, estimated marginal cost of coal generators, the estimated marginal cost of combined cycle generators, and estimated marginal cost of simple cycle gas generators.

may signal opportunities for investment in new generation of one type while generation of another type is suffering losses.

As shown in Chapter 4, generator costs can be divided into fixed costs expressed in \$/MW/year and variable costs expressed in \$/MWh. The recovery of fixed costs from energy sales occurs when electricity prices P_i exceed a generator's variable costs.

Defining,

$F_n =$ Fixed costs of generator n,

$V_n =$ Variable costs of generator n, with $V_n < V_{n+1}$,

$P_i =$ Offer price of energy block i,

$T_i =$ No. of hours per year where prices are equal to P_i,

$R_{n,i} =$ Availability of generator n when prices are equal to P_i,

$Q_{n,i} =$ Average dispatch of generator n as a fraction of available capacity when price is equal to P_i and,

$k =$ No. of generator offer blocks in the market.

Prices signal opportunities for generation additions when over an extended period fixed cost recovery exceeds fixed costs (5.1).

$$F_n < \sum_{i=1}^{k} (P_i \;-\; V_n)\; T_i \, R_{n,i} \, Q_{n,i} \tag{5.1}$$

such that $0 \leq T_i \leq 8760$, $0 \leq R_{n,i} \leq 1$, $0 \leq Q_{n,i} \leq 1$ and the sum of T_i from i = 1 to k is equal to 8760.

As shown in (5.1), the distribution of hourly prices above variable costs for each type of generator is key to determining opportunities for generation to profitably enter the market.

5.2.4 Modeling Existing Markets with Entry and No Exit

New generators can be anticipated to enter the market when the expectation for long term prices supports the full recovery of both fixed costs and variable costs. However, existing generators can be expected to continue to operate even if fixed costs are not fully recovered as long as prices are above their avoidable fixed and variable costs.

Since markets present continuously varying opportunities for entrance of new generation and existing generation is unlikely to exit, medium term expectations for prices, reliability of supply, and emissions can be modeled assuming the entry of new generation where profitable but assuming existing generation does not exit unless generator revenues over a period such as a year fall below that necessary to cover avoidable fixed and variable costs.

5.3 Proposed Method for Anticipating Prices, Reliability of Supply, and Emissions in the Medium Term

To anticipate electricity prices, reliability of supply, and emissions in existing systems in the medium term, a methodology is proposed where generators responsive to observable market parameters are identified as flexible and a residual demand net of inflexible generators created. Models of the market behavior of the flexible generators are created and combined with a probabilistic model of generator availability in a model of an energy-only market with a price cap. Several market simulations are then performed to estimate the potential for new generation additions and the resulting prices, reliability of supply, and emissions are estimated.

The methodology is summarized in the following steps. Each step is discussed in more detail later.

Step 1) This work focuses on modeling the behavior of generators whose output is responsive to price and other market parameters that are readily observable to all market participants. As a first step, generators are classified as either flexible or inflexible where inflexible generators are characterized as either not dispatchable, unresponsive to electricity prices, or whose dispatch is significantly restricted due to factors other than electricity price.

Step 2) Next, inflexible generators are treated as modifiers to demand. Using historical or forecast data, the hourly residual demand seen by the flexible generators over the study period is created by subtracting inflexible suppliers hourly MW output from the total demand.

Step 3) Behavioral models of the flexible generators are then created using historical market data. For each flexible generator, the historical hourly MW outputs over an extended period are classified into two to ten classes using a modified K-means clustering algorithm. Based on the historical market data, Probabilistic Neural Networks (PNN) are created and trained for each flexible generator that relate observable market parameters including price to the previously classified output levels of each flexible generator.

Step 4) One or more scenarios depicting the availability of each generator in each hour over a year are then created. To create the scenarios, a Monte Carlo simulation is performed that uses Markov models to depict the availability of each generator in each hour.

Step 5) A model of an energy-only electricity market is created and assumptions are made for the price cap and demand elasticity. The market model must be consistent with and fairly represent the market operation reflected in the historical market data used to create and train the behavioral models of generation

Step 6) The PNN models of all flexible generators and the hourly scenario of generator availability are then combined with an hourly residual demand into a market simulation where hourly prices, generation, emissions, and profitability of each generator are calculated.

Step 7) Market simulations are rerun iteratively to determine the MW of competitive new generation that can profitably be added. Once all profitable generation has been added, forecast hourly electricity prices are noted and forecast emissions are estimated by multiplying each generators annual energy output by its emission intensity.

Step 8) Finally, the reliability of supply after all profitable generation is added is estimated using standard methods described in Chapter 2 of this thesis.

5.3.1 Flexible and Inflexible Generation

In the proposed method, generators are first categorized as either flexible or inflexible. Flexible suppliers are those that are dispatchable and are responsive to changes in price. Examples of flexible generators are coal fired and gas fired stand alone generators. Inflexible suppliers are characterized as either not dispatchable, unresponsive to electricity prices, or whose dispatch is significantly restricted due to factors other than electricity price. Examples of generators that can be considered inflexible are wind and solar generation, some hydro generation, and co-generation. The effect of inflexible generators is to modify the residual demand seen by flexible generators. This is modeled by subtracting the historical or expected outputs of inflexible generators from total demand.

5.3.2 Modeling Generator Behaviors

Models of flexible generator behavior relate the generator MW outputs to observable market parameters. Over an extended period of time, generators will be exposed to a wide range of scenarios. Flexible generators whose output is not extraneously constrained may act strategically by offering available energy at different prices in response to varying market conditions. Generally, the behavior of these generators is considered to be related to prices, generator costs, availability, and prevailing demand and supply. For each flexible generator, the model output is the MW production of the generator and inputs are chosen from observable parameters including price that could signal opportunities for strategic behavior.

5.3.3 K-means Clustering of Generator Outputs

Models of flexible generators are simplified if the possible output levels from each generator are reduced. For this work, the K-means clustering algorithm [62] is applied to reduce the number of generator MW output levels modeled. Initially, the minimum and maximum hourly outputs for each generator observed over the study period are found. A level of zero output, the maximum observed output, and eight other initial guesses at cluster means evenly distributed between the observed minimum and maximum outputs are selected. The choice of ten possible offer levels balances granularity of generator output with simplicity and is consistent with normal restrictions on the number of price volume offer pairs that can be offered into the market. The generator output in each hour over the study period is then grouped with whichever of the ten initial cluster mean values it is closest to. After the generator outputs in each hour have been assigned to one of the ten groups, the mean value for each grouping other than the zero level and maximum output level groupings is calculated. This forms a set of ten new cluster means. The process is repeated with each observed generator output being reassigned to the new cluster mean that it is closest to.

Following this, the mean value for each grouping between zero and the maximum output level is again recalculated. The process continues until there is no further change in the assignment of data points to cluster means.

Since generator outputs may be adequately described by fewer than ten discrete levels, the number of observations associated with each cluster mean will vary. Some of the final cluster means may represent few observations. For this study, any time the number of observed outputs associated with a cluster falls below a threshold value (3% of observations was chosen in this thesis to provide for output levels that are supported by a reasonable number of observations), the cluster mean is eliminated and the number of clusters reduced by one. This process results in classifying the outputs from each individual generator into two to ten discrete values.

The K-means groupings can be considered reasonable and representative because the initial estimates of the K-means were evenly distributed over the possible range of values, the final K-means are based on groupings of observed output levels, are constrained to realizable values, and are constrained so that each is representative of a minimum number of observations. For the forty-four generators considered in this study, the application of the K-means algorithm resulted in the outputs of all generators being represented by fewer than the ten available levels. This indicates that assumption of ten possible groupings of output levels was adequate.

5.3.4 PNN Models of Generator Behaviors

In this work, PNN are proposed to model behaviors of existing flexible generators. Separate models are created for each flexible generator. Inputs to the PNNs are chosen to be readily observable parameters that could signal opportunities for strategic behavior. The inputs chosen for the proposed method were:

1. the hour of the day,

2. the electricity price,

3. the market heat rate calculated as the hourly price divided by the average monthly natural gas price,

4. a proxy estimate for the availability of flexible gas generation capacity in the previous hour calculated as the sum of the capacities of flexible gas generators displaying a non-zero output,

5. the dispatch level of flexible gas generators as percentage of the total capacities of flexible gas generators displaying a non-zero output in the previous hour,

6. the previous hours' residual hourly system demand less the sum of the available coal generation capacity,

7. the MW output of the generator whose behavior is being modeled in the previous hour and,

8. the MW output of the generator whose behavior is being modeled in the same hour of the previous day.

The output of each PNN classifies the individual generator output to one of up to ten possible MW levels based on the K-means clustering of generator outputs described earlier.

The PNN are then trained and tested on historical market data. The set of training examples should be sufficient to cover a broad range of market outcomes including seasonal and diurnal variations in both supply and demand and should include periods when planned maintenance of generators normally occurs.

The proposed application of PNN to model individual generator behaviors allows for the easy addition of new generators and/or removal of existing generators from market simulations. Further, because behavioral models are created for each generator, the effects of changes to individual behaviors can easily be investigated. All the models can easily be updated with new examples of observed behavior. This provides flexibility for models to change in response to changes in market rules. An advantage of these models is that no information on actual generator costs is required. By design, the outputs of the PNN are restricted to MW levels that are within the capabilities of each generator and are representative of observed operation. By focusing the inputs of the PNN on aggregate quantities of supply and demand in addition to price, the behavioral models are not sensitive to the behaviors or outages of other individual generators. In this application, in addition to price, all PNN models are trained on the same observable inputs. However, this is not a restriction on the approach. The inputs to each PNN model could differ. While the models may adequately reflect observed behavior, they are not a means to discover actual strategies of individual generators which may relate to other observable or unobservable parameters than those chosen as inputs to the PNN.

5.3.5 Modeling New Generator Behaviors

The proposed method models new generation additions as competitive suppliers who offer all available capacity at marginal cost. This was done to provide a conservative estimate of the MW of new generation additions that can be supported by the market. However, the model is not limited to this assumption. New generation additions can easily be assumed to mimic the strategies of any of the existing generators. New generators may elect to withhold output by offering some capacity at prices above marginal cost but would only do so if it were profitable. But any profitable withholding by new generation additions would always give rise to further opportunities for the profitable entry of generation with the same cost structure that offered all its capacity at marginal cost.

5.3.6 Market Simulation

A model of an energy-only market is created where the price in each hour is set by the intersection of flexible or price responsive supply and residual demand net of inflexible supplies. The residual demand is assumed to be inelastic up until a price cap. This type of market has been well described by others such as [6].

In each hour, a vector of input parameters including price is presented to the PNN associated with each flexible generator. The outputs of generators which are unavailable are set to zero. The MW output from all available generators is summed and compared to the total residual demand. Price is then increased from a low value in steps until the dispatched generation equals or exceeds the load. In cases where the price of the final step is higher than what is necessary for generation to meet load, the estimated market price is assigned to a value between the final price step and the previous price step. To balance generation with residual demand in each hour, the increment of generation dispatched in response to the last increase in step price is scaled. For each period, the generation and price are recorded.

5.3.7 Anticipated Reliability of Supply

The proposed method focuses on the reliability of supply from flexible generators to serve residual demand. The anticipated reliability of supply for both the existing system and for the system assuming entry of all profitable new generation is evaluated using standard Monte Carlo methods described in Chapter 2 of this thesis. The availability of each generator is modeled with a two state Markov model to have the simplest model possible to illuminate the key point in the analysis. Failure rates and repair rates derived from the generator availability and MTTR govern the probability of transitions between states at each time step. Multiple scenarios of the hourly availability of each generator over a year are developed that incorporate planned maintenance outage schedules. For each scenario, at each time step, the sum of available generation capacity is compared to the demand. Hours in which supply shortfalls occur indicating a need to interrupt load are flagged and summed for the year. The Loss Of Load Probability (LOLP) is estimated from the average number of shortfall hours over all scenarios. For this work, all LOLP values were estimated considering five thousand scenarios.

5.3.8 Anticipated Emissions

The proposed method focuses on annual CO2 emissions from the generation characterized as flexible. These are estimated by multiplying the anticipated annual energy production from each generator by assumed emissions intensities and summing the result. This method could be applied to other emissions that are related to energy production from different generator types through intensity factors. CO2 emissions were chosen as an example because of the availability of emission intensity data by generator type [2] and because CO2 is the dominant greenhouse gas emitted from conventional thermal generators.

5.4 Application: Case Study - Alberta

The proposed method is illustrated by a study that considers the Alberta, Canada, system over the period between September 1, 2009 and August 31, 2010 and anticipates how prices, reliability of supply, and emissions could develop over the medium term.

There were no supply shortfalls in the Alberta market over the study period. With the assumption of competitive behavior by all generators, prices would not have exceeded the marginal cost of peaking generation, new generation would not fully recover its fixed costs, and additions of new generation would not be anticipated.

To simplify the study and focus on the effects of generator behavior, load growth and announced generator additions or retirements are not considered. Load growth is an increase in demand that has to be met with either existing or new generation. Without new generation, price signals will reflect both the increase in demand as well as potential for new generation additions due to existing generator behaviors. Similarly, announced generator additions may be delayed or cancelled altogether [66]. Announcements are not commitments to build and may bear little relation to what can realistically be expected to enter the market. Modeling generation that may not materialize will mask price signals of the generation that could be anticipated to be supported in the market.

Publically available data on prices, generation, load, and natural gas prices over the study period was used to design and test PNN models of generator behavior [59] [76]. A market model was then constructed and simulations were performed. The model was validated by comparing observed and modeled prices and generation dispatch over the study period. To anticipate prices, reliability of supply and emissions in the medium term, new competitive combined cycle gas generation was added when profitable.

5.4.1 Description of the Alberta System

To provide context for the study, a summary of salient features of the Alberta system is given below.

5.4.1.1 The Alberta Electricity Market

Alberta has an energy-only electricity market and an ancillary services market. In the energy market, generators make offers of MW and price and these are aggregated into a supply curve by the system controller. Energy is then dispatched from least cost to highest cost to meet the demand. The price of the last energy dispatch sets the electricity price for all of the energy delivered. Anticipated transmission constraints are resolved by generation that is contracted to the AESO, is required to run, is dispatched prior to all other generation and does not set electricity prices. Transmission losses are charged to generators, imports and interruptible opportunity service loads. The costs of losses are incorporated into generator offer prices. A single wholesale price for energy applies across the province. Offer prices can be no lower than $0/MWh and no higher than $1000/MWh. Non-dispatchable resources such as imports, wind generation, and any generation capacity that must run must offer their energy at $0/MWh. Currently, several thousand MW of energy is routinely offered at $0/MWh [75].

In Alberta, the Independent System Operator (the Alberta Electric System Operator or AESO) is also responsible to procure the ancillary services required to operate the electric system. The primary services are regulating reserves, spinning reserves, and supplemental reserves. The AESO forecasts the system need over the next five days and then buys these reserves through a market run by the NGX exchange [76]. Typically, the operating reserves prices are indexed to energy prices and are traded in on peak and off peak blocks. In Alberta, much of the operating reserves are provided by hydro units. Reserves can also be provided over tielines to other jurisdictions. Load that can be interrupted can also provide non-spinning reserves. The case study presented in this chapter assumes that the residual demand for operating reserves from flexible suppliers is small and prices in the operating reserve market are such that they do not constrain the willingness of flexible suppliers to provide energy to the market. This a reasonable assumption because in all periods other than supply shortfalls, there will be undispatched capacity available to supply reserves without restricting energy production. During supply shortfalls, operating reserves would be offered into the market before interrupting firm load.

5.4.1.2 Electrical Supply

Data on the capacity and dispatch of installed generation and imports from other jurisdictions over the study period were accessed from the AESO website [59]. These were categorized into flexible and inflexible suppliers. Flexible suppliers were those that are dispatchable and are responsive to changes in price. Coal fired generators and non-cogeneration gas generators not dispatched as must run units for reliability were considered flexible. Inflexible suppliers were characterized as either not dispatchable, unresponsive to electricity prices, or whose dispatch is significantly restricted due to factors other than electricity price. In this study, inflexible generation included wind generation, co-generation, hydro generation, generators dispatched as must run for reliability purposes, biomass and other unconventional sources, and imports.

The hydro generation in Alberta is characterized as inflexible because it has limited storage capability and there are significant restrictions on how the water flows can be managed. The hydro system is dominated by plants on the Bow, Bighorn and Brazeau river systems. The plants on these river systems have a combined capacity of approximately 790 MW [77]. The combined output from these plants averages 186 MW in a normal year. However, the output in any one hour can vary from less than 40 MW to over 460 MW. Because the installed capacity is much greater than the average energy output, these plants are significant suppliers of regulating, spinning and supplemental reserves.

5.4.1.3 Flexible Generation

The flexible generation considered in this study is comprised of the total installed generation less the generation considered inflexible. The flexible generation comprised forty-four generators with a combined generating capacity of 7246 MW. The MW capacity of the generators characterized as flexible was estimated by the maximum observed output of each generator over the study period. Seventeen of the flexible generators are coal fired generators with capacities ranging from 144 MW to 456 MW and a combined capacity of 5846 MW. Twenty-seven of the flexible generators are gas fired generators and have a combined capacity of 1400 MW. Nine of the gas generators are modeled as combined cycle generators with capacities ranging from 46 MW to 182 MW and a combined capacity of 899 MW. The remaining gas generators are modeled as simple cycle gas generators and have a combined capacity of 501 MW.

Appendix B provides details of the generator capacity, type, and availability assumptions used in this case study.

5.4.1.4 System Demand

The total peak electrical load in Alberta over the study period was 10,236 MW and the annual energy demand over the study period was 70,908.5 GWh. The annual load factor over the study period was 79%.

This study concerns itself with the response of the flexible generation on the Alberta system to the residual demand after generation from inflexible suppliers has been subtracted from the total demand. The hourly residual demand over the course of the study period after the hourly generation from wind generation, hydro generation, co-generation, generators dispatched as must run for reliability purposes, biomass and other unconventional sources, and imports has been subtracted from total demand, ranged from a low of 3291 MW to a high of 6046 MW. The average demand was 4876 MW, giving a load factor of 80.6%. The installed flexible generating capacity of 7246 MW is 119.8% of the peak residual demand.

5.4.2 PNN Models of Flexible Generator Behaviors

The behavior of each of the forty-four flexible generators was modeled with a Probabilistic Neural Network (PNN) using the MATLAB Neural Network Toolbox [78]. Each of the PNNs were trained and tested on hourly market data covering the period of September 1, 2009 to August 31, 2010. Data from the first seven thousand hours of this period was used to design each of the PNNs. The remaining 1760 hours of data was used to test the PNNs. Each PNN was optimized by varying the σ_k smoothing parameter to minimize the sum of the square of the classification errors when the test data was presented to the PNN. By taking the square root of the average of the square of the classification errors for each generator, an expected classification error can be estimated. Using this calculation, the average expected classification error for all generators was 0.73 levels, meaning that on average, the generator output was expected to be misclassified by less than one output level.

Because coal generators have low marginal costs, long start times, and minimum stable generation levels, they are dispatched above zero MW whenever they are available and hours of zero output can be taken as periods of generator unavailability. PNN models of coal generators were trained and tested excluding periods of zero outputs.

Gas generators are typically not base loaded and can be started quickly. Periods of zero

Table 5.1: Generator fixed and variable costs ($ 2010) [2]

Gen. Type	Fixed ($/MW per hour)	Variable ($/MWh)
SC Coal	$46.64	$31.30
CC Gas	$19.08	$6.2 + 7.1 x Gas Price ($/Gj)

output cannot be taken as evidence of unavailability. PNN models of gas generators were trained and tested including periods of zero outputs and market simulations were performed assuming gas generators were always available.

5.4.3 Market Model of Supply and Demand

A model of an energy-only market was created as described in Section 5.3.6 and a price cap of $1000/MWh was assumed.

5.4.4 Market Simulation

A market simulation was performed as described in Section 5.3.6. Computing time requirements during simulations prohibited considering generation dispatch over many small price steps. Instead, price was increased over eight steps from $25/MWh to $999.9/MWh, including prices just below and above the marginal cost of a combined cycle generator given the modeled natural gas price.

Fixed and variable generator costs used in this study are given in Table 5.1 [2]. The natural gas prices used in this study varied over the study period and are shown in Figure 5.5. To simplify the study, it was assumed that these prices also reflected gas price expectations over the medium term. Over longer terms, the monthly variations in gas prices are generally not foreseeable and often not modeled.

Table 5.2 shows that observed prices over the study period were not always evenly distributed between price steps and estimating a market price in each hour that is midway between two price steps will tend to overstate prices. In this table, the first column labelled $P(n)$ lists the price steps n at which generation was evaluated. The second column indi-

Table 5.2: Price steps and estimated market price

P(n)	(P(n)+P(n-1))/2	Avg. Observ. Price
$25	$12.5	$17.89
$6.1+7.1 x Gas Pr.	($31.1+7.1 x Gas Pr.)/2	($31.1+7.1 x Gas Pr.)/2
$6.2+7.1 x Gas Pr.	$6.15+7.1 x Gas Pr.	$6.15+7.1 x Gas Pr.
$50.0	$56.2+7.1 x Gas Pr.	($56.2+7.1 x Gas Pr.)/2
$310.0	$180.0	$80.21
$540.0	$425.0	$424.51
$770.0	$655.0	$685.66
$999.9	$885.0	$939.77

cates what the simple average is of price step n and the previous price step $n-1$. The third column shows the average of observed prices between the two price steps $P(n)$ and $P(n-1)$ over the study period. It can be seen that over some price steps, the average of the observed prices significantly differs from the simple average of the two price steps $P(n)$ and $P(n-1)$. In this case, the error is greatest for prices between the $50/MWh price step and the $310/MWh price step. While the simple average of these two prices is $180/MWh, the average of the prices observed between these price steps was $80.21.

To provide a better estimate of market price in each hour, the observed price duration for the study period was used as a proxy of how prices between price steps will be distributed. In each hour of the simulation, the estimated market price is assigned to the average of the observed prices between the final price step where generation exceeds load and the previous price step where generation was insufficient to meet load.

5.4.5 Model Validation

To validate the model, a scenario with the historical hourly residual loads, monthly average gas prices, and outage patterns to coal generators was replicated. The scenario was presented to the model and the model produced hourly prices and generation outputs for each of the forty-four flexible generators modeled.

In the validation study, the unavailability of coal generators was modeled by replicating

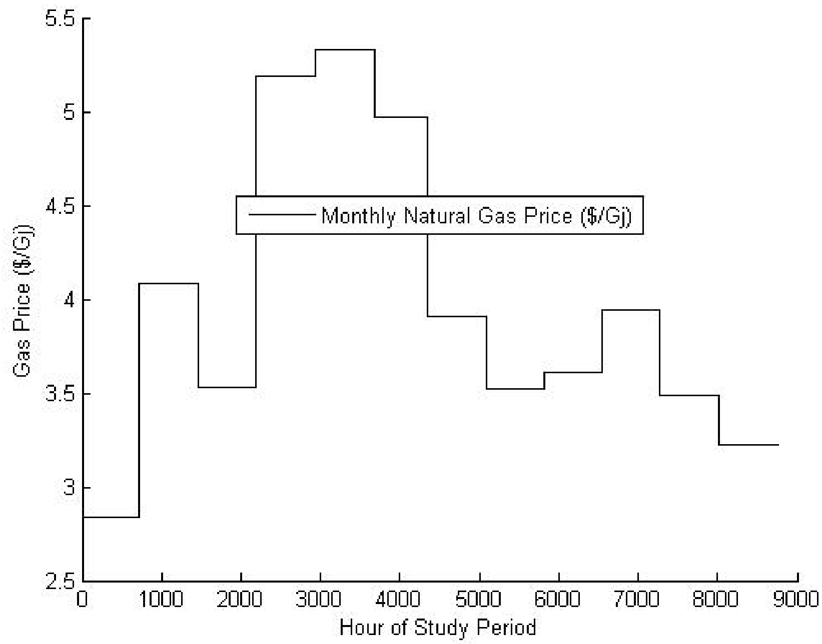

Figure 5.5: Natural gas prices ($/Gj)

the outage patterns observed in the study period. As discussed in Section 5.4.2, PNN models of gas generators were trained including periods of zero outputs and market simulations were performed assuming gas generators were always available.

5.4.5.1 Observed and Modeled Prices over Study Period

Over the study period, the observed prices averaged $54.65. In comparison, the average price produced by the model was $56.44/MWh. The observed and modeled distribution of observed and modeled prices are shown in price duration curves in Figure 5.6. A comparison of the modeled and observed price duration curves shows that the model captures salient features of the distribution of observed prices including extended periods of low pricing, significant periods of prices above the marginal costs of any generator but below the price cap, and very few hours at or near the price cap. The distributions of prices in the modeled case and the observed case are shown in Table 5.3. This shows that in the observed case and the modeled case the frequency of prices below the price points modeled are closely matched.

Table 5.3: Frequency of Prices below Price Points - Modeled and Observed Cases

Price Point	Modeled Freq. of Prices	Observed Freq. of Prices
$50/MWh	82.8%	78.4%
$310/MWh	93.1%	97.8%
$540/MWh	98.8%	98.6%
$770/MWh	99.6%	99.5%
$999/MWh	100.0%	100.0%

A price signal for new generation is sent when over an extended period such as a year, a new generator could be profitable and fixed cost recovery exceeds fixed costs. By summing the prices less the marginal costs of a new generator in every hour when prices exceed marginal cost and then multiplying the result by the assumed availability of a new generator, the fixed cost recovery of a marginally sized new competitive generator can be estimated. Price signals of the profitability of new competitive generation may not trigger investment decisions because they do not indicate the MW amount of new generation the market can support.

Prices and signals for profitable additions of competitive generation vary with realized patterns of generator availability. The observed prices in the study period are a single realization of generator availability. For this reason, the potential for profitable new generation additions should be evaluated over several market simulations. In addition to the validation study, five other market simulations were performed which reflected different generator outage patterns over a year. In practical application many more would be performed. For each simulation, a chronological Monte Carlo simulation was performed that uses two state Markov models to depict the availability of each generator in each hour. As discussed in Section 5.4.2, for market simulations, gas generators were assumed to always be available. However, for evaluating reliability of supply, the availability of gas generators was not assumed to be 100%. Each of the five simulations was performed three times depicting assumptions of high, medium, and low availability of coal generators. The high, medium, and low availability of coal generators outside of planned maintenance were assumed to be

Table 5.4: Price signals for new gen. adds. - Est. annual profit/MW of competitive combined cycle gas gen. ($1000)

Simulation	High Avail.	Medium Avail.	Low Avail.
Observed	-	$42.8	-
Validation	-	$143.8	-
1	$72.3	$334.3	$944.7
2	$20.8	$151.9	$855.8
3	$13.0	$268.6	$625.2
4	-$1.6	$271.9	$1031.2
5	-$0.6	$285.0	$909.3

99.5%, 95.2%, and 90.9% respectively.

This study considers the potential for profitable additions of combined cycle gas generators and assumes annual fixed costs of a combined cycle gas generator are $167,141/MW of installed capacity [2]. The price signal given by the estimated profitability of a marginally sized competitive combined cycle generator assuming the observed prices over the study period, the prices from the model validation simulation, and prices from the five other market simulations with high, medium, and low assumptions for coal generator availability are given in Table 5.4. In this case study, all medium and low availability scenarios and three out of five high availability scenarios are showing price signals that the market would support some new competitive combined cycle generation. If prices were lower or the costs of new generation were higher, the analysis could indicate reduced or no opportunity for new generation to profitably enter the market.

5.4.5.2 Observed and Modeled Generation Dispatch over the Study Period

Duration curves of the observed and modeled aggregate hourly MW generation from the flexible coal and gas generators are shown in Figure 5.7. The observed average hourly output of the aggregate coal and gas generation was 4554 MW and 321 MW respectively. In comparison, the average hourly output of the modeled aggregate coal and gas generation was 4526 MW and 349 MW. The Mean Average Percent Error (MAPE) for the aggregate coal generation was 0.6%, indicating that over a year close agreement was achieved on

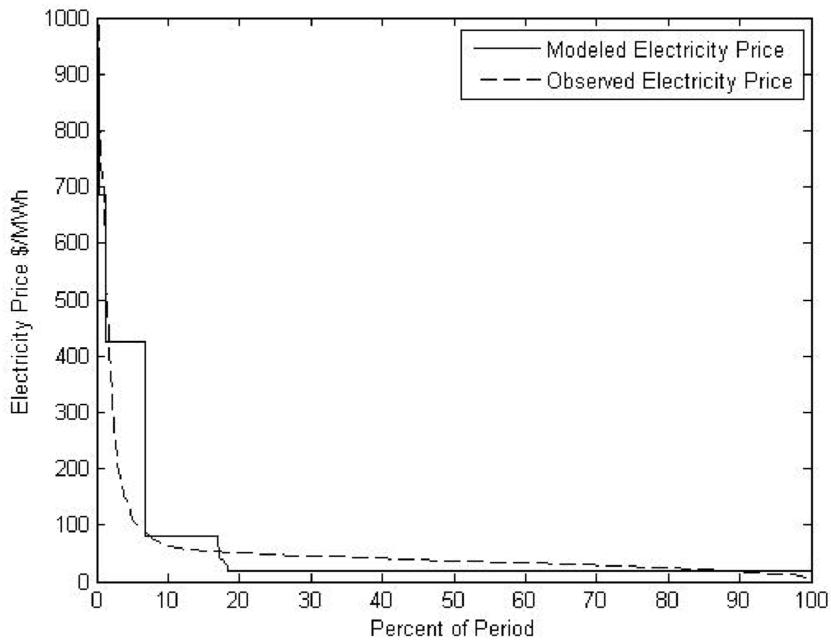

Figure 5.6: Modeled and observed electricity price duration curve over the study period

the anticipated generation from coal. For the aggregate gas generation, where the average hourly output is significantly smaller than that for aggregate coal generation, the MAPE was 30.1%. The modelling of gas generators is more challenging than coal because periods of zero output cannot be taken as periods of unavailability. Periods of zero output may be due to unavailability or because the generator offer is above the market price. Gas generators may also be part of larger portfolios where their operation is linked to contractual positions that are not observable. While the MAPE associated with gas generators is larger than the corresponding values for coal generation, the average generation levels for gas are much lower than for coal.

5.4.6 Anticipated Prices, Reliability of Supply, and Emissions

In this section, the prices, emissions, and expected reliability of supply of the existing system are compared to the prices, reliability of supply, and emissions that could be anticipated in the medium term. To anticipate medium term developments, five market simulations

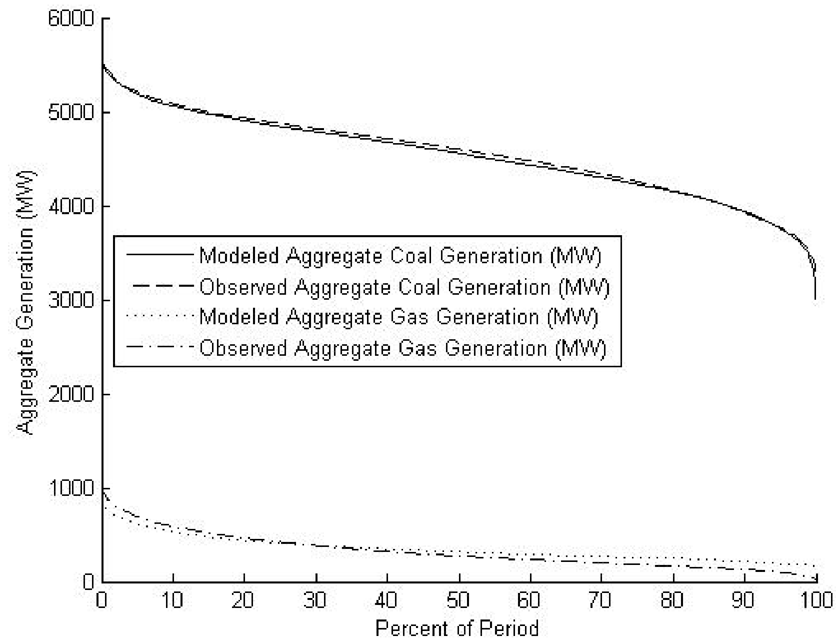

Figure 5.7: Aggregate coal and gas generation duration curves over the study period

were performed. Each market simulation required approximately ten hours of computing time to complete. In each market simulation a chronological hourly simulation of generator dispatch over a year was performed and then iterated to determine the capacity of new combined cycle generation that could be profitably added. The LOLP with all profitable new generation added was then estimated by Monte Carlo simulations. The parameters assumed in the simulations for evaluating the reliability of supply are given in Table 5.5.

The anticipated additions of new generation, prices, expected reliability of supply expressed as Loss Of Load Probability (LOLP) in hours per year, and CO2 emissions over the medium term are summarized in Tables 5.6 and 5.7

5.4.6.1 Electricity Prices

The average electricity price between September 1, 2009 and August 31, 2010 was $54.65 /MWh. For each of the five simulations performed to anticipate medium term developments, the additional combined cycle gas generation acted to reduce average prices and to reduce the number of hours when prices were above the marginal cost of the new compet-

Table 5.5: Assumed generator availability, planned maintenance outages, Mean Time to Repair (MTTR), repair rates (μ), and failure rates (λ)

Gen. Type	SC Coal	CC Gas	SC Gas
Availability (%)	90%	98%	98%
Planned Maintenance (hrs)	512	-	-
MTTR (hrs)	33.96	4.86	4.86
(μ) (repairs/hr)	0.0294	0.2058	0.2058
(λ) (failures/hr)	0.0013	0.0015	0.0015

Table 5.6: Summary of market supported generation additions and electricity prices

Simulation	CC Gas Gen. Additions (MW)	Average Price ($/MWh)
1	354	$43.62
2	174	$41.93
3	292	$42.88
4	324	$43.16
5	266	$43.50
Mean	282	$43.02
Existing	-	$54.65

Table 5.7: Summary of loss of load probability (hrs/year) and emissions (million tonnes CO2/year)

Scenario	LOLP (hrs/yr)	Emissions (Mt CO2/yr)
1	0.75	36.51
2	2.30	36.43
3	1.08	36.48
4	0.94	36.47
5	1.31	36.59
Mean	1.27	36.49
Existing	7.36	37.02

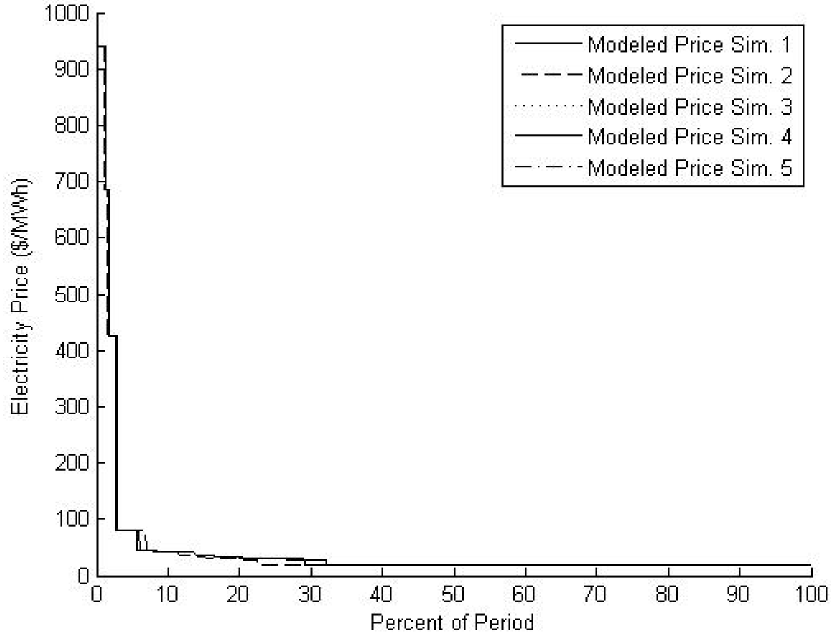

Figure 5.8: Price distributions after addition of profitable combined cycle generation

itive combined cycle gas generators. The average prices in the five simulations performed ranged from $41.93/MWh to $43.62/MWh. The distributions of prices in each of the five simulations following the addition of profitable combined cycle generation are shown in price duration curves in Figure 5.8.

5.4.6.2 Reliability of Supply

The anticipated reliability of supply was evaluated as described in Section 5.3.7. The overall availability of generators and the breakdown between planned and unplanned unavailability was based on an analysis of the operation of the flexible coal and gas generators in the study period. For each coal generator, the longest period of zero MW was assumed to be planned maintenance. The durations of the assumed planned maintenance for all coal units were averaged to arrive at an estimate of annual planned maintenance requirements for all coal units in the Alberta system. The assumed periods of planned maintenance for each coal unit were then removed and the durations of the remaining periods of zero MW output for all coal units were averaged to estimate a Mean Time To Repair (MTTR). Gas generators typically run at a lower capacity factor than coal generators, may have significant periods where they are not called upon to run, and have significantly reduced planned maintenance requirements. For gas generators, no planned maintenance was assumed. The overall availability was estimated by examining gas generators whose output has been observed to change, but normally remains positive in all periods regardless of price. For these generators, the number of hours of zero output was taken as a proxy for all gas fired generators' overall availability and the average duration of periods when output was zero MW was used to estimate the MTTR for all the gas generators. Using this approach, the overall availability assumed for coal generators is consistent with values reported by the North American Electric Reliability Corporation (NERC) [73]. However, the overall availability assumed for gas fired generation is higher than values reported by NERC.

Normally attempts are made to coordinate planned maintenance schedules. To simulate this, a proxy schedule for planned maintenance was developed where the objective function was to maximize the minimum capacity available after planned outages over forecast hourly demand. Details of this are given in Appendix C. Planned maintenance outages of 512 consecutive hours were assumed for all coal fired generators. The proxy schedule for planned maintenance for coal fired generators that was assumed for this study is shown in Figure 5.9. The planned maintenance schedule is not a claimed contribution and is not central to the methods proposed in this chapter.

Using the planned maintenance schedules and the estimated failure rates and repair rates of coal and gas generators, the LOLP for each simulation was estimated as described in Section 5.3.7. The estimated LOLP for the existing system was 7.36 hours per year. The five simulations performed to anticipate medium term developments indicate the additional combined cycle gas generation that could be profitably added would reduce the anticipated LOLP to between 0.75 hours per year and 2.29 hours per year.

Other assumptions for generator availability are possible. In this case study, assump-

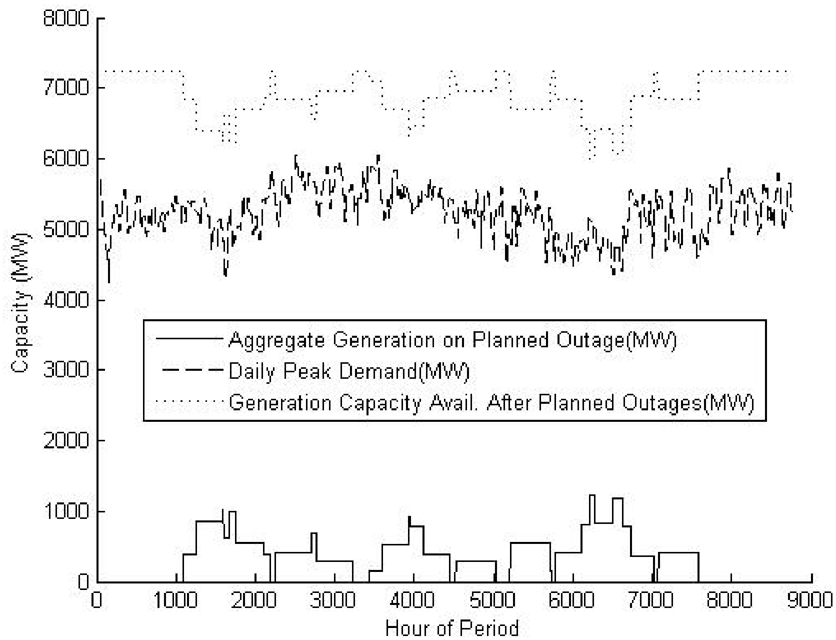

Figure 5.9: Assumed planned maintenance outage schedule over study period

tions of higher availability for existing coal generators will impact the market simulations and reduce the anticipated extent of new generation additions. However, assumptions of higher availability will also reduce the anticipated LOLP. If additional generating capacity can be supported by the strategic behavior of existing participants, it will lead to improvements in anticipated reliability.

5.4.6.3 Emissions

To estimate total emissions, coal generators were assumed to produce 0.9 tonnes of CO2 per MWh of production, combined cycle gas generators were assumed to produce 0.37 tonnes of CO2 per MWh, and simple cycle generators were assumed to produce 0.5 tonnes of CO2 per MWh [2].

Total CO2 emissions from the existing system were estimated to be 37,019,756 tonnes. The addition of profitable competitive combined cycle gas generation to existing generation acted to modestly reduce emissions as some existing generation was displaced by new gas generation with lower emission intensity. Since the existing generation was not retired and the anticipated entry of new competitive combined cycle gas generators in a range of 174 MW to 354 MW is relatively small in comparison to the installed flexible capacity of 7246 MW, no large structural changes in generation mix or emissions are anticipated in the medium term. The total annual emissions in the five simulations where profitable additions of combined cycle gas generation were included ranged from 36,428,317 tonnes to 36,591,450 tonnes. The mean annual emissions from the five scenarios was 36,494,982 tonnes which represents a 1.4% reduction from the estimated emissions from the existing system over the study period.

5.5 Summary

This chapter proposed a method to model generator behaviors and anticipate electricity prices, reliability of supply, and emissions in deregulated energy-only power markets over the medium term time frame associated with the build cycle for new generation. A model of the market in the medium term was proposed that allows for profitable entry of new generation but no exit of existing generation. Behavioral models relating observable market parameters, including price, to discrete MW output levels were created for each generator using PNN designed on observed market dispatch behavior. The PNN models were then combined in a market simulation that reasonably captured the strategic behavior of existing participants and electricity prices above generator marginal costs that send price signals for new generation to enter the market. The market simulation model was used to estimate the extent of new generation that could profitably enter the market and how prices could change. Reliability of supply was estimated assuming all new generation that can profitably enter the market will do so. The proposed method was applied to the Alberta system as it existed between September 1, 2009 and August 31, 2010. The study showed directionally that in the medium term, without considering load growth, the market could support additional generation, that prices could be anticipated to fall, and reliability of supply could be anticipated to improve. More specifically the study showed, with the assummed new generator costs and existing and new generator availability, and without considering load growth, between 174 MW and 354 MW of new competitive combined cycle generation could be supported by the market. Further, prices could be anticipated to fall from the $54.65/MWh that was observed over the study period to approximately $43.0/MWh and that reliability of supply expressed by LOLP could be anticipated to significantly improve from 7.2 hours per year to between 0.75 and 2.3 hours per year. The study also showed that emissions could be anticipated to fall between 1.2% and 1.6% due to a modest displacement of existing generation by new combined cycle gas generators with a lower emission intensity.

Chapter 6

Conclusions

In deregulated power systems, anticipating future system development is important to system planners and policy makers. This thesis was concerned with anticipating prices, reliability of supply, and emissions in deregulated energy-only markets in the medium and long term considering both the large-scale integration of wind generation and other inflexible generation and the strategic behavior of other flexible generators.

Chapter 3 of this thesis examined medium and long term effects of large-scale integration of wind powered electricity generation in a deregulated energy-only market on electricity prices, reliability of supply, the ability of a dispatchable conventional supplier to exercise market power, and the fixed cost recovery of dispatchable conventional suppliers. In this analysis, medium term referred to the time frame following the introduction of wind generation but before structural changes to the capacity and mix of generation technologies can be affected. Long term impacts considered possible responses of the market and/or regulator to the integration of wind generation that affect the generation capacity and mix of technologies available to serve load and expectations for reliability of supply. The work focused on the market impact of the large-scale integration of wind generation on load and dispatchable conventional generation rather than on the wind generation itself. The impacts on the load dealt with were the effect on prices and effect on reliability of supply.

The main contributions of Chapter 3 are:

1. An evaluation of the changes in the opportunities for a dispatchable conventional generator, acting strategically in an energy-only market, to exercise market power by economically withholding supplies following the introduction of wind generation.

2. An analysis of the effect of wind generation, in an energy-only market, on the fixed

cost recovery of dispatchable conventional suppliers.

The significance of the above contributions is as follows:

- The analysis in this chapter shows that in the medium term, increased penetration of wind generation can lead to lower electricity prices and increased reliability of supply, but this cannot be supported in the longer term. Adding wind generation to the system also results in less supply from the dispatchable conventional generation installed on the system. Because generators have fixed as well as variable costs, average costs of production increase as their capacity factor declines. In the long term, prices must at least equal the average cost of production or sufficient dispatchable supplies will not be built and reliability of supply will deteriorate. In the very long term, the deterioration in reliability can be addressed by a structural re-optimization of the generation mix.

- It is also concluded that at low to moderate levels of wind generation, the uncertainty in wind generation output and the consequent residual demand increases the ability of dispatchable conventional generators to profitably withhold energy. As the size of the dominant supplier relative to the peak demand increases, more opportunities will present to profitably withhold supplies. This creates a possible market response whereby prices may be supported or rise without a deterioration in reliability.

- The results of the analysis in this chapter indicate that raising the price cap as the installed wind generation capacity increases is an action the regulator may take to aid in fixed cost recovery of dispatchable conventional generators and provide an economic signal that is consistent with a shift in the generation makeup toward a cost minimizing mix of technologies (i.e. a shift from base load to peaking generators) and a higher reliability of supply following the large-scale integration of wind.

Chapter 4 of this thesis examined the long term effects of large-scale integration of wind powered electricity generation and other inflexible generation in a deregulated energy-only market on electricity prices, reliability of supply, and emissions. For the analysis in this chapter, long term referred to equilibrium states where any structural changes to the capacity and mix of generation technologies have been realized. Long term equilibrium models were developed that allow for the entry and exit of generation and which are based on the principle that at equilibrium all generators must neither take losses or make profits. The long term impacts of inflexible, competitive and strategic generator behaviors were considered. The long term equilibrium with and without inflexible suppliers where competitive behavior from flexible suppliers is assumed was considered as well as the equilibrium that occurs when a low marginal cost strategic supplier is assumed while other flexible suppliers exhibit competitive behavior.

The main contributions of Chapter 4 are:

1. An evaluation of the long term impact of wind generators and other inflexible generation on electricity prices and reliability of supply in competitive energy-only electricity markets.

2. An evaluation of the long term impact in an energy-only market of a low cost strategic supplier on the mix of generation technologies including wind generation, electricity prices, reliability of supply, and CO2 emissions.

The significance of the above contributions is as follows:

- The analysis in this chapter shows that under the assumptions of competitive or inflexible behavior by suppliers, long term equilibrium electricity prices and reliability of supply are independent of the load shape, or the amount or production pattern of inflexible generation such as wind generation on the system.

- The consideration of a strategic supplier provides an explanatory mechanism of market operation that can lead to large improvements in expected reliability of supply, a radical change in the generation mix, and a large change in expected emissions.

Chapter 5 dealt with the expectations in the medium term for electricity prices, reliability of supply, and emissions in existing energy-only markets. In this analysis, the medium term was defined as the time frame associated with the build cycle for new generation. This work used Probabilistic Neural Networks (PNN) designed on observed generator dispatch to model complex behaviors of individual generators in energy-only electricity markets associated with price and other observable market parameters. The models of individual generator behavior were then combined in a market simulation. The anticipated prices, reliability of supply, and emissions in the medium term were calculated assuming a continuation of existing generator behaviors and all profitable entry of new competitive generation. The proposed methods were illustrated with an example using publicly available historical data for the Alberta, Canada electricity market.

The main contributions of Chapter 5 are:

1. The application of PNN to the modeling of observed generator behaviors in response to observable market parameters.

2. The development of a method that combines PNN models of generator behaviors, hourly representations of generator availability, and a market model in a market simulation to anticipate prices and price signals for new generation to enter the market, the extent of entry of new generation, and the impact on prices, reliability of supply and CO2 emissions in the medium term.

The significance of the above contributions is as follows:

- The proposed method to model existing generator behaviors provides a means to model electricity markets that is consistent with observed system operation and can reasonably capture the strategic behavior of existing participants and electricity prices above generator marginal costs that send price signals for new generation to enter the market. This provides a basis for investigating the impact of future changes to generation or demand on existing power systems.

- Models of generator behavior based on observed operation can effectively capture the significant differences in generation dispatch among generators from what would be anticipated assuming competitive behavior from all generators.

- The case study in this chapter shows existing generator behaviors can significantly impact anticipated prices, entry of new generation, and reliability of supply over the medium term time frame associated with the build cycle of new generation. The proposed method also allows for impacts of generator behaviour on emissions to be estimated.

Appendix A

Equation 3.4 The Expected Profit of a Dominant Supplier in a Given Period

The Expected Profit of a Dominant Supplier in a Given Period given in Equation 3.4 of Chapter 3 of this thesis is described in this Appendix.

A.1 Introduction

In Chapter 3 a market model was developed to assess the effect of adding wind generation on the ability of a dominant supplier to profitably withhold supply. In this model possible scenarios of generating capacity available to supply load are paired with a demand level. In the model, generation is dispatched to meet demand on the basis of marginal cost with the lowest cost generation being dispatched first. The market clearing price is set by the marginal cost of the most expensive generator dispatched to meet the demand. If there is insufficient generation to meet demand, the market clearing price is set by the price cap. The expected profit of the dominant supplier in a given period is:

$$E\{Profit_d\} = \sum_{j=1}^{l}\sum_{i=1}^{N}(MCP(Q_i, D_j, MC, n, PC) - MC_d)Q_{(d,i)}np_{(Q_i)}p_{(D_j)} \tag{A.1}$$

where PC is the market price cap, MC is the array of marginal costs of all generator types,$\{MC_a, MC_b, MC_c, MC_d\}$, D_j is the residual demand level j of l equally probable demand levels in one period, N is the number of combinations of levels of capacity available from all conventional generators, n is the fraction of available capacity from the dominant supplier that is dispatched, $p_{(Q_i)}$ is the probability of supply capacity level $Q_{(i)}$, $p_{(D_j)}$ is the probability of demand level D_j, and MCP is the market clearing price as a function of Q_i,D_j,MC,n, and PC.

Each of the terms in (A.1) is further described below.

A.2 Possible Levels of Demand

Over the course of a year the residual demand seen by other generators is modelled as the total system demand less the expected value of wind generation in each hour. The residual demand is sorted from the highest to the lowest level to form a residual demand duration curve. This is then reduced to one hundred levels of residual demand spaced at equal intervals over the duration curve. Each level represents a single period.

In a given period, the uncertainty in the wind generation output is reflected in the uncertainty in the residual demand seen by conventional generators. In this model the uncertainty in the residual demand is modeled as zero mean normally distributed noise with a standard deviation that is related to the installed capacity of wind generation on the system. The zero mean normally distributed uncertainty in residual demand in a given period is modelled as one hundred equally probable outcomes that are added to the expected level of residual demand for the period. The demand in each period is then represented as a random variable with one hundred equally probable levels that could occur. For the analysis in Chapter 3, l in (A.1) equals 100 and $p_{(D_j)}$ = 0.01 for all demand level D_j.

A.3 Possible Levels of Supply

As described in Chapter 3, there are 3120 possible combinations of generating unit capacities that are available in any given period to meet the demand. Each of the possible combinations of generating unit capacity that is available to meet demand $Q_{(i)}$ has a probability of occurrence $p_{(Q_i)}$ associated with it. Thus N = 3120 in the model used in Chapter 3.

Each possible combination of generating unit capacities available $Q_{(i)}$ to meet demand, is made up of a set of capacities of the dominant generator, other base load generators, mid load generators and peaking generators. A supply function describing marginal cost as a function of available generator capacity is formed when the cumulative available generator capacity is ordered from lowest marginal cost to highest marginal cost.

The dominant supplier is the lowest marginal cost generator and its available capacity is split between its marginal cost and the price cap to maximize profitability. The fraction of the dominant generators available capacity that is available at its marginal cost is given as n. The effect of allocating more of the dominant suppliers available capacity to the price cap is to shift the curve describing the supply function so that for the same level of supply the marginal cost of the highest cost generation needed to serve the demand is higher. If more of the dominant suppliers available capacity is allocated to the low marginal cost of the dominant supplier the supply curve is shifted so that for the same level of supply the marginal cost of the highest cost generation needed to serve the demand is lower.

A.4 Market Clearing Price

In the model used in Chapter 3, the market clearing price is set by the marginal cost of the most expensive generator dispatched to meet the demand. The level of withholding by the dominant supplier allocates the available capacity of the dominant generator to either a low marginal cost or to the price cap. Since the dominant supplier has the lowest marginal cost of all generators, all of the capacity that the dominant supplier makes available at its marginal cost will be dispatched prior to any other generators being dispatched. If the total available generating capacity is less than the demand, the market clearing price is set to the Price Cap, PC.

As described above, the demand in any one period is represented as a random variable with one hundred equally probable levels D_j that could occur. This means for each level of withholding by the dominant generator n there are one hundred equally probable realizations of market clearing price due to the uncertainty in wind generation.

A.5 Expected Profit of Dominant Supplier

The expected profit of the dominant supplier is the product of the available capacity of dominant supplier $Q_{(d,i)}$, the fraction of the available capacity from the dominant supplier that is dispatched n, the difference between the market clearing price MCP and the marginal cost of the dominant supplier MC_d, the probability of the demand level $p_{(D_j)}$ and the probability of the supply level $p_{(Q_i)}$ summed over all levels of supply i and demand j.

Appendix B

Generator Assumptions

The assumptions made in Chapter 5 with regard to generator capacity, type and availability are given in this appendix. Generator capacity is derived from maximum observed output over the study period [59].

Table B.1: Generation capacity, type and availability assumptions

Gen.	Cap.(MW)	Type	Availability
Gen01	46.1	CC Gas	0.98
Gen02	57.0	CC Gas	0.98
Gen03	57.0	CC Gas	0.98
Gen04	98.0	CC Gas	0.98
Gen05	101.8	CC Gas	0.98
Gen06	116.9	CC Gas	0.98
Gen07	118.0	CC Gas	0.98
Gen08	121.8	CC Gas	0.98
Gen09	182.0	CC Gas	0.98
Gen10	Variable	CC Gas	1.0
Gen11	143.5	Coal	0.90
Gen12	154.7	Coal	0.90
Gen13	161.7	Coal	0.90
Gen14	283.7	Coal	0.90
Gen15	285.5	Coal	0.90
Gen16	356.0	Coal	0.90
Gen17	388.1	Coal	0.90
Gen18	391.5	Coal	0.90
Gen19	391.8	Coal	0.90
Gen20	393.0	Coal	0.90
Gen21	393.2	Coal	0.90
Gen22	403.2	Coal	0.90
Gen23	404.9	Coal	0.90
Gen24	408.4	Coal	0.90
Gen25	410.1	Coal	0.90
Gen26	421.2	Coal	0.90
Gen27	455.6	Coal	0.90
Gen28	0.4	SC Gas	0.98
Gen29	4.2	SC Gas	0.98
Gen30	4.6	SC Gas	0.98
Gen31	5.5	SC Gas	0.98
Gen32	5.6	SC Gas	0.98
Gen33	6.2	SC Gas	0.98
Gen34	7.2	SC Gas	0.98
Gen35	8.3	SC Gas	0.98
Gen36	11.4	SC Gas	0.98
Gen37	32.0	SC Gas	0.98
Gen38	43.1	SC Gas	0.98
Gen39	44.2	SC Gas	0.98
Gen40	44.4	SC Gas	0.98
Gen41	44.4	SC Gas	0.98
Gen42	46.4	SC Gas	0.98
Gen43	47.7	SC Gas	0.98
Gen44	56.2	SC Gas	0.98
Gen45	89.2	SC Gas	0.98

Appendix C

Planned Maintenance Assumptions

For the analysis presented in Chapter 5, a proxy planned maintenance schedule was constructed. The planned maintenance schedule used and the method for creating this maintenance schedule are described in this Appendix. The proxy planned maintenance schedule presented here is meant to be a reasonable representation of a planned maintenance schedule and is not necessarily an optimal schedule.

C.1 Introduction

The unavailability of generators can be classified into planned and unplanned unavailability. Planned unavailability is generally related to extended maintenance outages that are planned or anticipated. Unplanned unavailability is generally related to generator outages that cannot be foreseen but remove the generator from service until it can be repaired. Normally, efforts are made to coordinate the planned maintenance among generators so that the remaining available generating capacity in any hour is expected to be sufficient to meet the anticipated load. The coordination of planned maintenance acts to reduce the number of hours when the available generation is insufficient to meet the load and improves the expected reliability of supply.

C.2 Duration of Planned Maintenance

Coal fired generators have long start times, minimum run requirements, and low marginal costs. For these reasons, coal units are generally base loaded. Any periods of zero MW output from coal fired generators can be assumed to be periods of generator unavailability.

To estimate the planned maintenance requirements for the coal units used in the studies in Chapter 5, the historical records over the study period of September 1, 2009 to August 31, 2010 of the hourly MW output of the seventeen coal fired generators considered in the Chapter 5 studies were examined. The longest period of zero MW output for each coal generator was assumed to be planned maintenance. Other periods of zero MW output were taken to be unplanned unavailability. For all the coal generators, the assumed planned maintenance periods were averaged to arrive at a mean planned maintenance requirement of 512 consecutive hours for each coal generator.

Gas fired generators can be started quickly and have higher marginal costs. It cannot be assumed that a gas fired generator with a zero MW output is unavailable. In the analysis performed in Chapter 5, both the Combined Cycle and Simple Cycle gas generators are assumed to not have any requirements for extended outages for planned maintenance.

C.3 Method of Creating Proxy Planned Maintenance Schedule

Creating a satisfactory planned maintenance schedule is not straightforward. In the studies performed in Chapter 5, there are seventeen flexible coal fired generators of varying sizes. For each generating unit, the planned maintenance must be for 512 consecutive hours. The start dates and times for each generator could be any time from the first hour of the year to the 513th hour prior to the end of the year. It is easily seen that the number of possible schedules is extremely large.

C.3.1 Objective of Planned Maintenance Schedule

For the proxy planned maintenance schedule used in Chapter 5 of this thesis, the objective was to maximize over a year the minimum hourly margin between available generating capacity and the residual demand. This objective relates to maximizing the reliability of supply by minimizing periods of shortfall. In setting actual maintenance schedules, generators may have objectives that differ with the result that realized prices may be higher and reliability of supply lower than what is found in the studies presented in Chapter 5.

C.3.2 Solution using Genetic Algorithm

To solve the maintenance scheduling problem, a genetic algorithm was used [79]. To start with, a hundred possible maintenance schedules were created by randomly assigning a starting time, expressed as the number of hours from the beginning of the year, for the beginning of the planned maintenance for each generator. The starting times for generator maintenance form a vector describing a single possible maintenance schedule. The total available generating capacity in each hour was then calculated. In each hour, the margin of available generating capacity over load was found by subtracting the anticipated residual demand from the total available generating capacity. Over the year, the minimum hourly margin of available generating capacity over load was found. The one hundred possible planned maintenance schedules were ranked based on the minimum hourly margin of available generating capacity over load.

Once the trial schedules were evaluated and ranked, the schedules with the least minimum hourly margin of available generating capacity over load were discarded and replaced with another set of randomly generated maintenance schedules. The schedules with the greatest minimum hourly margin of available generating capacity over load were retained and new candidate schedules were created by combining a portion of the starting times vector from one candidate schedule with a complementary portion of the starting times vector from another candidate schedule. Finally, all new candidate maintenance schedules were subjected to mutation by making some random changes to a few of the starting times in each of the revised one hundred candidate maintenance schedules. The process of evaluation, discard, repopulation, recombination and mutation of a set of candidate schedules was repeated many times until the improvements in the best candidate schedule become smaller than a threshold value. The vector of start times from the best candidate schedule after the

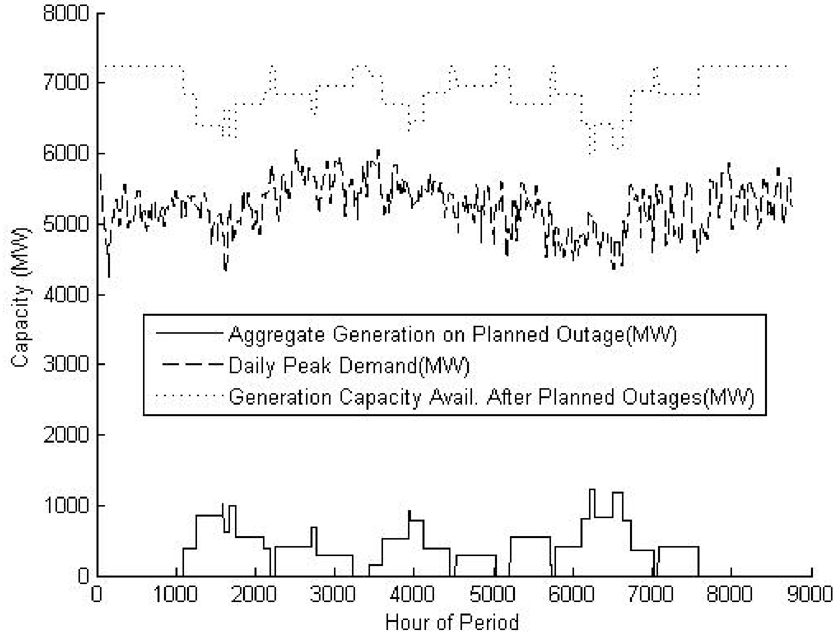

Figure C.1: Assumed planned maintenance outage schedule over study period

final iteration defines the proxy maintenance schedule.

C.4 Proxy Planned Maintenance Schedule

The proxy maintenance schedule for coal plants in the studies presented in Chapter 5 is shown in Figure C.1. Figure C.1 shows the forecast daily peak load over the study period, the available generating capacity and the aggregate generating capacity on planned outages.

Bibliography

[1] AESO, "Alberta Electric System Operator Long Term Transmission System Plan 2009 Appendix E," World Wide Web, 2009, accessed: August 2011. [Online]. Available: http://www.aeso.ca/downloads/AESO_LTTSP_Final_July_2009.pdf

[2] "AESO Long Term Transmission System Plan 2009," World Wide Web, http://www.aeso.ca/downloads/AESO_LTTSP_Final_July_2009.pdf, Alberta Electric System Operator, Accessed: June 2012.

[3] V. Nanduri, T. Das, and P. Rocha, "Generation capacity expansion in energy markets using a two-level game-theoretic model," *Power Systems, IEEE Transactions on*, vol. 24, no. 3, pp. 1165 –1172, aug. 2009.

[4] C. Ruibal and M. Mazumdar, "Forecasting the mean and the variance of electricity prices in deregulated markets," *Power Systems, IEEE Transactions on*, vol. 23, no. 1, pp. 25 –32, feb. 2008.

[5] P. Simshauser, "The emergence of structural faults on the supply side in deregulated 'energy only' electricity markets," *Australian Economic Review*, vol. 39, no. 2, pp. 130 – 146, 2006.

[6] S. Stoft, *Power System Economics Designing Markets for Electricity*. IEEE Press Wiley-Interscience, 2000.

[7] P. Joskow and J. Tirole, "Reliability and competitive electricity markets," *Rand Journal of Economics*, vol. 38, no. 1, pp. 60 – 84, Spring 2007.

[8] W. W. Hogan, "On an energy only electricity market design for resource adequacy," *Harvard University, John F. Kennedy School of Gov-*

ernment, 2005. [Online]. Available: http://www.ferc.gov/EventCalendar/files/20060207132019-hogan_energy_only_092305.pdf

[9] ——, "Reliability and scarcity pricing: Operating reserve demand curves," *Harvard University, John F. Kennedy School of Government, Mossavar-Rahmani Center for Business and Government*, 2006. [Online]. Available: http://www.hks.harvard.edu/fs/whogan/Hogan_hepg_030206.pdf

[10] B. F. Hobbs, M.-C. Hu, J. G. Inon, S. E. Stoft, and M. P. Bhavaraju, "A dynamic analysis of a demand curve-based capacity market proposal: The pjm reliability pricing model," *Power Systems, IEEE Transactions on*, vol. 22, no. 1, pp. 3 –14, feb. 2007.

[11] J. H. Roh, M. Shahidehpour, and Y. Fu, "Market-based coordination of transmission and generation capacity planning," *Power Systems, IEEE Transactions on*, vol. 22, no. 4, pp. 1406 –1419, nov. 2007.

[12] E. Sauma and S. Oren, "Economic criteria for planning transmission investment in restructured electricity markets," *Power Systems, IEEE Transactions on*, vol. 22, no. 4, pp. 1394 –1405, nov. 2007.

[13] M. Hesamzadeh, N. Hosseinzadeh, and P. Wolfs, "Transmission system augmentation based on the concepts of quantity withheld and monopoly rent for reducing market power," *Power Systems, IEEE Transactions on*, vol. 25, no. 1, pp. 167 –180, feb. 2010.

[14] J. Church, W. Rosehart, and J. MacCormack, "Transmission policy in alberta and bill 50," *University of Calgary, The School of Public Policy*, 2009. [Online]. Available: http://www.policyschool.ucalgary.ca/sites/default/files/research/transmissionpolicyonline.pdf

[15] S. Borenstein and J. Bushnell, "Electricity restructuring: Deregulation or reregulation?" *Regulation, The Cato Review of Business and Government*, vol. 23, no. 2, pp.

46–52, 2000.

[16] C. D. Wolfram, *Measuring Duopoly Power in the British Electricity Spot Market.* Unlisted: Elgar Reference Collection. International Library of Critical Writings in Economics, vol. 172., 2004, pp. 73 – 94.

[17] P. D. Klemperer and M. A. Meyer, "Supply function equilibria in oligopoly under uncertainty," *Econometrica*, vol. 57, no. 6, pp. 1243 – 1277, 1989.

[18] C. Supatgiat, R. Q. Zhang, and J. R. Birge, "Equilibrium values in a competitive power exchange market," *Computational Economics*, vol. 17, no. 1, pp. 93 – 121, 2001.

[19] S. Ede, T. Mount, W. Schulze, R. Thomas, and R. Zimmerman, "Experimental tests of competitive markets for electric power," in *System Sciences, 2001. Proceedings of the 34th Annual Hawaii International Conference on*, jan. 2001, p. 7 pp.

[20] L. Parisio and B. Bosco, "Market power and the power market: Multi-unit bidding and (in)efficiency in electricity auctions," *International Tax and Public Finance*, vol. 10, no. 4, pp. 377 – 401, 2003.

[21] T. Mount and H. Oh, "On the first price spike in summer," in *System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on*, jan. 2004, p. 10 pp.

[22] A. Baillo, M. Ventosa, M. Rivier, and A. Ramos, "Optimal offering strategies for generation companies operating in electricity spot markets," *Power Systems, IEEE Transactions on*, vol. 19, no. 2, pp. 745 – 753, may 2004.

[23] M. Cain and F. Alvarado, "The impact of uncertainty on incentives to collude in electricity markets," in *2004 International Conference on Probabilistic Methods Applied to Power Systems (IEEE Cat. No.04EX853)*, 2004, pp. 433 – 8.

[24] E. Hasan and F. Galiana, “Fast computation of pure strategy nash equilibria in electricity markets cleared by merit order,” *Power Systems, IEEE Transactions on*, vol. 25, no. 2, pp. 722 –728, may 2010.

[25] E. Hasan, F. Galiana, and A. Conejo, “Electricity markets cleared by merit order;part i: Finding the market outcomes supported by pure strategy nash equilibria,” *Power Systems, IEEE Transactions on*, vol. 23, no. 2, pp. 361 –371, may 2008.

[26] E. Hasan and F. Galiana, “Electricity markets cleared by merit order;part ii: Strategic offers and market power,” *Power Systems, IEEE Transactions on*, vol. 23, no. 2, pp. 372 –379, may 2008.

[27] C. Day, B. Hobbs, and J.-S. Pang, “Oligopolistic competition in power networks: a conjectured supply function approach,” *Power Systems, IEEE Transactions on*, vol. 17, no. 3, pp. 597 – 607, aug 2002.

[28] J. Valenzuela and M. Mazumdar, “Cournot prices considering generator availability and demand uncertainty,” *Power Systems, IEEE Transactions on*, vol. 22, no. 1, pp. 116 –125, feb. 2007.

[29] A. Hortacsu and S. Puller, “Understanding strategic bidding in multi-unit auctions: a case study of the texas electricity spot market,” *Rand Journal of Economics*, vol. 39, no. 1, pp. 86 – 114, Spring 2008.

[30] C. Chou, Karen and R. B. Corotis, “Simulation of hourly wind speed and array wind power.” *Solar Energy*, vol. 26, no. 3, pp. 199 – 212, 1981.

[31] B. McWilliams and D. Sprevak, “Simulation of hourly wind speed and direction.” *Mathematics and Computers in Simulation*, vol. 24, no. 1, pp. 54 – 59, 1982.

[32] M. Blanchard and G. Desrochers, “Generation of autocorrelated wind speeds for wind energy conversion system studies.” *Solar Energy*, vol. 33, no. 6, pp. 571 – 579, 1984.

[33] R. Billinton, H. Chen, and R. Ghajar, “Time-series models for reliability evaluation of power systems including wind energy,” *Microelectronics and Reliability*, vol. 36, no. 9, pp. 1253 – 61, Sept. 1996.

[34] R. Billinton and W. Wangdee, “Reliability-based transmission reinforcement planning associated with large-scale wind farms,” *Power Systems, IEEE Transactions on*, vol. 22, no. 1, pp. 34–41, Feb. 2007.

[35] R. Billinton and G. Bai, “Generating capacity adequacy associated with wind energy,” *IEEE Transactions on Energy Conversion*, vol. 19, no. 3, pp. 641 – 646, 2004.

[36] W. Wangdee and R. Billinton, “Considering load-carrying capability and wind speed correlation of wecs in generation adequacy assessment,” *IEEE Transactions on Energy Conversion*, vol. 21, no. 3, pp. 734 – 741, 2006.

[37] M. Conlon and W. Carr, “Generation adequacy assessment incorporating wind energy capacity,” *Universities Power Engineering Conference, 2004. UPEC 2004. 39th International*, vol. 3, pp. 1014–1018 vol. 2, Sept. 2004.

[38] R. M. Moharil and P. S. Kulkarni, “Generator system reliability analysis including wind generators using hourly mean wind speed,” *Electric Power Components and Systems*, vol. 36, no. 1, pp. 1 – 16, 2008.

[39] J. Cardell and S. Connors, “Wind power in new england: modeling and analysis of nondispatchable renewable energy technologies,” *Power Systems, IEEE Transactions on*, vol. 13, no. 2, pp. 710–715, May 1998.

[40] M. Doquet, “Use of a stochastic process to sample wind power curves in planning studies,” *Power Tech, 2007 IEEE Lausanne*, pp. 663–670, July 2007.

[41] R. Karki, P. Hu, and R. Billinton, “A simplified wind power generation model for reliability evaluation,” *IEEE Transactions on Energy Conversion*, vol. 21, no. 2, pp.

533 – 540, 2006.

[42] J. MacCormack, D. Westwick, H. Zareipour, and W. Rosehart, “Stochastic modeling of future wind generation scenarios,” in *North American Power Symposium, NAPS*, 2008.

[43] F. Olsina, M. Roscher, C. Larisson, and F. Garces, “Short-term optimal wind power generation capacity in liberalized electricity markets,” *Energy Policy*, vol. 35, no. 2, pp. 1257 – 1273, 2007.

[44] A. D. Lamont, “Assessing the long-term system value of intermittent electric generation technologies,” *Energy Economics*, vol. 30, no. 3, pp. 1208 – 1231, 2008.

[45] C. Obersteiner and M. Saguan, “On the market value of wind power,” in *Energy Market, 2009. EEM 2009. 6th International Conference on the European*, may 2009, pp. 1 –6.

[46] N. Stoughton, R. Chen, and S. Lee, “Direct construction of optimal generation mix.” *IEEE transactions on power apparatus and systems*, vol. PAS-99, no. 2, pp. 753 – 759, 1980.

[47] N. Jia, R. Yokoyama, Y. Zhou, and U. Kozu, “An effective dp solution for optimal generation expansion planning under new environment,” in *PowerCon 2000. 2000 International Conference on Power System Technology. Proceedings (Cat. No.00EX409)*, vol. vol.1, Piscataway, NJ, USA, 2000, pp. 37 – 42.

[48] J. Valenzuela and M. Mazumdar, “The electricity price duration curve under bertrand and cournot models,” in *2004 International Conference on Probabilistic Methods Applied to Power Systems*, 2004, pp. 38 – 43.

[49] R. J. Green, “Reshaping the cegb: Electricity privatization in the uk,” *Utilities Policy*, vol. 1, no. 3, pp. 245–254, 1991.

[50] R. Billinton, *Power System Reliability Evaluation*. Gordon and Breach, Science Publishers, Inc., 1970.

[51] N.-H. Von Der Fehr and D. Harbord, "Spot market competition in the uk electricity industry," *Economic Journal*, vol. 103, no. 418, pp. 531 – 546, 1993.

[52] J. Richter, C.W. and G. Sheble, "Genetic algorithm evolution of utility bidding strategies for the competitive marketplace," *Power Systems, IEEE Transactions on*, vol. 13, no. 1, pp. 256 –261, feb 1998.

[53] A. Chuang, F. Wu, and P. Varaiya, "A game-theoretic model for generation expansion planning: problem formulation and numerical comparisons," *Power Systems, IEEE Transactions on*, vol. 16, no. 4, pp. 885 –891, nov 2001.

[54] F. Murphy and Y. Smeers, "Generation capacity expansion in imperfectly competitive restructured electricity markets," *Operations Research*, vol. 53, no. 4, pp. 646 – 61, 2005/07/.

[55] E. Gnansounou, J. Dong, S. Pierre, and A. Quintero, "Market oriented planning of power generation expansion using agent-based model," in *Power Systems Conference and Exposition, 2004. IEEE PES*, oct. 2004, pp. 1306 – 1311 vol.3.

[56] F. Olsina, F. Garces, and H.-J. Haubrich, "Modeling long-term dynamics of electricity markets," *Energy Policy*, vol. 34, no. 12, pp. 1411 – 33, 2006.

[57] AWEA, "us and china race to top of wind energy ," World Wide Web, 2009, accessed: Feb 2009. [Online]. Available: http://www.awea.org/newsroom/releases/us_and_china_race_to_top_of_wind_energy_02Fed09.html

[58] "Alberta Electric System Operator 2011 Annual Report," World Wide Web, http://www.aeso.ca/downloads/AESO_2011_Annual_Report.pdf, Alberta Electric System Operator, accessed: July 2012.

[59] AESO, “Current and Historical Market Reports, Historical Reports,” World Wide Web, 2012, Accessed: June 2012. [Online]. Available: http://ets.aeso.ca/ets_web/docroot/Market/Reports/HistoricalReportsStart.html

[60] R. Baldick, “Computing the electricity market equilibrium: Uses of market equilibrium models,” in *Power Systems Conference and Exposition, 2006. PSCE ’06. 2006 IEEE PES*, 29 2006-nov. 1 2006, pp. 66 –73.

[61] R. Billinton and R. Allan, *Reliability Evaluation of Power Systems*. Plenum Press, New York, 1996.

[62] J. MacQueen, “Some methods for classification and analysis of multivariate observations,” in *Proc. Fifth Berkeley Sympos. Math. Statist. and Probability (Berkeley, Calif., 1965/66)*. Berkeley, Calif.: Univ. California Press, 1967, pp. Vol. I: Statistics, pp. 281–297.

[63] D. Specht, “Probabilistic neural networks for classification, mapping, or associative memory,” in *Neural Networks, 1988., IEEE International Conference on*, july 1988, pp. 525 –532 vol.1.

[64] L. Ljung, *System Identification Theory for the User Second Edition*. Upper Saddle River, NJ: Prentice Hall PTR, 1999.

[65] ——, *System Identification Toolbox for Use with MATLAB*. Natick, MA: 3rd edition The John Hopkins University, 2002.

[66] “AESO Long Term Adequacy Metrics May 2012,” World Wide Web, http://www.aeso.ca/downloads/2012_05_LTA.pdf, Alberta Electric System Operator, Accessed: July 2012.

[67] M. Tripathy, R. Maheshwari, and H. Verma, “Radial basis probabilistic neural network for differential protection of power transformer,” *Generation, Transmission Dis-*

tribution, IET, vol. 2, no. 1, pp. 43 –52, january 2008.

[68] X. Wang, T. Wang, and B. Wang, "Hybrid pso-bp based probabilistic neural network for power transformer fault diagnosis," in *Intelligent Information Technology Application, 2008. IITA '08. Second International Symposium on*, vol. 1, dec. 2008, pp. 545 –549.

[69] M.-S. Kang, C.-S. Chen, Y.-L. Ke, C.-H. Lin, and C.-W. Huang, "Load profile synthesis and wind-power-generation prediction for an isolated power system," *Industry Applications, IEEE Transactions on*, vol. 43, no. 6, pp. 1459 –1464, nov.-dec. 2007.

[70] A. Haidar, Z. Khalidin, and I. Ahmed, "Probabilistic neural network for vulnerability prediction on a practical power system," in *Electronics and Information Engineering (ICEIE), 2010 International Conference On*, vol. 1, aug. 2010, pp. V1–146 –V1–150.

[71] C. Kucuktezan and V. Genc, "Dynamic security assessment of a power system based on probabilistic neural networks," in *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES*, oct. 2010, pp. 1 –6.

[72] G. J. Stigler, "The dominant firm and the inverted umbrella," *Journal of Law and Economics*, vol. 8, pp. 167–172, 1965. [Online]. Available: http://www.jstor.org/stable/724788

[73] NERC.com, "Generating Unit Statistical Brochure for 2007," World Wide Web, http://www.nerc.com/page.php?cid=4|43|47, 2007, Accessed: July 2012.

[74] "2011 Annual Market Statistics," World Wide Web, http://www.aeso.ca/downloads/AESO_2011_Market_Stats.pdf, Alberta Electric System Operator, Accessed: June 2012.

[75] "Current and Historical Market Reports, Historical Reports, Historical Trading," World Wide Web, http://ets.aeso.ca/ets_web/docroot/Market/Reports/

HistoricalReportsStart.html, Alberta Electric System Operator, Accessed: June 2012.

[76] "Alberta Watt Exchange Limited," World Wide Web, http://www.ngx.com/wattex.html, NGX, Accessed: June 2012.

[77] "Current Supply and Demand Report," World Wide Web, http://ets.aeso.ca/ip_web/Market/Reports/CSDReportServlet, Alberta Electric System Operator, Accessed: September 2012.

[78] "MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation." World Wide Web, http://www.mathworks.com/products/matlab/, The MathWorks, Inc., Accessed: June 2008.

[79] T. Jones, *Artificial Intelligence: A Systems Approach*, ser. Infinity Science Series. Infinity Science Press, 2008.