Coupled Operation of a Wind Farm and Pumped Storage Facility: Techno-Economic Modelling and Stochastic Optimization

by

Kristin Wild
B.A.Sc., University of Toronto, 2009

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ABSTRACT

This thesis applies a stochastic programming approach to the techno-economic analysis of a wind farm coupled with a pumped storage facility. The production of an optimal day-ahead generating schedule is considered. Wind forecasts contain an element of random error, and several methods of addressing this uncertainty in the optimization process are compared. The methods include robust and reliability-based design optimization in addition to a combination of both approaches, and results indicate that reliability-based design optimization is best-suited to this particular problem. Based on a set of wind forecast error scenarios and historical data, a probability-weighted forecast wind generation scenario set is developed. Reliability constraints are imposed to meet a minimum of 80% of the generating schedule time intervals. This methodology is applied to a case study on Vancouver Island. Preliminary results show that when compared to the base case of a standalone wind farm on Vancouver Island, a wind farm coupled with pumped storage can prove to be economically competitive with pumped storage capital costs below $1.53 million/MW installed pumped storage capacity and a firm energy price of $130/MWh.

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List of Symbols

α	Probability Outside Confidence Interval
t	Time
k	Prediction Horizon
P	Wind Power
$\widehat{P}_P$	Persistence Wind Forecast
$\widehat{P}_{MA}$	Moving Average Wind Forecast
$\widehat{P}_0$	Climatology Wind Forecast
X	Wind Forecast Error Time Series
Y	Wind Forecast Error Time Series Connected to X
a	Auto-Correlation Coefficient
b	Cross-Correlation Coefficient
c	Random Error Coefficient
d	Offset Cofficient
$e(t)$	Random Error vector, or exponential function
N	Number of scenarios, or length of time interval
n	Current Scenario Counter
ρ	Scenario Probability
x	Energy Bid (Generating Schedule)
E	Energy in/out of Pumped Storage Facility
σ	Standard Deviation
μ	Mean
$\bar{\mathbf{W}}_{EV}$	Expected Value Wind Generation Vector
Q_i	i^th Quartile

List of Acronyms

BES	Best Easy Schematic
CAISO	California Independent System Operator
CPC	BC Hydro Clean Power Call
EPA	Electricity Purchase Agreement
EV	Expected Value
EEV	Expected Result of the EV Solution
EVPI	Expected Value of Perfect Information
IPP	Independent Power Producers
kW	Kilowatt
kWh	Kilowatt-hour
MAE	Mean Absolute Error
MOS	Model Output Statistics
MW	Megawatt
MWh	Megawatt-hour
NMAE	Normalized Mean Absolute Error
NMAFE	Normalized Mean Absolute Forecast Error
NWP	Numerical Weather Prediction
RDO	Robust Design Optimization
RBDO	Reliability-Based Design Optimization
R^2BDO	Robust-Reliable Design Optimization
RP	Recourse Problem
SOP	BC Hydro Standing Offer Program
UCAR	University Corporation for Atmospheric Research
UCP	University Corporation for Atmospheric Research Community Programs
UCTE	Union for the Coordination of the Transmission of Electricity
UWIG	Utility Wind Integration Group
VSS	Value of the Stochastic Solution

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Chapter 1

Introduction

1.1 Research Objective

Current-day power systems have been developed for large, centralized, and dispatchable power plants. Utilities have been faced with limits on the construction and operation of the seemingly inexhaustible source of CO_2-emitting coal-fired power plants. In the case of British Columbia, restrictions have been placed on additional large conventional hydropower. Interest has been directed toward the development of renewable energy to meet increasing demand and reduce greenhouse gas emissions, and with the introduction of these variable and nondispatchable energy resources such as wind, flexibility is demanded from the existing power system. To use these new resources to their fullest extent, business-as-usual operation has to be re-examined.

This subject requires input from multidisciplinary engineering fields as well as economic, social, and political fields. Projects can be formed around individual turbines, wind farms, utilities, or international interconnections. This analysis considers a single wind farm. Wind forecasting and energy storage are commonly suggested methods of addressing wind speed variability, and this work aims to assess the value of applying those methods to a wind generator in British Columbia. Specifically, the goal of the thesis is to assess the operational and economic feasibility of an independently owned wind farm coupled with a pumped storage facility in British Columbia, in part by applying wind forecasting and stochastic day-ahead generation schedule optimization. The following sections provide background information required to explain this overall concept and compile the necessary analytical tools and methodologies.

1.2 Wind Energy Background Information

1.2.1 Wind Power Integration

Power systems worldwide are experiencing a surge in the amount of installed wind capacity, whether it is to meet rising system demand or to replace fossil fuel plants with clean alternatives. The primary difficulties in integration of wind energy into the electricity grid result from its inherently unpredictable and variable nature. The variability of renewable energy technologies such as wind, solar, and run-of-river hydroelectricity introduces additional system operational constraints with respect to transmission and reserve requirements, system stability and security, and operating costs. As energy policy moves towards increasing renewable portfolio standards, setting wind generation targets, and reducing greenhouse gas emissions, these new system requirements must be addressed.

Electricity System Implications of Wind Power Integration

The effect of wind power on the electricity system is heavily dependent on the system generation mix and regional geography. For instance, several wind plants located throughout a large area, such as the United Kingdom, will experience less overall variability than individual plants, referred to as an aggregational or smoothing effect [1]. This may reduce the additional reserves required for short-term balancing. Another example involves load and generation balancing within the grid, which is relatively straightforward with a traditional thermal or hydroelectric power plant. Balancing a grid with variable generation may alter the efficiencies of thermal generators operating at reduced capacities.

Existing transmission networks may also be restricting in terms of line capacities and distance to favourable wind plant sites. Networks tend to be well-developed in heavily populated areas, and wind resources are often high in rather remote locations, which can result in high transmission infrastructure investments to avoid bottlenecks and reach plant locations.

According to The Utility Wind Integration Group (UWIG), following an unexpected offline plant or line outage, system stability may be improved by the presence of wind energy [2]. This is due to the reactive power control and low-voltage ride-through capabilities of state-of-the-art wind plants. Wind should be considered an energy resource rather than a capacity resource, resulting in the argument that no

Time Scale	Area	Impact
Up to several minutes	Local/System	Voltage management: Wind farms can provide reactive reserve
Several minutes to one hour	System	Reserves: Wind farms can provide some primary and secondary control
One to 24 hours	Local/System	Transmission and distribution system losses or benefits
One to 24 hours	System	Cycling losses: Suboptimal use of thermal/hydro capacity
One to 24 hours	System	Replaced energy: Wind energy replaces other production forms
Several Hours	System	Discarded energy: Wind farms can exceed the amount of energy that the system can absorb
One to several years	System	System reliability: Adequacy of power – Wind power has capacity credit

Table 1.1: Wind Power Integration Impacts – Adapted from [4]

additional new capacity is required as a back-up generator. However, spinning and nonspininng reserves are required in a system to cover fluctuations in load. With the addition of wind this flexibility requirement is increased [3]. Wind plants have associated capacity factors (roughly 10% to 40% of installed capacity) that can provide additional reserves for long-term planning, but not for daily operations planning [2]. Wind variability and unpredictability result in consequences for wind generators, for example, bidding into markets as price takers and being charged firming or energy imbalance penalties.

Time scale is an essential factor to consider when assessing the impacts of wind energy in the power system. Electricity system time scales range from several hundredths of a second to years. Table 1.1, adapted from [4], summarizes the general power system effects of wind power integration. The reader is directed to [5] for further discussion on the details of wind power integration.

Economic Implications of Wind Power Integration

UWIG estimates that wind penetrations of up to 20% of the system peak demand can increase the system operating costs by 10% of the wholesale value of the wind energy. This value could be imposed on the wind generator and, using the United States as an example, is significantly less than current energy imbalance penalties [2]. Additionally, in a region that applies a price to carbon dioxide emissions, the displacement of fossil fuel generators could place added value on wind energy while reducing fuel dependence, such as natural gas used for ramping control. In recent research done based on Ontario, Canada, it has been shown that this may be less effective than desired [6]. The specifics, however, will be dependent on the particular electricity system involved. Costs such as network connection, network upgrade, and system operation costs may be distributed differently among wind farm operator, network operator, and energy customers, depending on the system considered [7], [8].

Issues commonly addressed include the requirement for additional system reserves. Reserves can be classified into either primary reserves, which deal with regulation on the order of minutes and less, or secondary reserves, which are expected to be available within roughly 15 minutes to hours in advance. Wind forecasting errors are generally dealt with using secondary reserves domestically. Denmark is an example of a country which realized over 18% wind power penetration in 10 years with no additional primary reserve installation requirements[1]. In this market, up- and down-regulation can range from roughly 12 €/MWh and 7 €/MWh[2], respectively throughout the year. For perspective, the average price of energy in the Nordic market that year was roughly 25€/MWh[3]. Overall, experiences in Europe show that increasing wind penetration does negatively impact the price of energy [7], but studies must be done on a case-by-case basis. In North America various studies have shown an increase in operating costs of approximately 3-5 US$/MWh for penetrations around 20% [9]. It has been recently demonstrated that considering wind energy as a 'must-take' resource, or negative load, results in an unreasonably high integration cost of up to 10%

[1] The considerable international interconnection contributed to this result

[2] Values per MWh regulated in 2002

[3] Denmark is divided into two independent power systems: the Nordic synchronous power system (Nordel) in Eastern Denmark, operated by Elkraft, and the European synchronous power system (UCTE) in Western Denmark, operated by Eltra. Wind power development has taken place in both regions, with the majority located in the Eltra area. UCTE serves 23 European countries. Eltra uses the Nord Pool Elspot for regulation on a daily basis, which is inclusive of Nordic countries and Northern Germany. The pricing provided is for Elspot and is not inclusive of socialized interconnection costs.

higher than strategic dispatch and forecasting methods [10].

1.3 Pumped Storage Background Information

Before the present day large scale introduction of variable renewable energy sources, the concept of pumped storage was first used to store run-of-river energy generated at night for use during the day [11]. Used in conjunction with renewable energy, it can act as a form of energy reserve, similarly to conventional operating reserves. The concept of pumped hydro storage physically relies upon an upper and lower water reservoir, and economically, the price differential between off-peak and peak factoring round trip energy efficiency. Simply put, water is pumped from the lower reservoir to the upper reservoir during periods of low demand and therefore low price, typically at night. When demand and prices are high, the water is allowed to flow back down the system through turbines to generate electricity. It can be used for load leveling, peak shaving, and potentially import/export arbitrage. It is also inherently well matched with renewable energy sources such as wind, as it can offset the intermittency and firm up electricity generation forecasts when they are used in joint operation, as will be demonstrated in this work.

1.3.1 History of Pumped Storage

The first known conceptual demonstration of pumped storage was seen in Zurich, Switzerland in 1882 in which a reciprocating pump was proposed for energy storage. The first official facility was opened in 1909 in Schlaffhausen, Switzerland with a capacity of 1500 kW and a separate pump and turbine. Additional installations followed throughout Europe over the next few decades. The extent of its development was largely increased by two particular installations: The first plant over 20 MW near Dresden, Germany in 1928, and the first large-scale North American installation in Connecticut in 1929 which featured a reversible pump-generator [12].

Early arrangements typically included a horizontal arrangement of a separate pump/turbine assembly aligned with the generator/motor. These units in which the separate pump/motor and turbine/generator assembly were aligned were referred to as a 4-unit type and are seldom used today [11]. As installations increased in size the arrangement was moved to vertical. There were limited installations of 3-unit sets in which the turbine, pump, and generator/motor were together on one either horizontal or vertical shaft. Eventually in the 1930s, reversible pump turbines (or, 2-unit sets) were introduced, the first installation occurring in Baldeney, Germany. This advancement typically allows for a cost savings of approximately 30% while compromising on complicated starting modes, efficiency, and longer changeover times [11]. Although this resulted in an efficiency loss through compromise, the capital savings and system simplification were significant. This particular technology underwent major development in the 1960-70s and is often used to date. Staged pumping was seen in the 1970s in France and Japan to accommodate higher heads, which lead to the double staged reversible Francis turbine and several Japanese sea water installations. Pelton turbines are also used in high-head single stage situations. In the late 1980s the idea of variable speed reversible pump turbines was introduced by means of a two speed synchronous motor-generator followed by advancements in power electronics and continuously variable speed drives. Although potentially more expensive, these systems have significant efficiency gains when operating with large head differentials greater than a ratio of 1.25. The potential for a variable storage system is in-line with the requirements of renewables such as wind power and their variable nature. Many systems are still designed with a well-sized pump and constant flow rate, and unless a large head differential is required, the option of transient pumping may not be considered [12].

1.3.2 Technical Details of Pumped Storage Systems

Round-trip system efficiencies are generally between 70 and 85 percent [11]. The overall efficiency does depend on the project design and configuration. Due to the system inefficiencies, to generate profit from the peak and off-peak period pricing scheme alone, this pricing differential has to compensate for these losses. Occasionally old installations are retrofitted with more modern equipment to realize efficiency improvements on the order of 30% [13]. Ramping rates can reach up to 3 MW per minute, so plants are capable of very fast response [14]. It is considered that a two-mode system (pumping and generating) requires approximately four minutes between mode changes [15]. This means it may not be available for fine balancing, so in practice, additional resources may be required for this time period. It must be considered, however, that currently this is a more economically feasible alternative for large-scale energy storage than some emerging technologies, such as flow batteries, in part due to its longstanding establishment [16]. For appropriate geographical sites it is also often a feasible alternative in constrained small-scale grid settings when compared to alternative storage technologies [17].

1.3.3 Literature Review of Wind Energy and Pumped Storage

The coupling of a wind farm with a pumped storage plant has been previously studied in the literature, but there is room for additional study of this topic within the context of British Columbia. There has been work regarding wind farms coupled with pumped storage upgrades in BC Hydro's facilities [16], in addition to standalone British Columbia pumped storage facility analysis [18]. There does not appear to be a public study of the operational and economic feasibility of independent investment in a wind farm coupled with a pumped storage facility in BC, as proposed in this work[4]. The following section contains a helpful summary of results from previous studies that are relevant to the current project. One particularly interesting application of pumped storage is in a remote or isolated grid scenario. This has been examined, in an economic optimization for the Canary Islands in Bueno et al. (2006), an optimal power flow solution for Rhodes island in Anastasiadis et al. (2010), and detailed pumping system design optimization of isolated Greek island grids [20],[21],[22]. Although this work is part of the relevant wind energy – pumped storage literature, isolated grids have different characteristics than large interconnections. For example, they may require a larger storage system since there is no guaranteed available back-up capacity in case of an incorrect wind forecast or periods of calms. For the purpose of the background of the thesis work, the focus of the wind energy – pumped storage literature will be on the following studies:

1. In Castronuovo et al. (2004), optimal operation and hydro storage sizing of a wind-hydro power plant is considered in Portugal. The storage system was set at 20% of the wind farm's nameplate capacity, and it was found that for a wind farm of 11 MW, the addition of a pumped storage plant under optimal operating conditions in the Portuguese energy market increased the net profit by an annual average of 12% [23].

2. A similar approach to that used in this thesis was taken by García-González et al. (2008) in that a stochastic optimization of a wind-pumped storage system

[4]Benitez et al. (2008) present an interesting analysis on this subject within Alberta [19]

was considered in the Spanish electricity market. Both electricity prices and wind generation were considered as random parameters. Increases in profits with respect to a standalone wind farm were proven, and the most profitable configuration was determined to be a coupled system which is allowed to both sell and purchase energy in order to charge the pumped storage device [24].

3. Evans (2009) presented a masters thesis in which the level of wind curtailment in a hydro-dominated electric generation system was studied, in particular British Columbia. It was found that, for all cases, wind curtailment was less than 4% for wind penetrations between 3% and 12% [25]. This work was extended in the masters thesis of Guzman (2010) which used stochastic optimization to examine the value of pumped storage upgrades to several existing BC Hydro conventional hydro facilities. This could provide economic benefits that would increase with increasing wind penetrations [26].

1.4 Wind Energy Integration and Pumped Storage Potential within the British Columbia Electricity System

1.4.1 Wind Energy

British Columbia has very limited experience with respect to wind energy integration, especially compared to provinces such as Alberta and Ontario with over 800 and 1300 MW each, and in the next several years the province will likely see hundreds of megawatts installed as a result of the BC Hydro Clean Power Call (CPC). This call was for clean energy project proposals from Independent Power Producers (IPPs). IPPs are private companies involved in site selection, electricity bidding, contract submission, permitting, construction, financing, commissioning, and operation of these projects [27]. Six wind project proposals from various IPPs were accepted and electricity purchase agreements (EPAs) were reached for each project. The average price of firm energy was approximately $130/MWh for the wind projects [28].

Studies have been completed with respect to wind monitoring at various sites, wind forecasting, and expected generation and interconnection costs [29], [30], [31]. A previous study also shows that wind curtailment in British Columbia would not have a significant impact on wind farm operations, reaching approximately 2% annually for wind penetrations ranging from 3-12% [25]. Assuming a wind penetration of 20% and reasonable balancing reserve requirements, total wind integration costs are estimated between $9.9/MWh and $11.0/MWh, respectively, with regulating and load following costs accounting for approximately 40% of costs and energy shift costs comprising the remaining increase [32]. This average of $10/MWh would be passed on to the independent power developers as a 'wind integration cost'. BC Hydro is continually addressing the long-term impacts of wind integration in the province [33].

1.4.2 Pumped Storage Potential

Pumped storage requires suitable sites in order to provide an energy storage option for wind. British Columbia has such sites with reasonable elevation difference, storage reservoirs, and access points. Since the 1970s, BC Hydro has maintained an inventory of pumped storage sites which is updated periodically. The introduction of Geographical Information Systems (GIS) advancements in addition to traditional visual inspection have made it possible to complete a high-level study of the entire province's potential including estimated energy storage capacity, rated power, and construction costs. The most recent study was completed by Knight Piésold Consulting in 2010 [18]. This information was used upon consideration of the parameters required to conduct the case study.

1.4.3 British Columbia Energy Policy and Practices

Provincial policy developments are an integral component of renewable energy development in British Columbia, which is a regulated electricity system. This is different than a deregulated electricity market such as Alberta or California, where prices fluctuate with the market. BC Hydro does participate in electricity market activity such as the Mid-Columbia (Mid-C) market[5]. However, prices within the province are regulated. IPPs must reach an agreed-upon price of energy through an electricity purchase agreement (EPA), which are strictly confidential and therefore data are not available for economic validation. The components of the EPA include:

1. A firm energy amount, which is an estimate of the amount of energy produced over the resolution of each season and comprises the bulk of energy produced.

[5]This is an American electricity market trading hub within the Northwest Electric Power Market.

This represents roughly 80% of total generation.

2. A nonfirm energy amount, which can be subject to either a set nonfirm energy price based on region, a nonfirm energy price based on the Mid-C market, or a combination of both. Non-firm energy is not guaranteed to be bought by BC Hydro.

The wind energy is remunerated subject to the time-of-generation pricing scheme as a percentage of their agreed upon firm energy price, shown in Figure 1.1, and the $10/MWh firming penalty. The contract must be met with 80% certainty over a period of 5 years, and there is a 10% adjustment opportunity. This firm energy estimate framework does not provide incentives for IPPs to invest in advanced wind forecasting techniques or energy storage, since despite advancements in wind forecasting a time horizon of one year is unrealistic. The other form of firm energy contract is referred to as hourly firm and is better-suited to power plants and large conventional hydro, which is also unrealistic for wind generators. Therefore, for the purpose of this thesis, a theoretical policy scenario was developed in which day-ahead generating schedules are provided to the utility. This day-ahead generating schedule would not necessarily eliminate the need for an annual seasonal forecast. Specifically, the 80% contract requirement for IPPs is shifted to the day-ahead generating schedules. This allows the utility to know the hourly wind generation for the next day with at least an 80% certainty for each time interval over the course of the day while providing the IPP with an economically optimal generating schedule. From this theoretical structure it is possible to extend the policy to include other objectives such as smoothing or increased reliability during peak periods. Future sections discuss this policy in greater detail.

1.5 Model Scope and Key Contributions

Since British Columbia will be experiencing an increase in the installed wind capacity in the province in addition to the well-known ‘energy gap’, it is desired to investigate the potential to strategically use this resource for both planning purposes and offsetting peak demands in high load hours (referred to as peak or super-peak time periods), while maintaining an attractive investment opportunity for IPPs. The firming provided by pumped storage could also be provided by large conventional hydropower in British Columbia; however, its arbitrage capabilities are also desirable

	Off-Peak 10pm-6am Mon-Sat All day Sun	Peak 6am-4pm & 8pm-10pm Mon-Sat	Super Peak 4pm-8pm Mon-Sat
January	105%	122%	141%
February	101%	113%	124%
March	99%	112%	124%
April	85%	95%	104%
May	70%	82%	90%
June	69%	81%	87%
July	79%	96%	105%
August	86%	101%	110%
September	91%	107%	116%
October	93%	112%	127%
November	99%	112%	129%
December	104%	120%	142%

Figure 1.1: BC Hydro Time-of-Generation Pricing Scheme (% of EPA Price). Data Source: BC Hydro Clean Power Call [28]

and so independent investment is worthy of analysis. Although the variability of wind will not be eliminated, perhaps the unpredictability can be mitigated.

This study is not intended to provide a grid-wide or utility-owned perspective, both of which have already been studied [26],[34]. It is also not an electrical engineering or electricity market analysis. Rather it presents an approach using the application of wind forecasting methods and optimization techniques capable of accounting for the random error of wind energy forecasts to determine whether independent investment in pumped storage could present an attractive investment to wind generators in British Columbia. The investment in pumped storage is considered and is not compared to investments in additional renewables due to the services that pumped storage could provide and the desire for strategic wind energy operation within the province[6]. Variations on the current IPP contract with the provincial utility, BC Hydro, are introduced to explore the feasibility of various scenarios.

The model scope follows from the objective of analysing the program from the perspective of an IPP. The thesis is made up of several models that assess the overall operational and economic feasibility of a wind farm coupled with a pumped storage facility. An initial model is required to postprocess the numerical weather prediction (NWP) forecast data and size the storage facility. Next the postprocessed NWP forecast data are input to a wind power forecast error generator to generate the scenarios required for the stochastic optimization. The forecasted scenarios are then reduced to a computationally manageable size using a scenario reduction algorithm. Finally the processed forecast scenarios are input to a stochastic day-ahead energy generation schedule model, and then validated with a real-time hourly operational dispatch model for each day of the desired time period. At this stage, various methods of assessing the wind forecast error uncertainty are examined, and the best method is selected for further analysis. Economic analysis is then done for the selected time period which is then compared to the base case of a wind farm without a pumped storage facility under the BC Hydro Clean Power Call. Chapter 2 will discuss each computation stage in further detail. The methodology presented here is general and modular, making it readily extendable for analysing additional sites in a variety of jurisdictions and energy policy scenarios.

The overall findings indicate that it may be attractive for IPPs to investigate pumped storage options for sites that are less capital intensive. Pumped storage is an extremely site-dependent technology and so capital costs range widely in the lit-

[6]Investment in fossil fuel or nuclear power plants is also not considered

erature. Also there is not a standard policy in place for this type of development in British Columbia, so various energy policy assumptions were made. One site at Woss Lake proved to be competitive with the baseline of a standalone wind farm under the BC Hydro Clean Power Call despite the additional capital requirements. Considering these assumptions, results are favourable for projects with estimated capital costs below $1.53 Million/MW as defined in [18]. While this is more expensive than investment in additional wind generation resources, it is argued that the increased reliability and the grid services that pumped storage can provide justifies a higher price of energy.

1.6 Thesis Organization

Chapter 1 provides the research objective and background information essential to the research objective. Methodology-specific information is presented throughout the text. This section also contains the scope and key contributions of this masters thesis and is accompanied by the structure of the document.

Chapter 2 contains the details of model development and the methodologies used for analysis.

Chapter 3 is a results section in which several optimization methods are applied and compared against a baseline scenario of the current BC Hydro 'business-as-usual' contract with IPPs.

Chapter 4 applies the best method determined from the previous chapter to a case study project location on Vancouver Island.

Chapter 5 summarizes the results, future work, and contributions of this work.

Chapter 2

Model Development and Methodology

This chapter will outline the overall objective of the model and describe the required computational steps. Figure 2.1 displays the primary components of the overall computation process: initial storage system sizing and data processing; wind power forecast calculations; and stochastic day-ahead bid generation and real time operational dispatch. Topics that will be discussed include wind forecasting, types of uncertainty, scenario analysis, and stochastic programming approaches.

2.1 Model Objective

An appropriate modelling strategy has to be developed to determine whether a wind farm coupled with a pumped storage facility could present an attractive investment for IPPs. Recent publications and presentations validate the relevance of this particular topic [16], [35] for both present-day and future scenarios. For a wind project with pumped storage to be considered, it must meet or exceed the net income of a traditional wind farm to compensate for additional design requirements and capital costs. For it to be approved, it must also meet the operational and regulatory requirements of the provincial utility. The model that has been developed addresses both of these requirements.

Since current provincial policy does not favour the introduction of independent energy storage into the electricity system, decisions were made regarding a theoretical policy scenario that would allow for realistic analysis of a wind farm coupled with

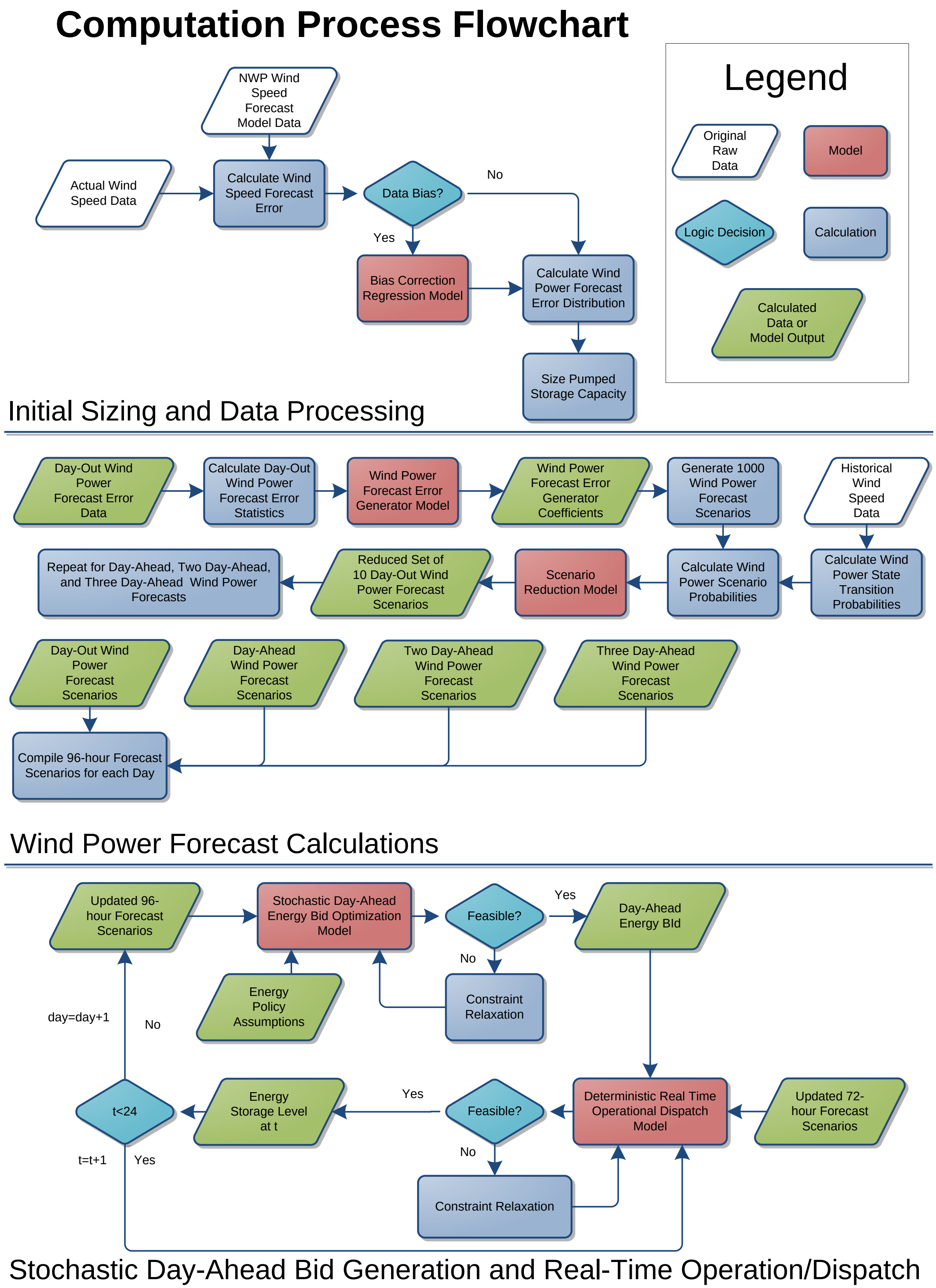

Figure 2.1: Model Flowchart

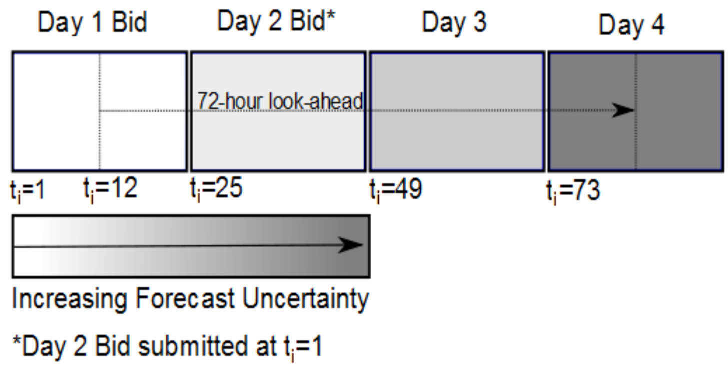

Figure 2.2: Energy Generation Schedule Schematic for $t = 1 : 24$ (hours) – Example Look-Ahead Time Shown for Operation at $t = 12$

a pumped storage facility. The idea behind this work is that day-ahead generating schedules, referred to as energy bids, are created with an hourly resolution by the IPP. This is based on a wind forecast that is done with up to a 72-hour prediction horizon, so consideration is given to the days following the bid time window to maintain strategic operation. The pumped storage is considered as both an opportunity for arbitrage when the bid is formed (i.e. it can be used to shift generation to peak or super-peak periods) and as a method of offsetting wind forecasting errors. The pricing for these schedules is not based on an electricity market. It is based on agreed upon price of energy, which, in the Clean Power Call, is set as an EPA firm energy price with an average value of roughly \$130/MWh. The BC Hydro time of generation schedule is then applied as a multiplier, so less is received in off-peak periods than peak or super-peak. This encourages arbitrage from the pumped storage facility. Once this day-ahead schedule is set, the facility is operated in real-time using the operational dispatch model, meeting the generation schedule with a set confidence interval in addition to strategically operating the facility to maintain contingency for a future timeline. (This is to ensure that shortsighted operation of the storage device is avoided.) The results of this operational dispatch model then provide the actual net income for the facility. Figure 2.2 displays how the look-ahead time applies to the energy generation schedule, or bid, formulation process in addition to the increase in forecast uncertainty with time. Bids are optimally formulated one day in advance at $t = 1$. Since $t = 12$ in the schematic, that means that the facility is currently in the real-time operational validation stage. At $t = 25$, the schedule would be reset to update the forecast and the process would repeat itself.

First, it is desirable to accommodate the uncertainties experienced in wind farm operation and analyze various modeling approaches to this when compared to the current policy scenario. There are several ways of incorporating uncertainty into optimization procedures. Depending on the characteristics of the uncertain variables, different approaches may be selected. It is also possible to combine approaches to reach the desired performance of the optimizer. This uncertainty is incorporated into wind speed forecasting.

2.2 Wind Speed Forecasting

Since the foundation of the stochastic energy bid generation is the wind forecast, in this section some background information will be provided on various methods and practices.

2.2.1 Wind Speed Forecasting Methods

Wind forecasting takes many forms, from common sense statistical predictions to complicated numerical models, and combinations of both. The prediction horizon often determines which approach should be taken. For example, an hour-ahead forecast will not use the same approach as a year-ahead estimate. The following types of forecast are essential to this project (notation is taken from [36] for consistency with the literature):

Persistence: This method is referred to as a reference model, and is not generally used in practice due to its longer horizon inaccuracy. Persistence assumes that the prediction is equal to the observation at the time the prediction is made:

$$\widehat{P}_P(t+k \mid t) = P(t) \tag{2.1}$$

This approach is appropriate for a prediction horizon of an hour, but not for that of one day. It can be extended to create a moving average predictor stating that the prediction is equal to the average of the last n observations:

$$\widehat{P}_{MA,n}(t+k \mid t) = \frac{1}{n}\sum_{i=1}^{n-1} P(t-i) \tag{2.2}$$

Climatology: Contrary to the Persistence approach, the Climatology predictor assumes that the prediction is equal to the global average of measurements for the area. This is not appropriate for a short prediction horizon of an hour, but surprisingly accurate for long prediction horizons.

$$\widehat{P}_0(t + k \mid t) = \overline{P(t)} \tag{2.3}$$

Statistical: Various statistical methods have been developed such as in [37] in which a correlation between the Persistence and Climatology methods is developed. More recently Pinson et al. applied multivariate Gaussian distributions to two- to three-day ahead forecasts [38]. These prediction errors have been studied and applied to the sizing of energy storage systems [39],[40]. Generally, although statistical methods can provide acceptable estimations of wind forecasts for analysis, they are not appropriate for operational purposes. This is due to the fact that wind speeds are a function of weather systems, and stand-alone statistical methods do not have the capabilities of predicting individual weather systems without including information regarding incoming weather systems.

Numerical Weather Prediction (NWP): These forecasts are based on advanced meteorological models which are used for weather prediction in general. Wind speeds are only a component of these models. They have the capability to predict incoming weather systems and their effects, and though they have limitations (predicting high wind ramping events, for example [41]), they provide much better forecasts in terms of capturing future trends and are in practice used from one hour ahead up to four days out [31]. NWP forecasts do have known issues such as forecast bias [42]. Bias correction of NWP forecasts will be discussed upon presentation of the case study in Chapter 4.

2.2.2 Wind Power Forecast Generation

Before the case study of interest was implemented and NWP data were obtained, a method of wind forecast generation was required. It was found that the statistical methods described above were not an accurate representation of current forecasting capabilities. A recent publication from Mello et al. (2011) at Pacific Northwest National Laboratories was used in which a first-order autoregressive wind power forecast error generator had been determined for real-time, hour-ahead, and day-ahead applications using the following relationship [43]:

$$X(t) = aX(t-1) + bY(t) + ce(t) + d \qquad t = 1, ..., T \tag{2.4}$$

Here it is acknowledged that wind power forecast error is not an entirely independent random variable. It is important to note that this time model results in a time series of wind power forecast *error*, not a wind power forecast. $X(t)$ represents the wind power forecast error at time t. The components of the equation include: a, autocorrelation to the error of the previous time step, $X(t-1)$; b, cross-correlation to the error of the time series of finer resolution, $Y(t)$ (e.g. hour-ahead for a day-ahead forecast error); c, a relationship to a normally distributed random error term, $e(t)$; and d, a constant term. Note that this error generator utilizes wind *power* forecast error statistics from historical utility data. These statistics would not necessarily apply to wind *speed* forecast error due to the nonlinear wind turbine power curve relationship. This method is not included in the previous forecasting section as it is not in itself a forecasting method[1].

The statistics for these values were calculated from a set of forecast data from the California Independent System Operator (CAISO)[2], and the coefficients were solved for in an unconstrained nonlinear optimization to produce a time series of forecast errors matching the data statistics. While this method could not be used in practice since it only generates the forecast error, it can be used exclusively to generate multiple error time series in conjunction with a wind forecast. For the purposes of the methodology comparison analysis, these error time series data are combined with historical data to simulate a wind power forecast. For the case study, the error time series data are combined with the NWP wind power forecast.

The reproduction of [43] was successful with the exception of the cross-correlation coefficients, which did not converge for the methodology comparison[3]. A similar situation was encountered in [43] with respect to the load forecast error time series. Refer to Appendix A for a summary of the optimization results. Figure 2.3 displays an example of the time series and the historical data from Environment Canada over a 24-hour period. Once the wind forecast error time series has been generated, it is possible to size the energy storage system.

[1]Forecasts can be simulated by combining the resulting wind power forecast error time series with actual wind power data to simulate a forecast. In the case study the bias-corrected NWP model data specific to BC are used to calculate the wind power forecast error statistics to then generate the required number of wind power forecast scenarios.

[2]Initially BC data were not available.

[3]These did converge for the case study, which Appendix A is based upon

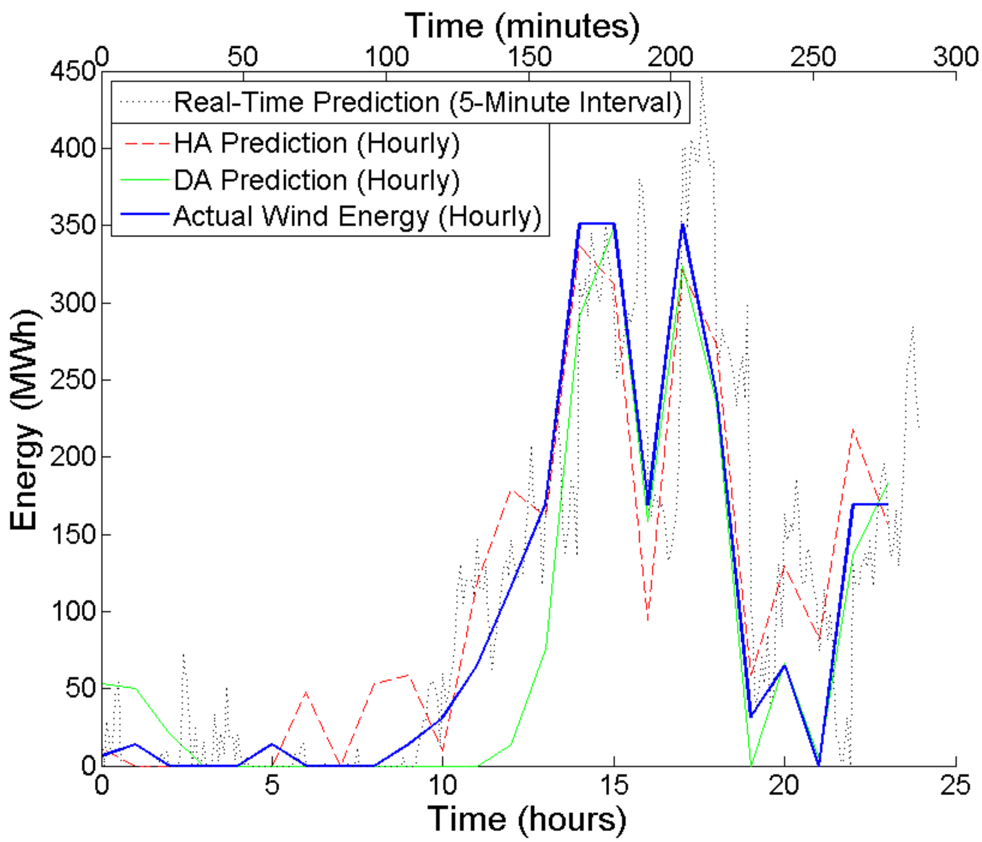

Figure 2.3: 24-hour Wind Forecast Time Series showing Real-Time, Hour-Ahead (HA), and Day-Ahead (DA), Forecasts in comparison to Actual Output

2.2.3 Wind Forecast Error and Pumped Storage System Sizing

First, it is important to note that the energy storage capacity of a pumped storage facility is largely site dependent. There is no standard value of project capital cost in $ per MWh of storage, and so it is not realistic to incorporate storage capacity as a design variable for a high-level analysis. A common assumption is sizing the energy requirements to meet six hours of generation capability at the rated capacity of the wind farm and so this value was selected [18], [22] . The important parameter to decide upon is how to size the rated capacity of the storage system in MW.

Many methods of energy storage system sizing have been presented in the literature. A thorough review shows that the sizing method is heavily dependent on the purpose of the wind farm, the electricity system in which it is connected, and the policy measures in place. For example, if the wind farm were intended as a significant component of the power system for an isolated island grid as previously discussed, the pumped storage system would almost need to fulfill the role of a backup generator. In Anagnostopoulos et al. (2007), this resulted in an pumped storage rated capacity of 113% installed wind farm capacity [22]. In Bueno et al. (2006), a study done in the Canary Islands with a separate pump and turbine configuration, the pump capacity was close to 90% of the rated wind farm capacity while the generation capacity of the energy storage system was 300% (this system used independent pump and turbine sets rather than revesible pump-turbines) [20]. In Castronuovo et al. (2004), which examines the Portuguese system, pumped storage capacity was directly selected as approximately 18% of the wind farm size [23]. The two studies that were most applicable to this approach were García-González et al. (2008) in the Spanish electricity market with a pumped storage capacity of 33% of the wind farm, and Pinson et al. (2009) in the Danish electricity system with a pumped storage capacity of 25% of the wind farm [24], [40] . Both of these studies examined energy imbalance costs in an interconnected grid, which is a similar approach being taken in this thesis.

Initially, the intent was to include the storage system size as a design variable in the optimization process over the course of an entire year; however, this approach was computationally expensive and not possible with the scenario-based stochastic approach. Another sizing method was hence required. The pumped storage rated capacity can be sized based on the probability distribution of the wind forecast error, namely in the frequency domain. To justify this method of day-ahead energy bid generation, the joint operated system must be capable of meeting the bids within a set confidence interval to fulfill the purposes of the proposed policy scenario. As previously mentioned, BC Hydro requires this to be 80% with current practices, and so this interval was carried over to this analysis as well. For reasons outlined below, the 80$^{\text{th}}$ percentile of forecast error does not necessarily correspond to an 80% confidence interval of energy bid reliability.[4]

Following several trials, the 95$^{\text{th}}$ percentile of forecast error distribution results in the required energy bid reliability. Based on the forecast error generation method applied, this corresponds to 24% of the rated capacity of the wind farm, which is in reasonable agreement with [24] and [40]. This is a conservative approach and it is believed that it meets the requirements for this type of high-level study. Potential recommendations for a more in-depth analysis will be presented in a future chapter.

2.3 Types of Uncertainty

To select a realistic optimization routine for this problem, the uncertainty must be considered. In an optimization problem, uncertainty can be addressed in any of three areas:

1. Objective function – may reflect the risk attitude of an IPP[5]
2. Constraints – may be dependent on resource availability
3. Technical coefficients[6]

When deciding how to represent uncertain parameters, it is important to select a method that properly represents the characteristics of the optimization problem. For example, Chance-Constrained Programming is one method of accounting for uncertainty in the constraints. It is possible to assume that the wind speeds at each hour follow a known distribution, which can be determined by statistical analysis and if necessary transformed to an appropriate distribution and normalized. It would

[4]Upon testing several percentiles of forecast error distribution, it was determined that having the capability of satisfying the 95$^{\text{th}}$ percentile of forecast errors resulted in the satisfaction of 88% of the energy bids. This is due in part to the fact that the errors are not strictly normally distributed, they are interdependent, and a small bias is present. In practice, occasionally the system needs to pump (store) energy at a greater rate than the 80$^{\text{th}}$ percentile-based sizing approach would allow.

[5]The objective function would also be affected by uncertainty within the constraints, however the uncertainty may not be addressed in the objective function itself.

[6]This analysis is not within the scope of this research.

then be possible to formulate the problem so it solves for a set confidence interval, or equivalently specify the likelihood that the constraint will hold to be (1-α), where α represents the allowable probability of constraint violation.

However, this does not account for the fact that wind speed uncertainty compounds throughout the day, is dependent on previous time steps (i.e. there is interdependence among right-hand side constraints), and this problem is dynamic in nature. If this method is selected and applied to a 24-hour day-ahead time interval, the result is a model that consistently underestimates wind speeds and is therefore overly conservative. This compounds over the time interval and ultimately reaches an unrealistic end state. For more information on Chance-Constrained Programming please refer to [44] and [45].

This work will examine methods of addressing the uncertainty in the constraints, representing wind forecast uncertainty, and also of addressing the uncertainty in the objective function, representing net income, which is a function of the wind forecast uncertainty.

2.4 Stochastic Programming

Decision-making processes must often take place despite the presence of uncertain parameters. Stochastic programming is a method of optimization for uncertainty that is used throughout the literature for generator and grid scenarios and is particularly well-suited to dynamic problems [46], [24], [38] . BC Hydro's own optimization models involve stochastic programming [26].

2.4.1 Scenario Selection

Figure 2.4 represents a simplified visualization all possible realizations of qualitative wind power states over a set time horizon, in hours. This is a dense tree of every possible scenario realization and it is clear that this would become extremely computationally expensive as time progressed. This figure is centred at the mean and potential deviations from the mean are represented by the diverging upper and lower branches of the plot. To make this a more reasonable computation, scenario selection is employed. Assuming the random variable, in this case a component of the wind forecast error, has a known distribution, it can be sampled to create a discrete scenario set. This sampling of the wind forecast error generator has a distinct advantage

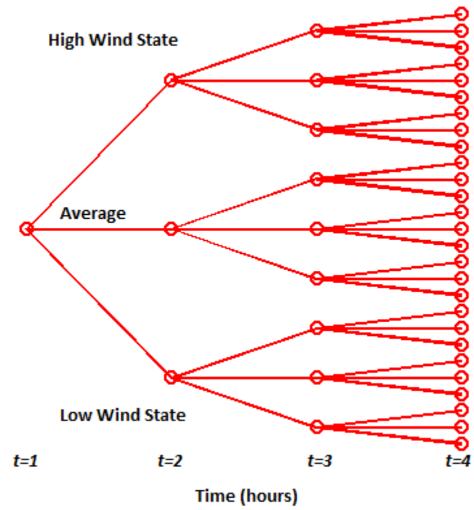

Figure 2.4: Dense Scenario Tree – Simplified Qualitative Example

when compared to traditional Monte Carlo methods involving the entire scenario tree.

When applied to this study, the upper and lower bounds in Figure 2.5 represent scenarios consistently residing in either the highest wind generation state, or the lowest wind generation state, respectively, for the duration of the time window. The probability for these states is very low and is influenced by:

1. Sampling the wind forecast error generator; and

2. Historical data.

Since the wind forecast error generator is based on historical NWP data and statistics, it inherently eliminates the extremely unlikely scenarios. The result is that, even if sampled over 100,000 times, these upper and lower bound scenarios do not appear. Figure 2.5 shows a qualitative scenario tree based on cumulative wind power state transitions. A horizontal line indicates that the wind generation is average, while divergence up or down indicates transition to higher or lower generation states for that particular time interval. Scenarios that tend either up or down overall are either above average or below average wind generation scenarios, respectively. The particular day represented in Figure 2.5 was a below average wind day. Refer to Appendix C for the wind state definitions and sample probabilities. This addresses the first probability item above.

The sampling size in addition to how many scenarios are selected from the sample population is an independent field of research, and more information is available in

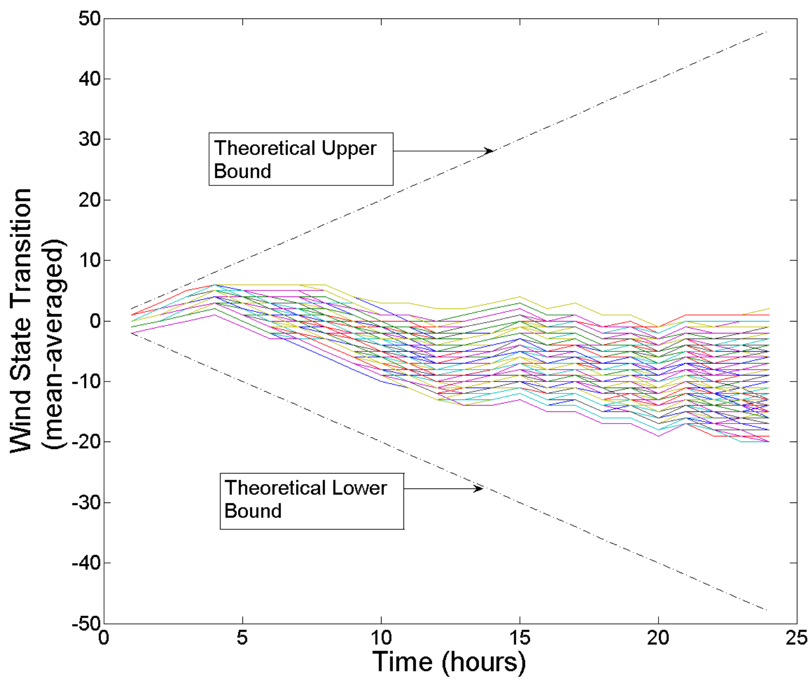

Figure 2.5: Forecast Error Generator Scenario Tree – Sampling size of 1000 Scenarios

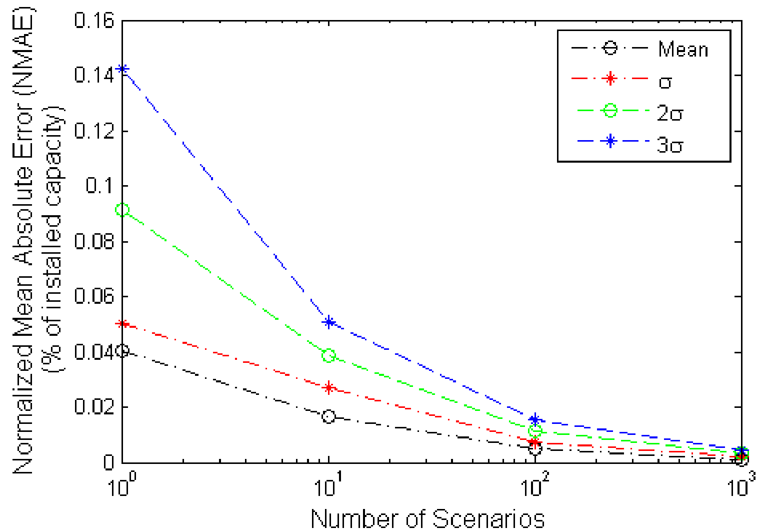

Figure 2.6: Wind Forecast Distribution Moments Convergence

[47]. The method used in this research was backward selection of single scenarios. In this work, the original set was reduced to 10 scenarios by scanning the scenarios for the most redundant scenario, deleting it, and then otpimally redistributing its associated scenario probability among the remaining scenarios. Equation 2.5 shows the optimization in which scenarios are selected for deletion, where l and j represent scenario indices, N represents the number of scenarios, ρ represents scenario probability, and ω represents the scenario set.

$$\min_{l \in 1,\ldots,N} \rho_l \min_{j \neq l} \|\omega_l, \omega_j\| \tag{2.5}$$

Figure 2.6 displays the distribution moments convergence, or normalized mean absolute error (NMAE), for various scenario sampling sizes based on a reference distribution of 10^4 scenarios, which provides suitable accuracy for these purposes.

With respect to computation speed, a sample size exceeding ten scenarios is unrealistic using a personal computer, which is a trait common to stochastic programs. Using the method in [47], a reduction algorithm can be performed on an initial set of 1000 scenarios to retain much of the distribution representation present with the 1000 scenario set while maintaining the reasonable computational speed of 10 scenarios.

As mentioned, the second probability item is the probability of scenario realization, which can be calculated using historical data and wind speed state transitions. In this case, 30 years of hourly wind speed data was available from Environment

Canada for a location near Victoria on Vancouver Island. Refer to Appendix B for details on this data. Wind state transition probabilities are calculated and used to define scenario probabilities. A sample wind power data correlation graph for various time horizons is shown in Figure 2.7. This clearly shows a 24-hour relationship that deteriorates to statistical noise after a period of roughly five days.

The method of sampling of forecast scenarios based solely on the forecast error generation method in [43] does not consider the locational wind speed state transition probabilities for Vancouver Island and ultimately neglects the probability of scenario realization based on locational data. (It is important to note that this sampling approach was not the original application of the forecast error generator developed by Mello et al. and therefore the scenario realization probabilities were irrelevant for their purposes. This is by no means a shortcoming of their research.) These scenario realization probabilities can be calculated using historical data as described, and then incorporated into the weighting factors involved in the reduction approach, which is an added benefit. From the results analyzed, this provides a set of scenarios that is representative of both the sampling distribution and the probabilities of scenario occurrences. This is clear in the improvement in the normalized mean absolute forecast error (NMAFE) for the reduced set, and could also potentially explain the very small shift in mean value from the reference distribution. Table 2.1 shows the improvement provided by the single-scenario backward reduction algorithm over a sampling set of 10 scenarios. Figure 2.8 displays the difference in the scenario tree after this scenario reduction, resulting in a manageable problem size. Once these scenarios are selected it is possible to begin the optimization formulation.

2.4.2 Stochastic Problem Formulation

The aforementioned optimization problem can be classified into the field of multistage stochastic programming with recourse. The first stage decisions are formulated considering the potential wind generation scenarios selected, and the generating schedule is optimized. Imbalance penalties are assigned for missing the set generation schedule. The second-stage, or recourse, decisions satisfy the various scenarios, utilizing the pumped-storage to offset any discrepancies in the forecasted wind generation for that scenario in order to meet the generation schedule for that hour. The optimally determined generation schedule is applied to all wind generation scenarios as it must satisfy a generation bid common to all scenarios. The second part of the problem is

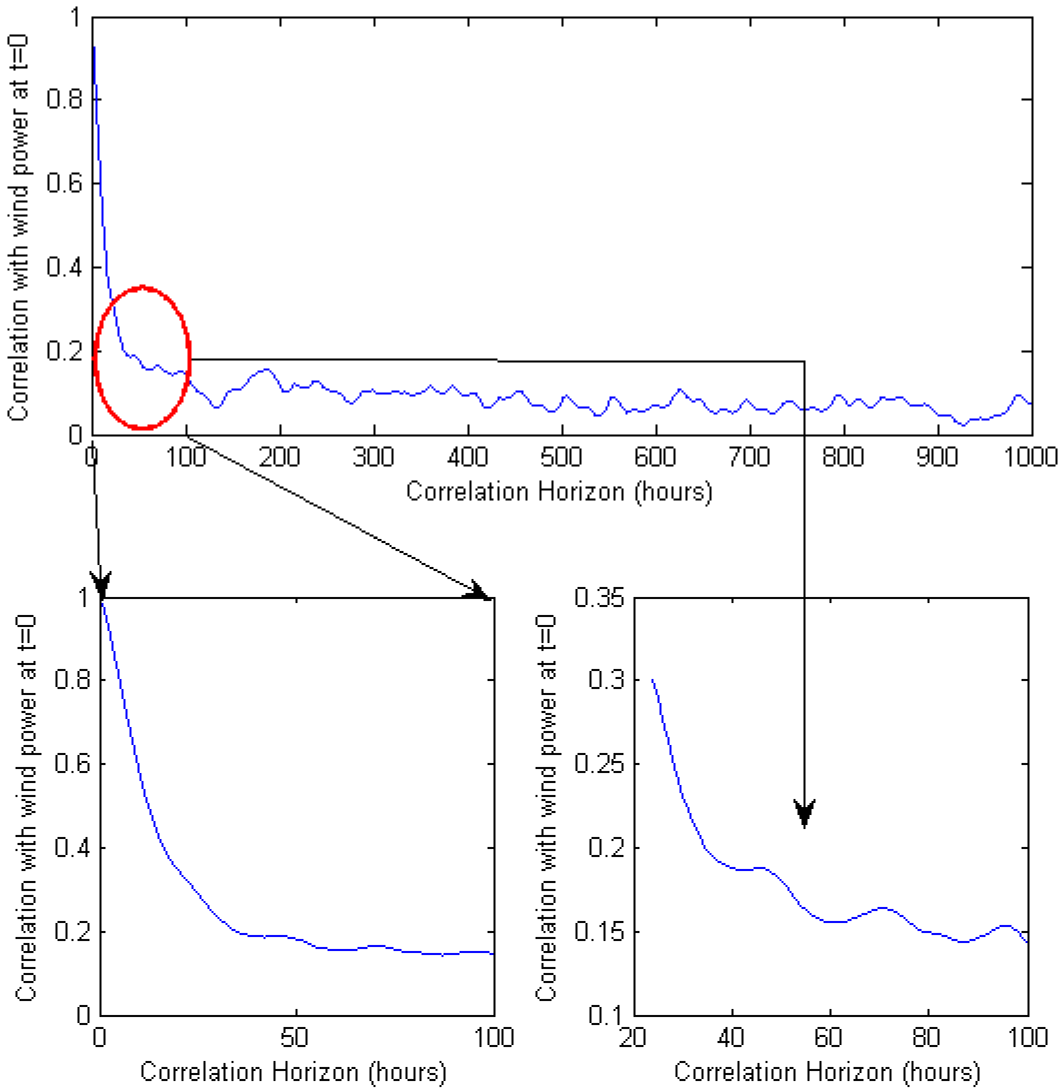

Figure 2.7: Sample Wind Power Correlation with Time Horizon

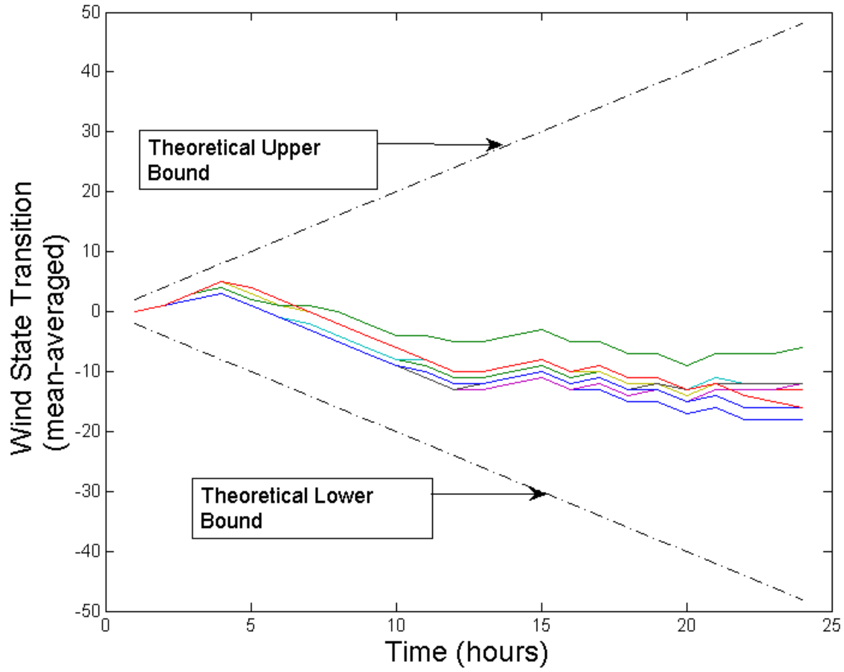

Figure 2.8: Reduced Scenario Tree – Sampling size of 1000 Scenarios Reduced to 10 Scenarios

	10 Scenario Sampling Set NMAE (%)	**Reduced 10 Scenario Set NMAE** (%)
μ	1.66	2.36
σ	2.69	2.52
$\mathbf{2}\sigma$	3.85	2.72
$\mathbf{3}\sigma$	5.07	3.58
$\mu_{\mathbf{NMAFE}}$[1]	7.71	6.36

[1] NMAFE based on actual wind generation, as opposed to NMAE which is based on deviation the reference scenario generation distribution

Table 2.1: NMAE Comparison - 10 Scenario Set vs. Reduced 10 Scenario Set

an operational dispatch model that operates the facility in 'real-time' with updated wind energy forecasts, which is not to be confused with the recourse decisions of the stochastic bid optimization. Considering the pricing scheme applied and pump-turbine efficiency curves, this is a nonlinear optimization problem and in its simplest form is formulated as follows:

$$
\begin{aligned}
\underset{x,\text{Storage Level}}{\text{maximize}} \quad & \sum_{n=1}^{N} \rho_n \sum_{i=1}^{t} \big(\text{Income}_{i,n} - \text{Penalty}_{i,n}\big) - \text{Capital Recovery} \\
\text{subject to} \quad & |P_{i,n}| \leq P_{rated}, \; i = 1, \dots, t, \quad n = 1, \dots, N. \\
& \text{Storage Level}_{1,n} = \text{Storage Level}_{end}, \; i = 1, \quad n = 1, \dots, N. \\
& \text{Storage Level}_{i,n} \geq 0, \; i = 2, \dots, t, \quad n = 1, \dots, N. \\
& \text{Storage Level}_{t,n} \geq \text{Storage Level}_{end}, \; i = t, \quad n = 1, \dots, N. \\
& x_i \leq \text{MaxGen}, \; i = 1, \dots, t. \\
& x_i \geq \text{MinGen}, \; i = 1, \dots, t.
\end{aligned}
\tag{2.6}
$$

where N is the total number of scenarios, t is the total time interval, P refers to the power generation or consumption of the facility, E refers to the energy in or out of the storage facility (design variables), Storage Level refers to the water level of the pumped storage facility (state variables), x refers to the generation schedule or bid for each time step (design variables), and ρ represents the probability of each scenario. Due to the relatively simple and straightforward governing equations of this system, as long as all variables are saved throughout the simulation, the results can be replicated for the purpose of model validation. The IPP is permitted to consume power from the grid to charge the energy storage reservoir. The net income function in Equation 2.7 and Figure 2.9 is represented as by an asymmetrical variable exponential function, which encompasses the step-function pricing scheme while smoothing the transition points for the sake of operation of the gradient-based optimizer. The function steps up once the sum of predicted wind generation and energy in or out of the storage system meets the energy bid for that time period, so the dynamic nature of this curve is that it varies with changing energy bids and predicted wind generation scenarios. This is representative of an energy imbalance penalty policy as a method of addressing deviations from generating schedules. Note that the slope in Figure 2.9 has been relaxed at transition points for the purpose of visualization and in reality the slope is much steeper, resulting in the firm energy price being awarded when the bid is met and simulating a linear step function without the curvature shown.

$$\begin{aligned}\text{Income}_{i,n} - \text{Penalty}_{i,n} = \text{Time of Use}_i \Bigg(\Big(& \text{price}_{firm} \text{x}_i \\ & + \text{price}_{nonfirm} (\text{WPower}_{forecast,i,n} + E_{i,n}) \Big) \\ & + \text{price}_{nonfirm} \frac{-\text{x}_i}{(1 + e^{-2(\text{WPower}_{forecast,i,n} + E_{i,n} - \text{x}_i)})} \\ & - \text{penalty} \frac{\text{x}_i - (\text{WPower}_{forecast,i,n} + E_{i,n})}{(1 + e^{-2(-\text{WPower}_{forecast,i,n} - E_{i,n} + \text{x}_i)})} \Bigg) \end{aligned} \tag{2.7}$$

For clarity, the pricing scheme can be described as follows:

- The pricing scheme is a variable step function that steps up from non-firm price to firm price once the bid is met[7]. This step depends on:

  1. The bid selected by the optimizer (design variable); and
  2. The forecasted wind energy, set by the forecast error generator and scenario reduction algorithm before the optimization begins.

  Once the energy in or out of the pumped storage facility (design variable) plus the forecast wind energy meets or exceeds the bid, the price steps up.

- If x-axis is energy in/out of the pumped storage facility in MWh and y-axis is price in \$/MWh, the pricing curve moves along the x-axis based on the bid selection, and the price awarded shifts along the pricing curve based on the energy in/out of the storage facility (again, it steps up when the sum of energy storage and wind meets bid). This is shown in Figure 2.9.

- If the bid *is not* met: A penalty is assigned for the amount missed (\$/MWh missed), and the nonfirm price is awarded for the amount produced.

- If the bid *is* met or exceeded: The firm price is assigned for the bid amount and nonfirm price is assigned for any overgeneration (\$/MWh overproduced).

The result is a pricing scheme with two levels of penalty, one that is proportional to the amount by which the bid is missed by (i.e. missing bid by 100 MWh is penalized

[7]The non-firm and firm prices are taken to be \$44.39/MWh and \$130/MWh, respectively, based on current provincial policy at the time of analysis. Time of use pricing is provided in Figure 1.1.

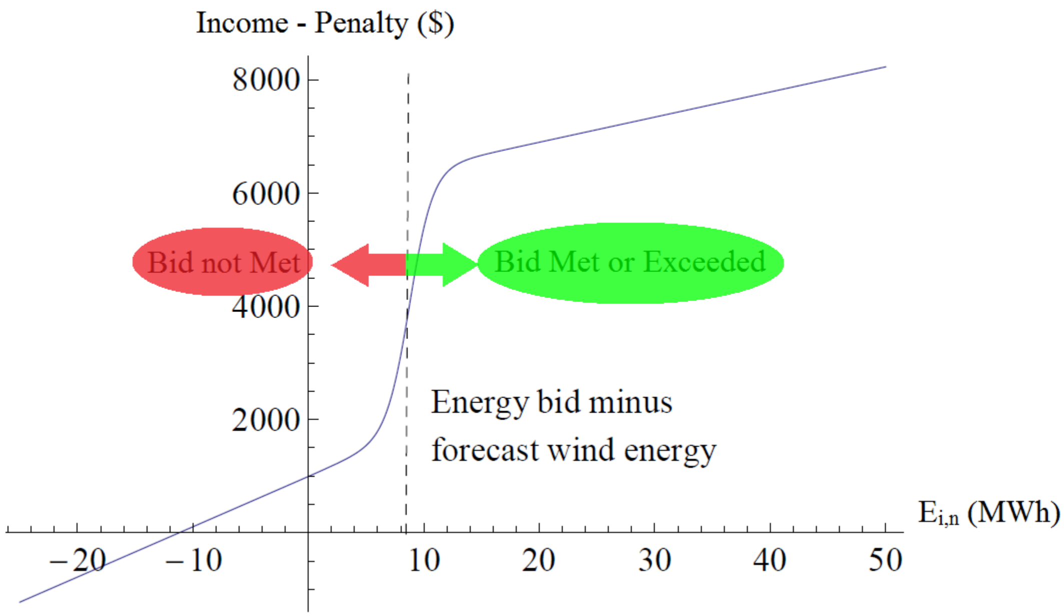

Figure 2.9: Income and Penalty Function

harsher than missing by 5 MWh) and one that stresses the importance of the formality of meeting the generating schedule for reliability purposes (the step function). For the reliability case in which constraints are added in order to meet a minimum of 80% of energy bids, this is not completely necessary. However, it still encourages good operation in scenarios with lower probability that are exempted from the reliability constraints. This pricing scheme also reflects the policy standpoint that the increased reliability justifies a higher price of energy. If these bids are not met that additional energy price may not be justified. It could be argued that the penalty of nonfirm price awarded for energy production when bids are missed is not necessary, but it is used in this analysis for the aforementioned reasons.

This problem will form the basis of the stochastic programming analysis. The following approaches will be compared:

1. Deterministic design optimization
2. Robust design optimization (RDO)
3. Reliability-based design optimization (RBDO)
4. Robust/Reliable design optimization (R^2BDO)

The concept of RBDO corresponds to typical power industry confidence interval standards of a required probability of meeting a generating schedule. Each solution will be compared with the base case of a standalone wind farm operation over the same time period in order to determine the value of the pumped storage facility to IPPs in this situation. Further details regarding the implementation of these methods are provided in the following sections.

2.4.3 Robust Design Optimization

Robust design optimization aims to optimize the problem about the mean in the presence of random parameters. A variance or standard deviation term is added into the objective function and weighted. This is a form of addressing objective function uncertainty, which represents the IPP's aversion to swings in income across different generation scenarios. Refer to [48] for application to design and a more comprehensive description. In economics, this sort of approach may be referred to as mean variance analysis, and the aim is generally to model risk aversion in an economic optimization [45]. The optimization problem in Equation (2.6) is modified so that the objective function is as follows:

$$\begin{aligned} \underset{x,\text{Storage Level}}{\text{maximize}} \sum_{n=1}^{N} \rho_n \sum_{i=1}^{t} \left(\text{Income}_{i,n} - \text{Penalty}_{i,n}\right) \\ - \omega\sigma_{scenarios} - \text{Capital Recovery} \end{aligned} \tag{2.8}$$

where ω represents the selected weighting factor and $\sigma_{scenarios}$ represents the addition of the net income standard deviation term into the objective function.

2.4.4 Reliability-Based Design Optimization

This design method accounts for safety margins, or target reliability. Reliability constraints are introduced in which the design variable may not exceed the reliability target. A thorough review of RBDO is available in [48].

In physical design or manufacturing this can be quantified as a design parameter, or tolerances in manufacturing. The problem addressed here, however, is an operational optimization, and so the reliability constraints can be imposed on scenario probabilities while the objective function remains the same as in Equation (2.6). This results in a scenario probability confidence interval, set by the IPP or BC Hydro, in which the facility will be able to meet its generating schedule based on wind forecasts. The allowable probability of error will be represented by α, resulting in a confidence interval of (1-α). Constraints are added in the case that the probability exceeds the confidence interval, (1-α), so that the generator must meet the generating schedule, or bid, for that hour. This helps avoid the event that a facility sets a schedule in favour of one particularly profitable scenario at the expense of missing the schedule for a less profitable scenario with equal probability. The added constraint is as follows:

$$E_{i,n} + \text{WPower}_{forecast,i,n} \geq x_i,\ i = 1, \ldots, t, \quad n = 1, \ldots, N, \forall \rho_n \geq \alpha \tag{2.9}$$

If this constraint was added to every time step of every scenario, i.e. $\alpha = 0$, this would be referred to as a 'fat solution', which is safe and will satisfy each possibility; however, it is unrealistically expensive and overdesigned for this situation. Although risk analysis is outside the scope of this thesis, this would represent complete risk aversion. Based on relatively modest current penalty levels for missing generating schedules in British Columbia, the main beneficiary of this method of optimization would be the utility, and the increased reliability could be represented by a higher price of energy for the IPP than the existing agreements in the Clean Power Call.

Chapter 3

Methodology Comparison Results

In this chapter, criteria required for comparing and analyzing the results of the programming approaches mentioned in Chapter 2 are introduced and discussed. This chapter is to act as a comparative analysis to be refined in the case study, at which point the best method from this analysis will be applied.

3.1 Case Definitions

The model was run under the following conditions:

- Deterministic: Single *expected value* (EV) wind generation scenario[1]
- Stochastic Robust (RDO): Added standard deviation term into the objective function of the basic stochastic problem to minimize income swings across ten scenarios
- Stochastic Reliable (RBDO): Added reliability constraints to the basic stochastic problem to meet generation schedule for a 95% scenario probability confidence interval across ten scenarios
- Stochastic Robust/Reliable (R^2BDO): Standard deviation term as in RDO in addition to reliability constraints for a 95% scenario probability confidence interval across ten scenarios as in RBDO

[1] This single scenario is calculated based on a weighted average of the set of 10 scenarios for each day.

The time interval examined was a one-week period with an hourly time step. Due to this coarse time step, ramping rates were not imposed, as pumped storage units can respond to changes on the order of several seconds to minutes.

For each scenario (with the exception of the deterministic expected value case), the *value of the stochastic solution* (VSS) will be determined as in Equation 3.1. This is done by running the model with the EV scenario (deterministic), yielding the *expected result of using the EV solution* (EEV). This is then compared to the outcome using the 10-scenario set (stochastic), resulting in the *recourse problem* (RP) solution and then computing the difference between the two. For the deterministic case, it follows that the VSS will be zero and it is therefore only to be applied to the stochastic cases. Each case is compared to operation under the current BC Hydro Clean Power Call policy as a reference, or base case, to evaluate whether the method could present an improvement for IPPs.

$$\mathrm{VSS} = \mathrm{EEV} - \mathrm{RP} \tag{3.1}$$

The *expected value of perfect information* (EVPI) will also be computed by determining the difference between the RP and the *wait-and-see solution* (WS) as in Equation 3.2, in which perfect information is known ahead of time in order to make optimal decisions. Although it will not be possible to obtain perfect forecast information, this number can give some insight into the value of increasing forecast accuracy. Further information regarding the applications and comparison metrics of stochastic programming is available in [49].

$$\mathrm{EVPI} = \mathrm{RP} - \mathrm{WS} \tag{3.2}$$

3.1.1 System Details and Assumptions

The wind farm capacity was selected to represent a large transmission-scale wind farm installation similar to that in the BC Hydro Wind Data Study [31]. The system examined for this section of the analysis is a theoretical 512 MW wind farm coupled with a 124 MW pumped storage facility with a typical round-trip efficiency of 80%, for which a two-part model optimally formulates a day-ahead generating schedule using stochastic programming with recourse and then in turn operates the facility in real-time. No limit to the number of mode changes for the pumped storage facility per day is imposed. This has proven to be more cost-effective despite reducing the lifetime of the plant [50]; however, specific details on the lifetime reduction were not available and do not seem to have been included in [15], for which a 50-year lifetime was selected based on [51].

The storage system sizing is not determined by the model due to computational restrictions that are discussed in later sections. The pumped storage system is sized to meet 80% of day-ahead wind forecast errors by analyzing the forecast error distribution in the frequency domain. The requirement of 80% originates from the BC Hydro Clean Power Call for which the project must meet its firm energy estimation, and is being applied to the day-ahead generating schedule for this analysis. A firm energy (guaranteed to be bought by BC Hydro) price of $140/MWh is used for the simulation, and is varied between $110 and $160 as a sensitivity test. The current Clean Power Call EPA average is approximately $130/MWh, from which a set $10/MWh 'firming' cost is deducted. Nonfirm energy (energy generated in addition to firm energy) may be sold in the operational stage of the model in addition to the amount of the day-ahead generating schedule at a price of $44.39/MWh. Capital costs as a function of capacity are assumed to be $2 million per MW for wind [52] and $1 million per MW [26] for pumped storage with a discount rate of 8% as used in the Clean Power Call and a capital recovery period of 40 years. This is consistent across all cases and therefore variations in capital costs or discount rate do not affect the primary purpose of this particular modelling analysis as it is testing the most appropriate optimization approach to take when considering uncertainty. (A sensitivity analysis will also be included in the case study section with a more thorough capital cost breakdown.)

As previously mentioned, optimal day-ahead generation schedules are simulated while satisfying a 36-hour look ahead time (to be extended to 72-hours for the case study with validated forecast data), and deviations from these schedules are penalized based on hourly energy imbalance penalties. It is important to note that energy imbalance penalties are not currently applied to wind energy in British Columbia – the $10/MWh firming cost is assumed to encompass the firming cost to the utility – however it is used by other utilities and is applied to other generators by BC Hydro. This analysis takes the perspective of other markets in forming agreements on a more short-term basis, which can be more representative of the wind resource, rather than the long-term schedule estimation currently applied in BC (although there is no reason not to include the current practice of seasonal energy estimation as well). It is therefore a theoretical scenario for British Columbia. The energy imbalance penalty schedule itself was taken from BC Hydro Ancillary Services, and varies depending on where the imbalance lies with respect to a bandwidth of 1.5% of generating capacity. It is currently assumed that all energy will be sold to the utility based on a very low British Columbia wind curtailment calculation in [25].

The wind data was taken over thirty years from a location near Victoria on Vancouver Island, publicly available from Environment Canada's National Climate Data and Information Archive, which allowed reliable calculation of wind speed state transition probabilities. Although the raw data did not have a suitable wind resource and scaling was necessary to reach an economically acceptable capacity factor, this location was selected due to the requirement for hourly data for each hour of the day[2]. A correction factor of 1.5 was applied to scale the average wind speed up to 6.5 m/s at 80m. It is acknowledged that this may not be completely representative of actual measured wind speed distributions; however, for the case study real data are utilized. For the purposes of this methodology comparison it satisfies the requirements.

3.1.2 Deterministic Expected Value (EV) Case

The deterministic case involves forming a single expected wind generation scenario for each 24-hour period by calculating the probability-weighted average of all scenarios as shown in the following equation, where $\bar{\mathbf{W}}_n$ represents the wind generation vector for scenario n over time interval $1 : t$ and ρ_n represents the individual scenario probabilities.

$$\bar{\mathbf{W}}_{EV} = \sum_{n=1}^{N} \rho_n \bar{\mathbf{W}}_n \tag{3.3}$$

This single-scenario analysis is treated as the baseline case for determining an optimal day-ahead bid, and provides the EEV solution. Recall the previously mentioned idea that the generator should have the ability to not only manage forecast error, but also shift generation to peak periods when profitable, referred to as arbitrage. This optimization allows for that, but as it is a single scenario analysis, there is no built-in accommodation for varying forecast error. Therefore, the simulation will optimize the energy bid and arbitrage for this single scenario within the allowable constraints, and cannot always accommodate changes in wind generation realized in the operational

[2]Many wind monitoring sites in British Columbia do not operate 24-hours a day and so it was necessary to use the Victoria location despite poor wind speeds.

optimization process. A more realistic case for a single-scenario analysis would be to treat the pumped storage solely as a forecast error buffer, but for consistency among methodology comparisons this was not done, nor is it an ideal configuration for the IPP since it does not fully utilize the capabilities of the pumped storage investment.

3.1.3 Robust Optimization

To justify the analysis of the robust problem, it was necessary to solve the problem without the standard deviation term in the objective function to analyze the distribution of net income across scenarios without reliability constraints. In particular, if the net income had no significant variance across scenarios, the attempt to reduce it would be trivial. This preliminary problem formation is referred to as the basic stochastic problem.

Basic Stochastic Problem Optimization

For this optimization, it has been mentioned that a single day-ahead generation schedule is decided upon based on a set of 10 potential wind generation scenarios. For the basic and robust problems, the individual recourse decisions are not required to meet the schedule at each point in time (no reliability constraints), and a simple penalty function is applied for undergeneration as part of the objective formulation in Equation 2.7. If a unique optimal generation schedule is calculated for each individual scenario with the requirement of meeting the schedule, a set of 1000 scenarios (chosen to show a representative distribution) leads to the distribution of income levels in Figure 3.1. This shows significant variance among scenarios which can therefore be shaped using RDO.

A histogram was also generated for the basic stochastic problem solution, in which a single generating schedule was optimally chosen for a set of ten scenarios. Figure 3.2 shows preference for scenarios with high probability and high potential for income. This figure shows the polarized outcomes for this problem, which may somewhat explain the results. This is at the expense of lower income or lower probability scenarios, and the potential for income swings based on the outcome of wind generation led into the motivation to analyze the robust case. These figures are also shown in Appendix D with the scenario income multiplied by scenario probability to see the preferential weightings to higher probability scenarios. Ideally this approach would improve the net income of the facility at the expense of missing several energy bids; however,

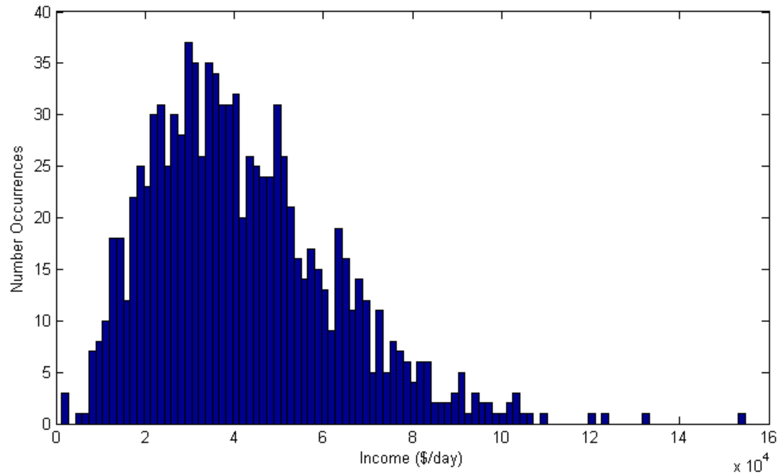

Figure 3.1: Daily Income over a Set of 1000 Scenarios - Optimal Generating Schedule for Each Scenario

this is currently having a negative effect overall due to the tendency to neglect lower probability and lower wind generation scenarios. A simplified schematic of this is shown in Figure 3.3. It is to be noted that in reality the distribution would likely be asymmetric, and would vary depending on the day and selected scenario set – a normal distribution is shown for the purpose of illustrating the concept.

Robust Optimization

Once the standard deviation term was added into the objective function the performance of the robust problem was similar to the basic stochastic solution. The income distribution across the ten scenarios is shown in Figure 3.4. When forming the generation schedule, there seems to be a clear preference of the optimizer to tend towards the higher income scenarios at the expense of the other potential wind generation scenarios. In the operational dispatch model, the energy generation schedule was missed 28% of the time, 26% of which were outside the allowable generation bandwidth.

The concept of modifying the standard deviation of the objective function across scenarios represents a level of risk aversion to unexpected swings in income; however, detailed risk analysis is not within the scope of this thesis and a survey of decision

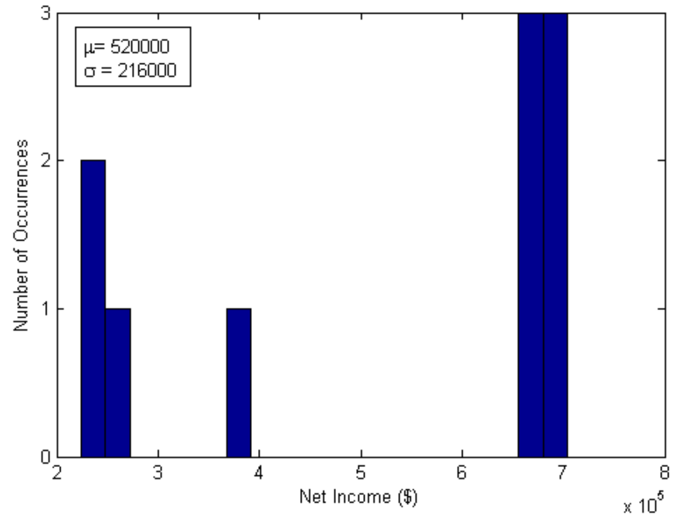

Figure 3.2: Daily Income over a Set of 10 Scenarios - Single Optimal Generating Schedule Applied to all Scenarios

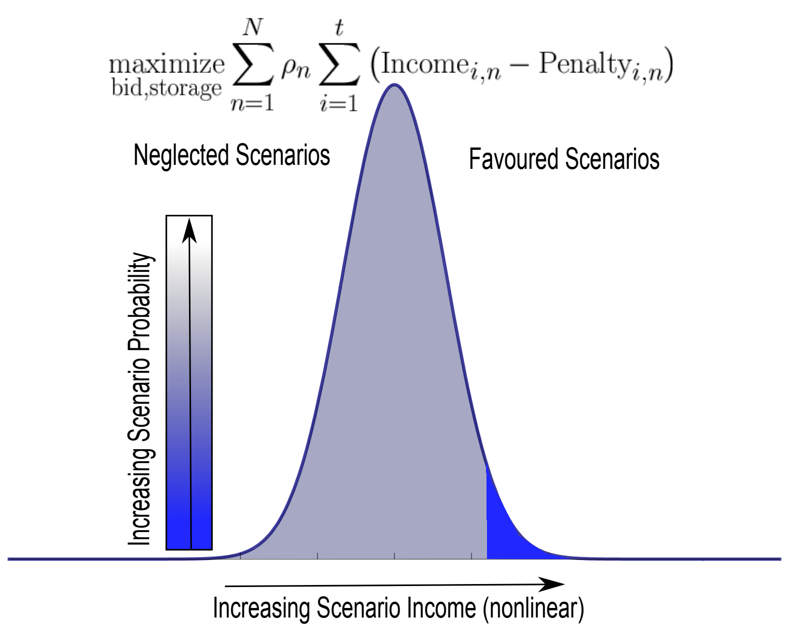

Figure 3.3: Scenario Preference Schematic - Basic Stochastic Case

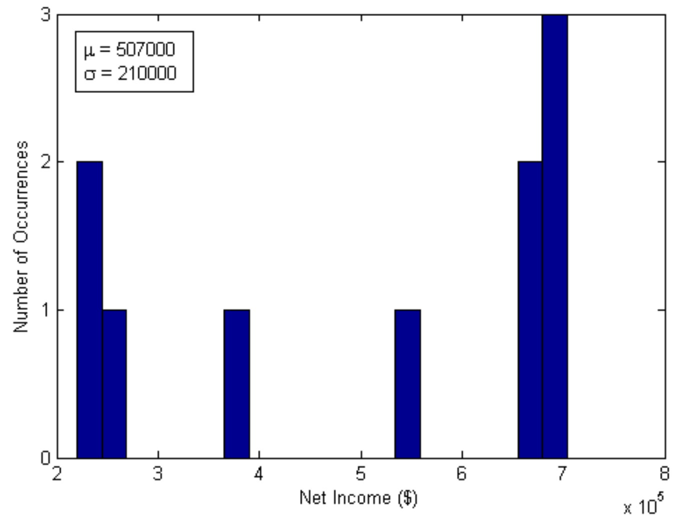

Figure 3.4: Daily Income Histogram - Robust Case

makers was not conducted to determine the weighting. Upon consideration, the addition of the standard deviation term will negatively impact income overall, which can be seen in Figure 3.4, though it is also clear that the standard deviation term did not have a dramatic effect due to the moderate weighting[3]. The income from low wind generation scenarios cannot necessarily be increased, thus acting as the limiting factor, and if the distribution is to be tightened it must be by reducing income in high wind scenarios by selling as extra non-firm energy for reduced compensation or curtailing. The result is a trade-off between an overly conservative generating schedule tailored to lower energy bids (standard-deviation motivated) and an ambitious generating schedule (income-motivated) tailored to high probability and income scenarios. This does not fare well in the optimizer, resulting in a negative change from the current BC Hydro Clean Power Call wind-only scenario. If the penalty function is increased substantially, more reasonable energy bids are created, effectively creating reliability constraints similar to the R^2BDO method, which will be discussed in the following section. It is therefore not recommended to employ Robust Design Optimization as an operational strategy for this problem.

[3]The weighting decides the level of tradeoff between net income and standard deviation across scenarios, and they were set to result in relatively equal magnitudes between each which will change depending on the scenario sets. It was not realistic in terms of computational time to test many weightings, but in the following section the effect of a variance term substitution is discussed.

3.1.4 Reliable Optimization

The performance of the reliable problem was far superior to the deterministic and robust methods with respect to optimal bid selection and its effect on net income. It is believed that this is because of the addition of constraints requiring the optimizer to meet the generating schedule for both the low and high wind generating states assuming a probability greater than 5%. The reliable problem succeeded in meeting 88% of energy bids, with 11% of bids outside the 1.5% allowable bandwidth. It is shown as an attractive investment in Table 3.1, as opposed to the other two scenarios. Note that these income levels are based on the operational dispatch model in which the energy generation schedules are validated, not the stochastic robust or reliable optimization results in which the optimal bid is determined. Figure 3.5 shows the interesting distribution of income across all scenarios. The income distribution is clustered around the generating schedule for scenarios within the confidence interval, as expected, at a value of $688,000 for the sample day chosen. Although due to data shortcomings in this comparison analysis the figures themselves are not representative of real income levels, this demonstrates that the reliability constraints (in this case, an equality constraint) perform as expected for scenarios within the confidence interval. For the particular day chosen, there were four scenarios with a combined probability of greater than 80%, while the remaining scenarios had probabilities of less than 4%. The results of this case indicate that it may be a suitable choice in operational strategy for this problem, as it had both a positive VSS and also exceeded the net income of the BC Hydro Base Case at an energy price of $140/MWh.

3.1.5 Robust-Reliable Optimization

Using the R^2BDO method solved the issues associated with the purely robust approach. The performance of this method was much better, resulting in only 15% missed energy bids. To test the optimizer's performance with the objective function weightings, the optimization was performed first with a standard deviation term and then with a variance term in the objective function. It is clear in Figures 3.6 and 3.7 that changing the weight has the intended effect, and also that decreasing the standard deviation has a significant effect on the overall net income due to the limits imposed by the low-wind scenarios. The effect of the reliability constraints is seen by the fact that the net income for the selected day is clustered for scenarios within the confidence interval at $673,000 and $33,000 for the standard deviation and variance

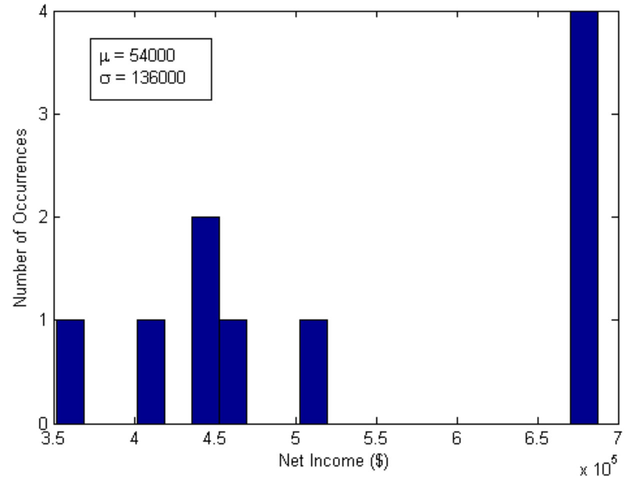

Figure 3.5: Daily Income Histogram – Reliability Case

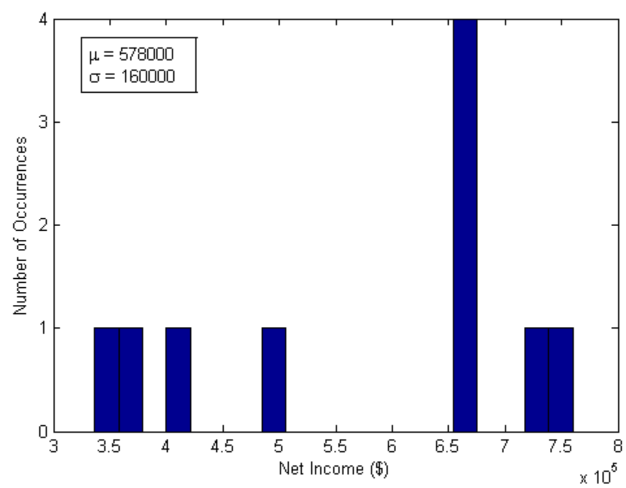

Figure 3.6: Daily Income Histogram – Robust-Reliable Case - Standard Deviation Term in Objective Function

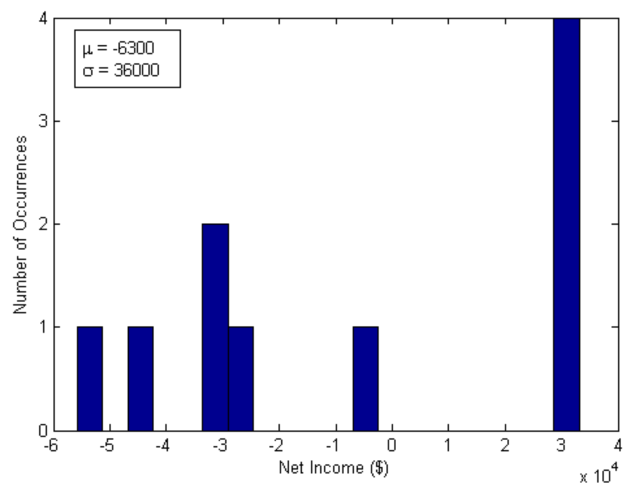

Figure 3.7: Daily Income Histogram - Robust-Reliable Case - Variance Term in Objective Function

	Net Income ($CAD)[1]	EVPI ($CAD)	VSS ($CAD)	Total Missed Bids (%)	Missed Bids Outside Bandwidth (%)
Wind Only	113000	N/A	N/A	N/A	N/A
Deterministic Problem	-246000	610000	0	25	21
Robust Problem	-343000	707000	-97000	28	26
Robust-Reliable Problem (σ)	29000	335000	275000	15	14
Reliable Problem	133000	231000	379000	12	11

[1] $130/MWh for wind only (minus $10/MWh for firming) and $140/MWh for comparison problems

Table 3.1: Results Comparison from Operational Dispatch Model - One-Week Period

analysis, respectively. This approach had a positive VSS and was profitable over the week-long term, but did not represent an improvement over the current BC Hydro Clean Power Call base case.

3.2 Net Income Comparison

The goal of this particular analysis is to determine which optimization method may best suit this optimization problem for application in the case study; however, the overarching goal of the project is to analyze the performance of a coupled wind farm and pumped storage facility with respect to improving reliability while maintaining an attractive IPP investment. It is therefore necessary to analyze the net income over a one-week period when compared to the base case of a standalone wind farm. The energy price was assumed to be $140/MWh, which is $10/MWh in excess of the CPC EPA firm energy prices due to the increased reliability the storage system and day-ahead generating schedule provide. Figure 3.8 shows the relationship between net income and energy price for each case. It is to be noted that this is an hourly average of wind energy production, and analysis has not been done on sub-hourly time intervals, such as, those affecting the balancing market. It is suspected that this would be somewhat of a site-specific analysis.

It was previously mentioned that for the robust case a higher penalty function in the bid generation stage of the model could alter the behaviour of the system, forcing the optimizer to meet the generating schedule rather than trying to attain higher income at potentially lower probability scenarios. Figure 3.9 shows the trend with net income during the operational stage of the model for various penalty values for

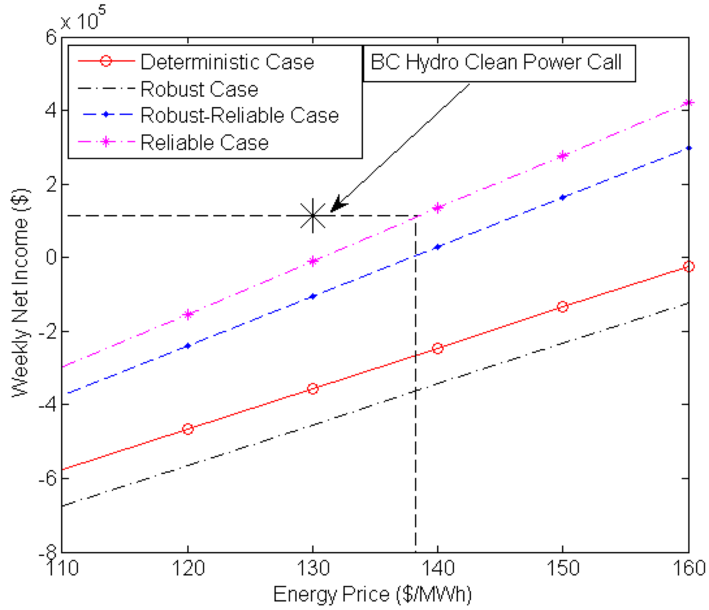

Figure 3.8: Net income comparison with respect to energy price

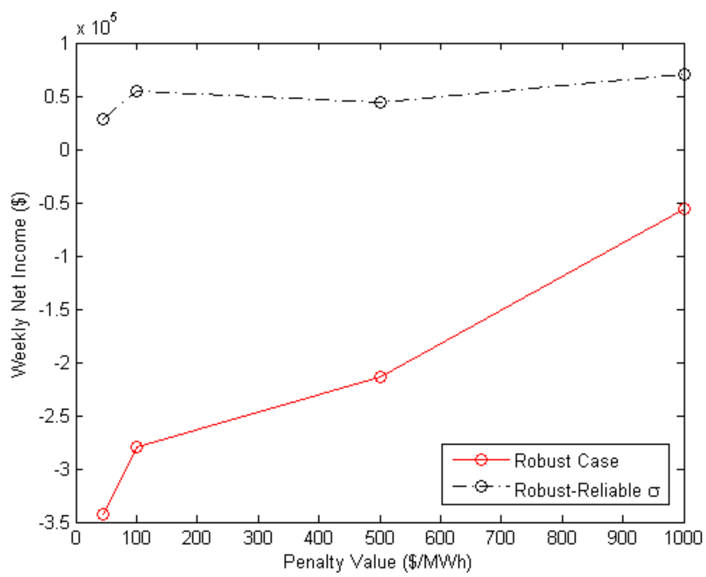

Figure 3.9: Weekly net income with respect to various penalty functions

the robust and robust-reliable cases. This was not applied to other cases. There is much more improvement visible with the robust case. There is also some potential for improvement with the robust-reliable case but this is limited due to the reliability constraints and the majority of bids already being met within the scenario probability confidence interval. Due to simulation run times it was not possible to complete an in-depth sensitivity analysis; however, it is clear that with a higher penalty function overall the unlikely scenarios that initially had a relatively small effect on the objective function are weighted higher if they are consistently missing bids. With a time-compounding nonlinear problem such as this at a concept-level analysis, the location of the global optima is not known, so perhaps a global solver could be employed for further analysis.

It is important to note that this week-long period had a capacity factor of below 15% (i.e. it was below the average annual wind generation levels for the theoretical site), so income levels would be lower than expected over the course of a year. (It was also an interesting time frame to examine because at times the wind speeds were exceeding the cut-out value, which is problematic for forecasting since power fluctuation from rated power to zero is difficult to predict.) The important distinction to make is the relative difference between each problem. At energy prices of $140/MWh the reliability case became financially viable, surpassing the reference case of a stand-alone wind farm under the Clean Power Call. If this is normalized for a net-zero storage level (i.e. no income from the storage level difference over the time period), this financial viability level is reached at roughly $145-150/MWh depending on the random error component of the simulation run, which is still within a reasonable range[4]. It could be argued that, depending on the overall system effects, the reliable case would be eligible for a higher price of energy. For the deterministic and robust, it is shown that the VSS is negative, which indicates that it is a poor decision compared to the EEV, whereas the reliable and robust-reliable cases present an improvement. It is also apparent how important an accurate forecast is by the extremely high EVPI, and how investment in superior forecasting tools could significantly improve income. Future work will be applied on valuing the accuracy of wind forecasts more thoroughly and the economic analysis will be refined in the case study.

[4]This section is based upon 100% wind energy for the CPC base case, which is realistically probably closer to 85% firm, 15% nonfirm as shown in the case study. This is conservative and income levels in this section are likely higher than would be expected. Forecasting shortcomings of this section were also apparent once case study data was obtained.

3.3 Modelling Challenges

3.3.1 Constraint Relaxation

Upon beginning this research, the problem was originally configured with reliability constraints, so feasibility was easily reached in the second operational stage of the model. Once the reliability constraints were removed for the robust case analysis, despite the penalty for undergeneration, there were multiple hours in which the generating schedule was missed. Since it is a two-stage model, the second stage was not initially configured to handle these infeasibilities. This had the result that if several consecutive hours did not meet their targets early on in the optimization process there was a cascading effect throughout the rest of the simulation period.

Even with reliability constraints on the stochastic optimization, there is a chance that due to forecast error the bids may be unattainable in the operational optimization. A method of constraint relaxation was applied on bid requirements for these scenarios to avoid infeasibilities and examine the entire week-long period. There are two particular points in which constraints can be problematic: meeting a specific bid and meeting a specific storage level. The first step in addressing this problem of infeasibility was to scan the constraint vector within the operational optimization and determine whether any of the bids were impossible for the storage to accommodate based on the recent forecast wind speeds with reduced uncertainty. If they proved to be impossible for the generator to meet in the operational stage of the model, the constraints were relaxed to a feasible point. The consequences were missed energy bids for those intervals.

For the robust case without reliability constraints, the constraints on meeting the energy bid were completely removed from the operational stage of the optimization. Generally it was the case that this constraint relaxation or removal would facilitate feasible storage level constraints; however, the second stage was to scan the constraint vector for these violations, and, if necessary, relax the storage constraints. It is important to note that physical constraints such as minimum/maximum generating capacity and minimum/maximum/end storage levels remained firm. The end storage level should also not be relaxed as it is set in advance by the stochastic energy generation schedule optimization stage. If it is lowered, it results in a lower storage level for the start of the following day, which in turn cascades throughout the remainder of the time period as expected.

It is also important to realize that when the reliability constraints are removed, the design space of the problem is considerably increased, and so computation times for the basic problem and robust simulation were greatly increased. This limited the number of simulations available to analyze due to time restrictions.

3.3.2 End Storage Levels

It was just mentioned that it was necessary to set the end storage level for the first stage of the optimization. Ideally this would be a design variable; however, due to the absence of day-out forecast data (from one hour ahead to 24-hours ahead), this was not possible, so assumptions had to be made without adequate knowledge of these hours. The only forecast data available were real-time, hour-ahead, and day-ahead. Another option would have been to include the day-ahead forecast as a day-out forecast; however, this would have been overly conservative since the accuracy of a day-out should be better than that of a day-ahead forecast. Through manual testing, it was determined that between 15-25% of the total storage capacity (or approximately 5 hours of discharge capacity at the rated size of the generators) was required to maintain feasibility for the reliability case. For the case study, forecast data are available for day-out all the way to three day-ahead, so this will not present the same issue and the end storage level will be included as a design variable. Overall this assumption did not hurt this analysis since it is a comparison and conditions were constant across each case; however, it is necessary to remove it for a realistic case study analysis.

3.3.3 Computation Time and Optimizer Difficulties

A fundamental issue with stochastic programming is the required computational time. The scenario reduction approach was one method of improving computation time without entirely sacrificing accuracy. The next method explored was the configuration of the design and state variables, which went through the following iterations:

1. Initially, the project was formed with a long variable vector containing energy bids, energy in/out of the storage system, and storage levels for all scenarios. This was extremely time consuming and it was not efficient to contain state variables within the design vector.

2. Next, all pumped storage variables were represented by storage levels, and the energy consumed or generated would be the difference between the storage levels at times $t + 1$ and t. This was somewhat of an indirect approach in the sense that the income function had to do additional computations. This was more efficient than the previous approach but it became clear that it was not the ideal configuration in terms of reaching an optimal solution due to the cumbersome nature of time-compounding computations. At this point analytic gradients were also supplied to the optimizer which improved the simulation time as well.

3. The final and current approach was to represent the pumped storage variables as energy pumped/generated at each time step. Storage levels are computed within a constraint vector and stored as a global variable in order to perform model validation afterward. This has proved to be the most efficient approach to date. An interesting difference between approaches 2 and 3 is that when bids are missed in the reliability case they are almost entirely outside of the allowable bandwidth. Approach 2 provided suboptimal bid selection but met those bids within the allowable bandwidth over 95% of the time, whereas approach 3 provides a more optimal bid which is met 89% of the time. This is likely because more constraints are active in approach 3. Bids are also generally missed within the last few hours of the day, so there is room for additional analysis here. With the acquisition of 96-hour forecast data, this will be less of an issue since data used in this comparison analysis are only for day ahead forecasting errors, which is a considerable limitation.

With the current configuration, additional ways to improve the simulation time have not been explored. However, if a considerably faster simulation is required, perhaps for longer term results such as one year, this problem could be formulated as a mixed-integer program, which would require linearization steps. Currently it involves a nonlinear efficiency term, storage level term, and pricing scheme, in part to avoid discontinuities and modelling difficulties associated with step functions. If long-term results are required it is recommended to make this change and configure for use with a program such as GAMS. Due to software availability at the time of modelling and the project timeline this was not done.

Chapter 4

Vancouver Island Case Study

This chapter presents the practical application of all previously discussed methodologies. A potential wind farm site on Vancouver Island is coupled with a nearby potential pumped storage facility to analyse both its operational and economic feasibility when compared to a standalone wind farm of the same size under the BC Hydro Clean Power Call. A project description is included for both the wind energy and pumped storage components in addition to the post-processing methodology and results for the NWP site data. Results of the RBDO and real-time operational dispatch analysis of this project are then reported and discussed.

4.1 Project Description

The previous research led to the application to a site on Vancouver Island. Vancouver Island was chosen because of the nature of the island's grid within British Columbia. Figure 4.1 shows the interconnection to the mainland transmission system along with the location of electricity demand percentages. If Vancouver Island is to see significant wind installations and rising electricity demand, there is a chance that this connection could present a transmission bottleneck. Additionally, in the event of a transmission failure at this linkage, wind energy on Vancouver Island may represent a disproportionately high percentage of generation, which can cause grid issues. Pumped storage could potentially aid in regulation. Therefore, it might be desirable for both IPPs on Vancouver Island and BC Hydro to investigate the coupling of wind farms with storage in this location.

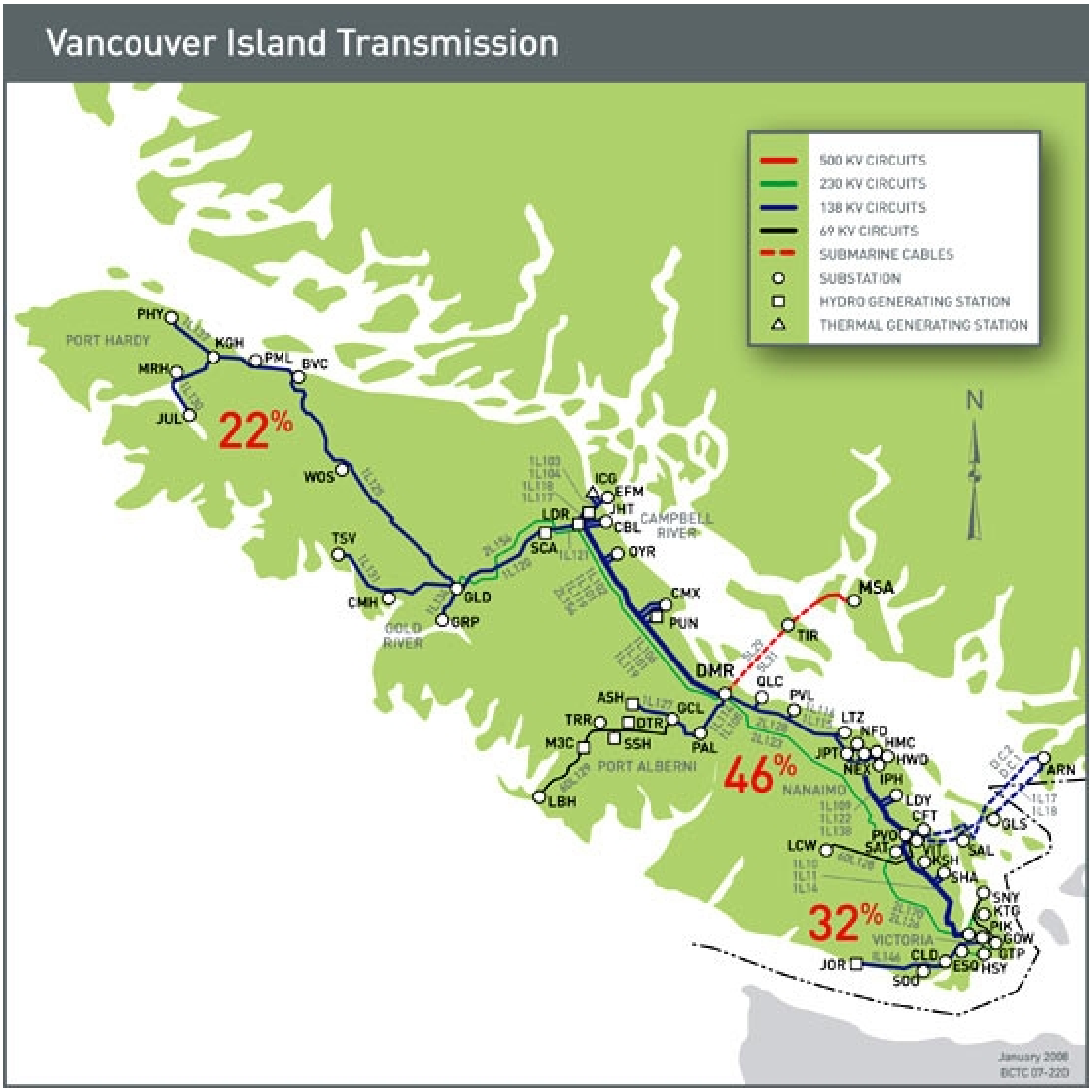

Figure 4.1: Vancouver Island Transmission and Electricity Demand Locations (Image used with permission from BC Hydro transmission website [53])

4.1.1 Wind Resource

In 2009, DNV Global Energy Concepts prepared a study for BC Hydro for which the goal was to:

> '...assess the characteristics of wind resources in regions of British Columbia that are likely to experience significant wind energy development in the future.'

Simulated wind data were modelled based on measured wind data from both IPPs and BC Hydro. BC Hydro agreed to provide the simulated wind resource data to complete this study. Due to confidentiality reasons the specifics of the data cannot be displayed in this thesis, although aggregated and qualitative results will be discussed. VI05, a 255.3 MW site on northern Vancouver Island has been selected for this case study. Its capacity factor is 26%[1] with an average wind speed of 6.9 m/s [31]. Capital cost is taken to be $2 million per MW installed based on an average from several references [46],[52],[54]. Fixed operations and maintenance costs are taken to be 1% of the capital costs [46], and variable costs are assumed to be negligible [55].

4.1.2 Pumped Storage Potential

The features of Google Earth are extremely useful when performing a high-level site assessment of this kind. In this case, it was used to select a potential site on Northern Vancouver Island at Lake-of-the-Mountains for the pumped storage facility. This was then cross-referenced with the recent BC Hydro pumped storage evaluation report [18], where this site had in fact been catalogued. The report provided a much higher capacity (1000 MW) than required for this work but the site is still applicable[2].

Natural inflows account for a very small (<1%) contribution to the levels in these lakes, which is in line with the assumptions of the model. Unfortunately, although geographically this site would be the most convenient as it is located right in the midst of the major wind resource, economically the estimated capital costs are quite high. It will be simulated along with another potentially more economical site at Woss Lake. This site is farther away from the wind resource and therefore could potentially cause transmission congestion issues and face higher interconnection and access costs which are outside the scope of this thesis (i.e., not reaping the potential benefits of project

[1] This is based on the 255.3 MW rated power.

[2] The aim of the study was to assess large scale pumped storage in British Columbia and was not related to wind integration.

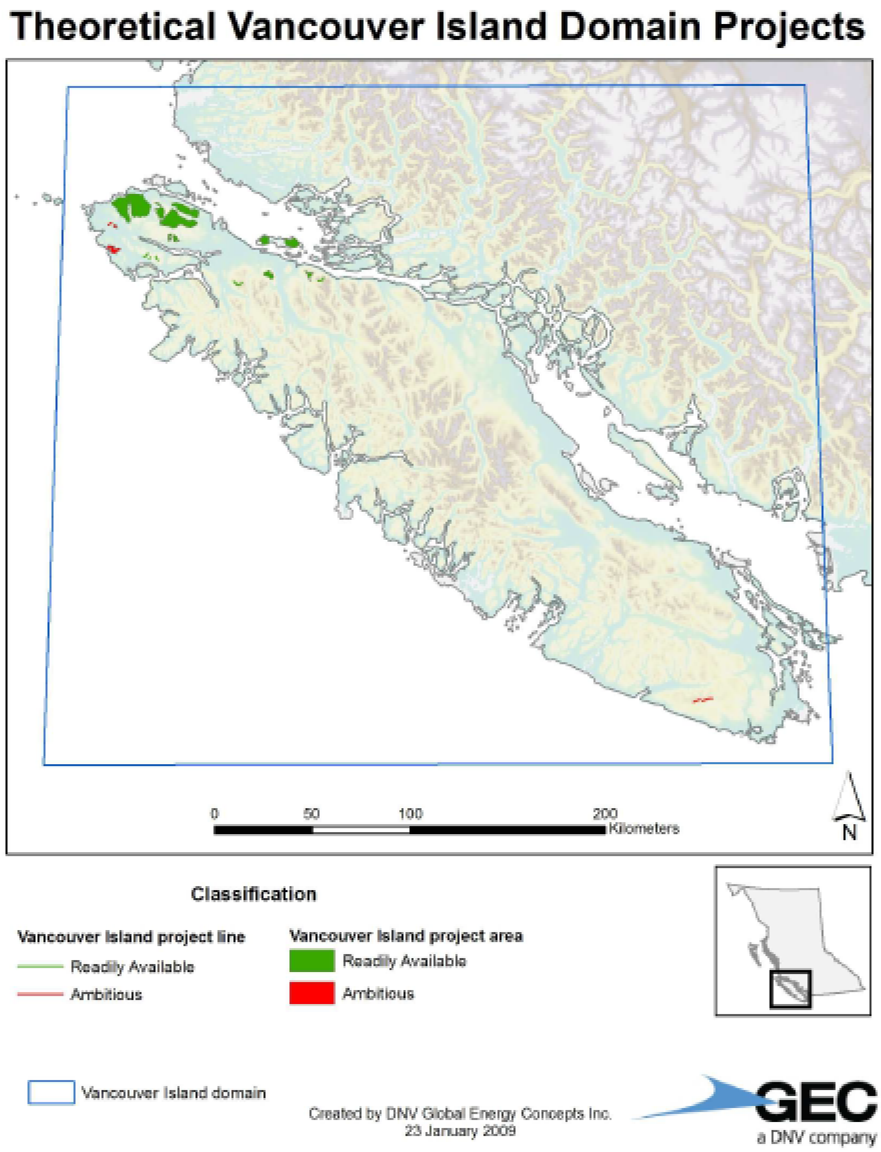

Figure 4.2: Vancouver Island Wind Sites (Image taken with permission from BC Hydro Wind Data Study Public Report [31])

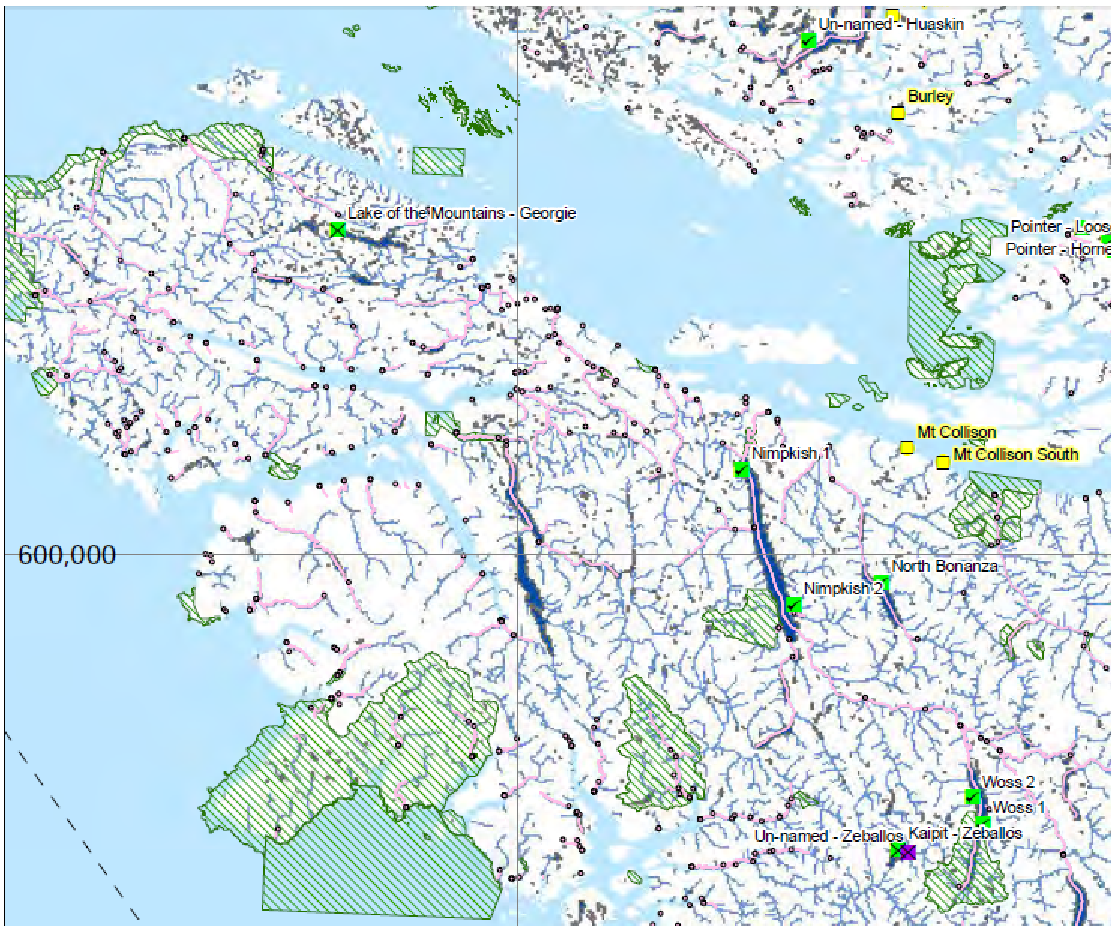

Figure 4.3: Lake of the Mountains – Georgie and Woss 1 Pumped Storage Sites[a] (Image cropped from Knight Piésold Pumped Storage Report with permission from BC Hydro [18])

[a]X represents no salmon present while a check mark indicates salmon species are present. Permitting processes for lakes containing salmon species can be more difficult and fish screening requirements can increase capital costs. These issues are not addressed in this report.

Site Name	Unit Cost of Capacity ($/MW)	Levelized Cost ($/kW-yr)
Georgie – Lake of the Mountains*	2,757,740	168.3
Woss 1*	1,536,640	93.8
Nimpkish 2	1,760,535	107.5
North Bonanza	1,571,592	95.9
Upper Quinsam – Upper Campbell	2,460,524	150.2

* These projects will be considered for the case study analysis

Table 4.1: Selection of Vancouver Island Pumped Storage Sites - Information adapted from [18]

clustering); however, the site itself is much more economically viable. Initially this transmission issue was within the scope of this study but this had to be removed due to data availability, which is discussed in further sections. Table 4.1 displays several other sites on Vancouver Island that were considered for this case study and their associated costs [18]. Fixed operations and maintenance costs are taken to be $4.70 per kW installed and variable are $0.004 per kWh in or out of the facility [15].

Upon selection of the project sites, it was necessary to analyze the project data from the 2009 BC Hydro Wind Data Study.

4.2 Numerical Weather Prediction Data

The following definitions will be used for the forecast terms and it is important to distinguish between Day-Out and Day-Ahead as they are the primary forecasts used:

Day-Out 1-24 hours in advance

Day-Ahead 25-48 hours in advance

Two Day-Ahead 49-72 hours in advance

Three Day-Ahead 73-96 hours in advance

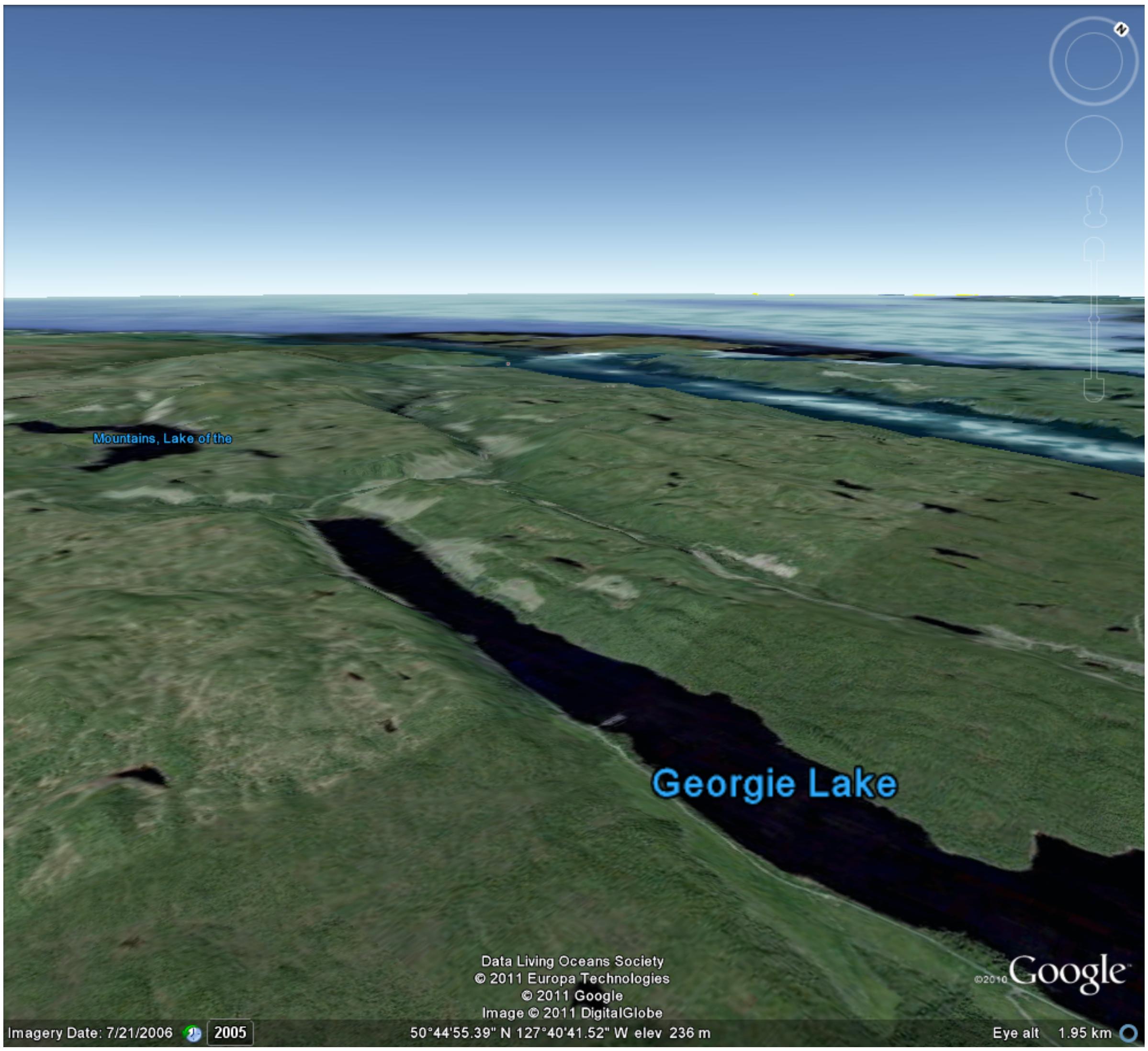

Figure 4.4: Lake of the Mountains – Georgie Pumped Storage Site (Image taken from Google Earth [56])

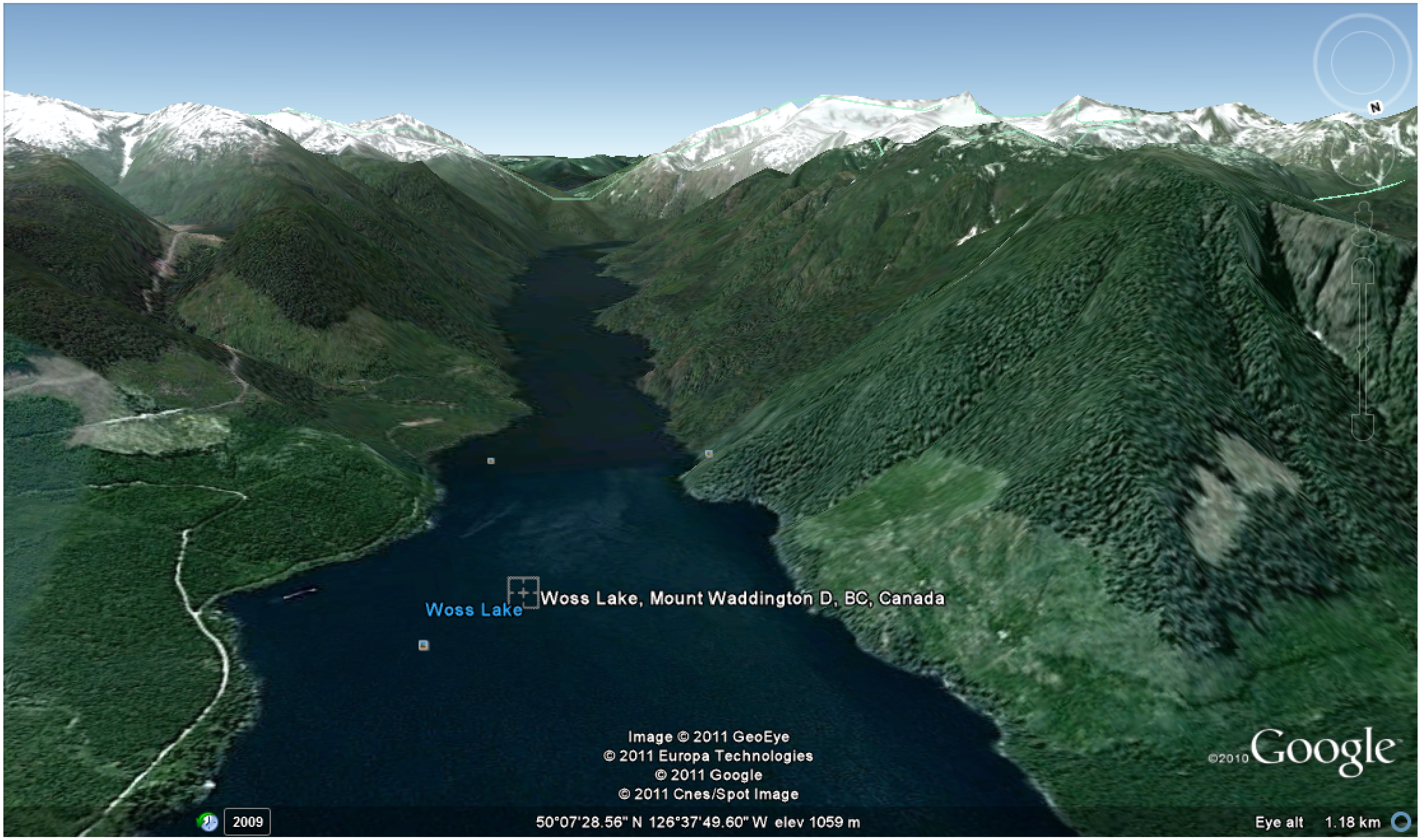

Figure 4.5: Woss 1 Pumped Storage Site showing an elevation of over 1000m (Image taken from Google Earth [56])

The wind data are from a set of NWP simulations done for the BC Hydro Wind Data Study. There is a set for 'actual' measured data and a set for day-out through three day-ahead forecasts. Getting an NWP simulation to simulate perfectly the measured wind speeds is not always possible, and various corrections can be applied for this. Upon analyzing the forecast error statistics of the raw data that were received, the statistics turned out to be significantly different than the expected outcome. Since the 'actual' measured data have been validated, they are assumed to be the correct set upon which to base the NWP data. However, that the data had intentionally not been post-processed to simulate real NWP results, so it was necessary to research post-processing methods to correct for the bias present in the relevant set. The reason a bias is undesirable in this situation is because the forecast will generally overestimate or underestimate the wind speeds. This will result in continual discharge and depletion of the storage device (ultimately, infeasible solutions) or underutilization of the device resulting in overly conservative energy bids, respectively. It is therefore required to have either a very small dataset bias or none at all.

4.2.1 Bias Correction of NWP Forecasts

As previously mentioned, it was assumed that the 'actual' simulated set was the reference set to base the corrections off of, since the average wind speed was within a reasonable range when compared to that in the Wind Data Study. On average there was roughly a 7-8% wind speed overprediction bias present. Due to the nonlinear power curve and the effect of the mean wind speed on turbine production[3], this led to an average wind power overprediction bias of between 13-16%, which would result in simulation infeasibilities due to storage depletion. Realistically any IPP using NWP software would be aware of the bias and would account for it, therefore bias correction methodologies are required.

Best Easy Schematic

Since NWP forecasting is its own field of research that is largely outside the scope of this thesis, a simple yet effective method of addressing this bias was desired. In Kay et al. (2009), a method known as Best Easy Schematic (BES) was used to address the bias over a 48-hour window. This window represents the observations of the past

[3]Siemens SWT-2.3-93 2.3 MW wind turbine

48 hours at the point of making the prediction [57]. The BES parameter is calculated as follows:

$$BES = \frac{(Q_1 + 2Q_2 + Q_3)}{4} \tag{4.1}$$

Here, Q_1, Q_2, and Q_3 represent the first, second, and third quartiles of forecast error over the past 48 hours, respectively. The BES parameter is then appropriately summed with the forecast data to reduce the bias. This is a single prediction, and double predictions can also be investigated but were not in this case. It was found that when this was applied to the 1- to 24-hour prediction set it matched the mean well but not the original standard deviation, so additional distribution points and associated weightings were tested to improve this. This slightly modified method was applied to the dataset, which worked relatively well for the 1- to 24-hour prediction set, however did not prove to be effective for the datasets with larger prediction horizons. For those datasets it was not possible to both reduce the bias and maintain the same distribution shape. It was mentioned in [57] that future research was planned to investigate longer prediction horizons, so this was not unexpected. Since it was desired to find a single bias correction method for all datasets, other methods were researched.

Model Output Statistics (MOS)

Upon beginning research of this field, the University Corporation for Atmospheric Research (UCAR) Community Programs (UCP) were used. MetEd is an online meteorological teaching and training website. They have a specific seminar that addresses bias correction in NWP model data which was very useful in providing background information for the current analysis [42]. MOS is referred to as a statistical guidance approach, and is used when there is a known systematic error in the NWP model, or to provide a confidence interval for the forecast [58]. The primary components for MOS development include a predictor (the forecast), a predictand (observations), and statistical analysis. A very simple analysis would be to create a linear fit between the predictor and predictand, but in practice it is generally done using multiple regression analysis using multiple predictors. The model forecast is then fed into the MOS forecast to generate improved results. It was not realistic to derive MOS equations considering the lack of both NWP model data (only wind speeds were provided while the models can encompass entire weather systems) and background knowledge in this

Prediction Horizon	Mean NWP Weighting	Mean Modified Persistence Weighting	Mean Climatology Weighting
Day-out	0.7190	0.1285	0.1094
Day-ahead	0.6887	0.1026	0.1601
Two Day-ahead	0.5985	0.1409	0.2210
Three Day-ahead	0.5074	0.1760	0.2846

Table 4.2: Mean Regression Coefficients for Bias Correction of NWP Data

area, however the concept of multiple regression analysis is a useful tool and knowing it is used in industry justifies the following approach that was eventually selected.

Multiple Regression Bias Correction Approach

A multiple linear regression model was developed for each of the datasets in order to remove the bias. The bias was addressed at the root source, the wind speeds, to capture the issues with the transition from wind speed to wind power using the power curve (e.g. nonlinear, case where wind speeds exceeds cut-out, etc.). The multiple regression function in MATLAB R2011a was used. By removing the bias, the NMAE is also improved since the average forecast error should theoretically lie at zero. Since only one NWP predictor was provided in the data set for each forecast time horizon, it was not possible to form the regression from several advanced predictors. Therefore, a modified version of the persistence forecast was applied in which the previous day's average wind speed was used at the point of observation, in addition to the long term climatology predictor of the global average wind speed for the site. These predictors are described in detail in Chapter 2.

Please note that there are limitations to this method including compromising forecast errors for very low levels of wind generation (due to the influence of the persistence and climatology predictors). This was offset, however, by the improved average and high wind generation forecast errors, and could potentially be remedied by applying a nonlinear regression formula. Table 4.2 shows the mean regression coefficients for each predictor, and the trend towards increased weighting on the climatology predictor with increasing prediction horizon, as expected. The regression coefficients were calculated based on the previous month of forecast errors at the time of observation [59]. The result of this calculation is a better predictor. Pre- and post-processing statistics are shown in Tables 4.3 and 4.4.

Prediction Horizon	Pre-Processing Statistics			Post-Processing Statistics		
	Mean (m/s)	**Standard Deviation (m/s)**	**MAE (m/s)**	**Mean (m/s)**	**Standard Deviation (m/s)**	**MAE (m/s)**
Day-out	0.4428	2.0006	1.5597	-0.0047	1.8307	1.4204
Day-ahead	0.4978	2.1122	1.6338	-0.0050	1.8910	1.4632
Two Day-ahead	0.4769	2.5116	1.9279	0.0076	2.2028	1.7181
Three Day-ahead	0.5050	2.9220	2.2477	-0.0147	2.4902	1.9445

Table 4.3: Wind Speed Pre- and Post-Processing Statistics

Prediction Horizon	Pre-Processing Statistics			Post-Processing Statistics		
	Mean (%)	**Standard Deviation (%)**	**NMAE**	**Mean (%)**	**Standard Deviation (%)**	**NMAE**
Day-out	0.1149	0.2039	0.1583	-0.0155	0.1570	0.1076
Day-ahead	0.1289	0.2131	0.1696	-0.0158	0.1621	0.1116
Two Day-ahead	0.1157	0.2441	0.1841	-0.0224	0.1908	0.1341
Three Day-ahead	0.1066	0.2807	0.2070	-0.0294	0.2158	0.1542

Table 4.4: Wind Power Pre- and Post-Processing Statistics[a]

[a]This is based on the raw spreadsheet power data that were provided with unknown assumptions. Mean and mean absolute error values are generally a few percent less if the actual and forecasted wind speed data are applied to the same power curve, but there is still a significant bias. Statistics are available in Appendix E.4. The regression model improves both data sets.

	Net Income (Million $CAD)[1]	EVPI (Million $CAD)	VSS (Million $CAD)
Wind Only	2.77	N/A	N/A
Woss 1 – Deterministic Problem	2.15	1.43	0
Woss 1 – Reliable Problem	3.13	0.46	0.98
Georgie – Deterministic Problem	2.01	1.44	0
Georgie – Reliable Problem	2.95	0.49	0.94

[1] $130/MWh for wind only (minus $10/MWh firming) and $140/MWh for comparison problems

Table 4.5: Case Study Results - One-Week Period

4.3 Case Study Results

The simulation was run for a period of one week based on wind speed data provided by BC Hydro and the methods outlined in previous sections. The rated capacity of the storage device was selected to meet 95% of the forecast error, as in the previous section, which resulted in 95 MW. The wind farm capacity was 255 MW. The scenario probability confidence interval for reliability constraints was set to 90% to meet 80% bid satisfaction. The storage levels at the end of each bid period were determined optimally by the optimizer, eliminating the assumption of 20% end storage level from the previous section. This was enabled by the presence of a 'day-out' forecast that was not available with the other data set.

It is important to note that this was a high wind week, with over a 60% capacity factor for the time period examined, so the high income levels would not be expected throughout the entire year. It was desired to test this period to see how the pumped storage device performed in competitive wind conditions. In low wind scenarios, wind during peak hours may be less and therefore the arbitrage capability of the pumped storage would be desirable. The wind only BC Hydro Clean Power Call base case was based on the wind energy generation over the week-long period and the assumption that 85% was sold as firm energy and the remaining 15% was sold as nonfirm energy under Option A[4]. The simulation was run once with rough tolerances, and those results were fed into a second run of the simulation with finer tolerances to further improve results. The pumped storage facility is shown to be economically attractive compared to the standalone wind farm at an energy price of $130/MWh at the Woss 1 site and $140/MWh at the Lake-of-the-Mountains site. The Lake

[4] This is based on the SOP guidelines from the 2008 BC Hydro LTAP Appendix 12[60]

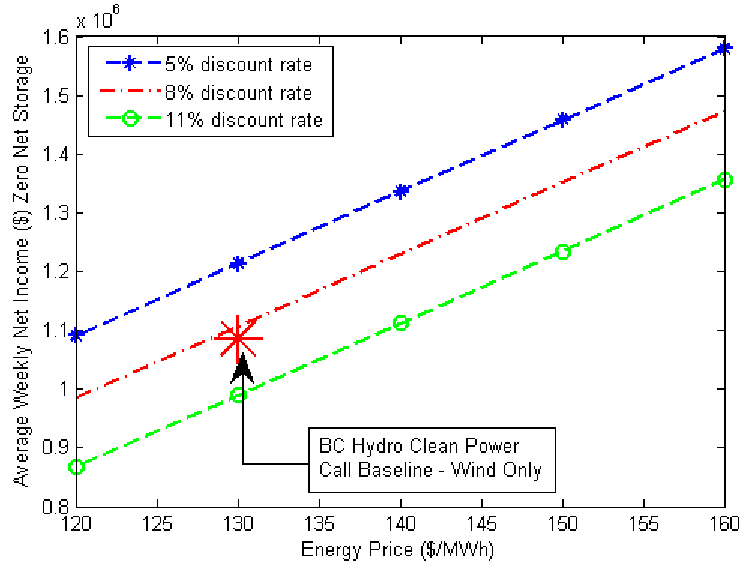

Figure 4.6: Woss 1 Discount Rate and Energy Price Sensitivity Analysis

of the Mountains / Georgie Lake site did not exceed the income of the standalone wind farm due to its high capital cost. The costs shown are levelized for a net-zero change in storage level (i.e. income is not from storage reservoir depletion). It is shown that there is significant room for economic improvement with increasing forecast accuracy, equating to roughly $50,000 per % accuracy improvement for the time period examined. Figure 4.6 is a sensitivity analysis based on the discount rate applied to the project for capital recovery, with typical daily income levels reflecting the 26% capacity factor of the project.

Figure 4.7 displays the operation of the facility for one day within the week period. Figure 4.8 displays the scenarios that were considered, the bid selected, and the actual wind generation for that same day. The model was validated by replicating results successfully by applying the governing equations, which for this problem is a simple procedure.

Overall, this analysis shows that for sites with a reasonable capital cost, the benefit of pumped storage addition may prove to be attractive for IPPs. This is heavily contingent on the policy direction of the provincial utility, however, and if a project such as this were to be considered discussion would be required.

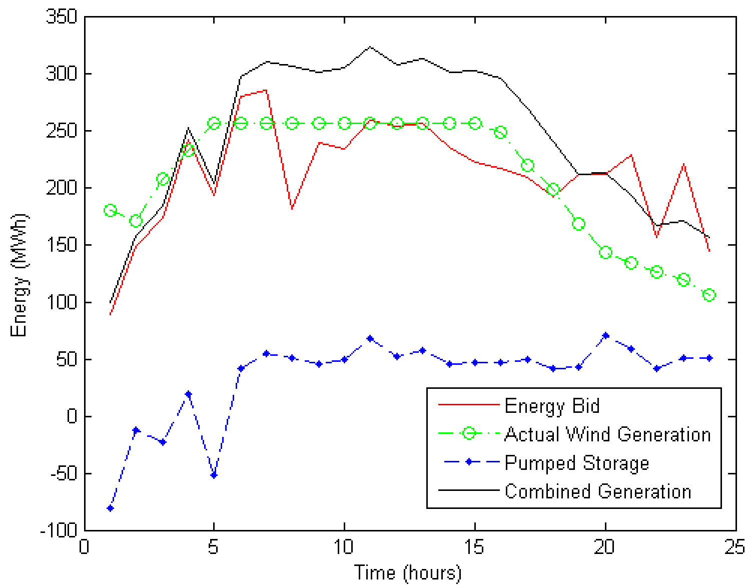

Figure 4.7: Case Study Facility Operation – Day 7

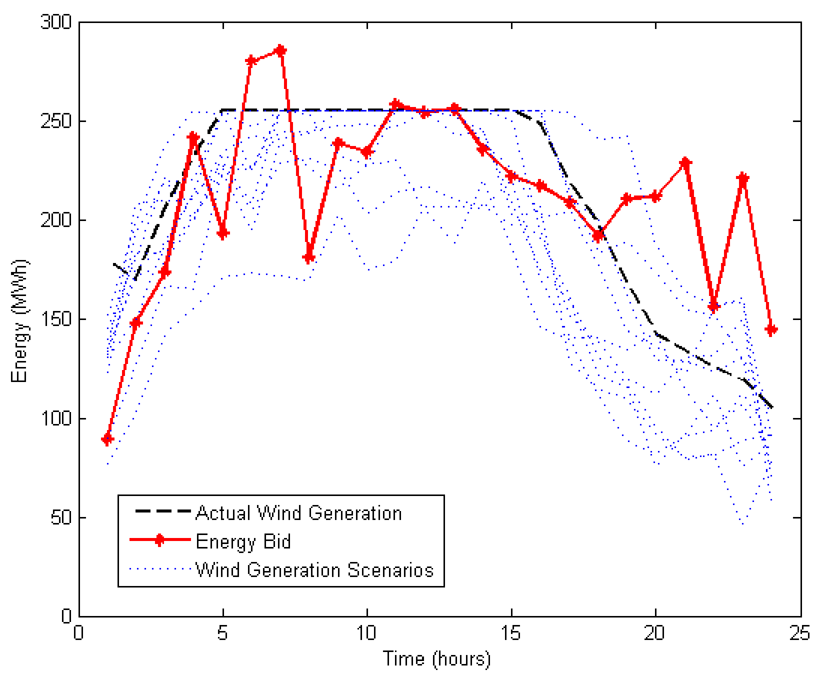

Figure 4.8: Case Study Scenario Plot – Day 7

Chapter 5

Conclusions

Upon completing the work presented in previous chapters, several areas for potential improvement and expansion became apparent that were not within the scope of this thesis. These areas for future work will be discussed in this chapter in addition to the overall summary and contributions of this thesis.

5.1 Options for Future Work

In terms of the simulation, several recommendations can be made. Stochastic optimization is inherently a time consuming programming approach. To further validate the sizing of the pumped storage system that was done based on the aforementioned analysis of forecast error distributions, it is recommended to run a simplified deterministic mixed-integer optimization in software such as GAMS, to allow for the analysis of an entire year. Due to software limitations at the time of the thesis and the number of variables required this was not done. The reason for testing this further is that although the current sizing does account for the amount required to meet forecast errors (i.e. it is conservative); however, it does not explore the potential benefits to installing additional storage capacity past the minimum requirements. It is therefore currently unknown how additional storage capacity would perform long-term.

It is also recommended to potentially explore the possibility of employing a global solver. There were issues with infeasibility throughout this process based on initial conditions. Since there is a random error component to this simulation it was not always possible to anticipate these problems for different testing conditions, and so built-in constraint relaxation methods previously discussed were occasionally required to maintain feasibility. Once a feasible region was found, the optimization was run with rough tolerances to reach a feasible and optimal solution based on these tolerances. These results were then fed into a second run of the stochastic optimization in which finer resolution tolerances were used. This was also time consuming and it is not known whether a global optimization could improve either the results or the required simulation time.

In terms of the wind forecasts, it would be desirable to acquire data that was professionally post-processed using MOS methods to be completely representative of a real wind forecast. Once the BC Hydro data were acquired, the simulation performance was considerably improved; however, manual correction was still required. It is shown that this manual correction significantly improved the forecast error statistics. It is not known how this would compare to industry standard correction, which is out of the scope of the thesis.

The case study itself is a high-level feasibility analysis, and for more in depth study it would be required to examine a longer time period of operation, assess the site-specific interconnection costs[1], and assess electricity grid impacts. It would also be recommended to investigate equipment degradation through increased cycling (pumping to generation and vice versa) and its effect on the lifetime of the facility and net income when compared to a limited cycle facility. This is only recommended if there happened to be significant interest in such a project. For that level of analysis policy discussions with BC Hydro would be required, as the assumptions in this work are hypothetical and loosely-based on current provincial policy.

5.2 Summary and Contributions

This thesis aims to address the question of the feasibility of pumped storage within British Columbia, and how it may be used to offset wind variability. This problem has not previously been addressed in the open literature from the perspective of an independent investor in British Columbia. There are many ways to address this problem, and the approach taken in this work was to assess the feasibility of the joint operation of a wind farm and pumped storage facility in satisfying optimally-determined day-ahead generating schedules. The argument for this is since the pumped storage

[1]This would likely require a site visit as digital elevation models (DEMs) available with geographic information systems (GIS) software may not have the necessary resolution to accurately assess the terrain

facility requires intensive capital investment, it requires extra income to account for this, and arbitrage itself would most likely not suffice. Day-ahead generating schedules with an 80% reliability, as required by the BC Hydro Clean Power Call, may justify a slightly higher energy price to recoup the additional capital requirements. To regulate and form these day-ahead bids, a theoretical policy and pricing scheme was developed.

By extending the work of Mello et al. (2011) and Dupaçova et al. (2003), a location-specific and probability-weighted wind forecast error generator and scenario selector was developed. Various optimization approaches (EV, RDO, RBDO, R^2BDO) were compared in order to address the uncertainty component of wind forecasts within the optimizer. Reliability-based design optimization proved to be the best-suited method, and it was applied to a case study on Vancouver Island.

To run the optimization, case study wind speed data, including NWP forecasts, were provided by BC Hydro. Since NWP forecasts often include systematic bias, correction was required, and a multiple linear regression model was developed. The predictors included the NWP forecast, moving-average persistence, and climatology. It was shown that for day-out time horizons the NWP forecast had the primary weighting, but for time horizons three days ahead, the long-term climatology method began to receive higher weightings, as expected. The model was successful in almost entirely eliminating the bias and improving the overall NMAE of the forecast without requiring professional software.

An aspect of pumped storage that is often questioned is the capital cost, and it was shown that for high capital costs, pumped storage will not compete with a standalone wind farm under the current BC Hydro Clean Power Call. However, for a competitive site with a capital cost of $1.53 million/MW installed, preliminary results show it to be economically attractive at an energy price of $130/MWh, which is comparable to the Clean Power Call average EPA firm energy price. If, due to rising demand, the ability of BC Hydro dams to absorb wind variability is affected, this type of project may be even more attractive. This report is a high-level feasibility analysis, and as previously mentioned, if this is to be considered further a more detailed analysis would be required. Ultimately, a testing tool was developed which facilitates the generation of optimal day-ahead generation schedules for a wind farm coupled with a pumped storage facility and successfully tests the operational feasibility of these schedules. This model is easily modified and built upon. Recommendations for future work have been provided, and it is important to note that the policy direction chosen is a very relevant factor. As the province moves towards energy self-sufficiency and renewable energy development in upcoming years, the option of pumped storage in British Columbia could prove to be promising for future renewable energy investors.

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Appendix A

Wind Forecast Error Generator

Based on Equation 2.4, also shown again below for reference, the regression coefficients were calculated by the unconstrained optimization for each optimized forecast set, where e is the standard deviation of the random error distribution. A modified version of fminsearch was used for the optimization. The day-out forecast had a high random error significance when compared to the other terms, which may be partially because it had no reference time series. Overall the statistics of the distributions matched well considering it is a weighted regression approach.

$$X(t) = aX(t-1) + bY(t) + ce(t) + d \qquad t = 1, ..., T$$

	a	**b**	**c**	**d**	**e**
Day-Out	0.8994	0	0.2407	-0.0019	.2674
Day-Ahead	0.7333	0.3181	0.0954	-0.0003	0.3285
Two Day-Ahead	-0.1919	1.0063	0.0346	-0.0084	0.4071
Three Day-Ahead	0.4040	.8158	1.6090	0.0012	0.0578

Table A.1: Forecast Regression Coefficients

	Mean	**Standard Deviation**	**Auto-correlation**	**Cross-correlation**
Day-Out	-0.0155 / -0.0102	0.1570 / 0.1477	0.9682 / 0.9064	0 / 0
Day-Ahead	-0.0158 / -0.0156	0.1621 / 0.1600	0.9701 / 0.9724	0.8712 / 0.7896
Two Day-Ahead	-0.0224 / -0.0224	0.1908 / 0.1367	0.9686 / 0.9570	0.8221 / 0.9749
Three Day-Ahead	-0.0294 / -0.0291	0.2158 / 0.2108	0.9686 / 0.8611	0.7590 / 0.8312

Table A.2: Forecast Regression Statistics – Data Listed as Desired / Achieved

Appendix B

Environment Canada Wind Data Details

The National Climate Data and Information Archive with Environment Canada maintains a climate database for select locations in British Columbia [61]. Data are available for download from various stations across the country. Depending on the location, data may be available up to the resolution of hourly measurements. Since no other data were available at the time of modelling, 30 years of historical hourly climate data were downloaded for Victoria, BC. Wind direction was not taken into account.

This data had to be adjusted from the measurement height of 25.6 metres in order to reach the height of the wind turbine hub at 80 metres using the following common formula:

$$u_{80} = u_{25.6} \frac{z_{80}}{z_{25.6}}^{\alpha_{atm}} \tag{B.1}$$

where u represents wind speed, z represents height, and α_{atm} represents the Hellman exponent, taken to be 0.140. This depends on the atmospheric stability, the surrounding terrain, and the coastal location.

Since the resulting wind speed was not viable for a wind farm, the data set was multiplied by a factor of 1.5 to reach an acceptable annual capacity factor. These data are not used for the case study and only for comparison purposes in the methodology section, so this assumption is not damaging to the final results. The importance of the intermediate results in the methodology section is the performance of various approaches relative to each other.

Appendix C

Wind State Details

C.1 Wind State Definitions

The following table outlines the definition of wind speed states from 1 through 5 and the associated wind speed and wind power output ranges. The qualitative state value column is used in order to compose the scenario state transition trees shown in the body of the report. They provide an idea of the level of wind resource throughout the day for each scenario – for example a scenario tree tending downwards overall is a below average wind day. These qualitative state values are cumulatively added together for each time step in each individual scenario to visually describe the wind power output throughout that particular day. It also allows for visual inspection of the diversity of the scenario set being examined.

Wind State	Wind Speeds (m/s)	Power Output (kW per turbine)	Qualitative State Value (Mean-Averaged)
1	<4 or >28	0-100	-2
2	<5 and >4	100-200	-1
3	<7.5 and >5	200-800	0
4	<10 and >7.5	800-1650	1
5	<28 and >10	1650-2300	2

Table C.1: Wind State Definitions for Siemens 2.3 WM Turbine

C.2 Probability Transition Matrix Examples

By cataloguing historical data it is possible to determine the probability that a wind speed will transition directly to any other wind state at the next time step. This can also be done for a state transition with a different time horizon, for example the wind state 2 hours from observation, or 24-hours from observation. The correlation relationship with respect to the time horizon is shown in the body of the text in Figure 2.7.

Scenario probabilities are calculated by calculating the state transition probabilities at each time interval within a 24 hour window (a larger window is not used due to increasing forecast uncertainty). The probabilities are calculated via state transition probabilities from one hour to the next (similar to a Markov chain) as opposed to calculating all probabilities based on the current observation. Example state transition matrices for a one hour-ahead relationship are shown below in Table C.2, which shows the clear correlation of wind states at small time horizons in the diagonally dominant probabilities. Table C.3 shows the more distributed range of probabilities throughout the wind states for 24 hours from the time of observation. This was not calculated using time of day or seasonal probabilities, and could be extended to address these factors.

		Probability at Time $t+1$				
		State 1	State 2	State 3	State 4	State 5
Time t	State 1	0.9028	0.0926	0.0046	0	0
	State 2	0.1729	0.6442	0.1826	0.0003	0
	State 3	0.0028	0.0760	0.8565	0.0641	0.0006
	State 4	0	0	0.1038	0.8486	0.0476
	Stage 5	0	0	0.0011	0.1352	0.8637

Table C.2: Sample Probability Transition Matrix for t and $t+1$

		Probability at Time $t+24$				
		State 1	State 2	State 3	State 4	State 5
Time t	State 1	0.3837	0.1553	0.2942	0.1298	0.0371
	State 2	0.3265	0.1691	0.2947	0.1508	0.0589
	State 3	0.2257	0.1319	0.3486	0.2044	0.0894
	State 4	0.1397	0.1035	0.3357	0.2727	0.1484
	Stage 5	0.0802	0.0887	0.3218	0.2961	0.2133

Table C.3: Sample Probability Transition Matrix for t and $t+24$

Appendix D

Methodology Comparison Details

D.1 Reference Plots of Wind Generation Scenarios

This appendix includes results from a sample day within the methodology comparison to be used as reference. In particular, it is useful to graphically view the energy bids with respect to forecasted and actual wind generation to verify that the model is operating within reasonable bounds of the forecasted scenarios. Note that for this comparison study, the simulation tolerances were not refined as they were in the case study due to computational requirements, since this would not change the results of the methodology comparison.

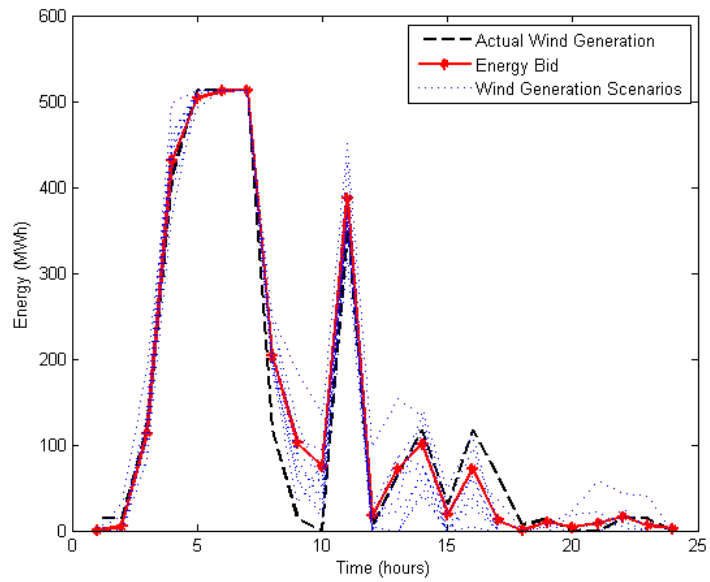

Figure D.1: Scenario Plot - Deterministic Case

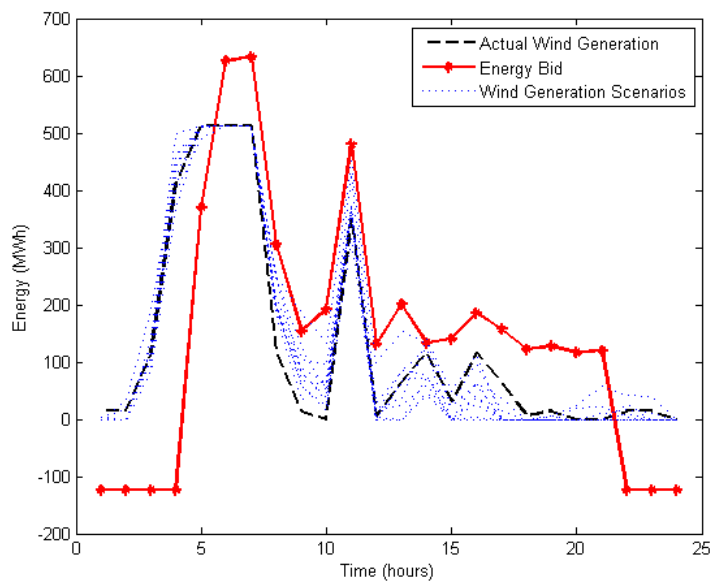

Figure D.2: Scenario Plot - Robust Case

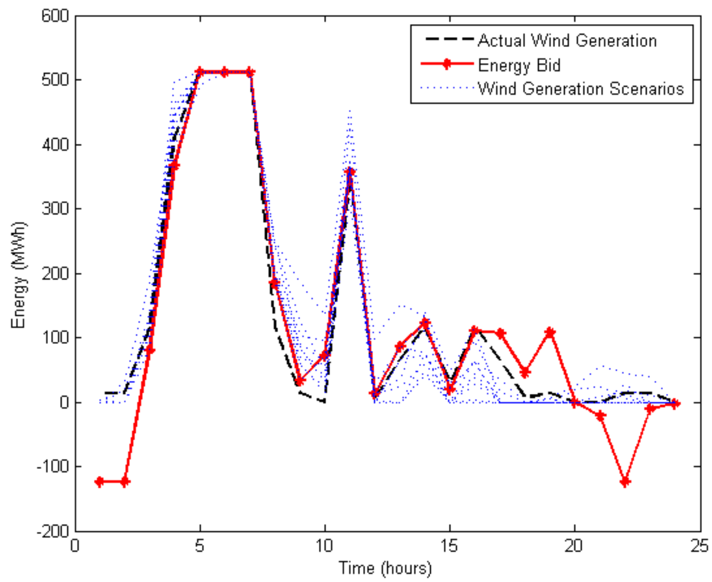

Figure D.3: Scenario Plot - Robust-Reliable Case

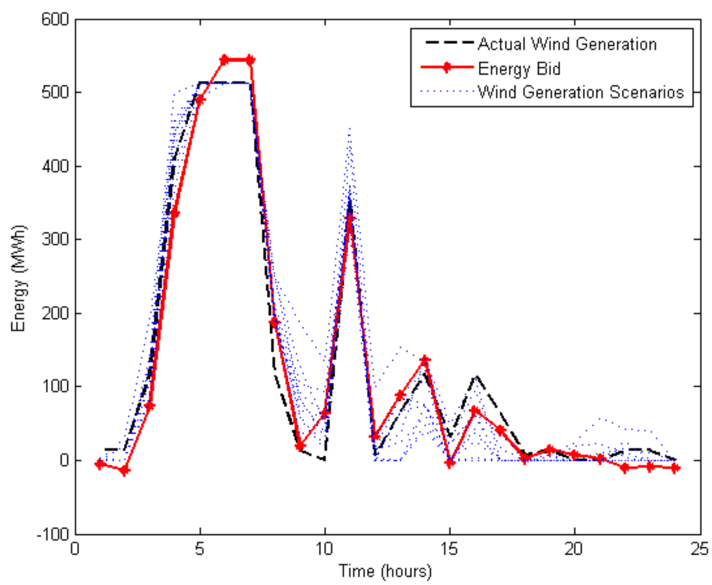

Figure D.4: Scenario Plot - Reliability Case

D.2 Operational Figures

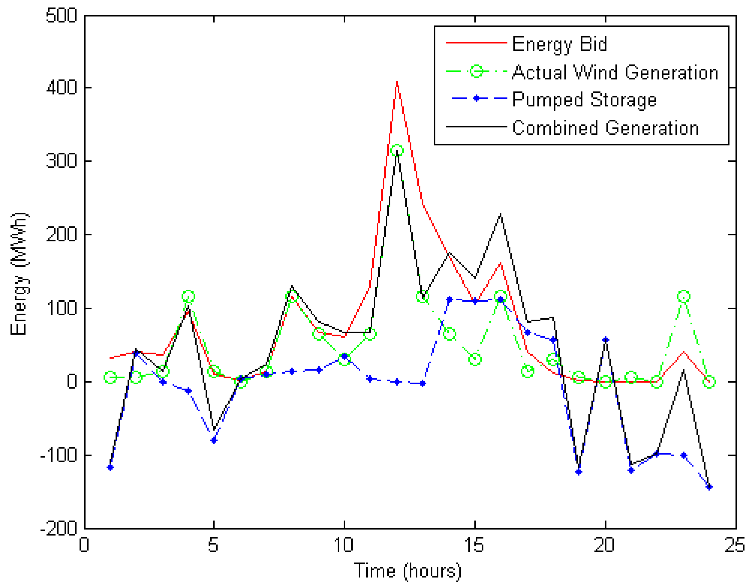

Figure D.5: Sample Day 5 Operation - Deterministic Case

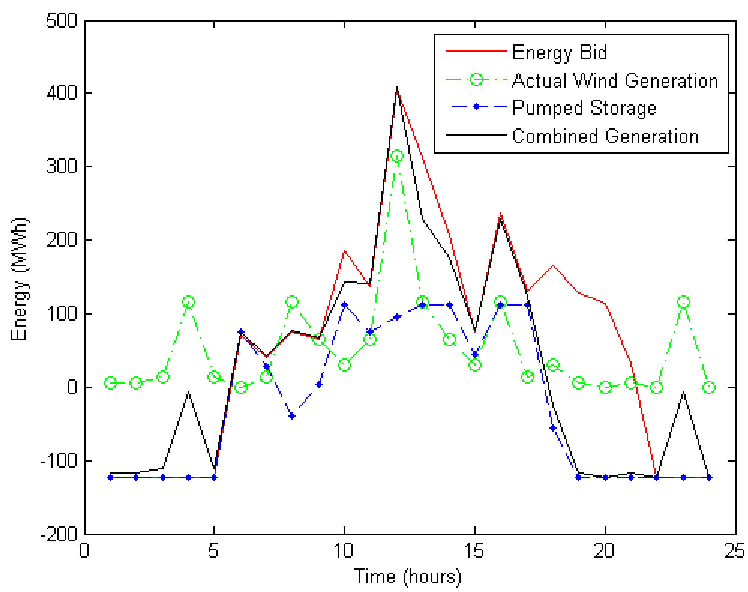

Figure D.6: Sample Day 5 Operation - Robust Case

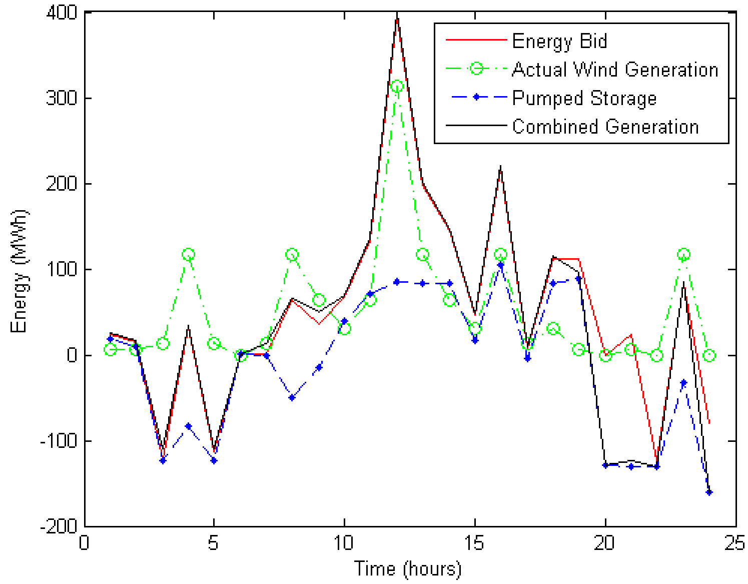

Figure D.7: Sample Day 5 Operation - Robust-Reliable Case

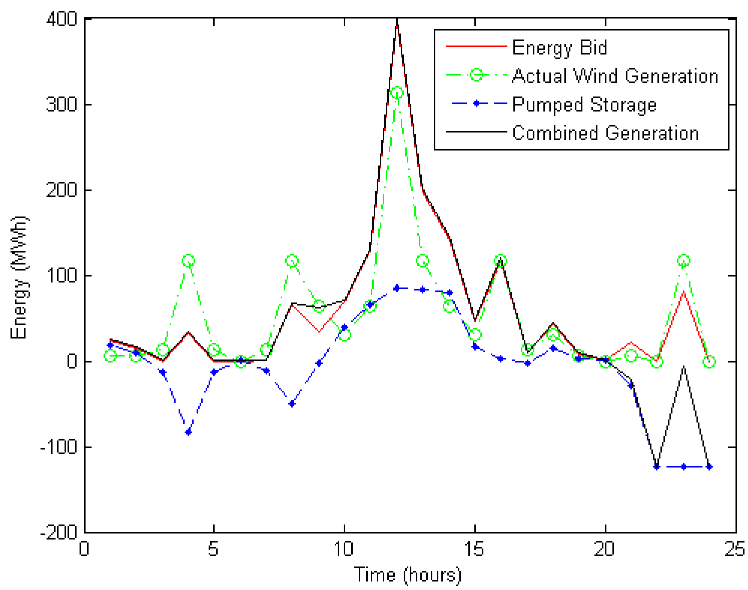

Figure D.8: Sample Day 5 Operation - Reliability Case

D.3 Product of Scenario Probabilities and Net Income Histograms

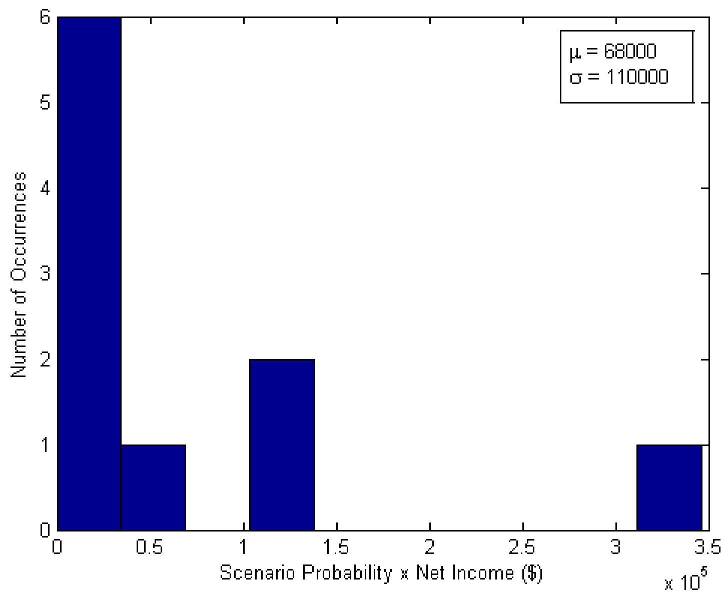

Figure D.9: Probability-Income Product Histogram – Robust Problem

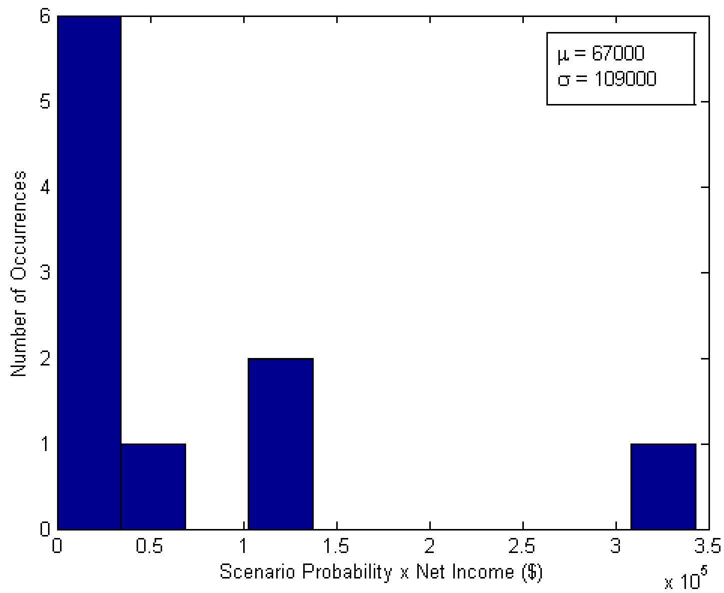

Figure D.10: Probability-Income Product Histogram – Robust-Reliable Problem (σ)

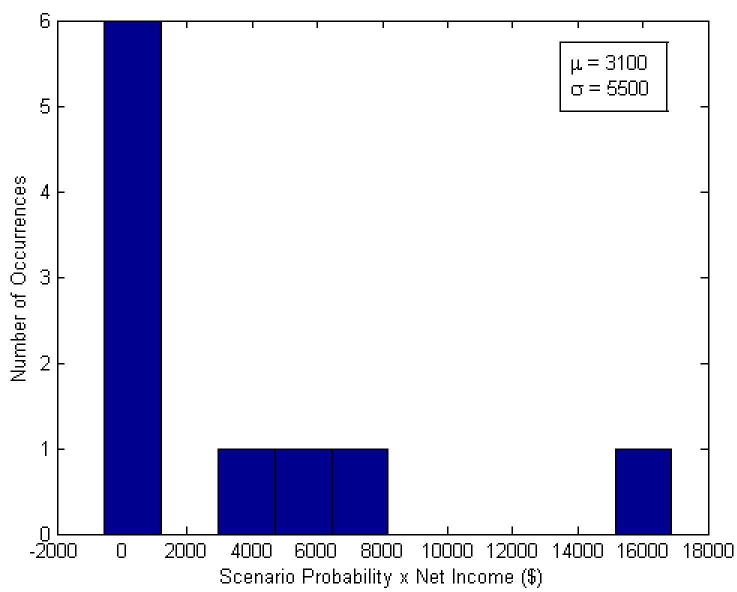

Figure D.11: Probability-Income Product Histogram – Robust-Reliable Problem (σ^2)

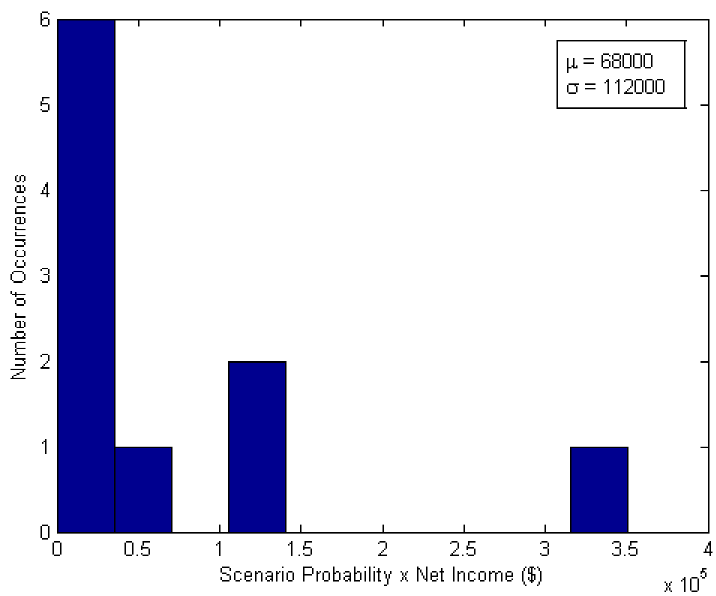

Figure D.12: Probability-Income Product Histogram – Reliable Problem

Appendix E

NWP Wind Data Processing

This appendix graphically and numerically summarizes the results of the multiple linear regression data transformation on the wind forecast error distributions for both wind speeds and wind power. The bias is not entirely removed and is actually slightly negative (indicating underprediction) but this is conservative and will not cause infeasibilities in the optimizer. Ideally this data would have been professionally post-processed but this technique provides sufficient results for these purposes.

One issue with the dataset that was received was that the 'actual' and 'forecasted' wind speeds were not put through the same power calculation, despite the fact there was a noticeable wind speed bias. The forecast statistics provided in the body of this thesis are for the raw data that was received versus the improved regression set of forecast data. To lessen the error by one degree both sets were manually put through the Siemens 2.3 MW wind turbine power curve. Overall the bias is less severe once this is done, however note that the distribution of forecast errors is still noticeably skewed towards overprediction. Even a small tendency towards this is detrimental to a feasible model solution. While ideally there would be zero bias this was not possible to achieve. The results from the regression model tend *slightly* towards underprediction (this error is exacerbated when transformed from wind speeds to wind power). That is not an issue for the model and represents a conservative solution.

The figures and tables in this appendix indicate the improvement presented by the regression model when compared to this manually calculated power data set based on forecasted wind speeds.

E.1 Wind Speed Forecast Error Distributions

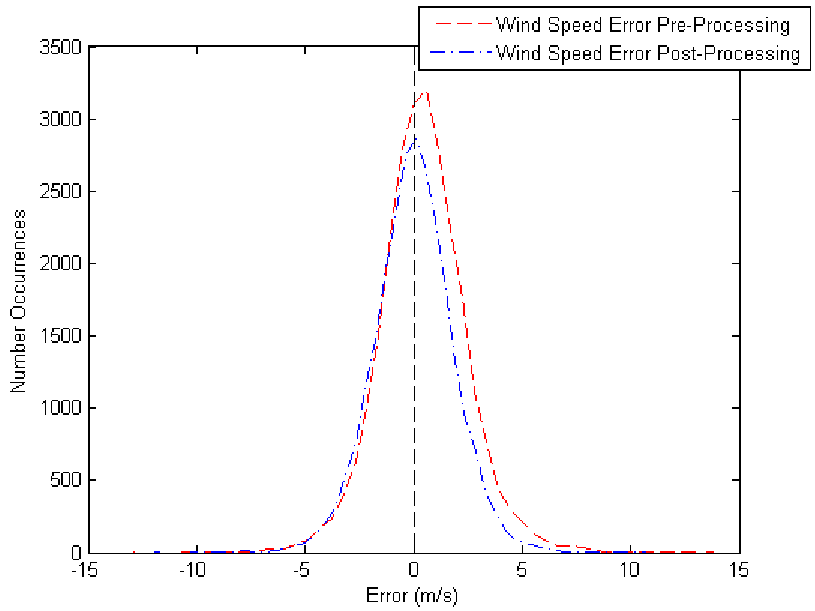

Figure E.1: Day-Out Wind Speed Forecast Error Distribution

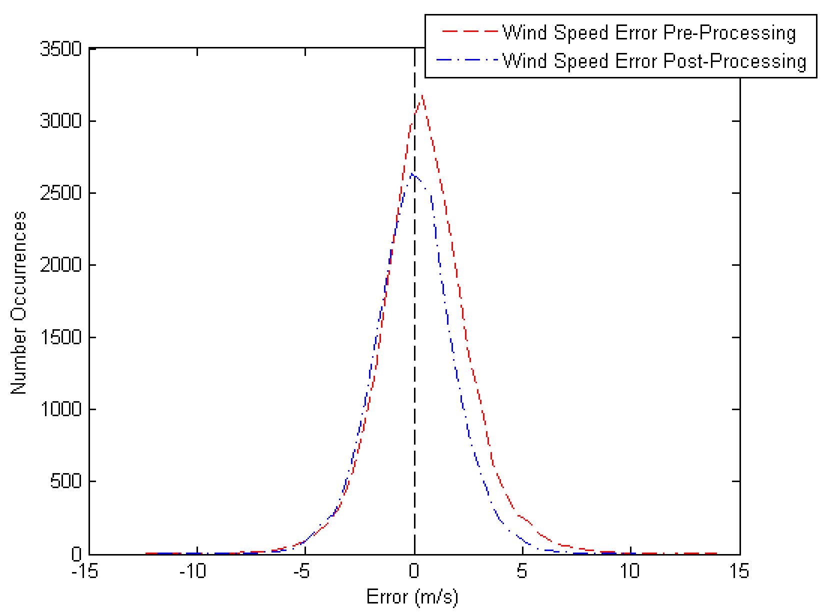

Figure E.2: Day-Ahead Wind Speed Forecast Error Distribution

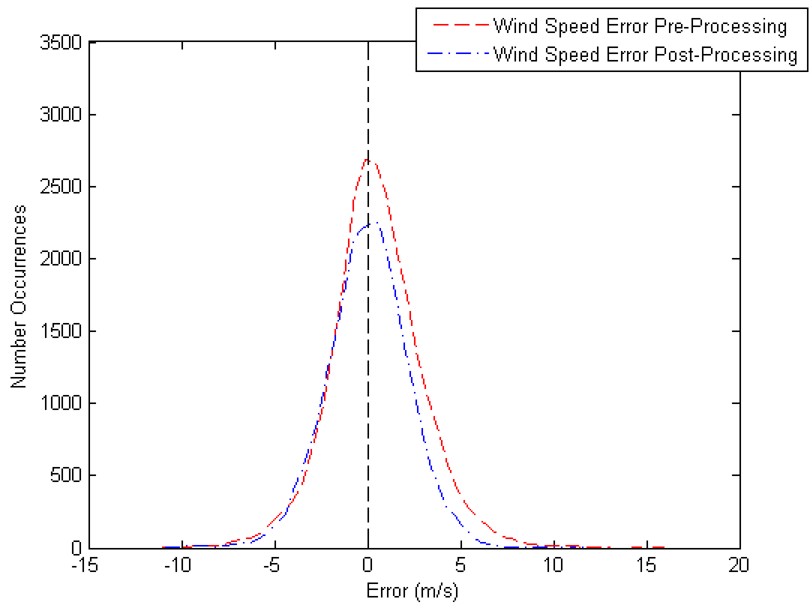

Figure E.3: Two Day-Ahead Wind Speed Forecast Error Distribution

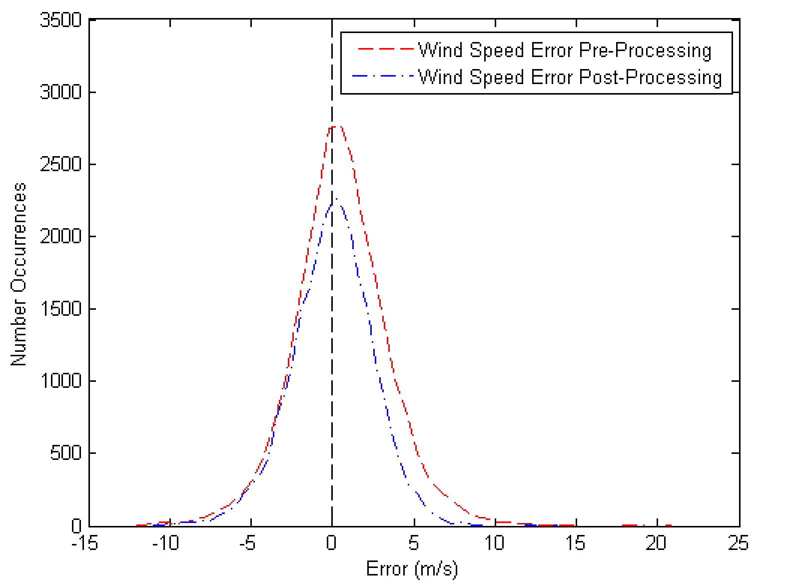

Figure E.4: Three Day-Ahead Wind Speed Forecast Error Distribution

E.2 Wind Power Forecast Error Distributions

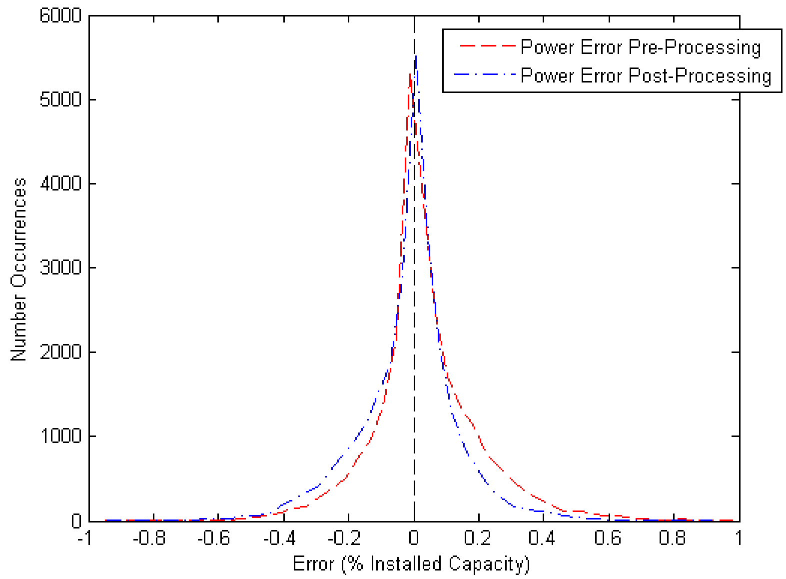

Figure E.5: Day-Out Wind Power Forecast Error Distribution

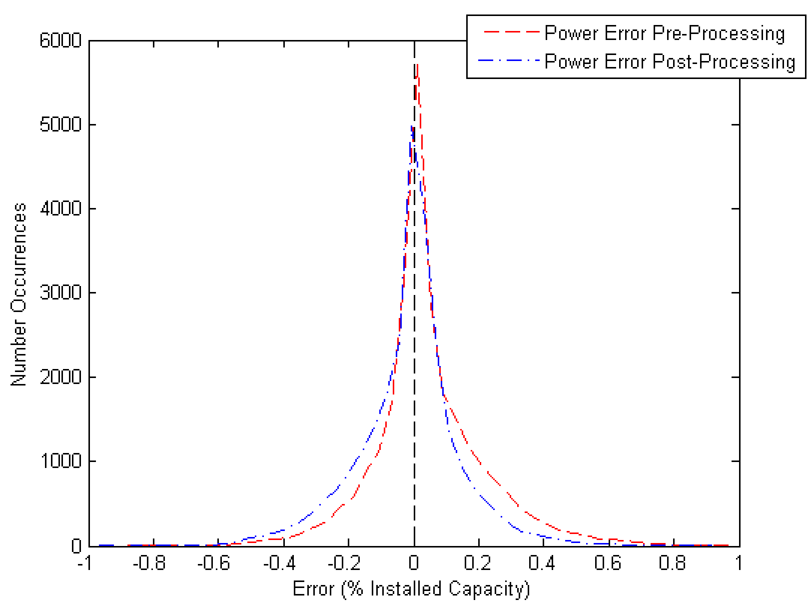

Figure E.6: Day-Ahead Wind Power Forecast Error Distribution

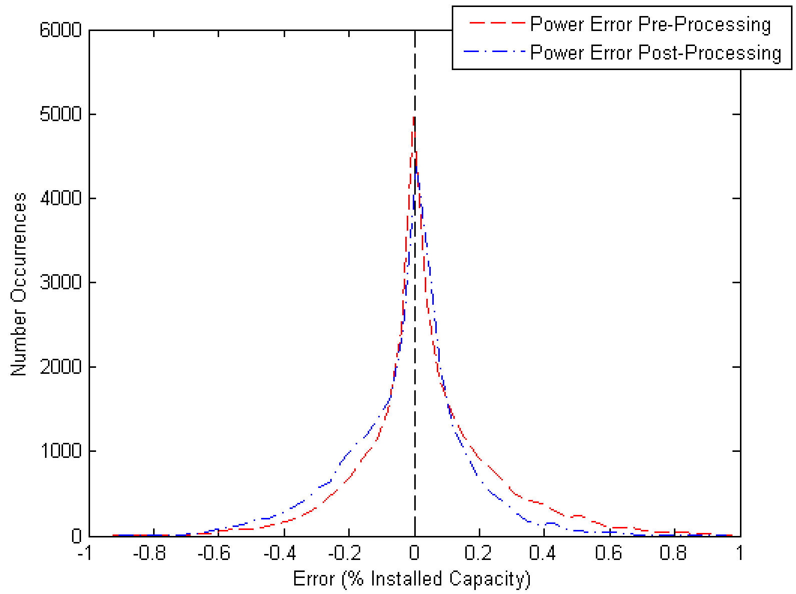

Figure E.7: Two Day-Ahead Wind Power Forecast Error Distribution

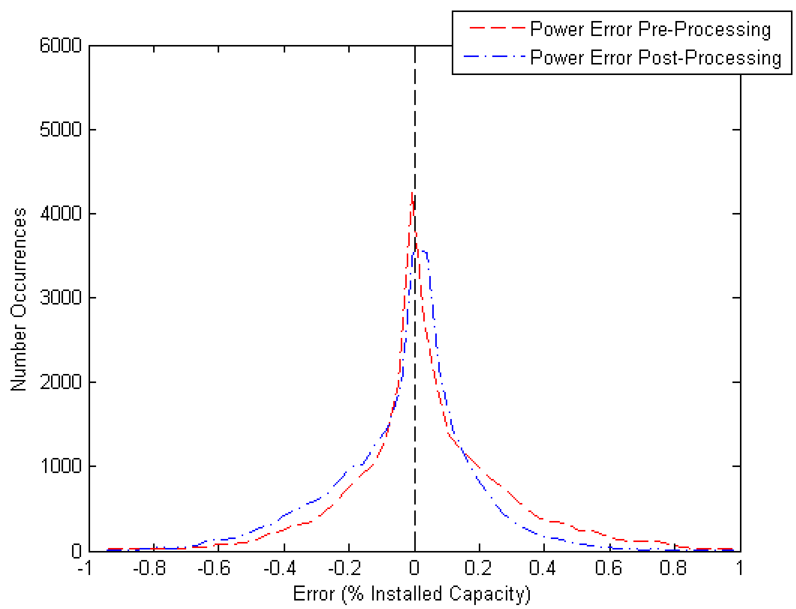

Figure E.8: Three Day-Ahead Wind Power Forecast Error Distribution

E.3 Wind Speed Scatter Plots

Please note that Figures E.9 and E.10 are shown qualitatively due to confidentiality reasons. The scales for each graph are identical, which shows a noticeable improvement in the corrected set for both in the bias (y-axis offset) and deviation from the actual wind speeds (represented by a tighter scatter plot).

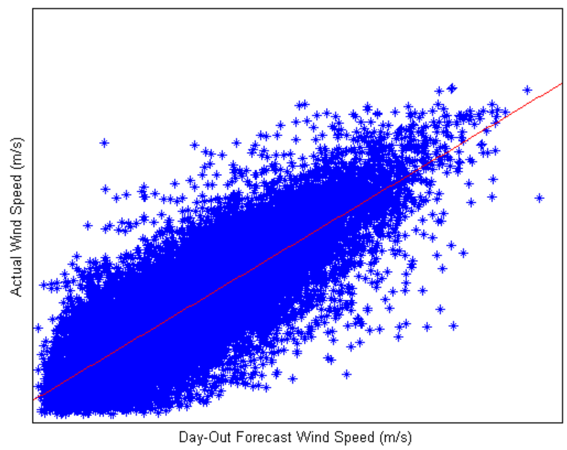

Figure E.9: Actual vs. Day-Out Wind Speed Forecast Pre-Processing

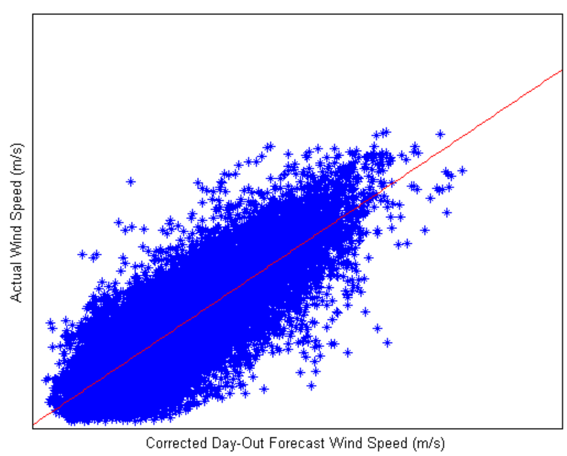

Figure E.10: Actual vs. Day-Out Wind Speed Forecast Post-Processing

E.4 Wind Power Forecast Error Statistics Summary

Prediction Horizon	Pre-Processing Statistics			Post-Processing Statistics		
	Mean (%)	Standard Deviation (%)	NMAE	Mean (%)	Standard Deviation (%)	NMAE
Day-out	0.0341	0.1710	0.1167	-0.0155	0.1570	0.1076
Day-ahead	0.0427	0.1779	0.1224	-0.0158	0.1621	0.1116
Two Day-ahead	0.0391	0.2156	0.1481	-0.0224	0.1908	0.1341
Three Day-ahead	0.0413	0.2483	0.1737	-0.0294	0.2158	0.1542

Table E.1: Wind Power Pre- and Post-Processing Statistics (Manual Power Calculations)