WIND TURBINE CAPACITY PLANNING APPROXIMATIONS FOR NORTHWEST UNITED STATES UTILITIES

By

Chad L. Edinger

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To the Faculty of Washington State University:

The members of the Committee appointed to examine the thesis of CHAD L. EDINGER find it satisfactory and recommend that it be accepted.

Chair

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WIND TURBINE CAPACITY PLANNING APPROXIMATIONS

FOR NORTHWEST UNITED STATES UTILITIES

Abstract

by Chad L. Edinger, M.S.
Washington State University
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Chair: Kevin Tomsovic

As global demand for electricity increases and the concern for its environmental impact comes to the center of political debate, the world is looking to new sources that will meet these increases while at the same time lessening environmental impact. In response to this, both utilities and governments are looking toward renewable resources. Hydroelectric has been the most prevalent form of renewable energy, having been in use in the United States for over 100 years. But due to the impact imposed on both the land and spawning fish, this form of renewable energy has fallen into disfavor in recent decades. As an alternative, wind energy seems to have become the large-scale renewable of choice. Recent strides in wind turbine technology have allowed for the placement of large wind generation sites or wind farms. However, wind is sporadic by nature and imposes a high level of uncertainty into utility operations. Moreover, wind has great seasonal and geographic dependencies that require intensive planning studies.

In this thesis, a simplified model is proposed that will allow utilities in the Northwest United States to plan the amount of wind generation capacity that will be needed to supply a modest portion of total load and to meet state mandated renewable

requirements. Assumptions are proposed that can convert collected wind speed data into a combined wind farm megawatt output. The model allows for analysis of wind turbine output from proposed sites with relative geographic dispersion to determine correlation. Based on this model, system load from Tacoma Public Utilities will be compared to the combined wind farm output using appropriate statistical computations. Throughout this work comparisons are drawn with previous efforts to determine if the conclusions reached are consistent with those studies that were similar in scope. The objective will be to determine with fair certainty the amount of wind generation Tacoma Public Utilities will require to meet both its own renewable goals and Washington State's Renewable Portfolio Standard.

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Chapter 1

Introduction

The United States is the largest consumer of electricity in the world, which the Energy Information Administration reports at 760,108 MW of net internal demand. The demand for electricity has grown from 1996 to 2006 by 26.1% with little investment in large scale generation [1]. What had been built were gas turbine generators that came into the market during times of relative inexpensive natural gas. But due to the strain put on generation capacity in the United States and high gas prices, utilities have been forced to consider other alternatives. In 2000, natural gas prices rose 63% while at the same time coal realized an actual 2% decrease [2]. Naturally, this caused utilities to begin revisiting the idea of building nuclear and coal fired power plants. But due to Nuclear's long lead-times for construction and high sunk costs, many utilities began to expand their coal fired generation capacity. Though coal has no long-term waste storage issues it does release carbon dioxide, sulfur and nitrogen oxides into the environment, which has more immediate effects.

By the late 1990's global warming due to gases such as CO_2 and NO_x had become a leading concern. Most scientists believed the record high temperatures and prolonged draughts being felt throughout the U.S. were caused directly by these gases. In 1997, the United Nations Framework Convention on Climate Change adopted the Kyoto Protocol. The protocol seeks a reduction in greenhouse gases to below pre 1990 emissions levels [3]. The United States signed but never ratified the treaty causing great debate among U.S. citizens. Today it appears that if the federal government is not going to take a strong stance on reducing emission of gases such as CO_2 and NO_x, also known as greenhouse gases, state voters would.

In 2000, electrical utilities accounted for 34% of the greenhouse gases emitted by the United States [2]. This makes electric generation the single largest producer of these gases in the country and an obvious target for reduction. Though states require utilities to offer a renewable energy option to their customers, some states believe a mandate for acquiring specific levels of renewable energy is needed to ensure green gas reduction. Through Renewable Portfolio Standards (RPS) states have found a vehicle by which they hope to achieve a reduction in emissions that lead to global warming while at the same time achieving energy independence and better price stability for their residents.

Starting in 2012, Washington State utilities will be required to either purchase or produce a portion of their energy from a renewable resource. Some of the larger state utilities such as Puget Sound Energy and PacifiCorp have already built wind farms that will help meet these requirements [4-6]. But most have not, presumably due to budgeting constraints and a lack of renewable planning experience. This thesis will use data collected by a federal power marketer and utility specific load information to build a model that will reliably evaluate the ability of a wind generator to serve load. The idea is to keep the model as simple as possible to allow for an approximate evaluation that can be used by any northwest utility to meet either self imposed goals or state requirements. In this respect a utility can choose to proceed further down a road to building their own wind farm asset or turning to the open market to meet their needs.

1.1 Creating an Economic Market for Wind Energy

To better understand how wind energy has come to dominate the renewable energy landscape one needs to consider the history behind its development. The bulk of its history is rooted in the worldwide dynamics of electricity production, which underwent significant changes over thirty years ago. The OPEC oil embargo of 1973 and Middle East conflicts caused world energy prices to rise throughout the 1970's. The United States was not immune and responded with legislation and tax incentives to promote alternative forms of generation. The most influential and beneficial of these was the Public Utility Regulatory Policies Act (PURPA) of 1978. The act required host utilities to purchase, at a favorable rate, the energy produced by a small power producer using renewable resources or by cogeneration. These facilities were required to meet specifications to become a "Qualified Facility" by the act. To be classified as a "QF" the producer had to either be less than 50% owned by a utility or produce less than 80 MW. The act defined favorable rate as the incremental cost of energy either generated by the host utility or purchased from another traditional source. The cost was not to exceed the avoided cost of generating renewable energies. But due to the high prices of energy, renewable energy was at the time already less costly [7].

By the early 1980's, California had become the center of wind generation capacity. Coupled with PURPA, the state mandated Standard Offer 4 (SO4) long term contracts that offered ten years of fixed, above market, feed-in tariffs. The state also added to the Federal Energy Tax Credit which resulted in an almost 50% tax credit to renewable projects [8]. In 1992, the US had 1,822 MW of installed wind turbine capacity of which over 1,600 MW was in California. By 1996 though installed capacity had decreased to 1,670 MW [1]. Suggestions have been made that this was due to the expiration of 10-year contracts that utilities had written when energy prices were still relatively high. In the late 1980's, energy prices had began to fall and the comparison of avoided cost to renewable cost had shifted back in favor of fossil fuels [7, 8].

In 1996, FERC Order 888 the "Open Access Policy" went into effect and made significant changes to how the geographical monopolies of electric utilities conducted business. The policy forced the unbundling of generation from transmission and marked the next significant step in energy deregulation. In practical terms, the only customer a QF could sell energy to was the utility in whose territory the generator resided. The only hurdle a QF had to overcome until 1996 was an economic one. As long as energy prices remained high QF's had a guaranteed customer which had to pay favorable rates. After Order 888, the utilities lost their monopoly on transmission assets and by default so did the QF's [9].

1.2 State RPS's

A renewable portfolio standard (RPS) is defined as *"a state policy that requires electricity providers to obtain a minimum percentage of their power from renewable energy resources by a certain date"* [10]. In October 1999, the state of Wisconsin became the first to enact an RPS. The law required utilities serving the state to purchase or produce 2.2% of the energy delivered within the state from renewable resources by 2012 [11]. Since that time, 30 states have enacted some form of an RPS [10].

In November 2006, the voters of Washington State passed Initiative 937 (I-937) entitled the Energy Independence Act. As directed by the initiative state lawmakers produced the Revised Code of Washington number 19.285. The law stipulates the levels that utilities must meet to increase energy conservation and renewable energy purchases. The latter is the state RPS, which requires utilities to generate or purchase 3% of their energy from a renewable source beginning in 2012. Included in the RPS is a stepped increase to 9% to take effect four years later and then finally to 15% in 2020 [12].

The Washington State Department of Community, Trade and Economic Development (CTED) reported in 2006 that the state's fuel mix was comprised of 69% hydro, 17% coal, 8% Natural Gas, 5% Nuclear and 1% wind energy [13].

That same year, Washington State generated approximately 2,560,745 MW-hours of renewable energy including landfill gas, biomass, wood, geothermal, solar/PV, and wind [14]. Wind accounted for 867,392 MW-hours of the renewable fuel mix [13]. According to I-937 any utility serving over 25,000 customers must comply with the RPS. A 2005 report by the CTED, stated those utilities that fall into the grater than 25,000 category provided 68,989,871 MW-hours of electricity to their customers. To achieve 15%, the utilities must purchase or generate 10,348,480 MW-hours of renewable energy relative to today's load [15]. By 2020 when 15% is actually enacted and assuming a load growth of 1.3% [16], the needed renewable energy supply would grow to 12,560,827 MW-hours or a six-fold increase. This, of course, does not include other utilities that pass the 25,000-customer mark over the next 15 years.

Note that hydro electricity is specifically excluded as a renewable resource by I-937. Traditionally hydro electricity has been considered a renewable resource and some states still include it in their RPS [11]. But in Washington State, only incremental improvements made to improve the efficiency of existing hydro plants may be counted.

1.3 Wind Energy Integration

As mentioned earlier, historically California dominated wind capacity with over 90% of the world's installed capacity in 1988. Within California, three large wind farms had been developed at Altamont Pass, Tehachapi Pass and San Gorgonio Pass. These three lie within the service areas of Pacific Gas and Electric and Southern California Edison. Therefore any transmission connection issues that came about after Order 888 for the few installed large scale wind projects were handled by just two utilities. In a 2006 report prepared for the Public Interest Energy Research Program for the state of California, it is suggested that the fact that only two companies resolved the connection issues resulted in the prevention of the dissemination of lessons learned to the utility industry as a whole [8].

The connection of wind farms to pre-existing transmission systems was only a portion of the difficulties faced by utilities, the other being transmission capacity itself. From May 2000 to September 2001, California was hit by electricity shortages and spiking energy prices. Though the main culprit was gaming by energy traders, a weakness in the western U.S. electrical transmission system had been exposed, further complicating the integration of wind energy.

1.4 Wind Turbine Technology

Harnessing the wind to produce electricity reached its first milestone in the United States when a 1.25 MW wind turbine was constructed in Vermont during World War II. Unfortunately, wind technology had to wait until the energy crisis of the 1970's to see any significant improvements. The most difficult problem for engineers was building a turbine that was both large scale and reliable. Early wind turbines sized over 500kW were prone to mechanical failure in a relatively short period of time. This caused wind turbines to scale down in size and wind farms to compensate by installing many more wind turbines [17].

At the peak of California's wind generation boom in 1992, over 16,300 turbines were in operation but only 6 were greater than 400kW [18].

By the mid 1990's, wind technology had become fairly stagnant again. This was due in large part to the relative cheap cost of fossil fuels and natural gas and the high cost of building and connecting a wind farm [9]. The three areas in California had been in operation for almost 15 years with no new wind generators planned. But in 1999, the U.S. began to see an increase again in wind turbine construction with 2,500 MW of capacity and the first 1 MW turbines being installed [18]. By 2001, 4,261 MW of capacity was operating in the U.S. with Washington State seeing its first wind farm, sized to 178 MW [19].

As of December 31, 2007 the U.S. totaled 16,596 MW of capacity [19]. Wind technology has allowed the production of a 3 MW wind turbine with a forced outage rate of between 1 to 3 percent [20]. To compensate for the extremely varying nature of winds, even from minute to minute, turbines have been developed with pitched blades. This has resulted in capacity factor gains from 22.5% before 1998, to 36% after 2006 [21]. Each of the turbines in a wind farm can be controlled by a single computer, which helps optimize the wind farm output and provides greater control of electricity placed onto the transmission system. This coupled with improvements in wind forecasting has helped make wind a viable option for renewable energy. In fact, the Washington State Utility and Transportation Commission (WUTC) ranks wind energy as the number one potential renewable resource based on projected capacity and dollars per megawatt hour [22].

1.5 Today's Wind Farms

By their very nature, wind farms have three major hurdles they must overcome. The first is the fact that wind is not a steady and reliable energy source. The basic principle behind the electric power grid is that power generated must equal power consumed. Therefore, a generation mix needs to adjust its output to meet demand or demand needs to adjust to meet generator output. Obviously the latter is only the case in an emergency and leads to a curbing of wind generator output during excessive generating hours and the need for reserve generation during time of output deficiency. If the energy during excessive times could be stored for deficient periods, wind energy could be optimally employed. Unfortunately, the lack of large-scale economically feasible storage options forces utilities to curb output. At the opposite extreme, the lack of storage causes the scheduling of extra generation reserve margins and increased system regulation requirements [23]. This of course is to ensure load is met, but concerns also arise in regard to transmission line owners and users who wish to optimally use available transmission capacity. Transmission line scheduling takes place hours to days before the power is actually transmitted across it and a predictable power source is desired. Today we have better technology to forecast wind, and storage options are on the horizon, but transmission scheduling is still a major concern [21].

The second hurdle of most wind farms is that they are usually sited in areas that are far from load centers. Economies of scale dictate building as large a generator as possible, which allows transmission costs to become less of a factor.

But the sizing of wind farms depends on the land available for the site as well as economical feasibility. For example, Puget Sound Energy's (PSE's) Hopkins ridge wind farm contains 83 wind turbines for a combined capacity of 150 MW. The wind farm footprint is only 100 acres. But to maximize the efficiency of each turbine, they must be placed in strategic locations relative to the terrain and each other. Therefore, the project actually occupies 11,000 acres [4]. This equates to over 17 square miles of area and leads to more difficulties when trying to site wind farms close to urban load centers. This forces the placement of wind farms to more rural areas where transmission lines would need to have long right-of-way corridors established, assuming they are not preexisting.

Finally, the relationship of generator output profile to load profile is very important. Load changes based on many factors such as time of day, time of year, and temperature. These changes are due to demand cycles, which are dictated by both humans and nature. Optimally a generator could vary its output to change with the load. Though this is efficient for meeting load, it is not efficient for the generator. Therefore having a mix of generators that can be reliably counted on to form many different combinations of total generation is desirable. This ensures a single generator within the mix is operated at an economically efficient level. Generators within the mix are individually evaluated to determine its probability of failure or forced outage rate. This allows for the overall evaluation of the probability that generation will be able to serve the ever-changing load and in an efficient manner.

For a wind farm, the forced outage rate can be quite subjective. This is due to the fact that the wind generator is actually made up of many individual turbine generators that produce anywhere from zero to full output. This can lead to a low probability of forced outage for the wind farm as a whole but the exact level of output can be uncertain. In this respect, a wind farm's performance or capacity factor is most usually referred to in lieu of the forced outage rate. Just as the load varies due to cycles, so too does the wind farm output but it is exclusively dependant on nature. This thesis seeks to find a natural cycle in wind energy production that coincides with load cycles. Optimally wind farm output will be the highest during the higher load demand times. If this is the case, it can be argued that wind energy contributes to meeting load more than its capacity factor alone, thus becoming more of an asset to a generation mix.

1.6 Problem Statement

In Washington State, utilities such as PSE, Avista and PacifiCorp have the resources and data to predict and integrate wind energy into their systems. The problem for a smaller utility with no previous wind energy experience is in gathering representative data and performing an evaluation of the cyclical capacity of wind generation. This would allow for two different types of evaluation. The first is the comparison of generation cycles to load cycles for reliability purposes. This would be used in the case of a utility trying to add a generator to its existing mix. The second being an evaluation of the average load to average wind farm output to help the utility determine the amount of generation needed to meet RPS requirements. For the latter case, the convenient alternative could be to purchases renewable energy certificates via the Western Renewable Energy Generation Information System (WREGIS) [24] or possibly through bundling offered by BPA.

This thesis will look at the possibility of how Tacoma Public Utilities (TPU) either on its own, or as a member of a consortium, investing in wind turbine generation. Economic consequences and integration issues will be deferred to future work. The focus of this thesis will be on the modeling of a wind resource for TPU using readily available data, how well those resources can serve the utility's load and to what extent those resources can meet the Washington State RPS.

1.7 Contribution of Thesis

This work will look at specific wind speed data colleted from August 2002 to December 2006 at four different sites along the Columbia River Basin. Hourly load data from TPU's service area is used as the sample utility for calculations. Specifically the data presented will

- Extrapolate wind speed into wind energy.
- Provide supporting evidence that when taking multiple sites in aggregate one can make a case that wind speed can be directly correlated to wind farm output.
- Characterize individual wind site output both on a seasonal and historical basis.

- Correlate TPU's load to individual and combined wind sites on a seasonal and historical basis.
- Calculate effective load carrying capacity of the wind farms.
- Estimate the capacity needed by TPU to meet Washington State's Renewable Portfolio Standard.

Chapter 2

Valuing Generation

Measuring the ability of a generator to perform when it is called upon is an important first step in the evaluating the benefit a generator brings to a generation mix. The most simplistic of which considers at any given time the generator is able to produce. To further narrow the evaluation, planners prefer an evaluation using worst-case scenarios, which by nature include only peak load times. The idea being that during low load periods other generators within the mix will be able to produce if a particular generator cannot. But during peak loads each generator's reliability is crucial in meeting demand. This allows for an evaluation of the generation mix as a whole within which each generator significantly affects generation mix reliability.

The factors affecting generator reliability are, for the most part, the same independent of the generator. However the degree to which each has an affect is different. For example, repairs and maintenance most impact thermal power system reliability. For the renewable power systems such as hydro, solar and wind, the fuel source has the largest impact. Therefore trying to apply the same reliability measurements or capacity measurements to both can be very difficult. Chapter 2 will present common reliability standards and capacity measurements applicable to both types of system.

2.1 Forced Outage Rate

When considering the reliability of electricity supply one must look at all aspects including generation, transmission, and delivery of the electricity. The most common and simplest term used to describe probability of failure for equipment is Forced Outage Rate. FOR is a measure of the amount of time that an asset is unable to generate or deliver electricity. The term "forced" in this case means an unforeseen event that the operator has no control over in both time and cause.

$$R = \frac{\sum[D]}{\sum[D] + \sum[U]} \tag{2.1}$$

where:

R = forced outage rate;

D = time generator is unable to produce over a representative period;

U = time generator is able to produce over a representative period;

Forced outage rate is mainly used to help illustrate probabilities of failures in power systems. This is because FOR can be applied to a single asset and combined with the remaining assets to obtain a reliability indices such as loss of load probability and effective load carrying capacity. FOR also helps illustrate how redundancies in the utility system can help utilities to cope with a myriad of contingencies [25].

2.2 Loss of Load Expectation

Today the most widely used probabilistic technique for evaluating the adequacy of a generation system is loss of load probability and expectation. The loss of load probability or LOLP is determined by the number of times the load is not met by a generating system at a specific load time. There can be a number of different generation combinations depending on the number of generators. Each combination represents a discrete generating level that when calculated can become a labor-intensive task. Various approximating techniques have been developed that can help simplify and speed up this process [25].

Loss of load expectation or LOLE index is used to express the amount of time a generating system is unable to meet a load over a specified time period. To calculate LOLE one needs load data over the fixed period. For example daily peak load data obtained over a year can be compared to an LOLP table. Every probability that correlates to a total level of generation that is insufficient to meet the peak load on that day is summed. If the daily peak is at discrete levels, the LOLE for the year would be calculated by [25]:

$$LOLE = \sum_{i=1}^{n} P_i(C_i - L_i) \quad days/period \tag{2.2}$$

where:

n = the number of discrete peak levels;

C_i = available capacity on day i;

L_i = forecast load on day i;

$P_i(C_i\text{-}L_i)$ = probability of loss of load on day i. This value is obtained directly from the capacity outage cumulative probability table;

The units of measurement for LOLE in this case would be days per year. Another approach would be to use hourly load data over the year by which the LOLE would be defined as hours per year [26]. The reliability goal is often equated to an LOLE of one day per decade [27].

To clarify, a simple example is presented here of nine 100 MW generators with a FOR of 5% connected to a system with a daily peak load of 550 MW for 200 days a year and 650 MW for the rest. Using a binomial distribution, the probabilities can be calculated and collected in tabular format [25]. By adding the probabilities of the outage combinations, one may calculate the cumulative probability that a maximum number of generators are unavailable [28].

$$LOLP_i = \frac{n!}{i!(n-i)!} p^i (1-p)^{n-i} \tag{2.3}$$

where:

p = forced outage rate;

n = number of generators available;

i = number of generators on outage;

Alternatively one may refer to the cumulative calculated as the maximum amount of generation available vice minimum amount on outage. Table 2.2 below displays the results of the probabilities for this example.

MW on Outage	MW Available	Probability	Cumulative Probability
0	900	0.630249409725	1.000000000000
100	800	0.298539194080	0.369750590275
200	700	0.062850356648	0.071211396195
300	600	0.007718464852	0.008361039547
400	500	0.000609352488	0.000642574695
500	400	0.000032071184	0.000033222207
600	300	0.000001125305	0.000001151023
700	200	0.000000025383	0.000000025719
800	100	0.000000000334	0.000000000336
900	0	0.000000000002	0.000000000002

Table 2.1 Conventional outage probabilities

There is a probability of $6.0935 \cdot 10^{-4}$ that exactly 500 MW is available. But the cumulative probability is $6.426 \cdot 10^{-4}$ that 500 MW or less is available. The latter number represents the LOLP for the 550 MW load since any outage greater than or equal to 500 MW will result in 400 MW or less available. The LOLE would equate to 1.006 days per year, i.e.:

$$LOLE = 6.426 \cdot 10^{-4}(265) + 8.361 \cdot 10^{-3}(100) \qquad (2.4)$$

The chronological order of the load does not matter, simply the total at each discrete level. Therefore it is common for loads to be represented as a load duration curve. This is a plot with minimum peak load days on the horizontal axis and the peak load on the vertical axis. Figure 2.1 demonstrates a typical load curve but in this case hourly load is used instead of daily peak load. The load curve represents 43,800 hours of load data collected over 5 years from Tacoma Public Utilities. Rather than a simple 550 MW or 650 MW load, this shows the entire 1 MW increment load seen by the utility.

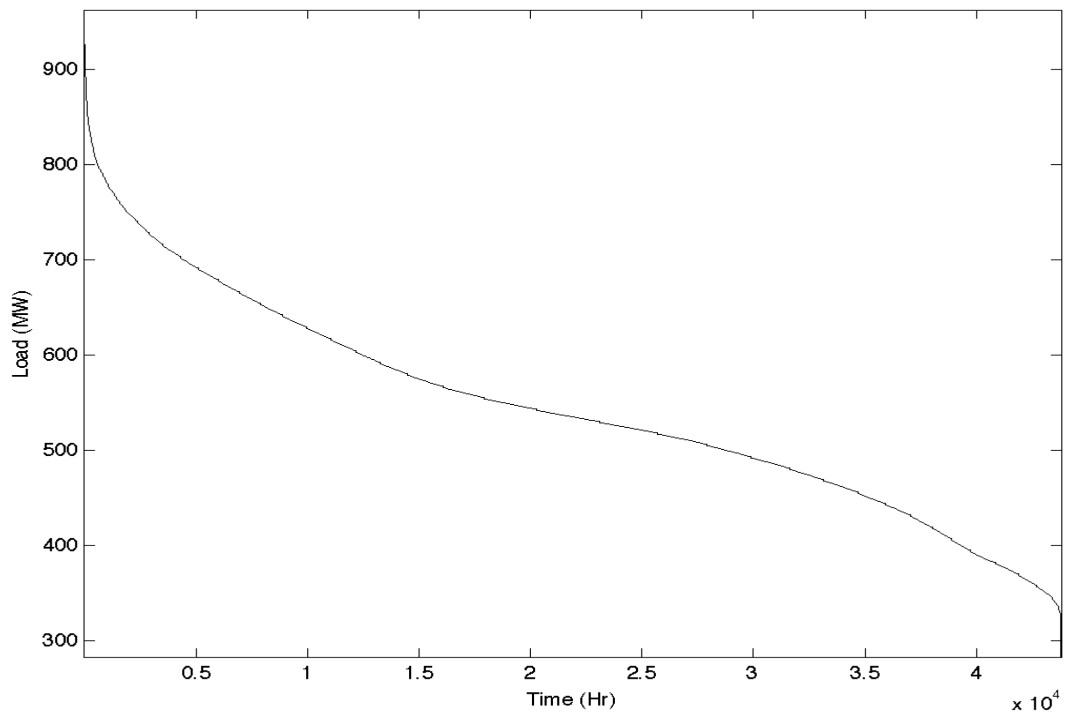

Figure 2.1 A typical load duration curve

By converting the above load duration curve into discrete levels and using a generation mix table similar to the previous example, one can easily convolve the data using [26]:

$$LOLE = \sum_{j=1}^{N_G} \sum_{i=1}^{N_L} P_i P_j I_{ij} \cdot T \tag{2.5}$$

$$I_{ij} = \begin{cases} 0 & L_i \le G_j \\ 1 & L_i > G_j \end{cases}$$

where:

T = the total time length of the load curve;

L_i = the i^{th} load level;

P_i = the probability of L_i (fraction of total time when the load is equal or bigger than L_i);

N_L = number of load levels in the discretized load curve;

G_j = the j^{th} generation capacity level;

P_j = the probability of G_j;

N_G = number of generation capacity levels in the generation capacity probability table;

2.3 Effective Forced Outage Rate

Applying LOLE measurements to wind energy can be very subjective. For traditional generation, the FOR assumes a fuel source that is uninterrupted. If the same were true for the evaluation of wind, a FOR from 1-3% is very realistic [20]. Using a FOR of 3% and a wind farm size of 50 wind turbines sized to 2 MW each, Table 2.2 below demonstrates what the resulting probabilities will be.

MW Available	Probability	Cumulative Probability
100	0.2181	1.0000
98	0.3372	0.7819
96	0.2555	0.4447
94	0.1264	0.1892
92	0.0459	0.0628
90	0.0131	0.0168
88	0.0030	0.0037
86	0.0006	0.0007

Table 2.2 Wind turbine outage probabilities

One can see that the probability of losing 14% or more of the wind farms capacity is on par with loosing 45% or more of the combined capacity of the standard generators shown previously. Due to the quickly falling probability of losing multiple turbines the wind farm seems to be an obvious choice. But one must remember that the assumption made is that the fuel source is uninterrupted. For wind turbines, the fuel source is wind and it clearly is not an uninterruptible source.

Milligan and Porter suggest using a qualifier to describe wind turbine's FOR called an effective forced outage rate or EFOR [27]. It is described as the time in which the turbine does not produce an output at all. Milligan and Porter's proposed number is an EFOR of between 50% and 80% [27]. At first appearance these numbers look very poor but when other factors such as load are taken into account they can become more meaningful.

Still, FOR is only a measurement of the generator itself and says very little of its ability to help serve a load when connected to a system. If a 100 MW wind generator with an EFOR equal to 80% were connected to the system mentioned before, with a total of 1000 MW of generation, the outage probabilities would be as shown in Table 2.3. If the generation were serving the previously mentioned peak loads of 550 MW and 650 MW, the LOLE would decrease from 1.006 to .819 days per year from 1. This shows that although wind turbines could have a very high EFOR they can still contribute to improving LOLE.

MW Available	Probability	Cumulative Probability
1000	0.126049882	1.000000000
900	0.563907367	0.873950118
800	0.251401427	0.310042751
700	0.051823978	0.058641325
600	0.006296642	0.006817347
500	0.000493896	0.000520704
400	0.000025882	0.000026808

Table 2.3 Mixed generation outage probabilities

2.4 Effective Load Carrying Capacity

LOLE is an important value for system planners and is used when planning reserve capacity. The reserve capacity not only needs to meet that which was lost but must also maintain the LOLE at an acceptable level. Figure 2.2 below shows how LOLE varies according to load level and generator mix capacity. The generators used in this example are the same as before with a single generator able to produce 100 MW with a FOR equal to 5%.

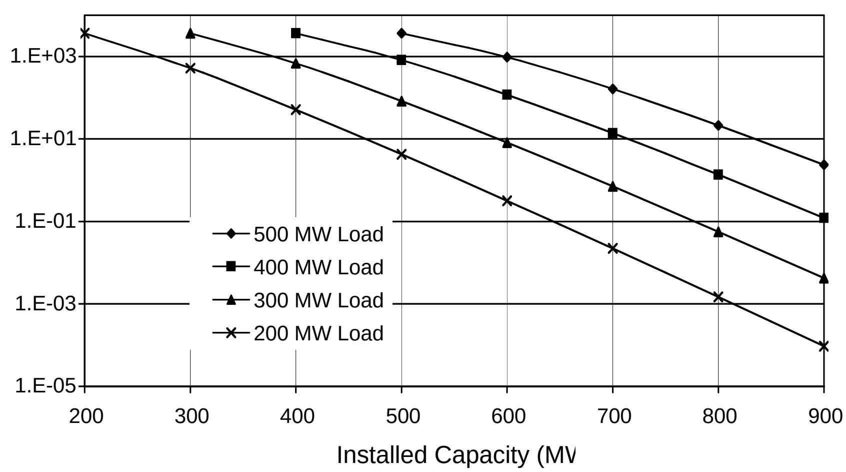

Figure 2.2 LOLE variations due to load and capacity

Returning to the example of nine 100 MW generators supplying a 400 MW load. If a 100 MW wind farm with an EFOR of 80% replaced one of the generators, the LOLE would change by some amount. The example in Fig. 2.3 shows that the LOLE would rise from the previous 0.121 days to 0.446 days per ten years. Again, this is if a wind farm of 80% forced outage rate replaced a gas turbine with a FOR of 5%. As you can see the change in LOLE depends on generator size and FOR, which planners must take into account.

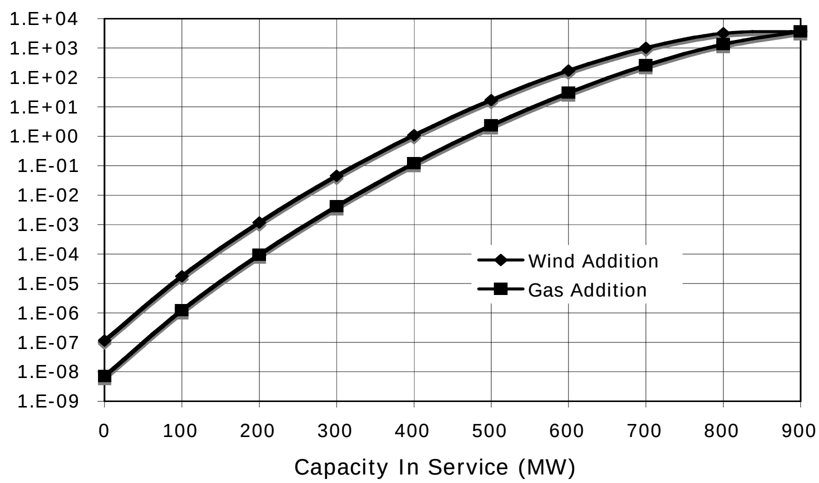

Fig. 2.3 LOLE variation due to different generator additions

When evaluating a renewable generator's Effective Load Carrying Capacity (ELCC), the renewable under study is placed into a mix and LOLP is measured. The new LOLP is noted and the renewable is taken back out of the mix. It is then replaced in small increments by a benchmark generator until the LOLP is lowered to that which was achieved with the renewable [29]. Therefore, ELCC is a measure of the amount of benchmark generation that is required to achieve the same level of LOLP as when the wind generator is connected. By extension, the higher the FOR of the benchmark generator the lower the equivalent capacity of the 80% EFOR wind farm and vice versa. One must strictly take into account these factors to accurately compare renewable generators of differing types.

2.5 Loss of Energy Expectation

Another metric sometimes employed is that of energy not served (ENS), which is mostly applied to renewable resources. By measuring the difference between load and generator output every time there is insufficient generation, the ENS can be derived. This thesis will use ENS as a means of evaluating past data to determine how well load is served during different time periods. This allows for a loss of energy expectation or LOEE that can contribute to future wind integration planning. In this case LOEE is defined by Li [26] as:

$$LOEE = \frac{1}{N}\sum_{i=1}^{N} ENS_i \qquad (2.7)$$

where:

N = number of time periods evaluated;

2.6 Capacity Factor

The capacity factor (CF) of a wind turbine is defined by the amount of output over a period of time divided by the capacity rating of the wind turbine. By summing all turbine outputs over the same period and dividing by the wind farm capacity over the period one can obtain the wind farm capacity factor.

$$CF = \frac{\sum_{i=1}^{k} OP_i}{\sum_{i=1}^{k} ROP_i} \tag{2.6}$$

where:

OP_i = output of i^{th} turbine;

ROP_i = rated output of i^{th} turbine;

k = total number of turbines within the wind farm;

Capacity factor is very much dependent on the time period over which it was measured. The longer the period of time the more accurate the evaluation of capacity. It appears though that many northwest utilities use a single capacity factor for all wind generation projects. For example, Portland General Electric's 2002 Integrated Resource Plan uses a straight 33% in calculating wind capacity factor [30]. PacifiCorp, which has some wind farm experience, used a sequential Monte Carlo method in their Integration Resource Plan in 2007. The capacity contribution came to approximately 20% of rated capacity, which is being used in studies for future wind integration [31]. Puget Sound Energy's IRP for 2006 uses a wind availability of 30%, although Hopkins Ridge showed an actual output of 34.2% from Jan 1, 2006 to Nov 1, 2006 [32]. The Washington State Utility and Transportation Commission Report on Actions and Policies Dealing with Climate Change reported PSE anticipates a 32.1% capacity factor at the Wild Horse wind project [22].

As has been shown here, there are many different types of techniques for evaluating a generator's ability to serve load. Some lend themselves well to only nonrenewable generators while others apply well to all types. This thesis will apply the techniques presented above to historical wind speed and load data. But due to restrictions on the amount of data available some assumptions will need to be made in order to make these calculations possible, specifically the unavailability of generator statistics for TPU's generation mix. The final discussion will focus on capacity factor and ELCC as the means by which the wind generator's performance will be evaluated.

Chapter 3

Data Collection

To properly value the capacity of a given wind site, one must take many factors into consideration, including transmission constraints and load shapes. Barring the ability to build and gather output data from an actual wind turbine at a site, the most useful parameter, which is easily obtained, is wind energy, usually measured in W/m^2. To determine this, prospectors of wind energy construct towers at possible sites to measure and record over a long period of time various parameters for the calculation of wind energy. The height of the tower from which the measurements are taken need to correlate to the hub height of the turbine model proposed for the site or data needs to be extrapolated so as to represent wind speed at the hub height. It is also important that measurements be taken over as long a period as possible to determine a baseline from which to evaluate and help determine cyclical behavior. Of course greater data accuracy can also be achieved by constructing multiple towers over the proposed wind farm to account for variations caused by local terrain.

3.1 Wind Energy

Wind energy depends on air density and the velocity of air moving perpendicular to the turbine face measured over a suitable period. Density in turn depends on pressure, moisture content, and temperature. These factors also have an affect on wind velocity.

$$P = 1/2\,\rho V^3 \tag{3.1}$$

where:

P = wind energy potential;

ρ = density of air averaged over a suitable time in kg/m^3;

V = wind velocity averaged over a suitable time in m/s;

Wind is caused by atmospheric pressure differences caused by uneven heating of the surface of the earth by the sun and heat transferred by the ocean's current or by weather fronts. Also moist air is lighter than dry air and will result in greater wind velocities [33]. One can see that by trying to hold air density constant and only considering wind speed can lead to inaccurate measurements of wind energy. Still, many studies to determine wind energy potential rely solely on wind speed measurements [34-40]. In fact turbine manufacturers often publish only a wind speed-to-output curve for their generators [41].

It is true, that to accurately calculate the output of a wind turbine one must calculate wind energy minus mechanical and electrical losses. But it is also argued that wind speed is of the utmost importance because it has the most direct impact on both wind plant behavior and actual power delivered [42]. A practical way to determine the future value of a wind sight is a combination of site data and wind farm operating experience in the same region. Some studies have actually used this combination to study future production [40].

3.2 Previous Studies

The following section is a brief overview of previously published studies that were similar either in scope or geographic location to this thesis. One will see some similarities between how this study was conducted and that of other work. But in every case presented here, no attempt was made by the authors to study variations on a seasonal basis either for wind energy potential or correlation to load. Further more, no study had been conducted using wind speed and load data from as long of a period as this study. Even though, it is widely acknowledged that a long period of time is needed to accurately evaluate wind energy.

Study 1

Previous studies have been performed using the output of sites along or near the Columbia River. A study by Hirst in 2002 [43] used data provided by the Bonneville Power Administration (BPA) from wind farms near the Columbia (Table 3.1). Ten-minute data from January to April 2002 were used. The results of the preliminary study found that the sites had a combined capacity factor of 32% over the four-month period with an average correlation coefficient of 0.56. The correlation coefficient between the wind output and BPA's system load was essentially zero [43].

Site Name	Year Completed	Number of Turbines	Total Capacity (MW)
Condon Phase I	2001	42 (.6)	25
Klondike I	2001	16 (1.5)	24
Stateline	2001	136 (.66)	90
Vansycle	1998	38 (.66)	25

Table 3.1 Hirst study wind farms [43-47]

It has been shown though, that capacity factors of recently constructed wind farms have increased due to improvements in technology and turbine size. A 2% weighted capacity increase reported by the U.S. Department of Energy between wind turbines installed in 2000-01 (period of Hirst's study [43]) and those installed in 2004-05 suggests that Hirst's study may undervalue a more modern wind farm [34]. The change seen in both the size and number of turbines of more modern wind farms in the Columbia River area are reflected in Table 3.2 below.

Site Name	Year Completed	Number of Turbines (MW)	Total Capacity (MW)
Hopkins Ridge	2005	83 (1.8)	150
Klondike II	2005	50 (1.5)	75
Wild Horse	2006	127 (1.8)	228
Big Horn	2007	133 (1.5)	200
Leaning Juniper	2007	133 (1.5)	200

Table 3.2 Recently constructed northwest wind farms [4-6, 44, 48, 49]

Study 2

A study on the "Hourly Wind Power Variations in the Nordic Countries" was conducted using data from 2000 to 2002. A combination of actual wind power production and modeling using wind speed was used. The actual output came from 24 sites in Finland, Sweden, and Norway with installed capacity less than 100 MW was utilized, in addition to two sites in Denmark with over 2,000 MW of installed capacity. The theoretical output data was generated using wind speed data measurements taken in 14 different locations in Finland, Sweden, and Norway. The 24 sites that had actual output data were scaled up over 10 fold to simulate a wind farm. The hourly wind speed data for the model was smoothed using a 2-hour sliding average technique. The smoothed data was then converted to power production using an aggregated, multi-turbine power curve. The model's production at each hour was weighted using the capacity factors of the four countries as its basis. The two different data sets were then combined to form a single model for study.

The study showed an average standard deviation equal to 28.2% of installed capacity for the hourly wind production for a single site. When considering all the sites across the four countries, a standard deviation of 14.5% of installed capacity was calculated. As for the correlation coefficient between the sites, a value of 0.42-0.45 was measured for Sweden/Norway/Finland and 0.22-0.33 for Denmark/Finland/Norway. The study found the relationship between correlation coefficient and distance between wind sites could be described by equation (3.2) below [40].

$$y = \exp(-d/500) \tag{3.2}$$

where:

y = correlation coefficient;

d = distance between sites measured in kilometers;

Study 3

EnerNex Corporation conducted a study for Avista Corporation of Spokane, Washington in March of 2007. The study utilized wind speed data from Oregon State University's Energy Resource Research Laboratory. The 10-minute measurements used were from 5 different sites, 3 of which were in the area of the Columbia River. The other two were from Montana and the Oregon cost. The 3 Columbia River sites were Kennewick, Goodnoe Hills and Sevenmile Hill. Actual wind farm output was available from Vansycle, which is also in vicinity of the Columbia River.

To account for a single point of observation (one anemometer per site), a smoothing algorithm for wind speed was introduced, which the author claims had been validated in previous models. To model the wind turbine production, a wind speed to power curve was used based on a NEG 750, 2.75 MW wind turbine. The portion of the study that is relevant to this thesis was a scenario in which 100 MW was modeled using 50 MW of actual production from Vansycle and 50 MW of theoretical production from Kennewick. The data was collected from August 2002 to the end of 2004. The capacity factor was found to be 34% with Figure 3.1 showing the production distribution for this case [35].

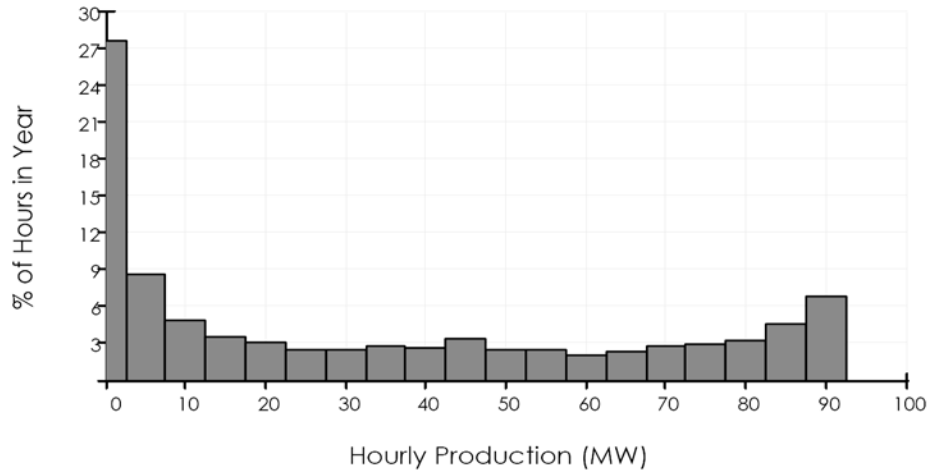

Figure 3.1 EnerNex study results [35]

Study 4

The National Renewable Energy Lab's wind power plant monitoring project has been collecting data at seven locations in Minnesota, Iowa, and Texas to enable utilities to assess operating impacts and to gain information for system planning. A report by Y. Wan in December 2005 using this data compared the actual output of 3 sites in the Buffalo Ridge region of Minnesota. Wan showed that due to extreme variations in wind speed one could not simply scale up a small number of wind turbines to model a large wind farm. Using data over a 720-hour timeframe Table 3.3 shows the hourly changes found as a percentage of wind farm capacity. The largest power level change of a wind power plant containing turbines was about 70% of the wind plant capacity in 1 hour during a 12-month period [42].

	14 turbines x 9.6	138 turbines (actual)	14 turbines x 22.3	250+ turbines (actual)
1 Hour Average	7.0%	6.4%	7.0%	5.3%
1 Hour Std Dev	10.7%	9.7%	10.7%	7.9%

Table 3.3 Wan study wind farm hourly step changes [42]

Study 5

A report by Milligan in 2002 cites a study he conducted in 1995 in which one year of wind data was collected from instruments mounted at 70 m. The wind speed data was used as an input to a modern utility-scale turbine at a hub-height of 65 m. The data was obtained from six geographically dispersed sites in the state of Minnesota. The theoretical output was then compared to a nearby electrical load and a correlation coefficient was calculated. Table 3.4 displays the results [36]. As you can see the study found negative correlation that was small in magnitude.

	Correlation to Load
Alberta	-0.0135
Becker	-0.0436
Brewster	-0.0395
Crookston	-0.0035
Currie	-0.0539
Luverne	-0.0317

Table 3.4 Minnesota correlations to load

Although the discussion of each study has been brief, keep in mind the results obtained. As you will see later in this thesis, the data published in these studies will be used as a comparison to results of this work. Specifically note:

1) The Columbia River study used actual output over a 4-month period.
   -Result: a capacity factor equal to 32% and correlation coefficient of 0.56.

2) The Nordic study used a combination of actual and theoretical outputs based on wind speed over a 2-year period.
   -Result: an hourly output step change average standard deviation of 28.2% for a single site and a standard deviation of 14.2% when all sites were considered.
   -Result: an output correlation coefficient of 0.42-0.45 for one region and 0.22-0.33 for another.

3) The EnerNex study combined actual output from Vansycle and a theoretical output from Kennewick collected over a 28-month period.
   -Result: a capacity factor of 34% with the distribution shown in Figure 3.1.

4) The Buffalo Ridge study argued against linearly scaling actual wind farm output by analyzing data collected over a 720-hour period.
   -Result: scaling from a small number caused hourly step change averages and standard deviations that were greater than those actual output.
   -Result: increasing the geographical distribution decreased the hourly step change average and standard deviation.

5) The Milligan study used wind speed data collected at six different sites as input to a utility grade turbine and actual load data from nearby cities.
   -Result: an output to load correlation coefficient from -0.0035 to -0.0539

3.3 Selection of Wind Data Sites

Since 1978 the Energy Research Resource Library (ERRL) has been managed by Oregon State University for the Bonneville Power Administration's Wind Forecasting Network. The purpose of the ERRL is to facilitate the collection, quality assurance and analysis of data collected at the five long-term collection sites. In recent years more sites have been added to ERRL's responsibilities, some in conjunction with BPA and some with other research activities [50]. All together BPA has eight different sites where data such as wind speed, wind direction, barometric pressure, and temperature have been recorded. The timeframe for which this information is available does vary.

Having a diverse data set is beneficial because it is believed, and studies have shown, that having geographically dispersed wind sites enhance generator availability and reduce variability when combined to form a single source [23, 36, 37, 40, 43]. Optimally wind sites need to be located as far apart as possible and in the windiest environments. In Washington most of the prime wind sites reside along the Columbia River east of the Cascade Mountains, near Ellensburg, Northeast of Walla Walla and along the state's coastline [51]. Due to the remote nature of these wind sites from major load centers, transmission is of major concern.

BPA is a likely supplier of bulk transmission for northwest utilities looking to build wind generation due to assets that cover the region along the Columbia River in support of hydroelectric generation. This is in addition to the fact BPA already has over 1,500 MW of installed wind capacity in its control area

[23]. It would make the most economical sense for utilities to use this capacity if any extra exists and even more so for public, municipal and co-op utilities who receive some of the best rates from BPA today [52]. Therefore it is extremely beneficial to have BPA's facilities located near the wind generation sites.

After consideration of site location, site information, available wind data and load location it was determined that four sites were best suited for evaluation as suppliers to TPU. The sites chosen are located at Sevenmile Hill, Goodnoe Hills, Kennewick, and Vansycle Ridge. Of these four sites, three are part of the Wind Forecasting Network and one, Vansycle, is at an actual wind farm. Note that Vansycle has been used in two of the studies mentioned before, and Kennewick in one. Figure 3.2 below shows the geographic location of the wind sites and load; Table 3.5 lists the actual distances between the wind sites.

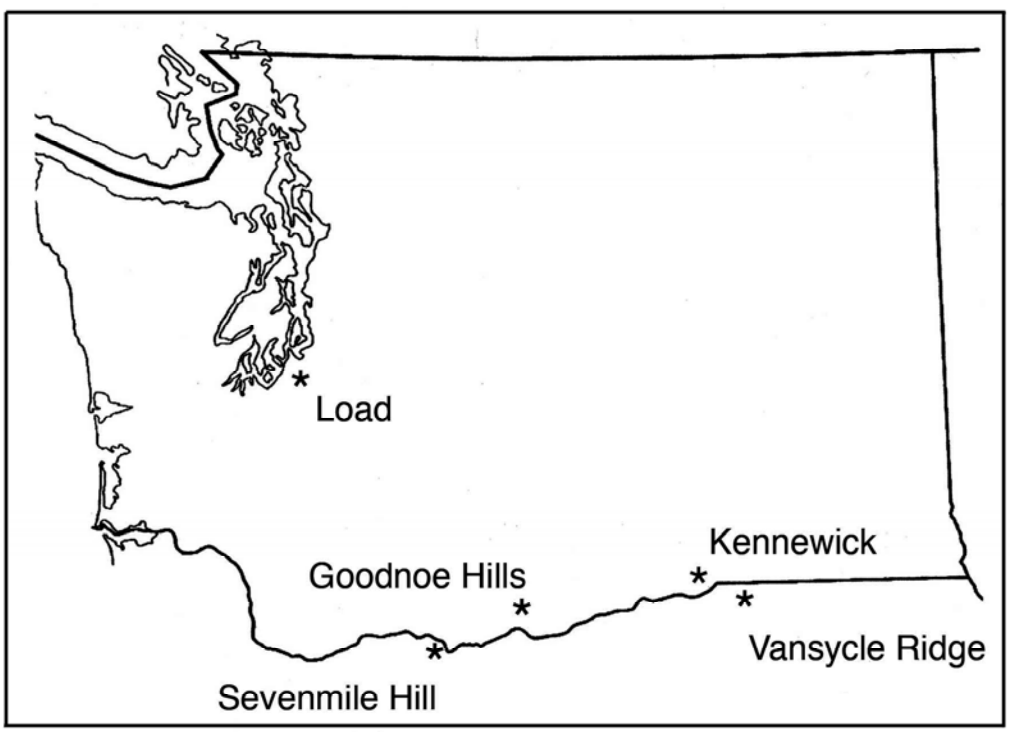

Figure 3.2 Wind site map

	Sevenmile	Goodnoe	Vansycle
Kennewick	107.9	72.3	23.6
Vansycle	126.5	91.1	-
Goodnoe	35.7	-	-

Table 3.5 Distances between wind farms
* All distances are in statute miles

3.4 Wind Data

Oregon State University's Energy Resources Research Laboratory (ERRL) was able to provide data from sites monitored by BPA's network [53]. The information obtained was divided into year and site with data at 10-minute intervals. The data was collected at 1-second intervals (except Vansycle which is 2-3 seconds) added together and averaged to form the 10-minute data. For example at time 12:10, the 1-second intervals from 12:05:00 to 12:14:59 are used. That is, the data 5 minutes before and the 5 minutes after 12:00, 12:10, and so on, were used in the determination of 10-minute data.

In the Northwest, there exist three bilateral markets for purchasing electricity futures: a forward (month to 1 year), day ahead, and real time. Day ahead and real-time purchases are made in hourly blocks [44]. Due to the fact that Northwest utilities schedule for loads no shorter than on an hourly basis, it is beneficial to turn the wind data into hourly information. Therefore the same averaging is used for the hourly data but using the 10-minute averaged data. For example at 1:00 am, the 10-minute intervals from time 12:40:00am to time 1:30:00am are used. That is, the 10-minute data 20 minutes before to 30 minutes after the hour were used in the determination of 1-hour data.

In structuring the data for analysis in Matlab, daylight savings was disregarded and time was unadjusted. The last day of 2004 was disregarded due to the extra day incurred by a leap year. This was done in an attempt to keep the data in a format that allowed for easy comparison across years and seasons. It is believed wind cycles can be seen most prevalently between seasons. Therefore it is beneficial to isolate these variations and not rely solely on yearly comparisons.

For the purpose of this thesis, spring will be defined as March, April, and May; summer as June, July and August; and fall as September, October and November. Winter will span two different years, as it will encompass December, January, and February. Therefore, winter 2003 would include December 2002, January 2003 and February 2003.

The most crucial assumption made in this study is that the four wind sites are acting together as a single generator. As previously mentioned, the diversity offered by the geographical dispersion of the generators is critical to the work in this thesis with respect to serving load. However, some comparisons will be made with regard to how one wind site compares either to another site or load.

It is important that at each hour of every day, data be available for all four generators. Therefore if even one site has data unavailable for an hourly data point, it will require that data for the other three sites at that time be disregarded. Table 3.6 shows the significant periods of data omission by wind site. One will notice that a majority of the missing data is during winter months. ERRL explained this was due in large part to icing that occurred on the instruments, which caused them to measure erroneous data.

Sevenmile	Goodnoe	Vansycle	Kennewick
Dec 3 - 10,2002	Nov 30 - Dec 10,2003	Jan 1 - Aug 2,2002*	Aug 30 - Sep 3,2002
Oct 22 - Nov 4,2003	Jan 9 - 12,2003	Nov 28 - Dec 10,2002	Nov 30 - Dec 8,2002
Dec 9 - 12,2003	Jan 19 - 22,2003	Jan 6 - 12,2003	Jan 9 - 11,2003
Dec 28 - 31,2003		Sep 8,2003 - Feb 23,2004*	Jan 19 - 22,2003
Jan 13 - 15,2004		Nov 19 - 24,2005	Nov 19 - 25,2005
Jan 1 - 5,2005			Dec 15 - 18,2005

Table 3.6 Prolonged periods of data unavailability
affecting seasonal and combined calculations
* Significantly affected seasonal data

An important evaluation that will be made in this thesis will be that of seasonal variations. To give the reader a better understanding of the data that will go into evaluating seasonal cycles, Table 3.7 is presented. This table indicates the yearly data from all four sites that was used for the seasonal calculations. Note that all the seasonal data is comprised of measurements from a minimum of three different years.

	Winter	Spring	Summer	Fall
2002	N/A*			X
2003	X	X	X	
2004		X	X	X
2005	X	X	X	X
2006	X	X	X	X

Table 3.7 Seasons used for seasonal calculations
* Some data unavailable

3.5 Turbine Data

The wind turbine used for modeling the wind farm output is the Vestas V80-2.0 MW turbine. This turbine was chosen due to the fact that a few of the larger, and more modern, wind farms in Washington use this type of turbine. The manufacturer of the wind turbine publishes a wind speed at the hub to generator output curve [41]. Figure 3.3 below is an estimate of the turbine curve using the assumption of four distinct linear functions. Specifically, note this wind turbine will cutout at 55.92 mph to prevent damage. Refer to the wind speed to output table (Table A.1) in the appendix for the exact values. By using the manufacturer's published curve, one can take into account the mechanical and electrical loses previously mentioned. This will leave only transformer and transmission losses unaccounted for, and will be assumed negligible.

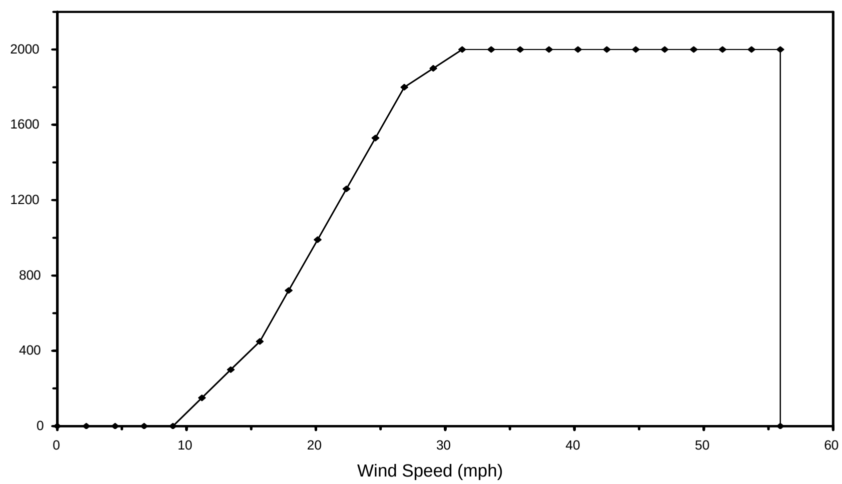

Figure 3.3 Wind turbine output curve [41]

Depending on the exact model, hub height variations come in 60, 67, 78, 85, and 100 m [41]. A hub height of 67m, or 221ft, will be used due to the fact PSE used this V-80 hub height at Wild Horse and Hopkins Ridge [4, 6]. As for the wind data obtained from BPA, each site measured wind data at different heights. Sevenmile was measured at 100 ft, Goodnoe at 195 ft, Vansycle at 201 ft, and Kennewick at 86 ft. To be able to compare how the wind sites perform in relation to each other, and to accurately model turbine output, the wind speed at common height had to be computed. The 1/7 power law was used to extrapolate this data to the 221 ft hub height. Similar methods have been employed in other studies using geographically dispersed wind monitoring sites [36-38].

$$V_x = V_m \left(\frac{H_x}{H_m} \right)^{\frac{1}{7}} \tag{3.3}$$

where:

V_x = velocity to be determined;
V_m = measured velocity;
H_x = height to be determined;
H_m = height of velocity measurement;

Wind speed's contribution to generator capacity factor is only a portion of a proper evaluation of a site. As was discussed earlier, wind generator performance is geographically dependent. A wind farm in the Northwest could have a capacity factor that is much less than a wind farm of equal capacity in the Great Plains (Table 3.8). To properly evaluate the value of a wind asset one must also look at the load it serves. Electric loads are geographically dependent also adding an extra level of complexity to finding the right combination of sites to serve a load.

Installation Date	Heartland	Texas	California	Mountain	Northwest	East	Great Lakes
1998-99	30.1%	30.0%	30.0%	35.2%	30.1%	-	19.6%
2000-01	32.6%	37.4%	37.4%	30.1%	29.5%	22.2%	23.8%
2002-03	34.6%	37.0%	30.3%	30.1%	31.1%	30.3%	21.9%
2004-05	38.7%	38.9%	34.2%	41.0%	31.5%	26.7%	32.3%

Table 3.8 United States 2006 capacity factors by region and installation date [34]

3.6 Defining Loads and Scaling Wind Sites

Load data form TPU was obtained from January 1, 2002 to December 31, 2006. The average load during this time was 545.6 MW with a peak demand of 962 MW and a minimum of 283 MW. This basic data is an important first step in the search for a properly sized wind farm with an appropriate capacity factor.

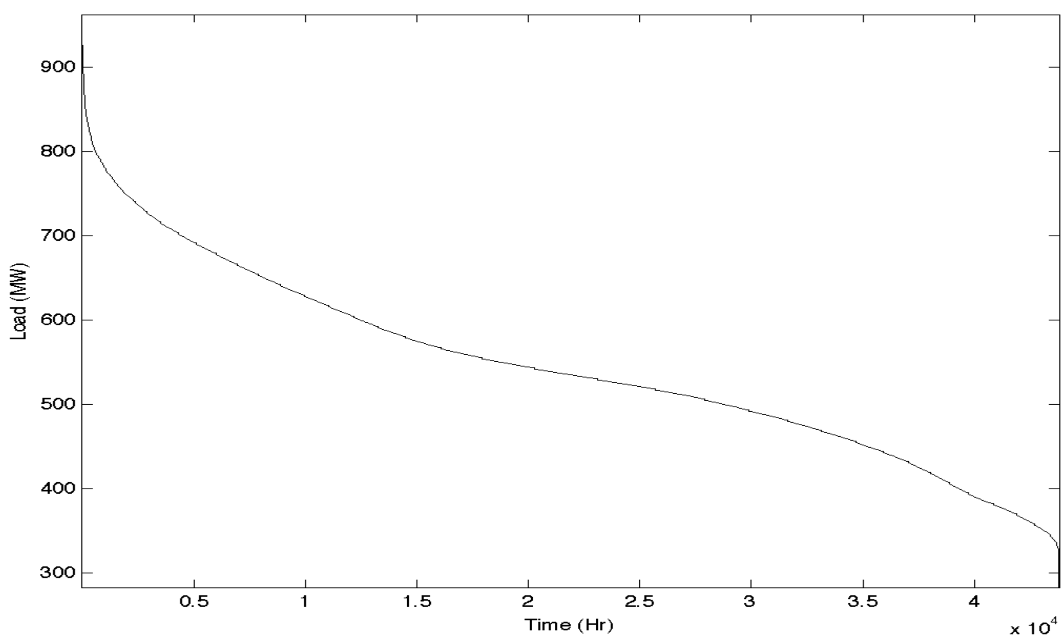

Figure 3.4 Tacoma Power load duration curve

Without looking at wind data, it is difficult to determine which of the four sites is best and therefore should receive the largest number of turbines. Recall only one set of wind speed data for each site is recorded. Therefore one can only precisely model four different wind turbines. The assumption will be made that if the wind farms are equal in size, the variations between the sites will correct for the linear scaling that was argued against by Y. Wan [42]. Given the typical size of a modern turbine located in the Northwest (Table 3.2) and a conservative estimate of 20% capacity, the model will use a wind farm size based on 15% of TPU's average hourly load. The reason for using 15% of TPU's average daily load is two fold. The first being a rough estimate is needed from which to start the model. The second of which is based on the Washington State RPS for year 2020 requiring 15% of average load be served by renewables.

$$F = \frac{P(L)}{(C)(W)(G)} \tag{3.4}$$

where:

P = percentage of load to be carried;
L = average daily load;
C = capacity factor of the wind park;
W = number of wind parks;
G = individual turbine capacity;

Using the Vestas V80-2MW model mentioned before, the total number of turbines at each site will number 50. This will equate to a total of 200 wind turbines for a nameplate capacity of 400 MW.

3.7 Analysis Plan

In Chapter 4, the data collected in this chapter will be used to create a wind farm model and to evaluate its performance based on the methods discussed in Chapter 2. The use of data from four different sites that are all of equal size is very important for the model used in this thesis. By ensuring all sites are of equal size the characteristics that define a single site will be prevented from weighting the calculations. In this respect, linearly increasing or decreasing the size of the generators will ensure equal weighting, while at the same time allowing for the evaluation of how well load is served. This will help lead to the overall goal of creating an accurate model using readily available information while at the same time allowing for the greatest flexibility in initial planning.

CHAPTER 4

Analysis

This chapter will present the analysis and findings of the wind and load data collected, and compare the results to those of the studies previously mentioned. Due to the fact that total wind farm production relies heavily on wind speed itself, the aggregate wind farm output will first be analyzed to determine if the hourly variations appear reasonable. The individual wind farm correlation coefficients will then be calculated both over the history of the data collected and seasonally. This, in addition to the aggregate calculation, will help determine if the wind farms display geographical dispersion. The final step in evaluating the wind farm generator characteristics regardless of load will involve calculation of the yearly and seasonal capacity factors. Particular attention will be made to seasonal variations to see if a cyclical behavior is observed. TPU's load data will then be scaled to 15% and load duration curves determined. The load will be analyzed to determine the correlation coefficient between year-to-year and season-to-season.

The second part of the analysis will involve comparing generation to TPU's load. The daily peak will be used to calculate a traditional LOLP along with an hourly LOLP, or HLOLP, using all hourly data. Having the LOLP will allow for a calculation of LOLE and effective load carrying capacity (ELCC). From this an LOLE and ELCC will be calculated both on a yearly and seasonal basis. Seasonal analysis will allow insight into the wind generators ability to serve load during different times of the year. Finally, the wind farms will be evaluated for their ability to meet the requirements of I-937. Different generator sizing scenarios will be ran to discover the amount TPU would need to meet near and long-term Washington State RPS requirements.

4.1 Variability

Hourly wind turbine variations were determined for the sites based on wind speed and the manufacture's output curve as mentioned above. At first only the individual wind sites were considered. Table 4.1 shows the average hourly step change for each site based on the percentage of nameplate capacity. As you can see, the step changes are larger in every case but case 3 when compared to the actual output of the 14-wind turbine scenario in the study conducted by Y. Wan [42]. Those results had an average step change of 7.0% at a single wind site for the 720-hour period (see Table 3.3). Knowing the time of year when Y. Wan conducted his analysis would have made for a more accurate comparison due to the fact that fall showed an average of 7.16% in this study, the closest in value of all the seasons.

	Winter	Spring	Summer	Fall	Combined
Seven Mile	6.7117%	8.0647%	6.4912%	7.1606%	7.1261%
Goodnoe	8.1749%	8.6798%	8.0949%	7.6041%	8.0977%
Vansycle	7.3487%	8.1659%	7.7192%	6.3813%	7.4648%
Kennewick	8.5562%	9.0057%	8.3231%	7.5128%	8.3283%

Table 4.1 Average hourly step change of total capacity for 1 site

Note that in the tables presented here that "combined" refers to all data collected for the site. But "combined" does not reflect all seasons divided by four. For example, August 2002 data points were used in the "combined" calculation but August 2002 was not used in the summer season calculation because June and July 2002 were not available and therefore would have weighted the overall summer calculation toward August. Also, recall 3 different years worth of winter seasons went into calculating winter, where as 4 years worth were used for spring, summer, and fall (Table 3.8).

Next, two wind site combinations were considered. Table 4.2 shows the step changes, which in every case but case 4 are less than the 7.0% of the 14-turbine scenario in Y. Wan's study. In some cases, it is even lower than the 6.4% of the 138-turbine single site that Y. Wan used. As you can see, the benefits of having geographical dispersion in this model begin to become evident.

	Winter	Spring	Summer	Fall	Combined
SM & GU	6.1515%	6.8547%	6.2869%	6.0767%	6.3445%
SM & VZ	6.0822%	6.7076%	5.9887%	5.6371%	6.1277%
SM & KZ	6.4871%	7.1347%	6.2597%	6.1995%	6.5208%
GU & VZ	6.6180%	6.9399%	6.5322%	5.7882%	6.4557%
GU & KZ	7.1045%	7.2336%	6.6474%	6.2268%	6.7561%
VZ & KZ	6.9311%	7.3432%	6.5865%	5.8672%	6.6860%

Table 4.2 Average hour step change of total capacity for 2 sites
* SM (Sevenmile), GU (Goodnoe), VZ (Vansycle), KZ (Kennewick)

Next, three wind site combinations were calculated and compared. As you can see the hourly step changes in every case are below the 138 turbine-single site case, and approaching the 5.3% calculated for the 250+ turbines found in [42].

	Winter	Spring	Summer	Fall	Combined
SM, GU & VZ	5.5874%	5.9866%	5.5622%	5.1029%	5.5605%
SM, GU & KZ	5.8180%	6.1736%	5.6456%	5.3857%	5.7402%
SM, VZ & KZ	5.8233%	6.2613%	5.5014%	5.1898%	5.6980%
GU, VZ & KZ	6.2030%	6.3752%	5.7681%	5.2561%	5.8740%

Table 4.3 Average hourly step change of total capacity for 3 sites

Finally, all four wind sites were combined and the results shown in Table 4.4. As you can see, only two step changes exceed Y. Wan's 250+ turbine output from 3 different sites (see Table 3.3) [42]. The combined average found here, was 5.2099% of rated capacity. This holds true whether a wind site contains 1 turbine or 100 turbines. One must ensure though, that each site maintains an equal number of turbines for this to be consistent or else the variations of a single site will weigh the results.

	Winter	Spring	Summer	Fall	Combined
SM, GU, VZ & KZ	5.3744%	5.6529%	5.1167%	4.7371%	5.2099%

Table 4.4 Average hourly step change of total capacity for 4 sites

The results show that the aggregate model, on average, has the least variation during the fall and the most during the spring. Table 4.5 below displays the standard deviation of these measurements. Winter shows the greatest standard deviation, with summer having the least. Due to the fact TPU is a winter peaking load, optimally the least deviation would occur during this period. Further analysis that includes the actual load is needed though, before any conclusions can be drawn.

	Winter	Spring	Summer	Fall	Combined
σ (% Capacity)	6.4%	5.9%	5.1%	5.3%	5.6%
$\pm 1\sigma$	.8576	.8289	.8138	.8409	.8357
$\pm 2\sigma$	.9483	.9355	.9372	.9392	.9400
$\pm 3\sigma$	.9790	.9717	.9772	.9766	.9757
$\pm 5\sigma$	.9959	.9953	.9960	.9962	.9958

Table 4.5 Cumulative frequencies of wind turbine step changes

Table 4.6 below directly compares the results obtained by Wan to those found in this thesis. Note the 14-turbine group is a portion of a single site containing the 138-turbine group and that the 250+ turbine group is spread over 3 different sites along Buffalo Ridge area. Both this work and Y. Wan's [42] are in stark contrast to the results of the Nordic study [40]. The standard deviation across all four countries in that study was 14.5% of the rated capacity. In any case, one can confidently conclude by this first analysis that the model in this thesis is performing in manner that is consistent with these earlier studies due to the relatively small variations.

	14 Turbines*	138 Turbines*	250+ Turbines*	Model
σ (% Capacity)	10.7%	9.7%	7.9%	5.6%
$\pm 1\sigma$	.78389	.78813	.78629	.8357
$\pm 2\sigma$	.94628	.94462	.94601	.9400
$\pm 3\sigma$	.98307	.98339	.98419	.9757
$\pm 5\sigma$	.99831	.99823	.99803	.9958

Table 4.6 Hourly wind turbine step change standard deviation and cumulative frequency of change * [42]

4.2 Wind Turbine Measurements

As pointed out before, it is important that each wind site receives the same number of wind turbines to ensure the model's accuracy. This will help smooth drastically large variations between hours as seen in Tables 4.1 and 4.2, and to help ensure the study keeps with the idea of geographic dispersion. The sites were modeled as though they each had 50 (2 MW) wind turbines to prevent the output of a site from weighting the data toward a single wind farm. The output of the total wind generation mix, by history and season, are displayed in the generation duration curves (GDC) below. The data range includes August 2002 through December 2006.

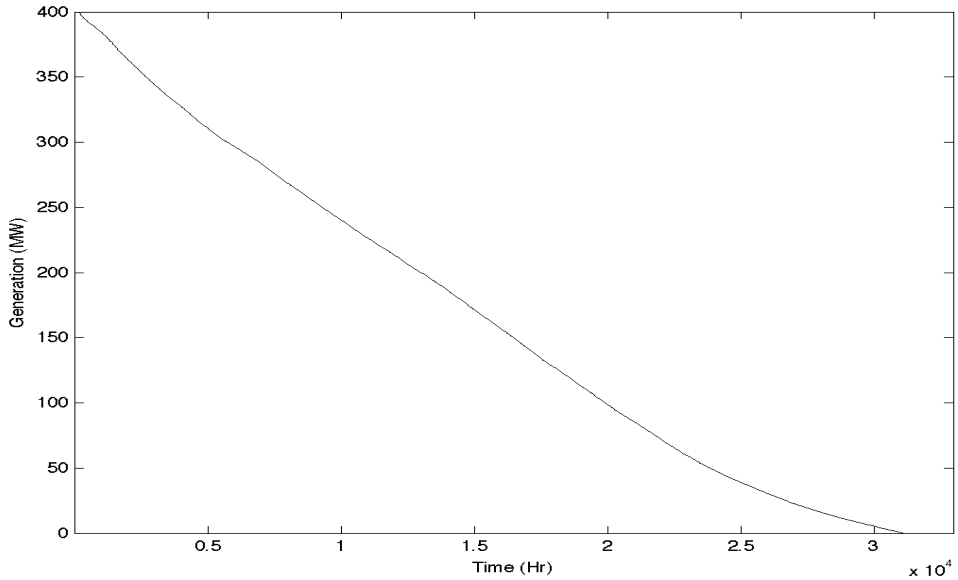

Figure 4.1 Combined GDC from Aug. 2002 through Dec. 2006

The aggregate GDC displayed in Figure 4.1 represents 32,968 hours of data. The term “combined” is specifically used due to the fact that it retains 1,457 hours of data that is not used in the seasonal scenarios. The reason for using the extra 1,457 hours will be for use in calculations of inter-annual and site statistics. Every available piece of data is used to ensure the analysis is as accurate as feasibly possible. Note in Figure 4.1, wind generation equals 0 MW for 1,847 hours, 400 MW for just 162 hours, and is below 150.2 MW or 37.6% of capacity for half of the time.

	2002	2003	2004	2005	2006	Combined
Hours Used (Hours Possible)	3,175 (8,761)	5,738 (8,761)	7,298 (8,761)	8,241 (8,761)	8,516 (8,761)	32,968 (43,805)
Total GWh Generated	438.5	1,011.4	1,232.5	1,298.5	1,323.0	1,410.6*
Avg MWh	138.1	176.3	168.9	157.6	155.4	160.9

Table 4.7 Yearly wind turbine statistics
* Average per year

To fully understand the dynamics of the wind farms one needs to take into account inter-annual variations. Table 4.7 shows that as the years progressed more and more data was available for analysis (hours possible). As mentioned before only the last five months of 2002 were collected, compared to all but 245 hours that were included in 2006. This obviously weights the historical data more toward the later years of the analysis. Due to this fact, only the last two years of data really provide enough information to properly analyze inter-annual variations. Although this is true, inter-annual statistics will still be presented to allow for as much analysis as is practically feasible.

One way to narrow the data and allow for more data points to remain is to evaluate according to season. Any season that does not contain at least 90% of the hours possible will be omitted. When this is done 95.8% of the data points are used over 15 different seasons as compared to the 75.3% used over 5 years in the annual analysis. As reported by ERRL, the major reason for lost data points was due to icing that occurred on the measurement instruments [50]. This obviously would result in more winter season points lost than in any other season. Having more winter data lost not only affects the winter characteristics shown here, but also weights the "combined" data more towards the three other seasons. Refer to Tables 3.7 and 3.8 for more detail on prolonged periods of data omitted and seasons used.

The additional benefit of using seasonal data is the ability to analyze seasonal variations, with which the load also varies. This is in addition to the fact Washington State obtained 69% of its electricity form hydro projects [13], which are also seasonally dependent. An inter-annual comparison can also be obtained, but on a seasonal basis rather than the full year. Figures 4.2 to 4.5 below show the seasonal GDC's for aggregate wind generation by season.

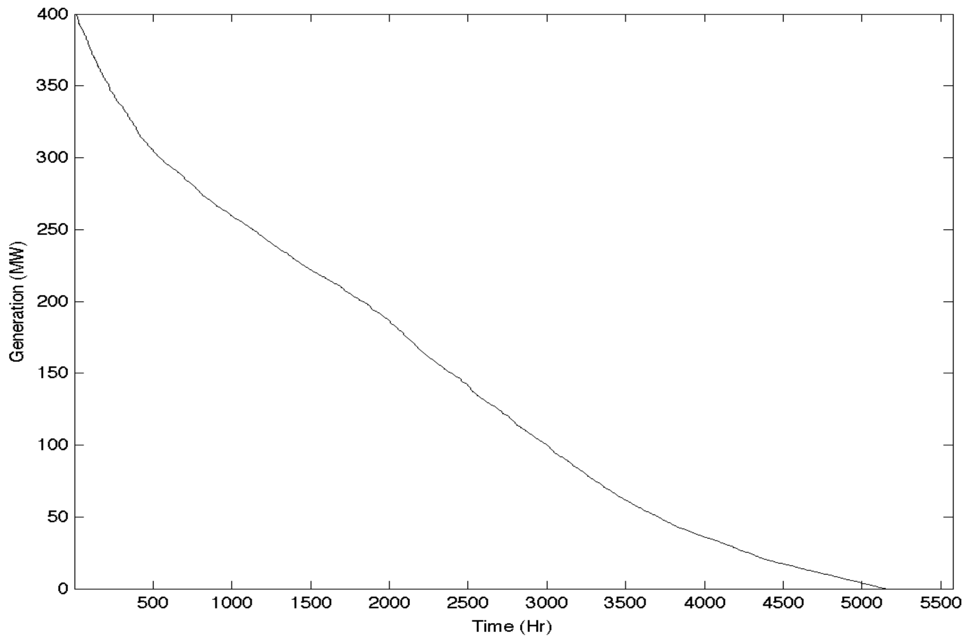

Figure 4.2 Total GDC for winter seasons 2002/03, 2004/05, and 2005/06

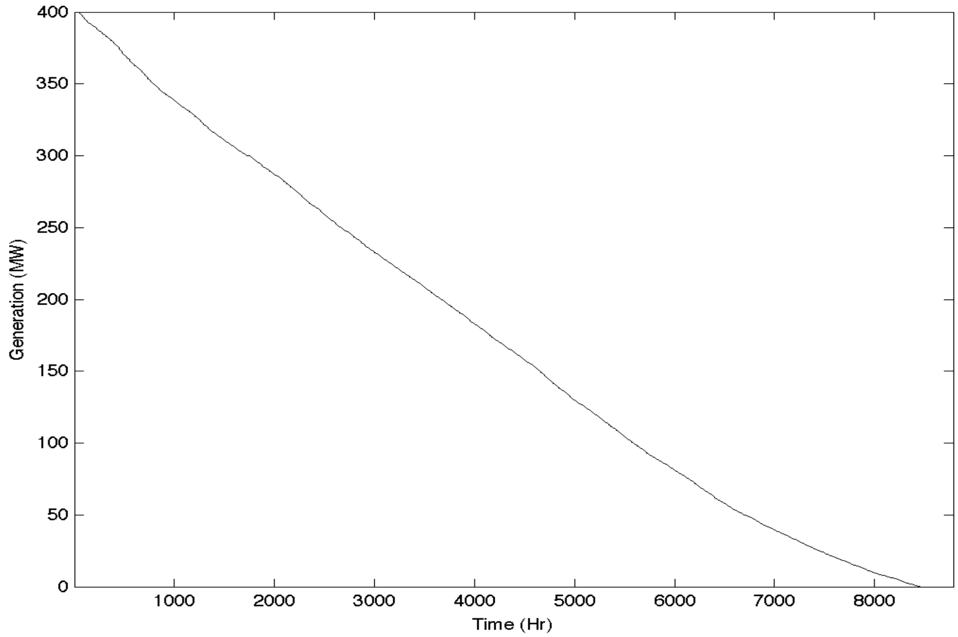

Figure 4.3 Total GDC for spring seasons 2003,’04,’05, and ’06

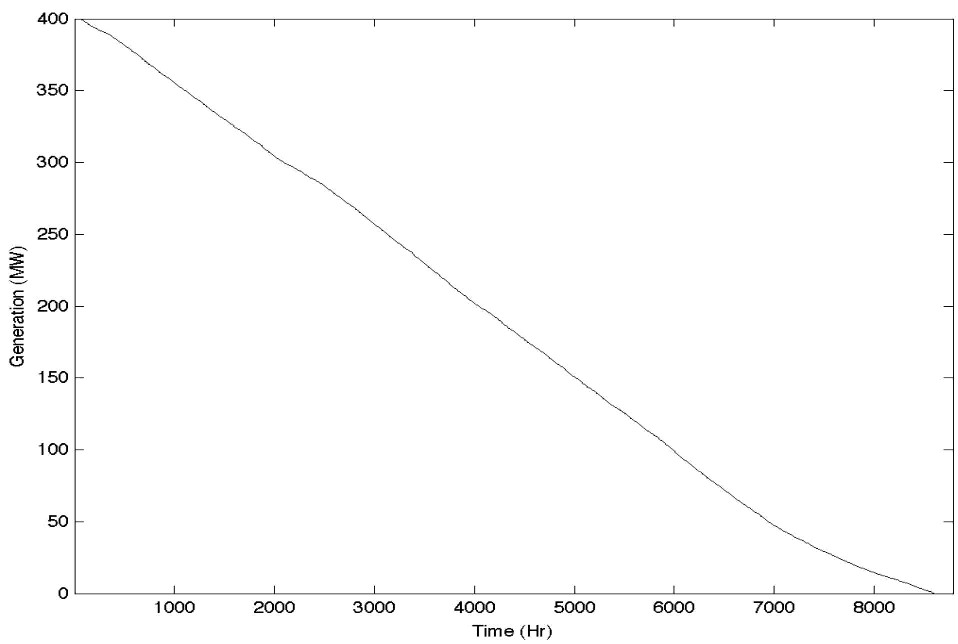

Figure 4.4 Total GDC for summer seasons 2003,’04,’05, and ’06

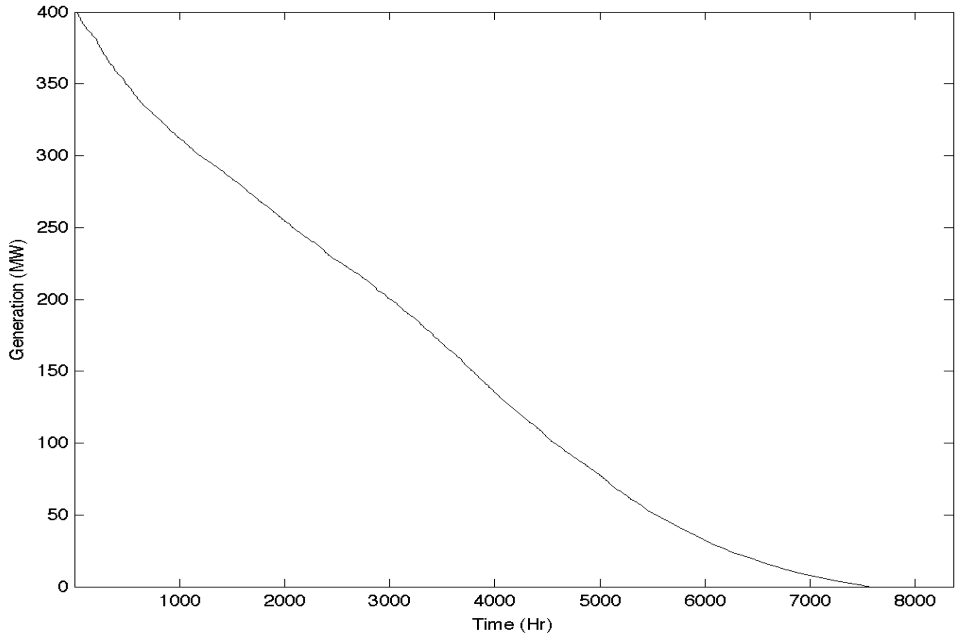

Figure 4.5 Total GDC for fall seasons 2002,'04,'05, and '06

Table 4.8 below displays how energy production changes with the seasons. Summer shows the most promise by outperforming the other seasons in every category. Fall spent the largest percentage of time at 0 MW (9.5%) and the least at 400 MW (7.6%); but winter had the worst average megawatt-hour and median megawatt-hour. Equation 4.1 shows how total GWh generated per season, on average, was calculated.

$$S_{avg} = \sum_{i=0}^{n} P_i * \frac{m}{n} \qquad (4.1)$$

where:

P_i = power output at hour i;

n = number of hours measured;

m = number of days in the season;

Season (Days/Year)	Winter (90)	Spring (92)	Summer (92)	Fall (91)
Hours Used (Hours Possible)	5,576 (6,486)	8,786 (8,836)	8,787 (8,836)	8,362 (8,740)
Hours at 0 MW	421	328	187	796
Hours at 400 MW	14	51	68	26
Mean MWh	136.6	170.6	185.7	145.0
Median MWh	116.5	163.8	182.5	124.0
Total GWh Generated per Season on Avg.	12.2899	15.6926	17.0885	13.1909

Table 4.8 Seasonal wind turbine statistics

4.3 Wind Turbine Correlations

The wind farm correlations were next calculated and each site was compared. Table 4.9 displays the results of the calculations, which are relatively low. Looking back to Table 3.5 the distances between SM (Sevenmile) and GU (Goodnoe) was 35.7 miles and between VZ (Vansycle) and KZ (Kennewick) which was 23.6 miles. The mean distance between these two groups was almost 100 miles. This helps to explain the high combined correlation between SM and GU, which was 0.633, and VZ and KZ, which was 0.6875. The lowest correlations across all seasons were between SM and KZ (107.9 miles). The largest distance was between SM and VZ (126.5 miles), which had a correlation coefficient that was the next lowest across all four seasons.

	Winter	Spring	Summer	Fall	Combined
SM/GU	.5872	.6324	.6660	.6151	.6330
SM/VZ	.3065	.3551	.4425	.3838	.3428
SM/KZ	.1803	.2211	.3210	.2221	.2063
GU/VZ	.5421	.6171	.6483	.6837	.6176
GU/KZ	.4434	.4962	.5749	.5298	.5035
VZ/KZ	.6893	.6785	.6712	.7221	.6875

Table 4.9 Wind farm turbine correlations

Winter consistently received the lowest correlation coefficient across the sites with the exception of Vansycle to Kennewick, which happens to also be the highest of all winter correlations. This is not too surprising given the fact it is the shortest distance between any two stations. The lowest correlations in effect show a greater independence of the wind sites during the winter. This bodes well for TPU, which sees the largest electrical loads during the winter season. Summer shows the largest correlation in every case but two, GU/KZ and VZ/KZ. These measurements help to show that correlations cannot be made simply by distance measurements, but that seasonal variations need to be taken into account.

Recall that in the Nordic study [40] the correlation coefficient was 0.42 - 0.45 for Sweden/Norway/Finland and 0.22 - 0.33 for Denmark/Finland/Norway. This study dealt with distances much greater than the Columbia River sites and would explain why lower coefficients were observed. Recall also equation 3.2 from that study, if used in this study a correlation coefficient of between 0.67 - 0.93 would have been measured. This of course is not the case and it is believed this is due to the greater distances that were used in the Nordic study. The geographical area of the four countries involved was roughly the size of 1,060 by

680 miles. However, these two studies do show that in fact there is a lessening of correlation with geographic dispersion. Unfortunately, as dispersion becomes greater so to does the amount of planning and costs to integrate.

A study conducted by Hirst and the Bonneville Power Administration found an average correlation coefficient of 0.56 using actual generation data from four sites in the same general area of the Columbia River [43]. The data was gathered over four months starting in January 2002. Therefore a direct comparison between the seasonal data calculated here and Hirst's is not possible. Still, if all of the correlation coefficients found in the seasonal data were averaged using both winter and spring, a coefficient of 0.48 would be found, which compares well to the previously mentioned number.

4.4 Wind Turbine Capacities

Having shown that the hourly variations are reasonable and correlations are acceptable and given the geographic constraints, the capacity factors were next calculated. Each site's capacity factor was derived along with all sites acting as a single generator. The term "all" reflects the sum of all sites divided by four due to the way in which the erroneous data was dismissed. As mentioned before, "combined" does not reflect all seasons divided by four. Refer to Tables 4.7 and 4.8 for the number of hours used in calculating the capacity factors.

The results show that the combined wind farm over the fours seasons has a capacity of 40.22% of rated output capacity. Sevenmile and Goodnoe show the greatest capacity factor in the summer and both were lowest in the winter. The combined value for Sevenmile shows the greatest capacity, while Goodnoe's shows the least. Further east at Vansycle, the capacity factor is lowest in the fall and highest in the winter. Kennewick also experiences a sudden change where the spring is highest and the summer the lowest. In the case of all wind sites acting together, the peak is in the summer and the low is in the winter.

	Winter	Spring	Summer	Fall	Combined
Sevenmile	20.6%	41.2%	64.4%	35.5%	42.5%
Goodnoe	29.2%	38.1%	42.7%	30.6%	35.6%
Vansycle	43.3%	43.1%	40.1%	39.0%	41.0%
Kennewick	43.4%	48.3%	38.6%	39.8%	41.9%
All	34.1%	42.6%	46.4%	36.2%	40.2%

Table 4.10 Wind site capacity factors as a percentage of rated capacity

Looking back to the correlation of the wind farms, the majority of seasonally high correlations occurred during the summer, which has the highest capacity factor when all sites are added. The opposite is true for the winter where a majority of the lowest seasonal correlations occurred, and winter was also the lowest capacity factor season. This seems to lead to a result that shows seasons affect correlation and capacity. Capacity is the highest when wind is consistently high. The data shows, by extension, that consistently higher summer winds will cause the greater correlation seen during the summer, between the wind farms.

Figure 4.6 below shows the historical relative frequency of the output of all the wind farms together. When compared to Figures 4.7 through 4.10 one can see how geographic dispersion can create a more even wind resource output.

Recall that the median output of all the wind farms together was 150.2 MW. Figures 4.7 - 4.10 show that the individual wind farms spend a majority of their time either below 20% or above 90% of rated capacity.

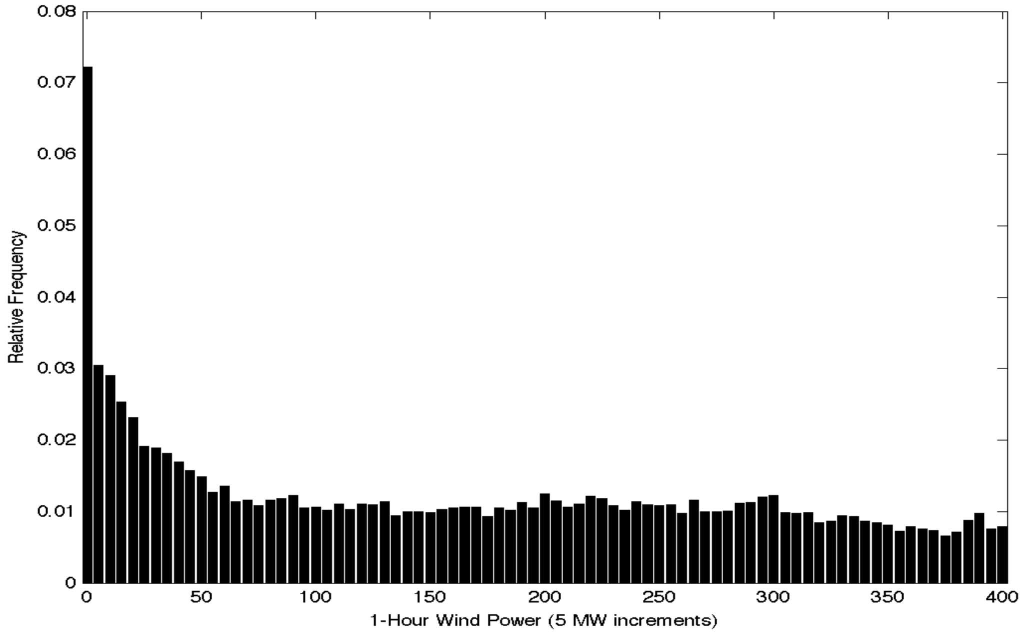

Figure 4.6 Relative frequency of total wind farm output from Aug. 2002 to Dec. 2006

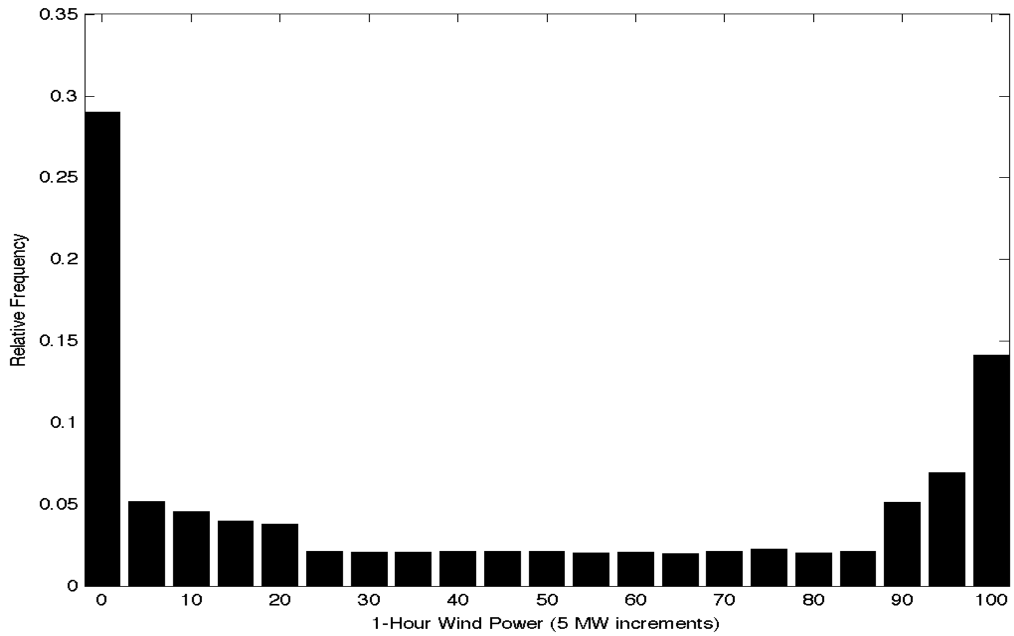

Figure 4.7 Relative frequency of Sevenmile wind farm output from Aug. 2002 to Dec. 2006

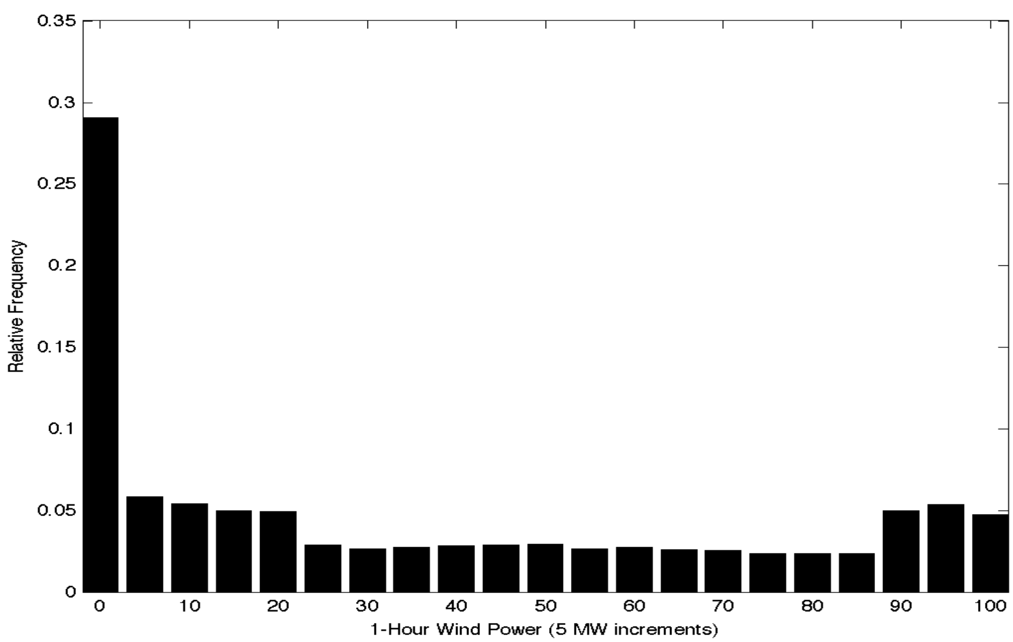

Figure 4.8 Relative frequency of Goodnoe wind farm output from Aug. 2002 to Dec. 2006

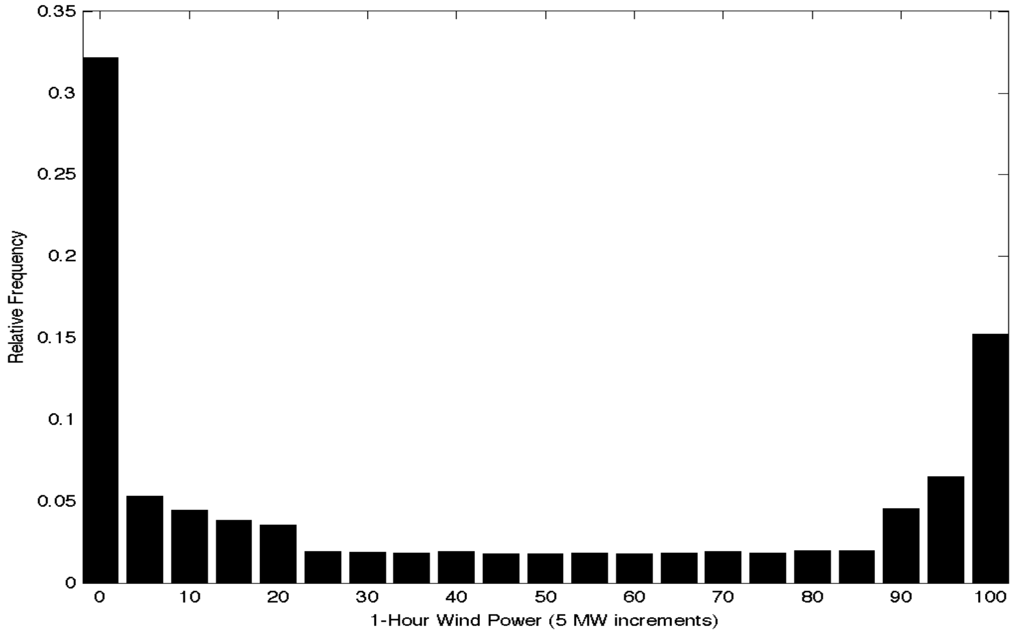

Figure 4.9 Relative frequency of Vansycle wind farm output from Aug. 2002 to Dec. 2006

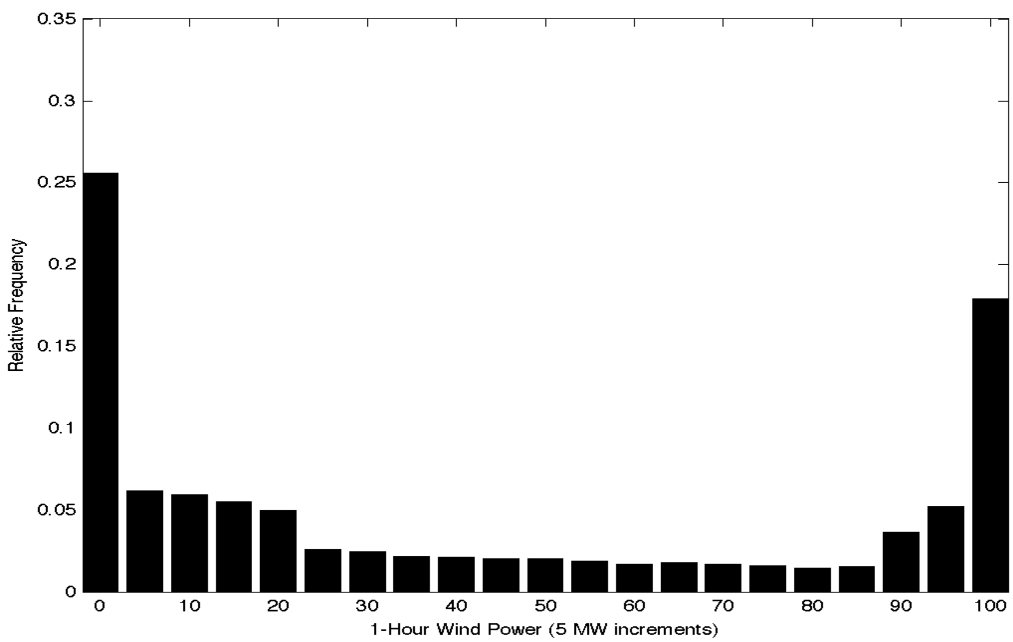

Figure 4.10 Relative frequency of Kennewick wind farm output from Aug. 2002 to Dec. 2006

Referring back to Figure 3.1 from the EnerNex study, the graph produced was based on a model using a theoretical 50 MW wind farm at Kennewick and an actual 50 MW wind farm at Vansycle. Note the similarities of Figure 3.1 to Vansycle and Kennewick above. It could be said that if the two were combined to form a single generator as in the EnerNex study, the results would look even more similar.

With the exception of Goodnoe, in every case the maximum (100 MW) output occurred with the second greatest frequency. Goodnoe also displayed the lowest capacity factor of all sites. Both Vansycle and Kennewick show the greatest polarity in their output and could be due to their common geographical area location in the eastern part of the state.

Overall the capacity factors seem to be quite good. The question is if perhaps they may be too good? Hirst's study found an overall capacity factor of 32% from the actual output of four wind farms in the same general locations [43]. The study was conducted from January 2002 through April 2002. Unfortunately this thesis had to discard this time period because of the unavailability of data from Vansycle, which happens to be included in his study. Hirst reported monthly capacity factors of 33%, 22%, 38%, and 32% for each of the four months in sequential order. If the first two months were averaged, 27.5% would result and could be compared to the winter average calculated here, which was 34.1%. In the same respect one could average the last two and find 35% and compare this to the spring average found here of 42.6%. One can see that the values calculated are about 7% larger than those reported by Hirst [43].

For the sites in the Hirst study, a capacity factor of 42% at Vansycle, 31% at Condon, 20% at Stateline, and 33% at Klondike were reported over the study period [43]. This thesis calculated a winter average at Vansycle of 43.3% and a spring average of 43.1%. Kennewick is not too far form Stateline but this thesis shows a much higher capacity in winter at 43.4% on average, and 48.3% on average in the spring (see Table 4.10). If these two were averaged together 45.8% would result, which is 25% greater than Hirst's findings [43].

Sevenmile and Goodnoe reside at the western end of the study area near Klondike, which was reported at 33%. On average, this thesis found that Sevenmile's capacity was at 20.6% in the winter and 41.2% in the spring. If the two are averaged together 30.9% would result. The percentages discussed here are shown in Table 4.11 for easier comparison. Goodnoe averaged a 29.2% capacity for winter and 38.1% for the spring. If these two are averaged together 33.7% would be found (see Table 4.10).

Much discussion is dedicated to the Hirst study here due to the fact it reports actual wind farm capacity factors in the same geographical areas. If the model presented in this thesis is accurate for preliminary planning, it should compare well to actual capacity measurements. Table 4.11 below shows that this is true when the previous discussed averaging is taken into account. In every case the capacity factors are close to those actually measured with the exception of Kennewick. Keep in mind also that the turbines used in this thesis are newer and larger. Therefore an increase of up to 2% for capacity factor would be reasonable [34].

	Capacity Factor
Vansycle*	42%
Vansycle	43.2%
---	---
Stateline*	20%
Kennewick	45.8%
---	---
Klondike*	33%
Sevenmile	30.9%
Goodnoe	33.7%

Table 4.11 Comparison to Hirst's study [43]
*From nearby actual output

Hirst's study also considers only a single year, where as the numbers reported from this model in Table 4.11 are from 3 and 4 years of data. As further evidence that wind capacity can vary, even between year to year for a specific period, Table 4.12 is presented below. The data was obtained from the Electronic Wind Performance Reporting System for the state of California [18]. As you can see the actual capacity factors can vary by as much as 39% between quarters in a given year and as much as 13% between years for a given quarter. This helps illustrate that in fact seasonal variations are much more extreme than inter-annual variations and warrant closer analysis. Note also, the 2nd and 3rd quarters consistently outperform the 1st and 4th.

	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	Total
2004 (.7 MW)	26%	52%	34%	17%	32%
2004 (1.8 MW)	16%	52%	55%	18%	35%
2005 (.7 MW)	22%	47%	35%	26%	32%
2005 (1.8 MW)	11%	38%	49%	16%	29%

Table 4.12 California capacity data for 90 (1.8 MW) and 96 (.7 MW) turbines [18]

The model presented in this study has the inter-annual seasonal variations shown in Table 4.13. Although data is missing for full analysis, one can see a pattern of spring and summer out performing winter and fall. As you can see the capacity factors can vary by as much as 19.7% between seasons in a given year and as much as 10.4% between years for a given season.

	Winter	Spring	Summer	Fall
2002	-	-	-	31.5%
2003	35.3%	47.3%	47.3%	-
2004	-	44.9%	46.8%	37.6%
2005	28.7%	41.5%	48.4%	38.4%
2006	38.6%	36.9%	43.3%	37.5%

Table 4.13 Model seasonal capacity variations as a percentage of rated capacity

Referring back to the individual site output frequency, a similar study conducted by Milligan and Berger [54] used three years of data collected from 2001 through 2003 at various sites by the Platte River Power Authority. The data obtained was both wind speed and turbine output data. The wind data was converted to hourly wind turbine output using current wind turbine technology characteristics to simulate a 100 MW and 500 MW wind farm. The actual turbine output data was produced by older model turbines and was only used to check the reasonableness of the wind to power model data.

Using a modern 1.5 MW turbine at an assumed hub height of 80 meters the authors calculated a capacity factor of 43%. Figure 4.10 below shows the frequency of turbine output for the 100 MW scenario. To simulate the 500 MW wind farm, the model was simply multiplied by a factor of five. The authors found that the wind plant was idle 24% of the time and produced between 90 MW and 100 MW for 30% of the time. The size of the area used in the Milligan and Berger study was unable to be determined, but the frequency of output curve does show a very close resemblance to the single site output modeled in Figures 4.7 through 4.10 for this thesis [43].

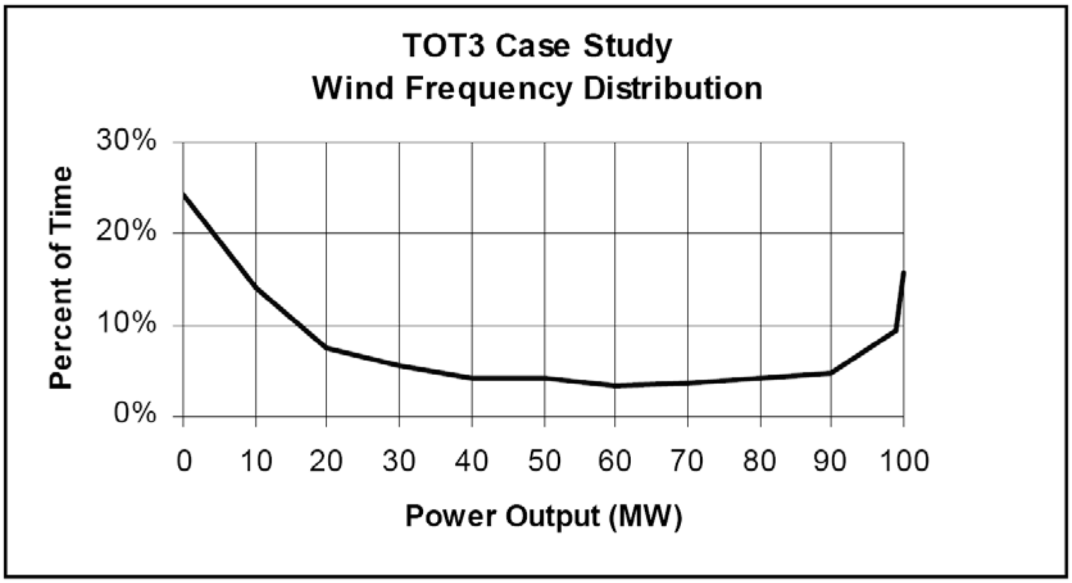

Figure 4.11 Platt River Power Authority output frequency [54]

4.5 Load Characteristic

With the wind turbine data collected and analyzed, the next step is to analyze the load data. As mentioned in chapter 3, TPU's load will be scaled to 15% to allow for hourly variations in load to be maintained and for RPS requirements. The scaled load by history and season are displayed in the load duration curves (LDC) below (Figures 4.12 - 4.16). The historical data range includes January 2002 through December 2006. Recall that the "combined" data for the GDC included only data from August 2002 through December 2006 and therefore a shorter time period than the "historical" load data. Due to the fact that all load data is good and that generation data spanned well over four different years, a decision was made to keep all load data during the calculation of LOLP for the historical portion.

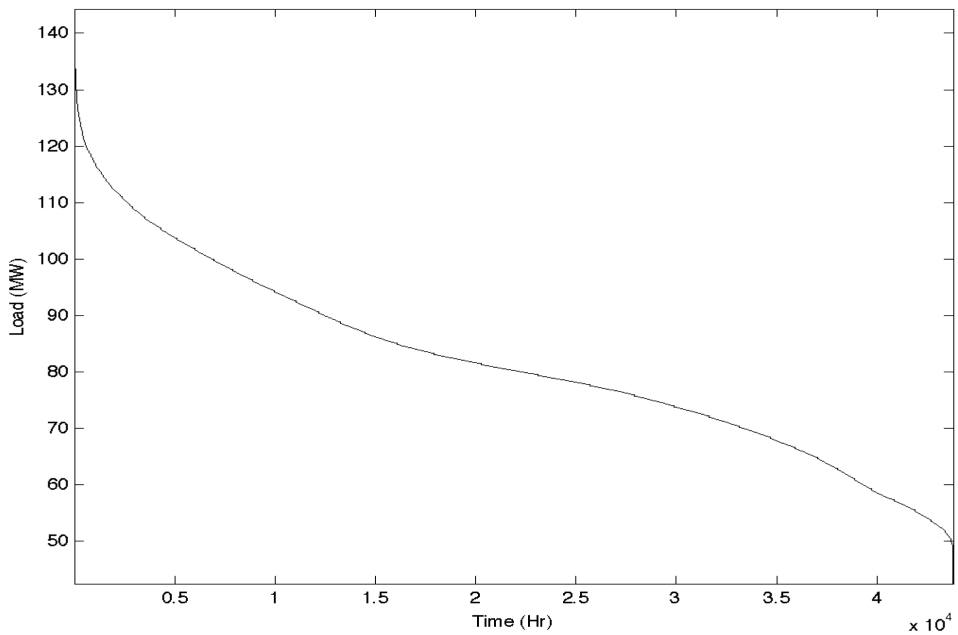

Figure 4.12 Scaled Tacoma LDC from Jan.
2002 through Dec. 2006

The total LDC displayed in Figure 4.10 represents 43,800 hours of data. Again the term "historical" is specifically used here versus "combined" due to the fact that it retains all five years of data. Every effort has been made to ensure all usable data is retained. For historical load, demand is never below 42.5 MW, never above 144.3 MW, and is below 79.4 MW half of the time. Recall the wind farm output is above 150.2 MW half of the time. Initially it seems we may have over valued the amount of generation needed to serve TPU's load. The load for the winter season (Figure 4.13) is relatively high with a maximum of 132.2 MW, a low of 56.7 MW and half the time it is above 96.6 MW. The spring season (Figure 4.14) shows a lowering of the load, compared to the winter, with a minimum of 50.4 MW, a high of 127.5 MW and is below 80.0 MW half the time. The load for the summer season (Figure 4.15) is relatively light with a maximum of 95.1 MW, a low of 48.0 MW and half the time it is below 72.6 MW. Summer seems to be the most skewed and therefore the hardest to predict. But load is relatively light, making generation planning somewhat easier. The fall season (Figure 4.16) shows a rising of the load compared to the summer with a minimum load of 48.6 MW, a high of 144.3 MW and is below 79.7 MW half the time.

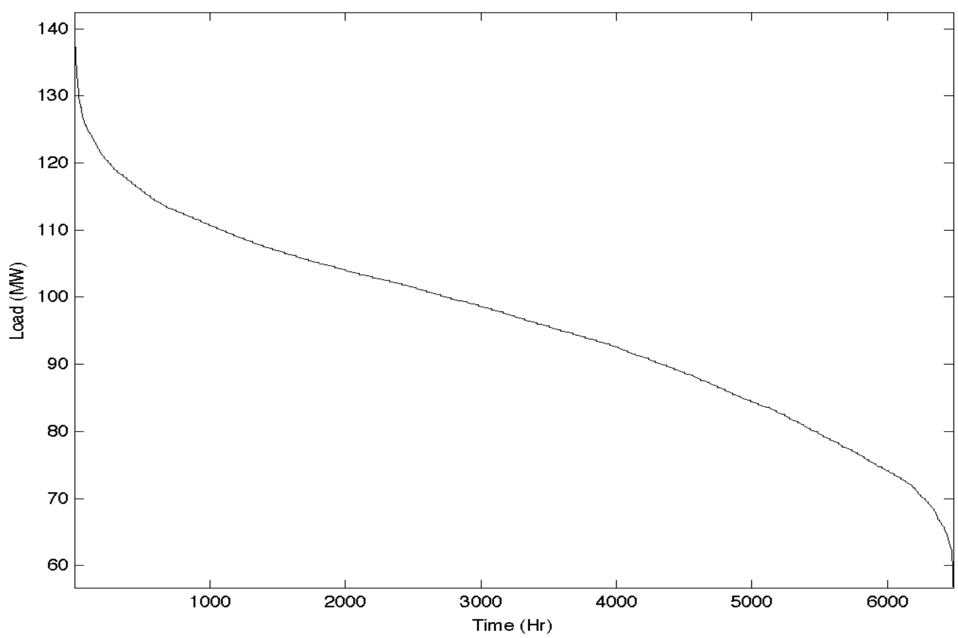

Figure 4.13 Scaled Tacoma LDC for winter seasons 02/03, 04/05, and 05/06

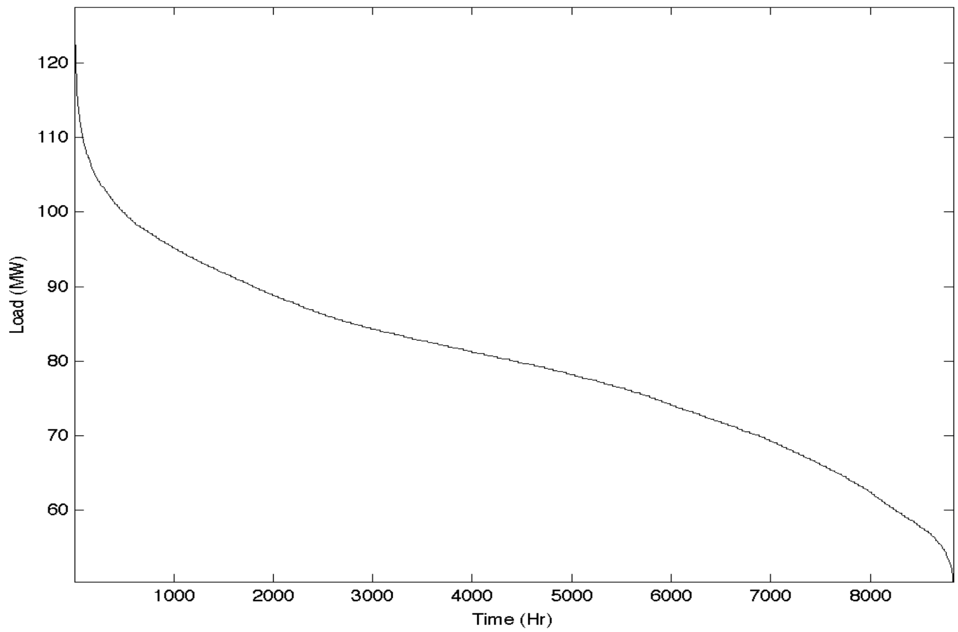

Figure 4.14 Scaled Tacoma LDC for spring seasons 2003, ’04, ’05, and ’06

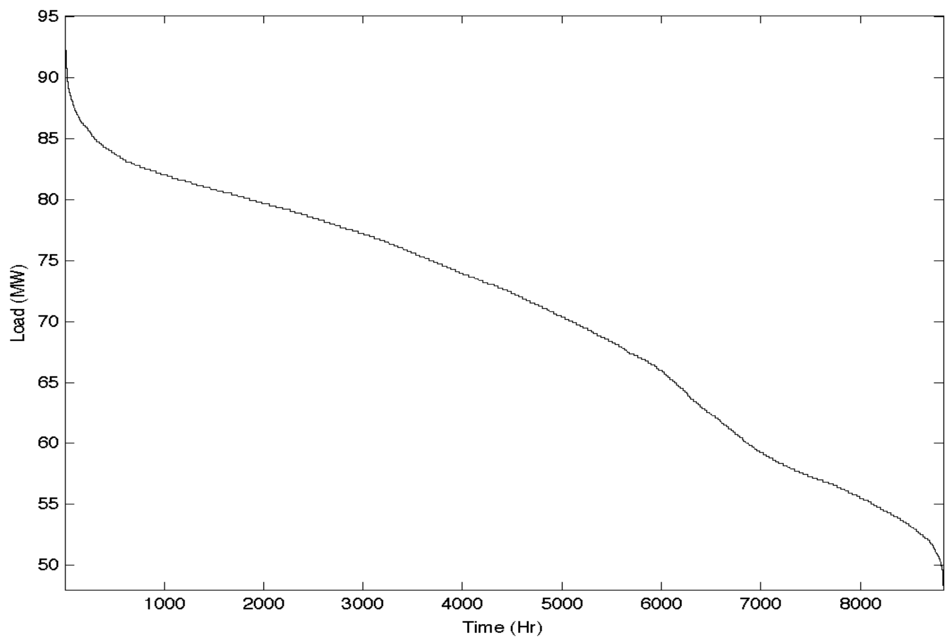

Figure 4.15 Scaled Tacoma LDC for summer seasons 2003, ’04, ’05, and ’06

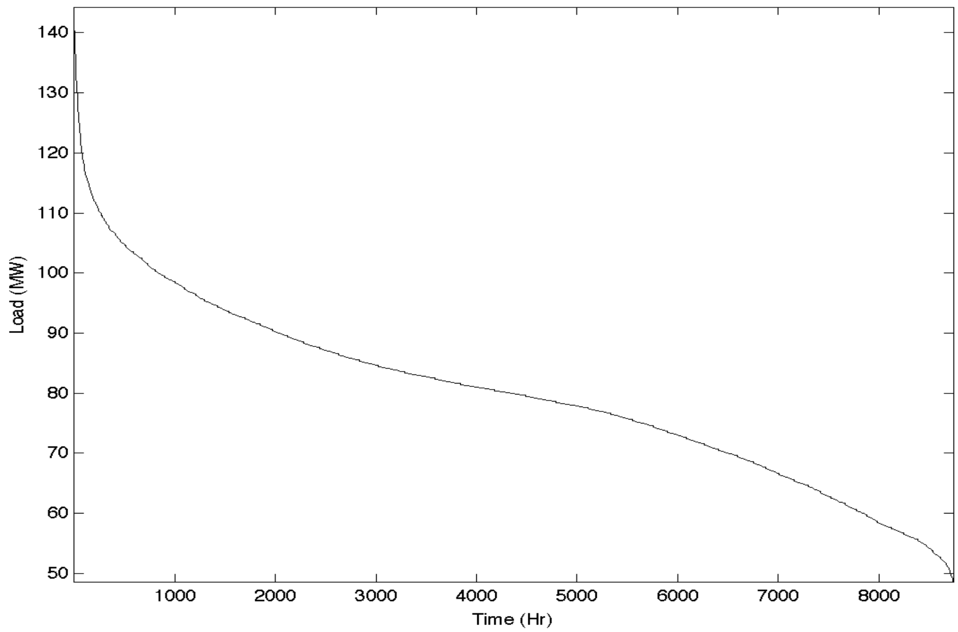

Figure 4.16 Scaled Tacoma LDC for fall seasons 2002, ’04, ’05, and ’06

Returning to the results of the historical load data, quick analysis will find that the wind farm is below 42.5 MW, minimum load, 25.3% of the time. Recall that the median value of generation for the combined data is 150.2 MW and load never exceeds 144.3 MW. Therefore at least half the time, the wind farms will be producing at a level that is in excess of load. By the same line of reasoning, at least 25% of the time the wind farm is producing at a level that is below the load. One can preliminarily see that trying to obtain an LOLP less than 0.0274%, or LOLE of one day in ten years, would be extremely difficult. If one refers back to section 4.2, you will recall that the model predicts no output for 1,847 hours out of the total 32,968 hours studied. This results in a minimum LOLP of 5.6% no matter how large the wind farm is scaled to, as long as the load never goes below 1 MW.

This, however, should not dissuade one from further analysis of the model. Valuable knowledge can still be gained through the further analysis of the load's seasonal characteristics. This will lead to the next step of allowing a comparison of wind farm to load on a yearly and seasonal basis; and then finally to the model ELCC and level required for Washington State's RPS.

Table 4.14 below displays the annual load statistics for TPU's scaled load. Due to the fact that all hourly loads were used for each year, the load shows a slight increase for the most part over the period. Table 4.15 below shows the seasonal loads. As expected the demand peaks in the winter and is the least in the summer.

	2002	2003	2004	2005	2006	Combined
Total GWh of Load	708.1	703.2	710.3	723.4	740.3	3,585.3
Mean MWh	80.8	80.3	81.1	82.6	84.5	81.8

Table 4.14 Yearly load statistics

	Winter	Spring	Summer	Fall
Total GWh Load per Season	207.8	176.3	156.1	174.9
Mean MWh	96.1	79.8	70.7	80.1
Median MWh	96.6	80.0	72.6	79.7

Table 4.15 Seasonal load statistics

Due to the fact a wind turbine generator's output varies, it is important to understand how the load varies also. The idea is that a more predictable load during higher load seasons is most desirable. This is especially true when trying to accurately size the generator to serve the load as efficiently as possible. The annual and seasonal load correlation coefficients were determined and the results displayed in Table 4.16. As one might expect, the annual correlations between two successive years were, for the most part, the highest in each case. This shows that there is some degree of repeatability in the annual data, which allows for better load prediction. In every case but three, fall showed the highest correlation between any two years. On average winter showed the least correlation across years. Recall the wind farms showed the least correlation during winter also. Having the lowest correlation during the highest load season will add more difficulty in trying to properly size a wind generator to this load.

	02/03	02/04	02/05	02/06	03/04	03/05	03/06	04/05	04/06	05/06
Yearly	.8397	.7987	.7442	.8251	.8465	.7947	.8014	.8080	.7999	.8474
Winter					.6734*	.6487*	.6118*	.6992*	.5871*	.6439*
Spring	.8094	.7461	.6071	.7697	.8222	.6343	.7033	.6303	.7019	.7370
Summer	.8578	.7349	.6987	.7432	.8680	.7369	.7507	.7385	.7553	.8392
Fall	.8426	.7616	.7657	.7782	.8425	.7863	.7390	.8192	.7503	.8676

Table 4.16 Yearly and seasonal load correlation coefficients
*Winter 03/04 is Dec 2002-Feb 2003 compared to Dec 2003-Feb 2004 etc.

4.6 Wind Turbine to Load Comparison

Next the wind generation and load will be compared to help understand the extent to which this renewable energy can help to serve a portion of TPU's load. Table 4.17 below displays the results of the correlation coefficient (χ) between load and generation as well as energy not served (ENS) and loss of energy expectation (LOEE).

	χ	ENS (GWh)	LOEE
2002	-0.1740	74.954	206.826 (GWh/Year)
2003	-0.1991	88.203	134.672 (GWh/Year)
2004	-0.1536	133.38	160.118 (GWh/Year)
2005	-0.2023	171.21	182.013 (GWh/Year)
2006	-0.0792	183.94	189.232 (GWh/Year)
Winter	-0.0842	168.08	65.170 (GWh/Winter)
Spring	-0.0070	138.14	34.732 (GWh/Spring)
Summer	-0.2234	104.38	26.241 (GWh/Summer)
Fall	-0.0942	202.11	52.812 (GWh/Fall)
Combined	-0.1583	651.68	173.179 (GWh/Year)

Table 4.17 Wind turbine and load calculations

In every case the correlation coefficient is negative. This equates to a generator that changes from hour to hour opposite of the load with which it is compared. It has been historically shown that temperature extremes cause the highest seasonal loads in TPU's system [16]. A study performed by BPA showed actual wind farm output had an increased probability of being low during times of extreme temperatures. The median total value of the wind farm outputs, reported by BPA, was less than 5% of nameplate capacity during periods in which temperatures were greater than 80°F and less than 30°F. The highest median output value (23% of nameplate capacity) was seen during times when temperatures were between 40°F and 50°F [23]. Using this as a baseline, it suggests a negative correlation coefficient between temperatures and wind farm output when temperatures are above 50°F. By the same logic, a positive correlation coefficient would be suggested between temperatures and wind farm output when temperatures are below 40°F.

If these arguments are true, the correlation coefficients for this model should be negative for the yearly analysis due to the fact a larger portion of the year is spent above 50°F, rather than below 40°F. But the seasonal analysis does not show this. Winter should be positive, or at a minimum the least negative, which it is not. Keep in mind BPA used a temperature to capacity factor comparison and this thesis used load to capacity factor. It is difficult to say how much temperature directly affects load and therefore caution must be taken when making a direct comparison to BPA's data.

In Hirst's study, the correlation coefficient between BPA load and the four-site output was zero [43]. His study occurred over winter and spring, which this thesis shows are the two lowest seasons, in magnitude, out of the four. If the two were averaged together a correlation coefficient of -0.0456 would result. Recall Table 3.4 from the study conducted by Milligan [36] showed a wind speed to load correlation of between -0.0035 and -0.0539 with an average of -0.031. What these numbers show is that indeed the model developed here compares well to other studies. It also seems to show that no matter the geographic location, the wind farm output to load correlation is not positive.

Energy not served (ENS) shows that the wind farm under serves TPU's load by approximately 173.2 GWh per year. This is the second indication that perhaps having a wind generator will not be able to keep LOLE at a one day in ten years limit. The worst-case value ENS could ever be, and still meet LOLE goals, is when the generator produces zero MW for 24 of the highest peak load hours of the ten year period. For TPU's scaled load, this would equate to about

3.5 GWh per ten years. LOEE for the later years studied in this thesis, when the most data is available, was calculated at over 180 GWh per year. Although the ENS and LOEE data in this case does not provide a good understanding of reliability in itself, it does provide the ability to rank the wind farm's ability to meet load by season.

To gain a better understanding of the relationship between wind farm production and load, a loss of load expectation is next calculated. First the loss of load probability or LOLP was calculated using daily peak load versus hourly wind farm output. Next the hourly loss of load probability or HLOLP was calculated to allow for a better understanding of how daily versus hourly load information can vary the results. Looking at Table 4.18 one can see that the LOLP and HLOLP are the lowest during the summer season. This is the same season in which the correlation coefficient between load and generation displayed the largest negative value. This shows that although correlation can be worse during certain seasons, the generator's ability to serve load can actually be better. This most likely is due to the average level of load during the season, versus the intra-seasonal variations, having the greater affect on LOLP levels. Therefore, the fact that there is a greater possibility of losing load during higher load seasons is expected even with a more positive correlation.

	LOLP	HLOLP
Winter	49.1%	45.4%
Spring	34.5%	31.3%
Summer	27.9%	25.7%
Fall	43.7%	40.8%
Combined	38.4%	35.4%

Table 4.18 Wind farm LOLP and HLOLP

In any case, the LOLP and HLOLP are still very high in this model. The LOLP for the entire study time frame from January 2002 to December 2006 is 38.4% with an HLOLP of 35.4%. But one must remember that the intention of this model is not to model the sole producer of electricity for a load, but as an addition to a generator mix. LOLP can give one an idea of how much generation will need to be purchased on the open market or made up for by other generators in the mix.

At this point, it is not useful to attempt to use LOLP to find a LOLE due to the fact that it is very high and will not result in an LOLE even close to one day in ten years. Instead it may be used in another meaningful way. Estimating load capacity for the wind farms utilizes the LOLP and HLOLP no matter the value. When evaluating a renewable generator's ELCC, the renewable under study is placed into a mix and LOLP is measured. The new LOLP is noted and the renewable is taken out of the mix. It is then replaced in small increments by a benchmark generator until the LOLP is lowered to that which was achieved with the renewable [29]. For this work though, no data for the generation mix is available. Even if TPU's generator data were available, the fact that Tacoma has an open-ended agreement with the Bonneville Power Administration to make up for any unserved load [52] makes finding the true LOLP next to impossible.

Since only a portion of TPU's load is used for the study it would be plausible to use the LOLP of the wind generation, on its own, to find the capacity of a benchmark generator that would provide the same level [29]. Using a benchmark FOR of 5% and starting with a capacity of 80 MW the LOLP was calculated at 83.3%. Next 5 MW was added for a total of 85 MW and LOLP recalculated. This was repeated until the LOLP was below that of the renewable generator. The process was then repeated to calculate HLOLP. Figure 4.18 shows the results of the capacity additions relative to the wind farm LOLP and HLOLP.

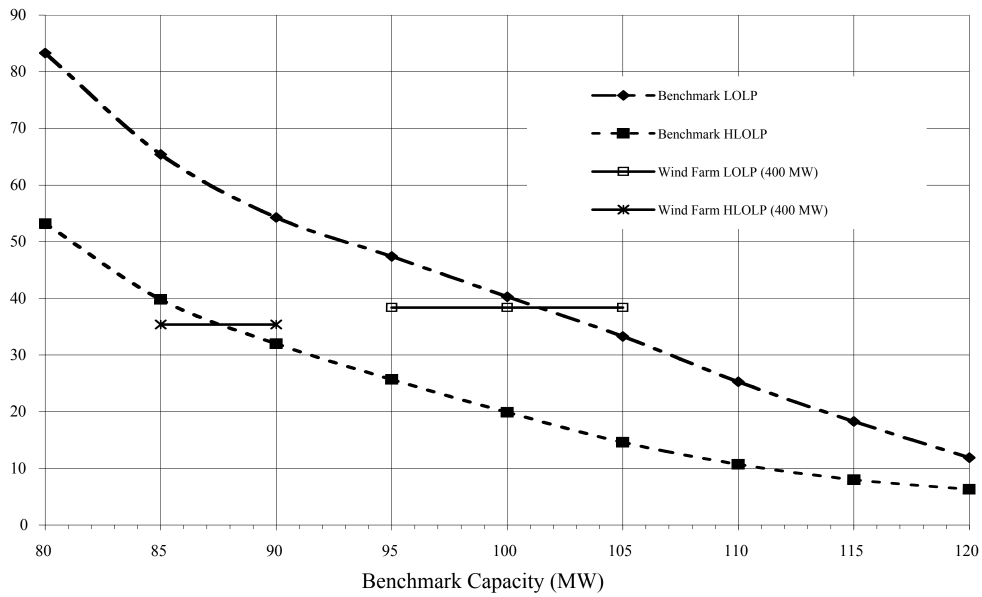

Figure 4.17 Benchmark generator LOLP and HLOLP from Aug. 2002 to Dec. 2006

As one can see, the effective load carrying capability of the wind farms based on LOLP is approximately 101 MW for the historical data. This is 60 MW lower than the 161 MW that would have been calculated by the combined capacity factor (0.4022). One must remember that load is factored into the ELCC calculation but not the capacity factor. Therefore no matter what the load is, capacity factor will never change. Table 4.19 below shows the variations of ELCC over the seasons.

	ELCC (HLOLP Based)	ELCC (LOLP Based)
Winter	100 MW	113 MW
Spring	87 MW	98 MW
Summer	80 MW	84 MW
Fall	83 MW	94 MW
Combined	88 MW	101 MW

Table 4.19 Effective Load Carrying Capacity

It is surprising that the ELCC is actually highest in the winter. As shown in Table 4.18, the LOLP data set for the benchmark is actually much higher when compared to other seasons and the combined data. Figure 4.18 below shows how the winter season LOLP and HLOLP differed from the combined data of Figure 4.17. This shows that the higher load actually has a significant affect on the benchmark HLOLP and LOLP, which causes ELCC to increase. Figures 4.19 through 4.21 below show exactly how the other seasons affect ELCC.

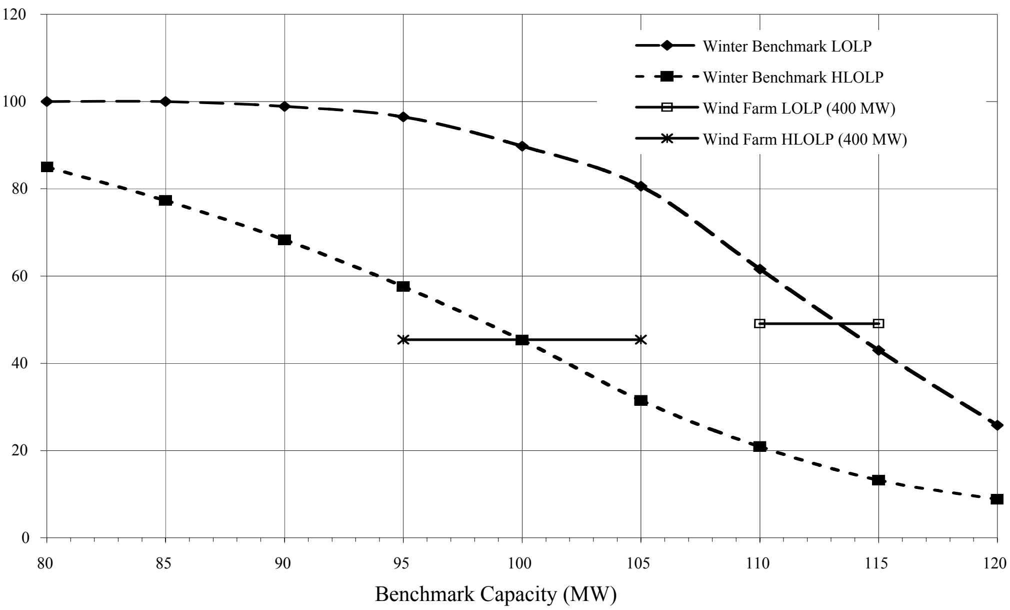

Figure 4.18 Benchmark generator LOLP and HLOLP for winter seasons

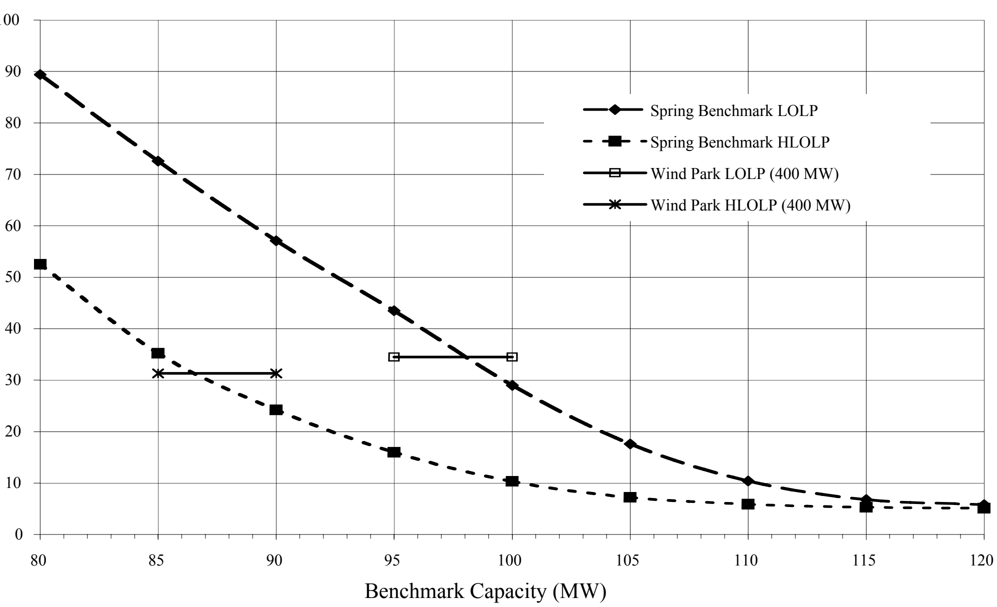

Figure 4.19 Benchmark generator LOLP and HLOLP for spring seasons

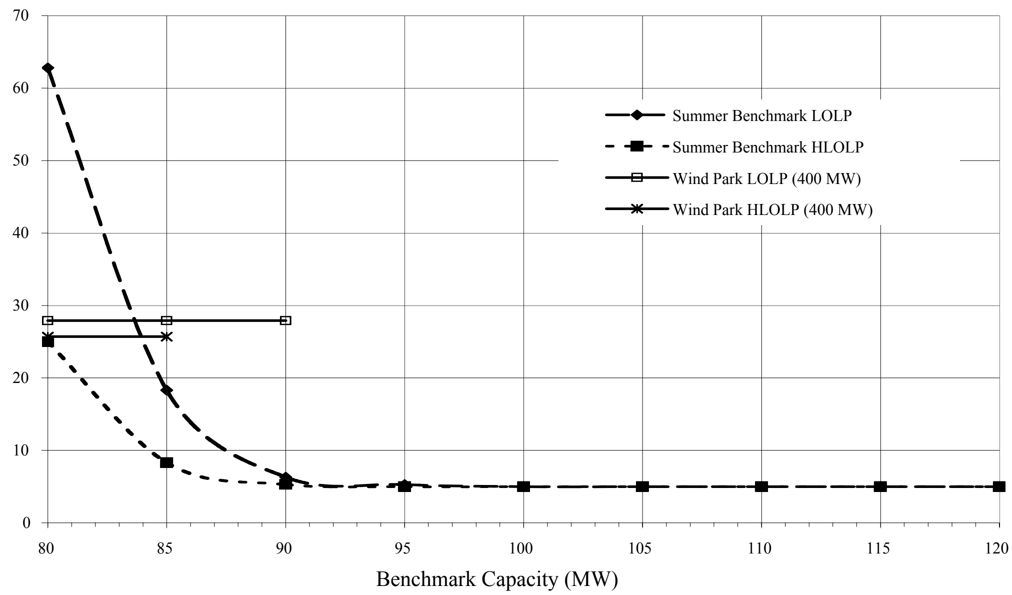

Figure 4.20 Benchmark generator LOLP and HLOLP for summer seasons

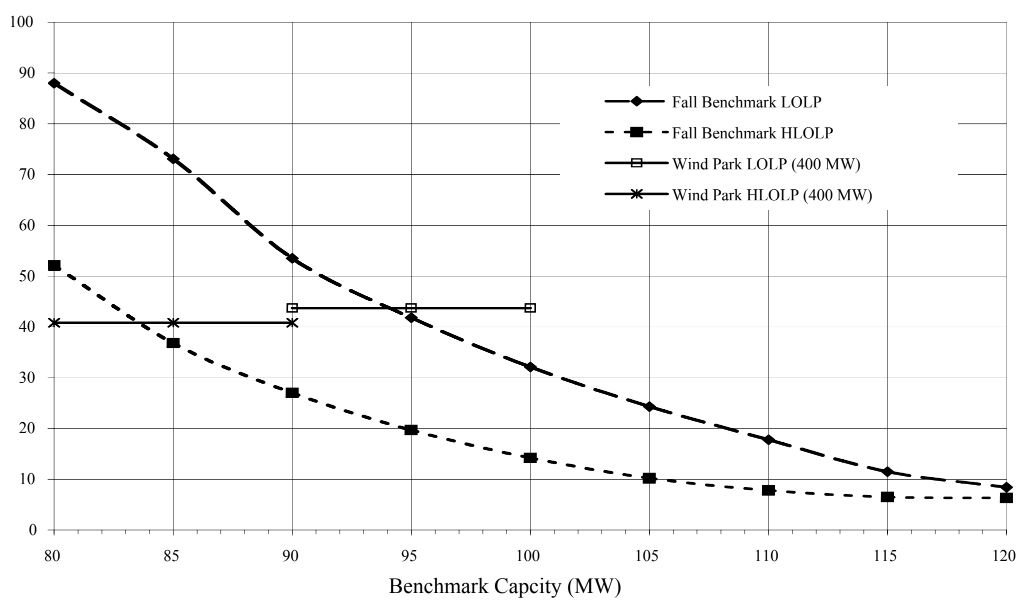

Figure 4.21 Benchmark generator LOLP and HLOLP for fall seasons

For further comparison, the ELCC as percentage of generator nameplate capacity was calculated and is displayed by season and combined in Table 4.20. Again note that capacity factor never changes as long as each site's turbine count is increased or decreased by the same amount as dictated by the premise of this model. ELCC on the other hand does change with load and nameplate capacity.

	Capacity Factor	ELCC (LOLP Based)
Winter	34.1%	28.3%
Spring	42.6%	24.5%
Summer	46.4%	21.0%
Fall	36.2%	23.5%
Combined	40.2%	25.3%

Table 4.20 Capacity factor and ELCC as a percentage of nameplate capacity

Using graphs 4.17 through 4.21 above and a recalculation of LOLP, Table 4.21 was created. This was done to illustrate the differences between ELCC values as the nameplate capacity of the wind farms are changed. Recall this model uses 200 wind turbines with an installed capacity of 400 MW. As you can see the amount of equivalent benchmark capacity that is obtained from increasing the size of the wind farms is minimal. Likewise the amount of equivalent benchmark capacity decreases very little with large decreases in the number of turbines.

Wind Farm Total Nameplate Capacity	ELCC (MW)				
	Winter	Spring	Summer	Fall	Combined
200 MW	107	91	82	88	88
280 MW	111	95	83	91	95
336 MW	112	97	83	92	98
400 MW	113	98	84	94	101
480 MW	113	99	84	95	105
800 MW	117	103	85	99	109

Table 4.21 ELCC as a percentage of capacity

4.7 Meeting I 937 Requirements

Beginning in the year 2012 utilities with over 25,000 customers in Washington State will need to purchase 3% of the electricity from a renewable resource such as wind. The manner in which this 3% is measured is simplistic in nature. The total load in 2010 and 2011 is added and averaged into a single year. Proof must be submitted to the state showing that in 2012 enough renewable energy contracts and or renewable energy credits have been purchased to cover at least 3% of this average. In 2016, this number will increase to 9% and then finally to 15% in 2020 [12].

In TPU's 2005-2020 Transmission and Distribution Horizon Plan the utility believes that a peak demand increase of 1.3% load growth is *"valid and appropriately conservative"* [16]. Figure 4.22 below shows that if this holds true, TPU would have to build 6 turbines at each site to achieve at least 3% of average load through 2016. In this case though, TPU could site all turbines in the most productive spot and perhaps decrease the total number needed. If TPU were to build out to meet I-937 requirements 30 years from now, 40 turbines at each site should provide sufficient average output.

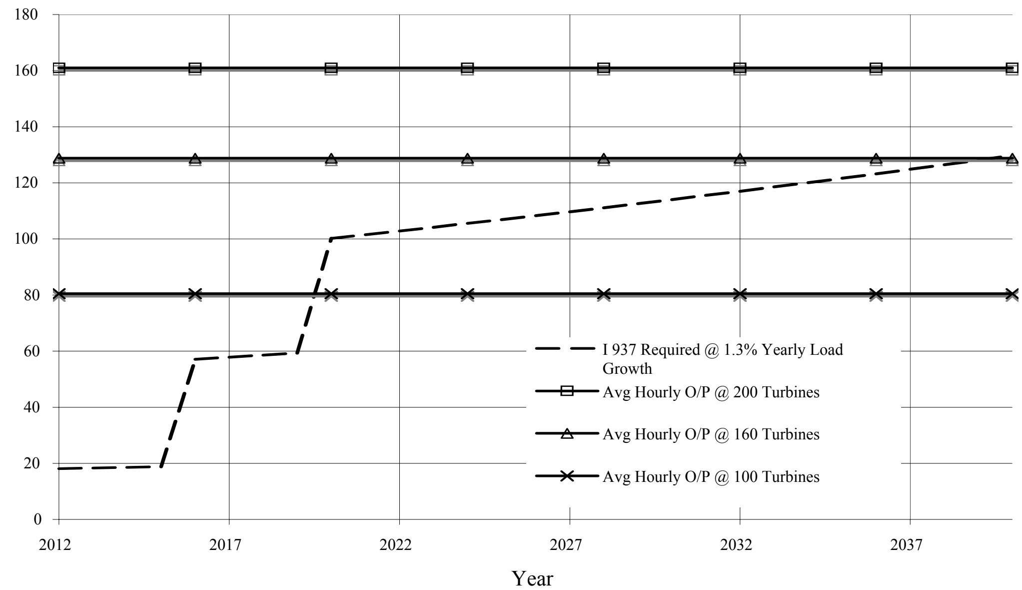

Figure 4.22 TPU's renewable energy requirements and wind farm output

As you can see, the model produced here compares well to both theoretical and actual outputs of similar wind farm studies. The correlation coefficients between generators and between generators and load were also similar to these studies. The LOLP has shown that trying to use a single wind turbine generator to supply load is very difficult but the results can lead to a meaningful ELCC. In addition, the seasonal information provided here is of particular use to the generation planner given the varying nature of the wind generator and the load.

Chapter 5

Conclusions

5.1 Results

This thesis has met the major objectives stated in chapter one. The first was the modeling of a wind generation resource based on readily available information. Using four different wind farms did indeed decrease the average hourly step change of the wind generation as a whole. When compared to similar studies, this model shows a lower hourly step change on average when compared to the output from three actual wind farms. The correlation between the wind sites showed that as distances increased, the correlation coefficient decreased supporting the value of dispersed locations. Total generation was measured and resulted in capacity factor of 40.22%. However, similar studies have shown much lower capacity factors for wind farms such as Hopkins Ridge (35.2%) [32], Wild Horse (32.1%) [22] and the combined output of the 4 Columbia wind farms (32%) [43]. This may be attributed to an overly optimistic wind speed-to-turbine output curve published by the manufacturer. Further analysis did show a seasonal capacity factor that was closer in value to those of studies conducted over limited time durations. In general, it can be said that winter has the lowest generating capacity and lowest wind site correlation coefficients. On the other hand summer, by and large, has the highest generating capacity and the highest correlation between sites. When load alone was studied, it was found that the correlation was the least during the winter. This, in itself, results in a more difficult ability to accurately predict what the load will be during the winter then during any other season. This is in addition to the fact the greatest loads occur during the winter seasons.

The second objective met in this thesis was in analyzing how well a portion of TPU's load would have been served by a wind generator alone. A negative correlation coefficient between generation and TPU's load was found. Other studies have found similar results and this should not preclude the Columbia River basin from being determined an adequate resource. Energy not served and loss of energy expectation where the highest during the winter months and lowest over the summer months. Overall, both indices showed a gross inadequacy of the generator in meeting a portion of TPU's load. The same was true for the calculation of loss of load probability and hourly loss of load probability. However, the benefit for TPU in calculating loss of load probability is to provide the ability to discover effective load carrying capacity.

Even though the wind farms were used as the only generator in the generating mix, value can still be gleaned from effective load carrying capacity's value. The effective load carrying capacity measurements can show that TPU can expect more generating value from a wind resource during the winter months. Also shown was that as the wind farm size decreased, the greater the equivalent output as a percentage of nameplate capacity. This is valuable information to TPU in deciding how large of a wind farm to build without regard to reliability or RPS requirements.

The final objective met was in calculating what capacity TPU will need if they choose to meet renewable portfolio standard requirements via wind generation. This is relatively easy to find if every megawatt generated is used to serve TPU's load. However, TPU would still need to know what it can expect for a wind farm output so that it may schedule other generators within the mix. Given that TPU supplies about 24% of its own electricity from hydroelectric under its direct control results in some flexibility in controlling generation mix [13]. If the wind resource cannot be optimally integrated into the mix, a larger resource would be needed.

As mentioned before, this work differs from earlier studies in that it looks at seasonal variations. Also, a similar study could not be found that utilized such a large time period of data for the Columbia Basin. These two points have made for a valuable study not only for TPU but potentially for others studying wind energy potential in the northwest U.S. and at other locations throughout the world.

5.2 Recommendations for Future Work

- Obtain generator mix information and recalculate LOLP and ELCC.
- Adjust the wind speed to output curve to obtain a more conservative capacity factor and rerun the analysis.
- Adjust the load to a different percentage to see how LOLP and ELCC are affected by different generating level scenarios.
- Obtain temperature information for the sites and determine how this affects wind speed and turbine output.
- Conduct an analysis to determine the amount of reserves needed to support wind generation given the hourly variations. Or conduct the same analysis but with the 10 minute data.

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APPENDIX A

The following are the assumptions made for this thesis:

1) No Transmission Losses
2) Unlimited Transmission Capacity
3) Cost considerations can be ignored
4) Wind turbine hub heights are all 221ft
5) All wind farms are of equal size
6) Wind is the only generator in the generation mix
7) Hourly wind speed data represents the entire hour's wind speed
8) At wind speeds greater than 55.92 mph wind turbines shutdown instantaneously
9) Wind turbine output changes instantaneously on the hour to coincide with hourly wind speed changes
10) The wind turbine output curve can be defined by 4 linear functions with a slope of 0, 100, 150, and 270
11) Only wind speed affects turbine output
12) TPU's load is 15% of its actual load
13) Hourly load represents the entire hour's load
14) All wind power generated is used to serve load

APPENDIX B

The following are tables and graphs of data calculated during the course of this work. While some of this data is not specifically discussed in this thesis, the information it provides will help the reader gain a greater insight into the model's behavior.

Speed (m/sec)	Speed (ft/sec)	Speed (mph)	O/P (kW)
0	0	0	0
1	3.28	2.24	0
2	6.56	4.47	0
3	9.84	6.71	0
4	13.12	8.95	0
5	16.40	11.18	150
6	19.69	13.42	300
7	22.97	15.66	450
8	26.25	17.90	720
9	29.53	20.13	990
10	32.81	22.37	1260
11	36.09	24.61	1530
12	39.37	26.84	1800
13	42.65	29.08	1900
14	45.93	31.32	2000
15	49.21	33.55	2000
16	52.49	35.79	2000
17	55.77	38.03	2000
18	59.06	40.26	2000
19	62.34	42.50	2000
20	65.62	44.74	2000
21	68.90	46.98	2000
22	72.18	49.21	2000
23	75.46	51.45	2000
24	78.74	53.69	2000
25	82.02	55.92	2000
>25	-	-	0

Table B.1 Wind speed to V-80 turbine output

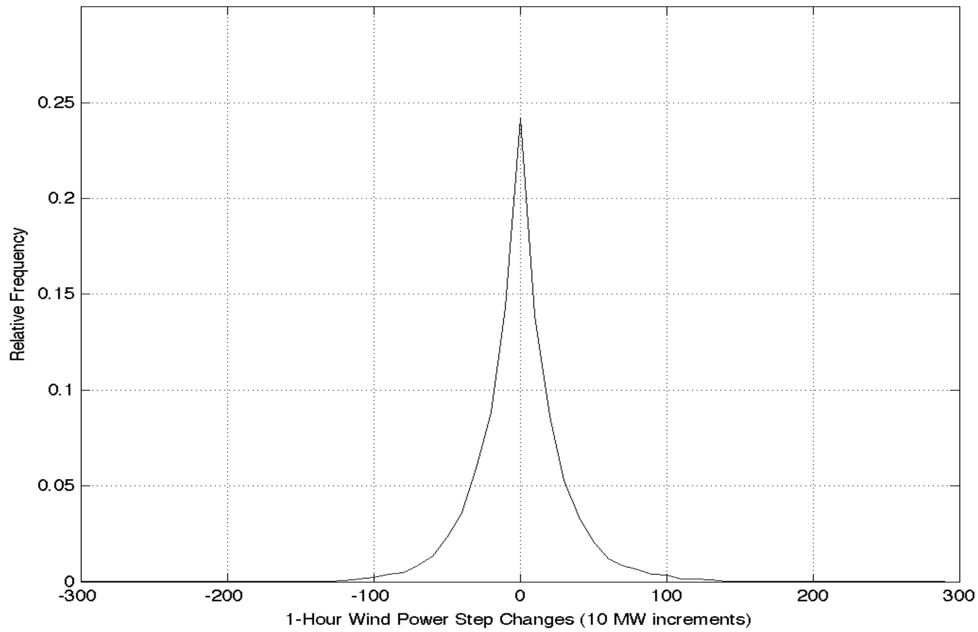

Figure B.1 Wind turbine step change distribution for combined seasons

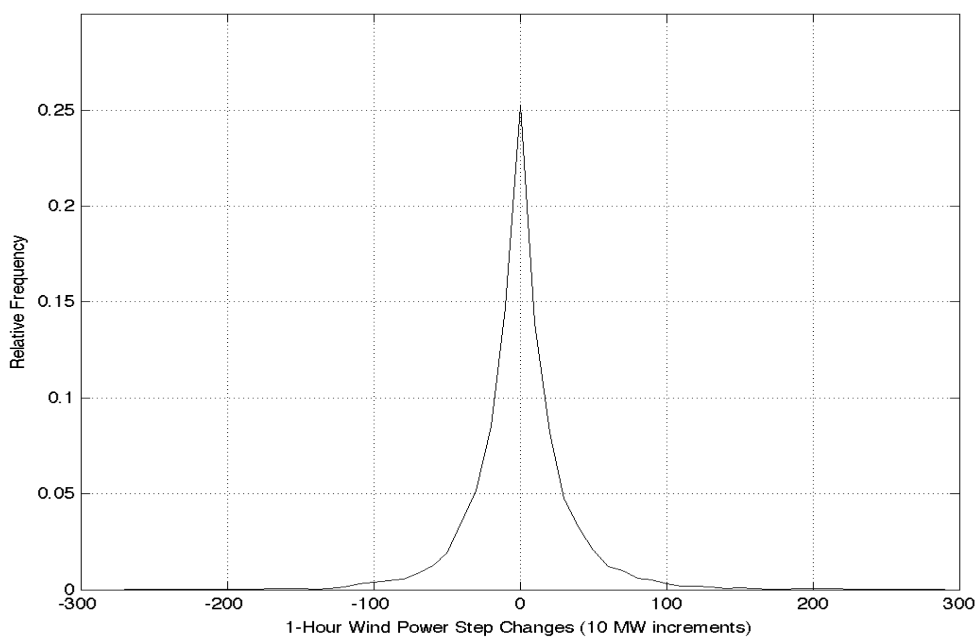

Figure B.2 Wind turbine step change distribution for winter seasons 2003, ’05, and ’06

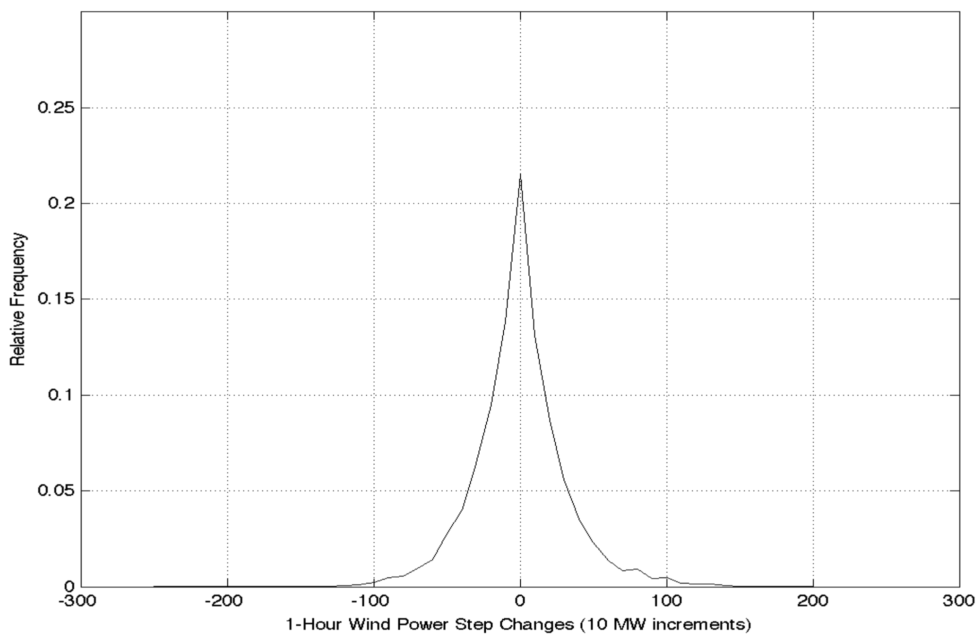

Figure B.3 Wind turbine step change distribution for spring seasons 2003, ’04, ’05, and ’06

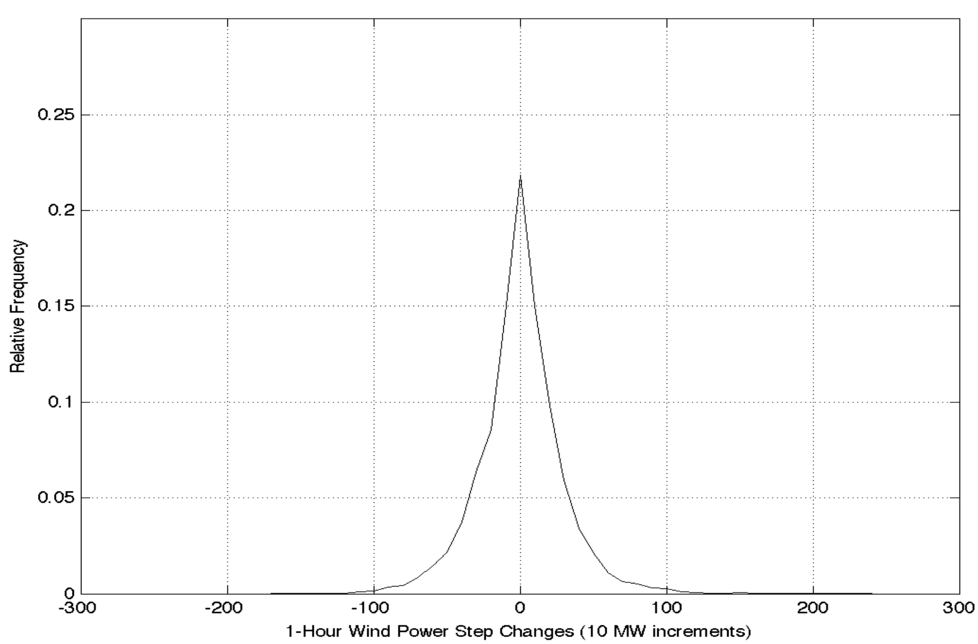

Figure B.4 Wind turbine step change distribution for summer seasons 2003, ’04, ’05, and ’06

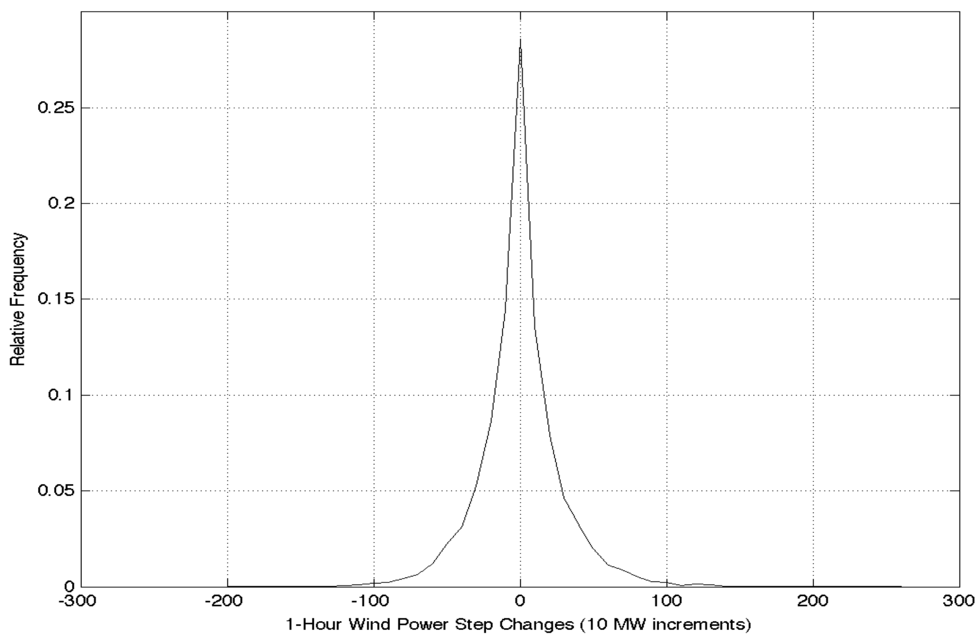

Figure B.5 Wind turbine step change distribution for fall seasons 2002, ’04, ’05, and ’06

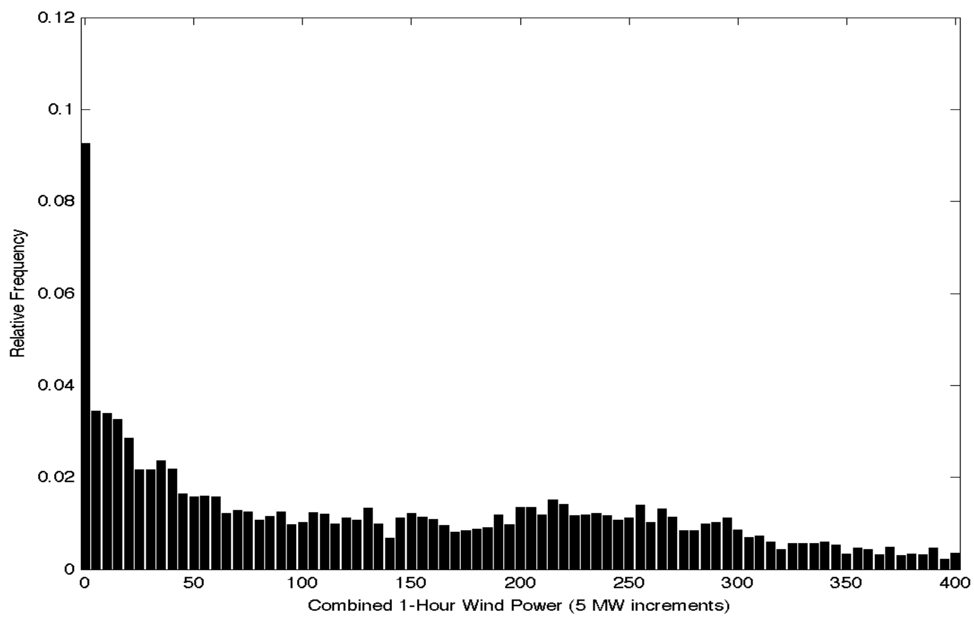

Figure B.6 Relative frequency of total wind farm output for winter seasons 2003, ’05 and ’06

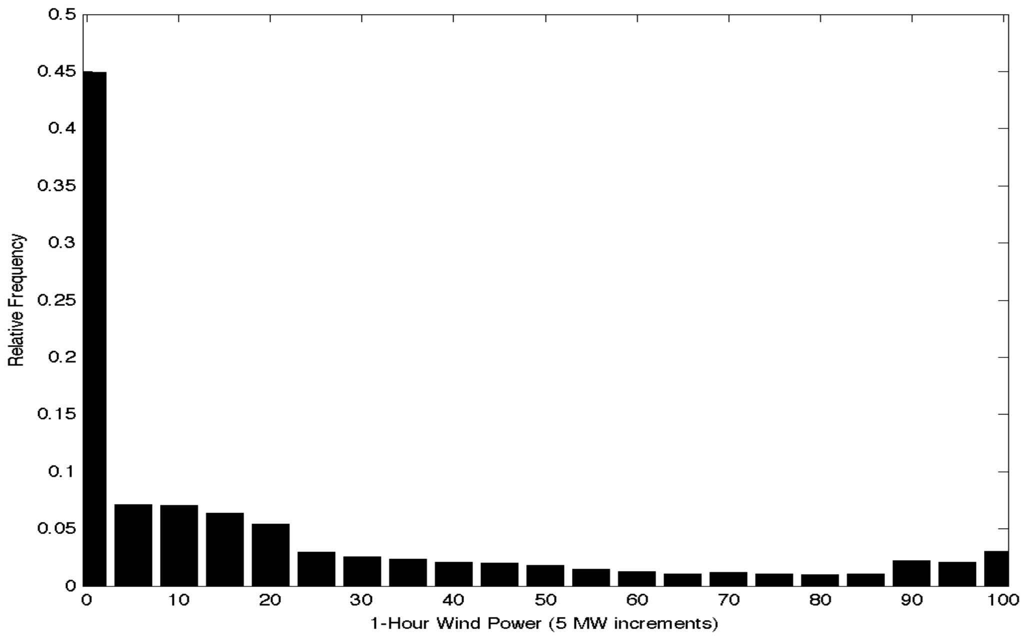

Figure B.7 Relative frequency of Sevenmile wind farm output for winter seasons 2003, ’05 and ’06

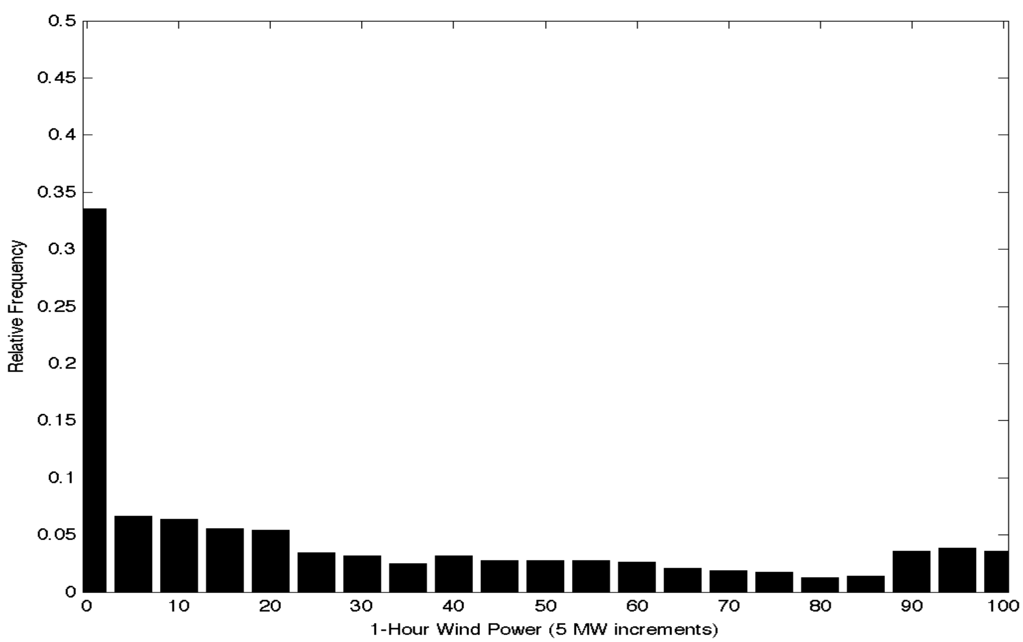

Figure B.8 Relative frequency of Goodnoe wind farm output for winter seasons 2003, ’05 and ’06

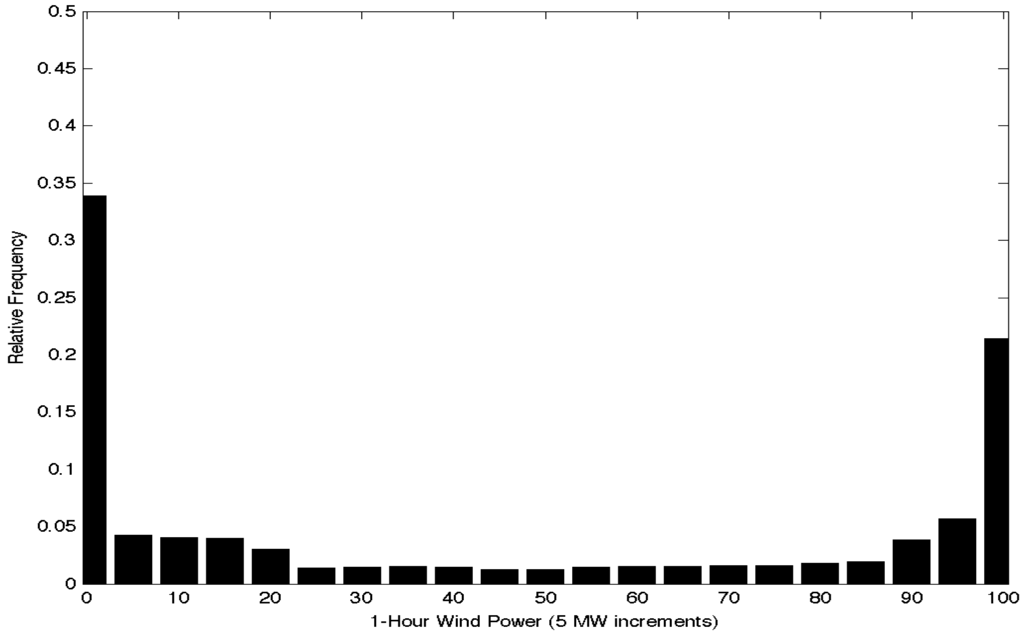

Figure B.9 Relative frequency of Vansycle wind farm output for winter seasons 2003, ’05 and ’06

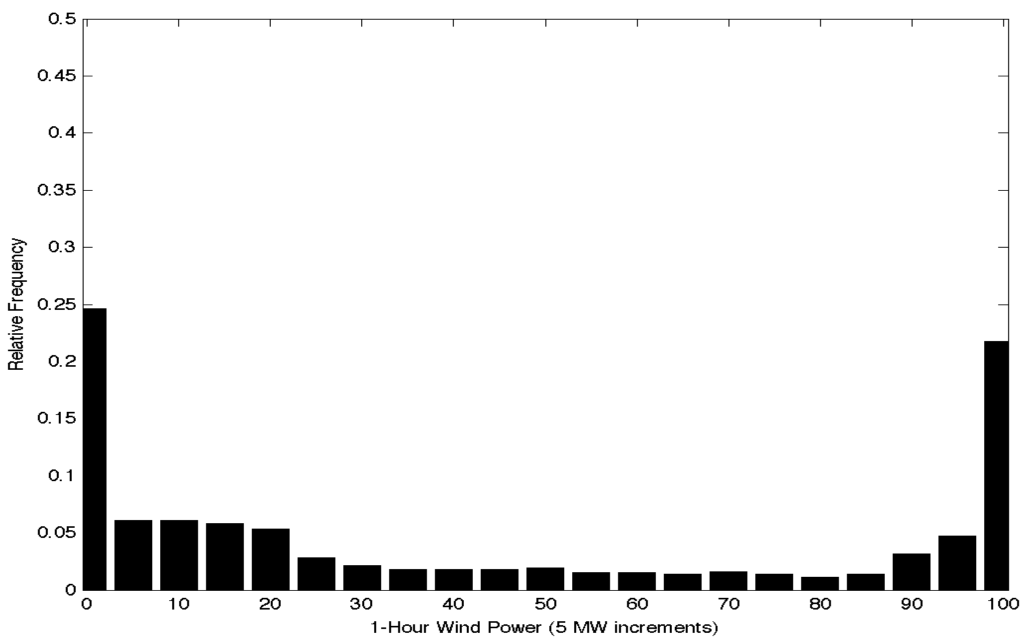

Figure B.10 Relative frequency of Kennewick wind farm output for winter seasons 2003, ’05 and ’06

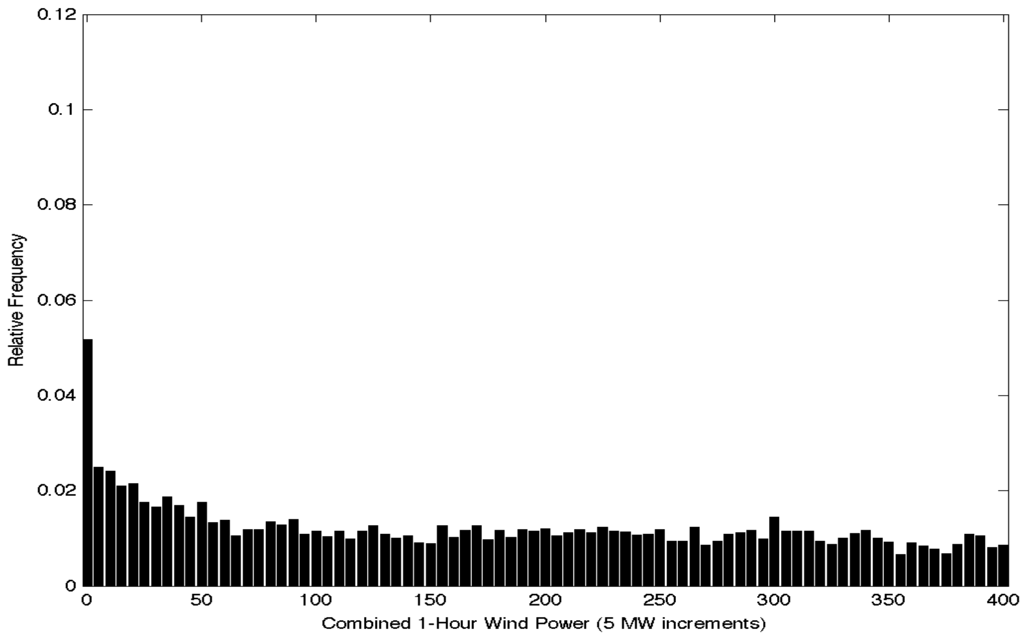

Figure B.11 Relative frequency of total wind farm output
for spring seasons 2003, ’04, ’05 and ’06

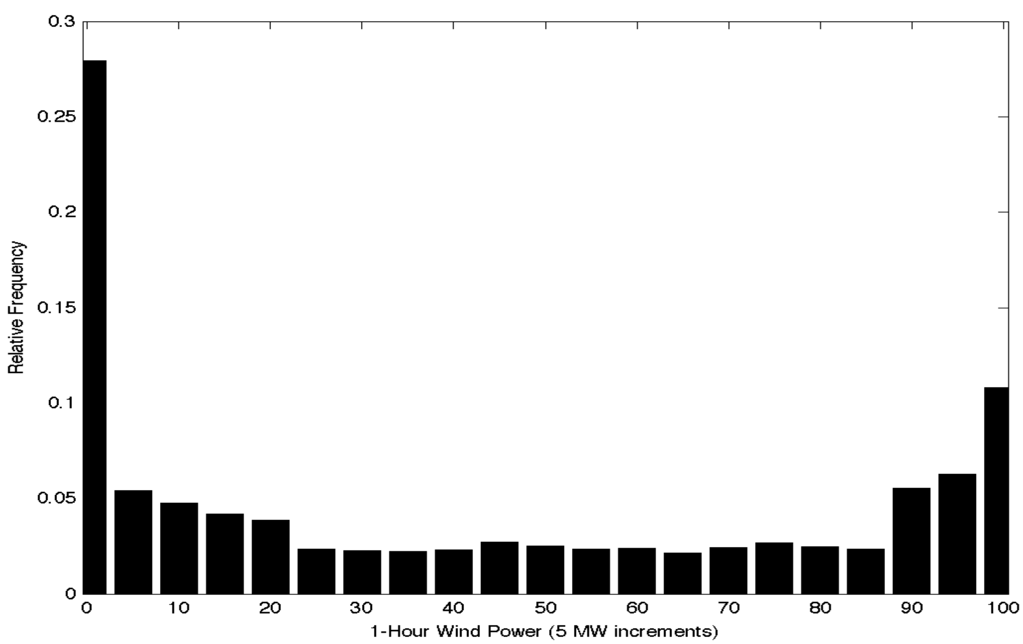

Figure B.12 Relative frequency of Sevenmile wind farm
output for spring seasons 2003, ’04, ’05 and ’06

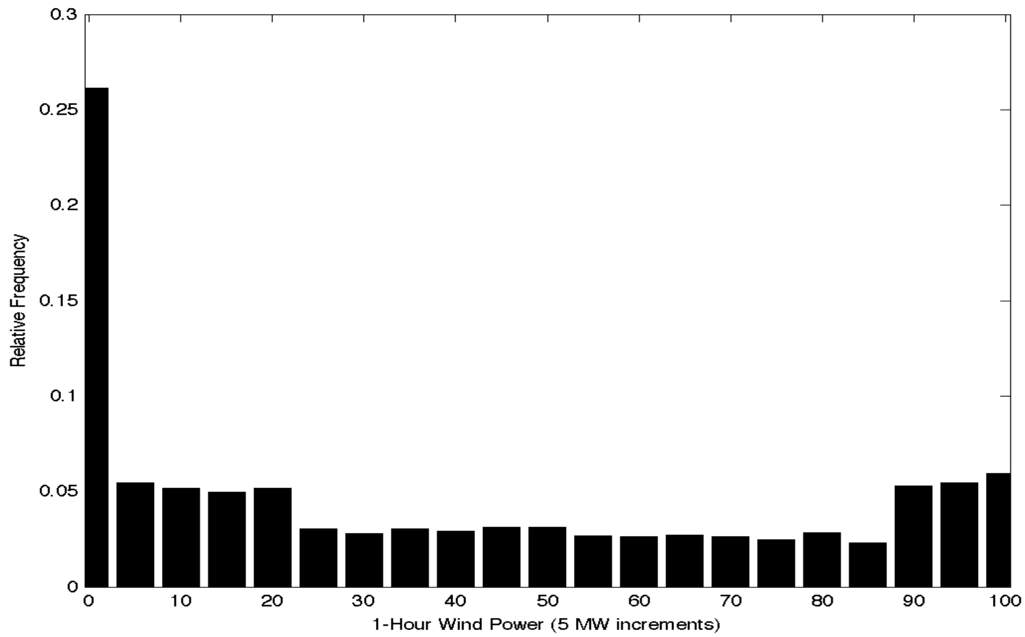

Figure B.13 Relative frequency of Goodnoe wind farm output for spring seasons 2003, ’04, ’05 and ’06

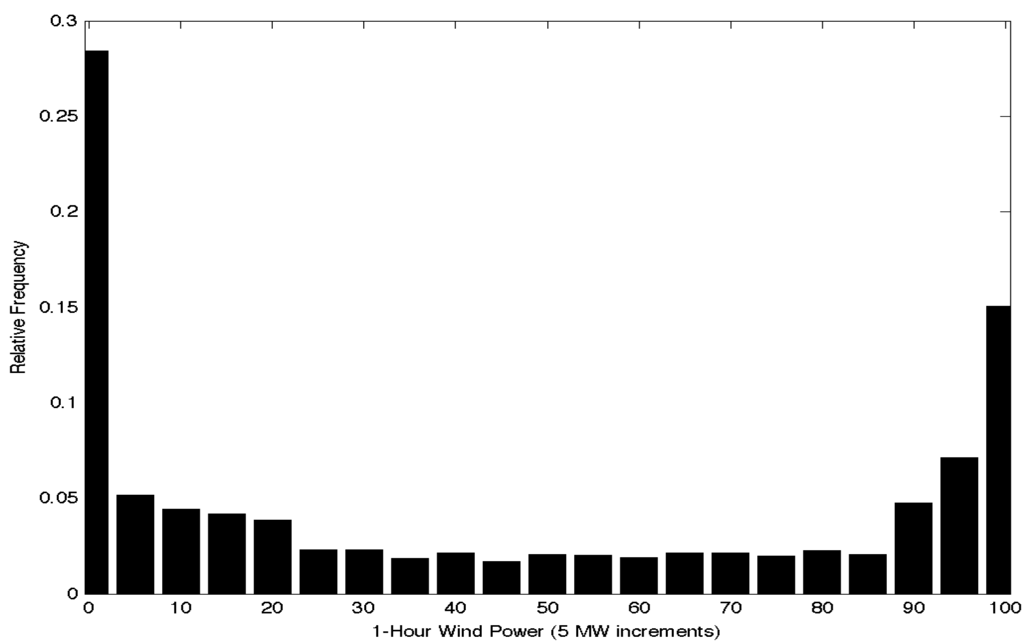

Figure B.14 Relative frequency of Vansycle wind farm output for spring seasons 2003, ’04, ’05 and ’06

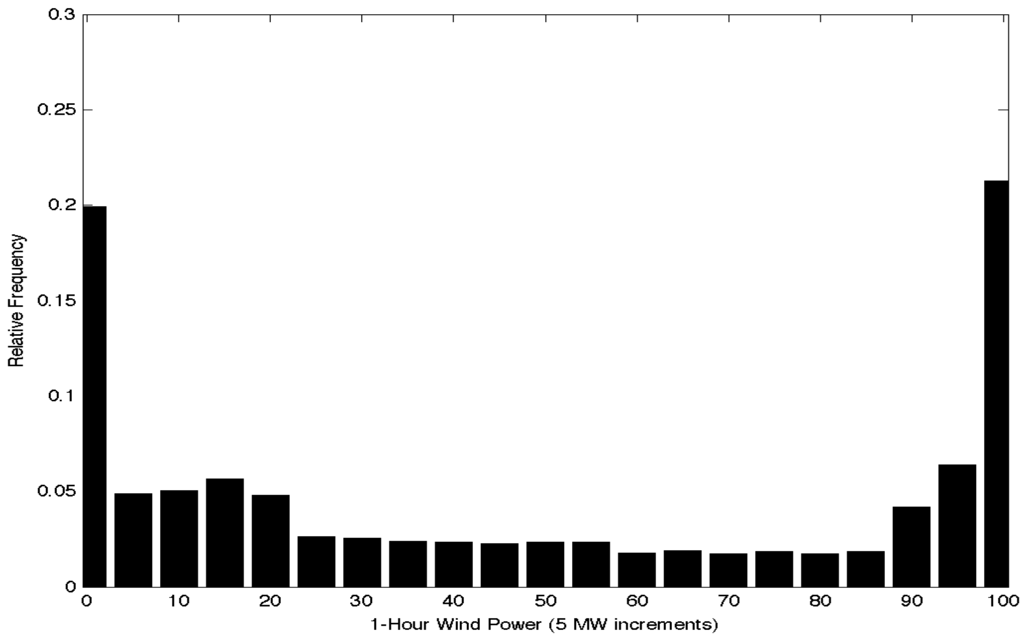

Figure B.15 Relative frequency of Kennewick wind farm output for spring seasons 2003, ’04, ’05 and ’06

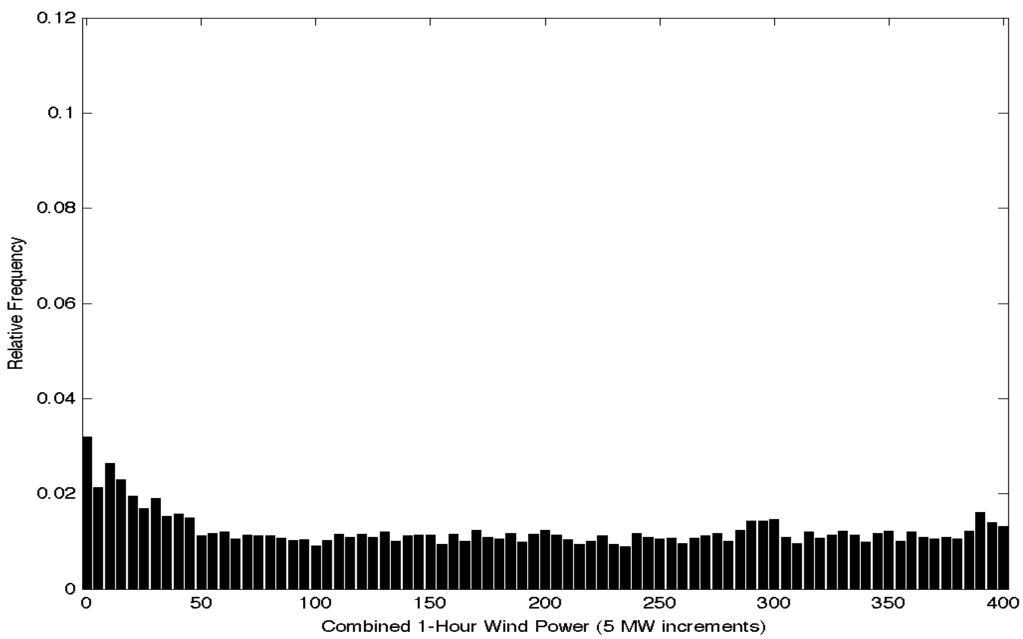

Figure B.16 Relative frequency of total wind farm output for summer seasons 2003, ’04, ’05 and ’06

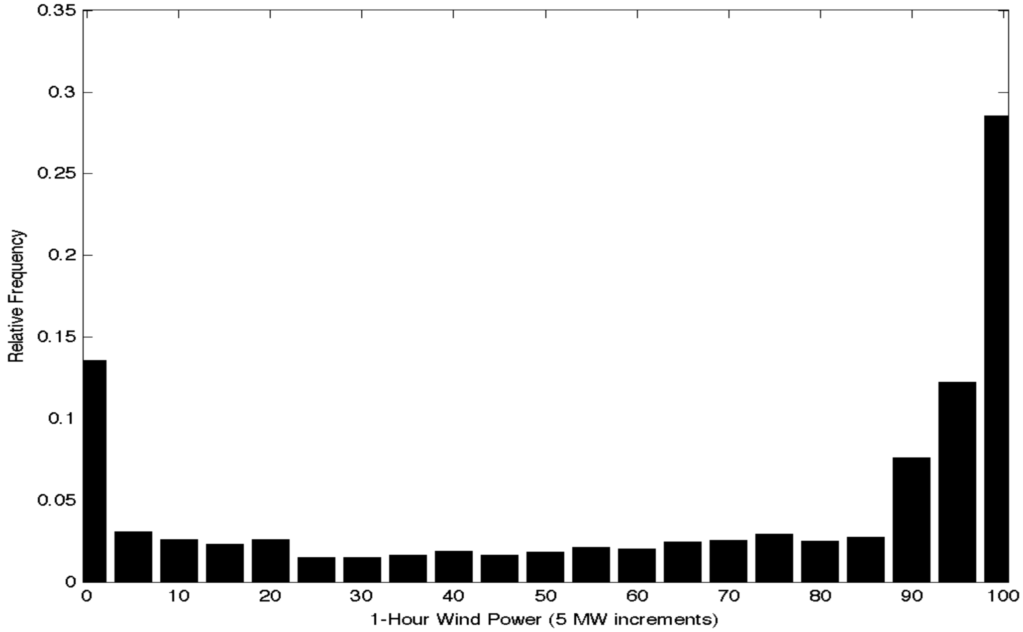

Figure B.17 Relative frequency of Sevenmile wind farm output for summer seasons 2003, ’04, ’05 and ’06

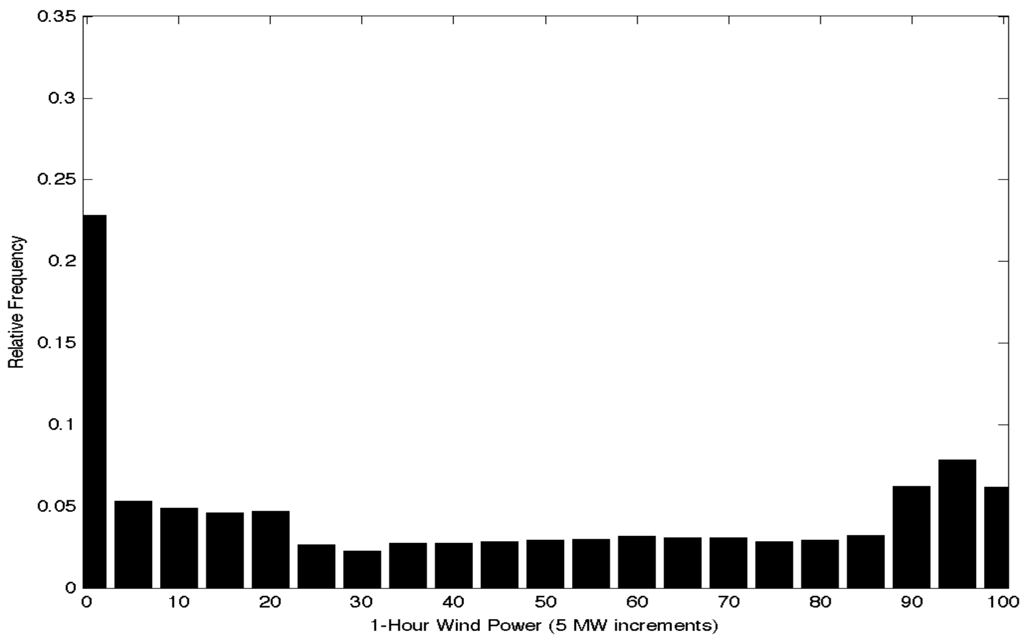

Figure B.18 Relative frequency of Goodnoe wind farm output for summer seasons 2003, ’04, ’05 and ’06

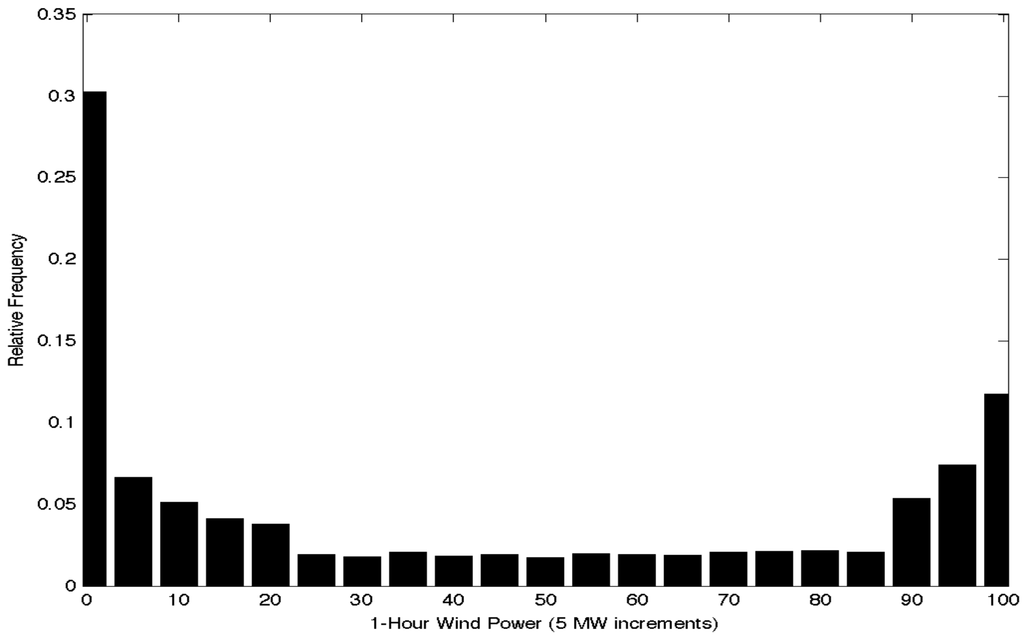

Figure B.19 Relative frequency of Vansycle wind farm output for summer seasons 2003, ’04, ’05 and ’06

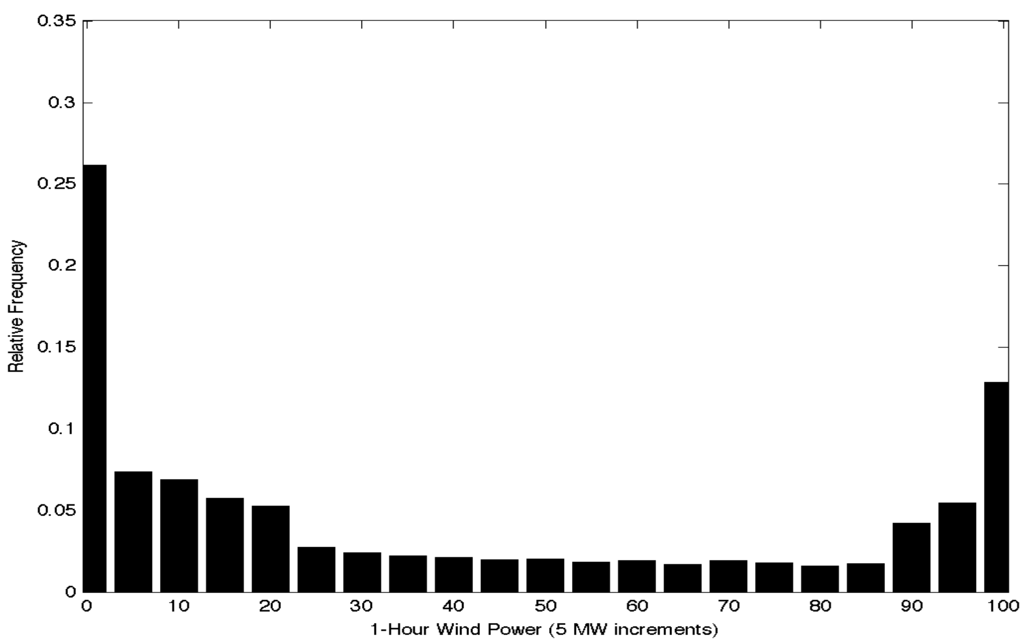

Figure B.20 Relative frequency of Kennewick wind farm output for summer seasons 2003, ’04, ’05 and ’06

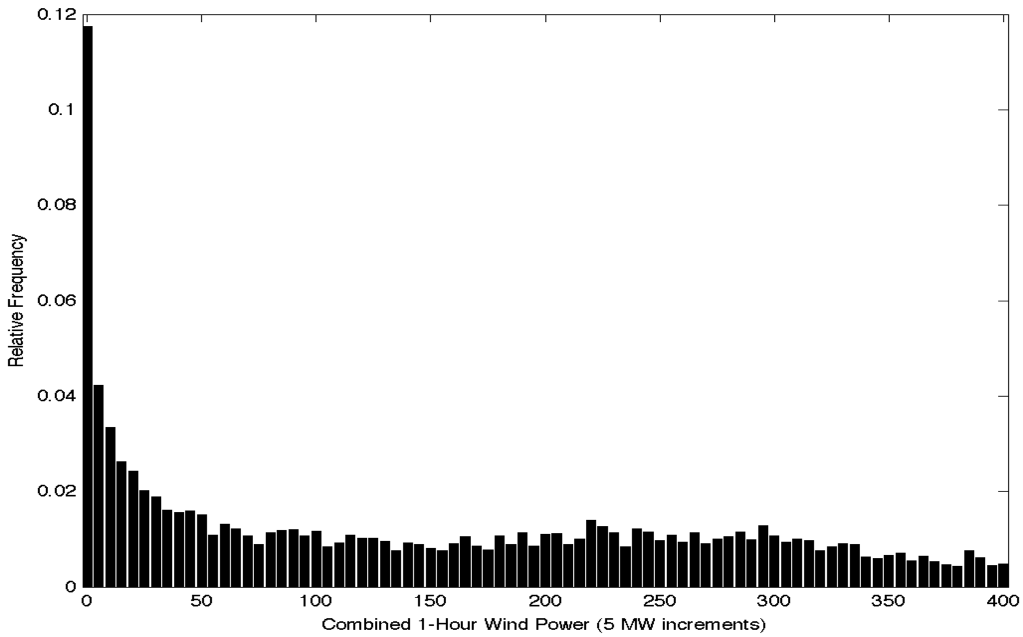

Figure B.21 Relative frequency of total wind farm output for fall seasons 2002, ’04, ’05 and ’06

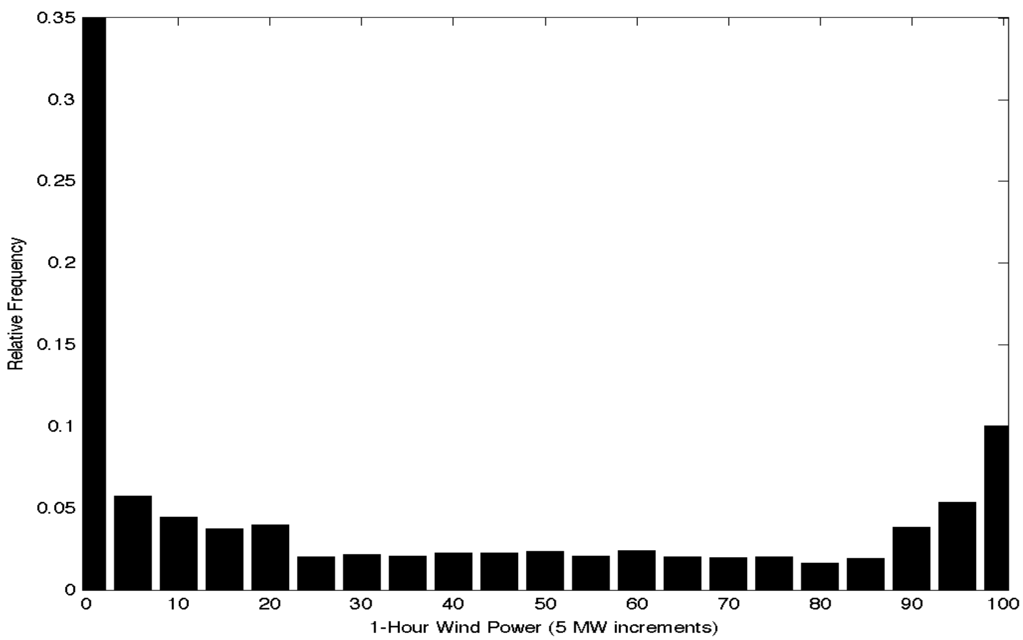

Figure B.22 Relative frequency of Sevenmile wind farm output for fall seasons 2002, ’04, ’05 and ’06

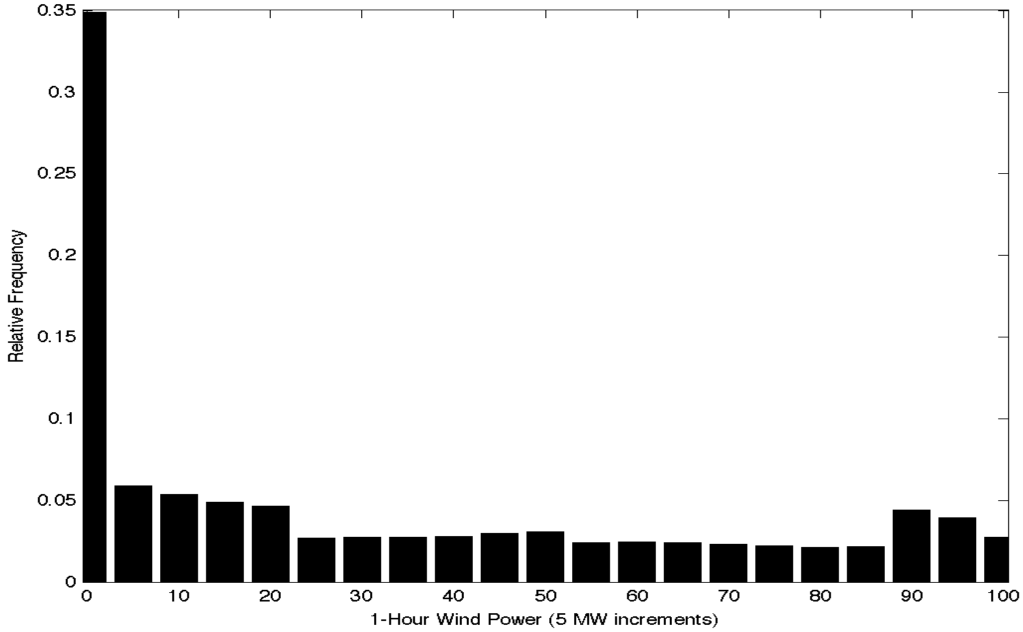

Figure B.23 Relative frequency of Goodnoe wind farm output for fall seasons 2002, ’04, ’05 and ’06

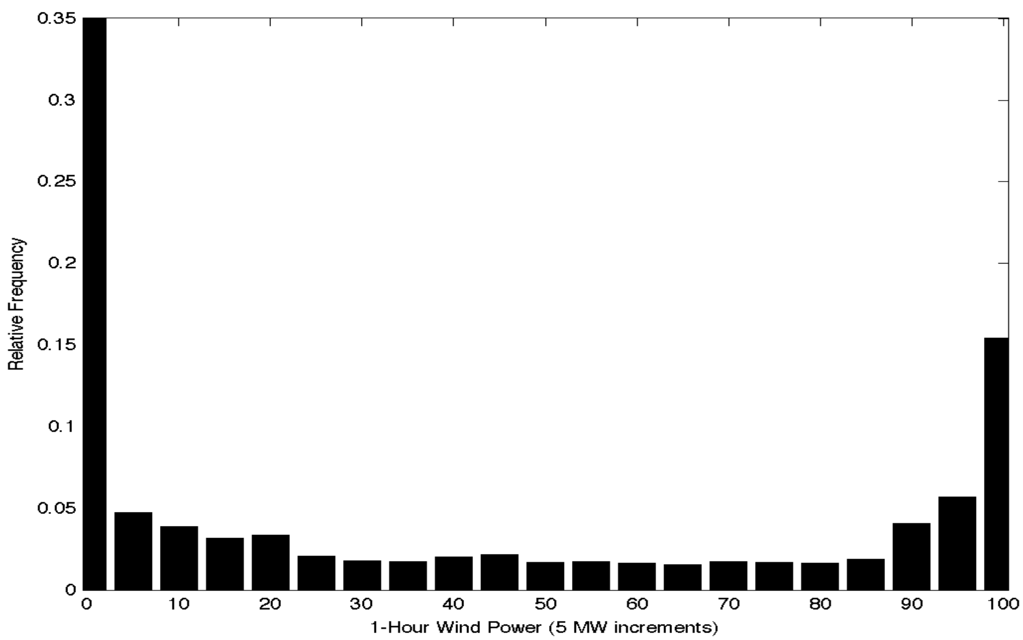

Figure B.24 Relative frequency of Vansycle wind farm output for fall seasons 2002, ’04, ’05 and ’06

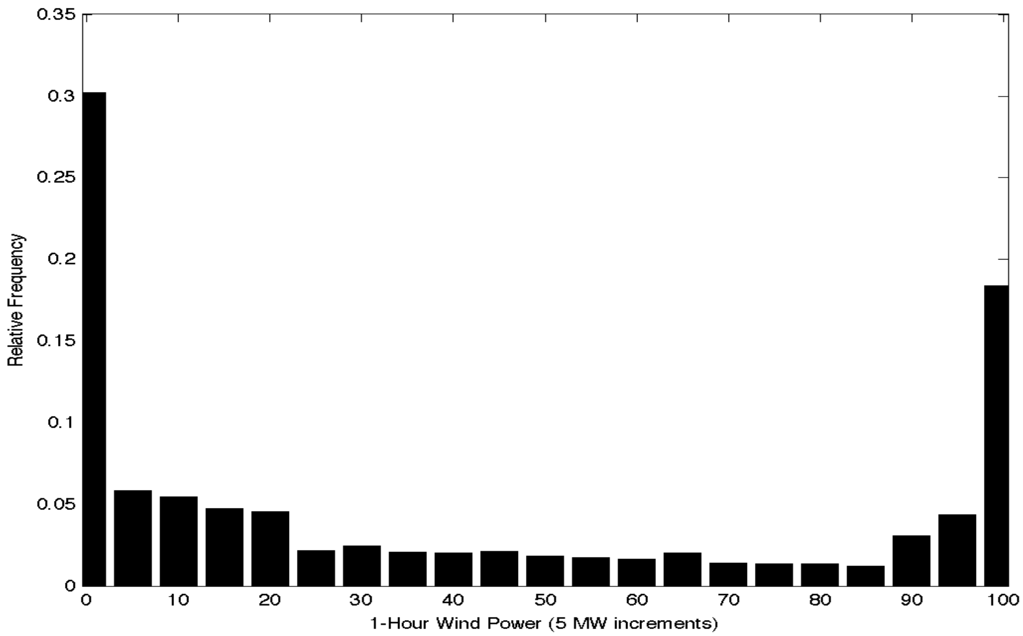

Figure B.25 Relative frequency of Kennewick wind farm output for fall seasons 2002, ’04, ’05 and ’06