AN ABSTRACT OF THE THESIS OF

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Renewable energy, particularly wind power, has increased dramatically over the past two decades. In the Pacific Northwest, the power system has accommodated a large amount of new wind power. The variability of wind power has introduced many challenges, requiring additional reserve generation to be available to maintain system stability. The primary source for reserves is the Federal Columbia River Power System, and the aging dams of this system are believed to be near their limit for providing this service. This paper will explore the dynamics of the power system as a whole, and investigate the relationships that wind power has to the rest of the power system. Several types of studies have been used to examine these relationships including Maximal Information Coefficient analysis, Correlation analysis, and Regression analysis. The results of these analyses demonstrate that the dynamics of the power system changed as wind power was added to the system. The results will also show that the power system is increasingly reliant on resources other than hydropower, including thermal power and interties to California and Canada, to provide balancing reserves for wind power.

An Advanced Study of Wind Power Variability on the Federal Columbia River Power System

by
Kelcey A. Lajoie

A THESIS

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APPROVED:

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Kelcey A. Lajoie, Author

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An Advanced Study of Wind Power Variability on the Federal Columbia River Power System

1 Introduction

1.1 Overview of Renewable Energy

Renewable energy resources have been widely developed across the world in recent years, from many different types of energy sources, including wind, solar, geothermal, biomass, and wave energy. Figure 1.1 demonstrates how drastically renewable resources have increased in the United States over the past two decades. In 2013, renewable energy sources accounted for 6% of electricity generated in the United States, not including hydropower ("April 2014 Monthly Energy Review"). Figure 1.1 also shows that wind power has grown far more quickly than other types of renewable power. In fact wind power comprised 66% of renewable power generation, not including hydropower, in the United States in 2013 ("April 2014 Monthly Energy Review").

Conventional hydropower has traditionally not been considered a renewable energy resource even though it fits most definitions of renewable, primarily because hydropower has been contributing to the power industry for over 100 years ("History of Hydro"). Lawmakers have limited the incentives provided for developing renewable powers to newer technologies, but recent bills have included language that allows newly installed hydropower to qualify for some incentives as well (V. Stori).

Hydropower alone accounts for another 7% of electricity generated in the United States in 2013 ("April 2014 Monthly Energy Review").

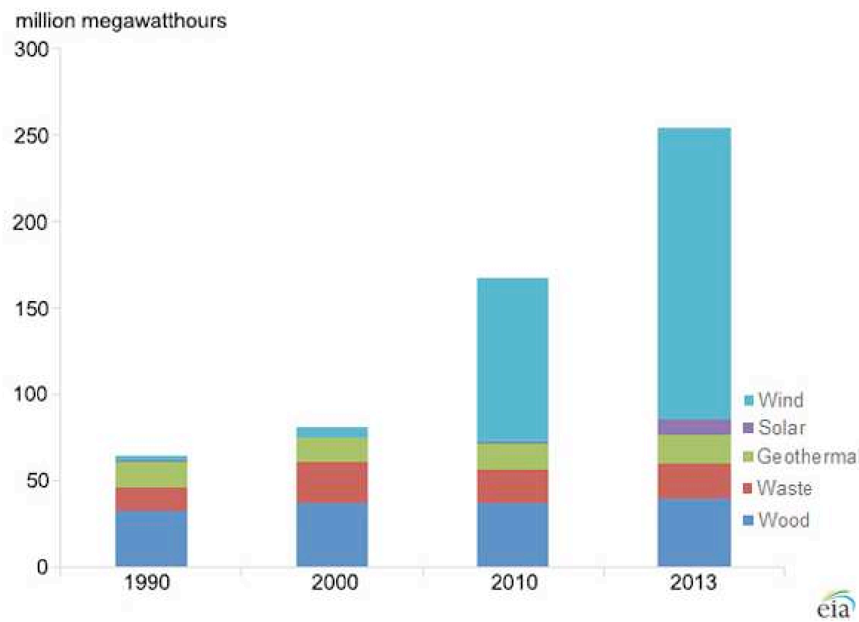

Figure 1.1. Non-hydropower renewable electricity generation by source (generated based on data from US Energy Information Administration, 2014)

In the Pacific Northwest, the growth of wind power has been even more significant. Bonneville Power Administration (BPA), which owns and operates about three-fourths of the high voltage transmission in the region, has connected over 4,500 MW of wind power to its system over the past 15 years ("BPA facts", "Wind Generation Capacity"). Additionally, BPA expects wind power to continue to grow, with up to 7,000 MW of wind power in the Pacific Northwest by 2017 ("Renewable Forecast Graph"). In comparison, the Federal Columbia River Power System, which provides about 30% of the total electric power consumed in the Pacific Northwest, has a nameplate capacity of approximately 22,000 MW ("BPA facts"). For further perspective, the yearly average BPA area load is just over 6,200 MW ("2014 Final Rate Proposal Generation Inputs Study Documentation"). So wind power accounts for a much higher portion of power generated in the Pacific Northwest than in the rest of the country.

As with every energy resource, there are benefits and challenges that come with the development of wind power. Wind power is clean and renewable, the fuel source is free, and wind power also qualifies for tax credits; all of these are strong motivations for installing wind turbines. In the Pacific Northwest, the Columbia Gorge is conveniently located to develop wind power because of the windy conditions and its proximity to BPA's high voltage transmission lines, which span the region, and connect to other regions such as California. But wind is challenging to forecast with accuracy and wind power is not completely controllable (E. Mainzer). Therefore, wind power is considered a non-dispatchable resource.

Wind power is also subject to significant variation in relatively short periods of time. As Figure 1.2 shows, the wind power generated over a week varied drastically ("BPA Balancing Authority Total Wind Generation & Wind Basepoint, Chart and Data, Rolling 7 days"). There are several instances over the course of this 7-day period where the wind ramped thousands of megawatts over time periods as short as a few hours. Figure 1.2 also demonstrates that while wind can be predicted to a degree, there is some error that must be accounted for. In the figure, the red line shows the predicted power generation, and the green line shows the actual power generation. The differences between the two lines in the figure can be particularly problematic, because the power generated at any given time must exactly match the power consumed, or else the power system could become unstable. When wind power generation deviates from the predicted output, then other generation must change to meet load. As illustrated on Sunday of Figure 1.2, earlier in the day, around 10:00 am, wind power generated about 200 MW less than was predicted, and in the same day, around 9:00 pm in the evening, generated almost 250 MW more than was predicted.

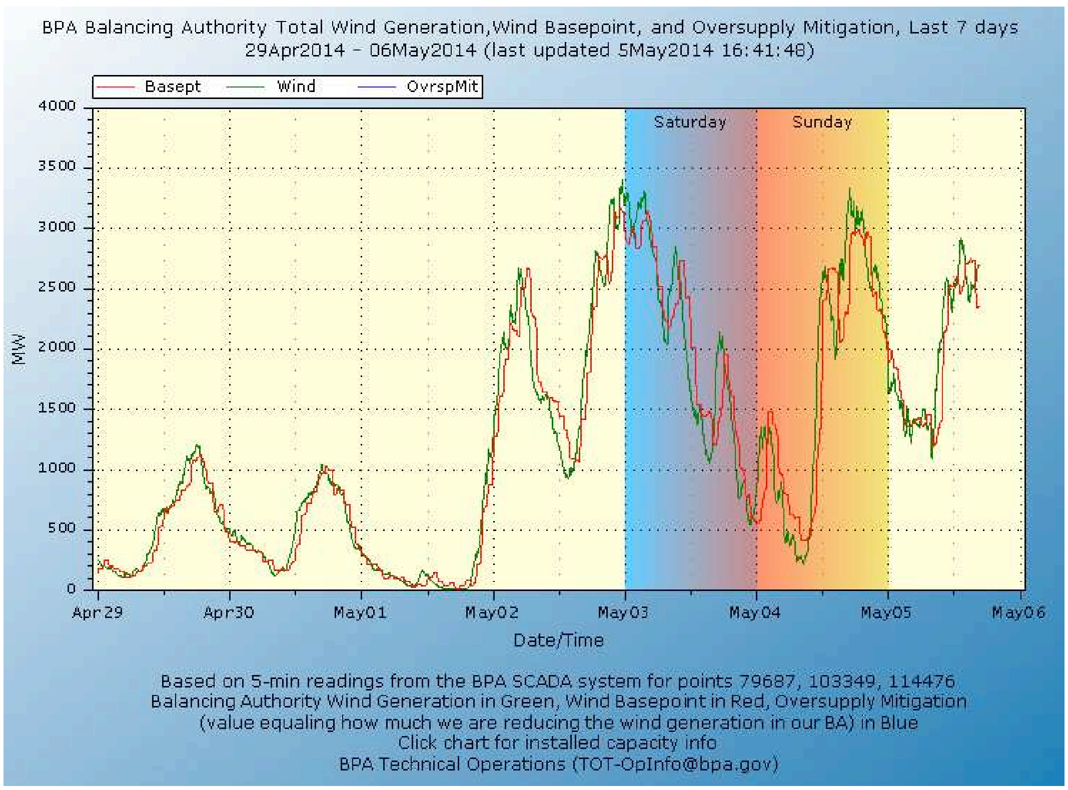

Figure 1.2. Forecast and actual wind power generation for seven days (from BPA Balancing Authority Total Wind Generation, Near-Real-Time, 2014)

1.2 Overview of Reserve Generation

One way to address the challenges that come with wind power is the use of balancing reserve generation. This refers to generation that remains on stand-by, and can be used to quickly ramp up or ramp down its power output. Balancing reserves are an important part of a power system, and are used for many reasons other than wind power variability. Balancing reserves are used to address variations in load, as well as contingencies such as loss of transmission lines or loss of a generator. There are several classifications of balancing reserves, based on what type of event they are used to address, what timescale their response is, and whether they increase or decrease their power generation (M. Milligan). Balancing reserves are commonly made up of spinning reserves, which are generators that are run at partial or no load, and are synchronized to the power system, so their response is quick. Non-spinning reserves may also be used, but they are not synchronized to the power system (M. Milligan). Figure 1.3 shows the balancing reserves deployed within BPA's balancing authority during the same 7-day period as Figure 1.2 ("BPA Balancing Reserves Deployed"). Figure 1.3 shows that balancing reserves are heavily relied upon, especially when predicted and actual wind power generation does not match.

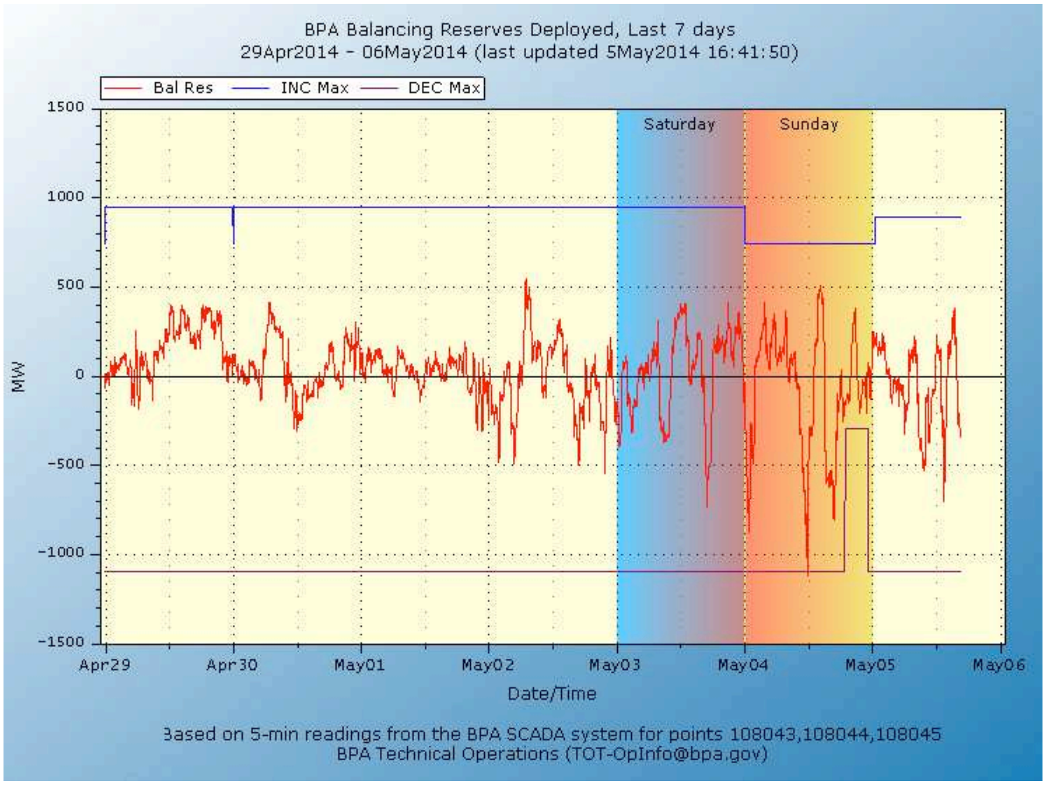

Figure 1.3. Balancing reserves deployed for seven days (from BPA Balancing Reserves Deployed, 2014)

Several types of energy sources can provide balancing reserves. Hydropower is particularly well suited to provide balancing reserves due to quick ramp rates. A hydropower unit can fully come online within minutes, and can change output power within seconds. Some natural gas and oil-fired power plants can also provide fast ramp rates, but generally have higher operating costs when subject to frequent changes in output power. In contrast, coal power and nuclear power have very slow ramp rates, taking hours or days to come online, and are therefore not used for balancing reserves ("The Importance of Flexible Electricity Supply").

Figure 1.4. Dams of the Federal Columbia River Power System (from US Bureau of Reclamation).

In the Pacific Northwest, the primary source of balancing reserves is hydropower, more specifically the Federal Columbia River Power System (FCRPS). This system refers to 33 dams located on the Columbia River and its tributaries that are owned and operated by the US Army Corps of Engineers and the Bureau of Reclamation and shown in Figure 1.4 (USBR). Bonneville Power Administration markets the power from these dams. Several dams, referred to as the "Big 10," are regulated using Automatic Generation Control (AGC) to provide balancing reserves for BPA ("2012 Final Rate Proposal, Generation Inputs Study Documentation"). These dams include Bonneville, Chief Joseph, Grand Coulee, Ice Harbor, John Day, Little Goose, Lower Granite, Lower Monumental, McNary, and The Dalles.

It has largely been believed over the past few years that the dams of the FCRPS are nearing, or have already reached their limit for providing reserves, due to the large amounts of wind power within BPA's system (E. Mainzer). As the dams are aging, significant upgrades are required, and many projects are currently under construction ("2014 Final Rate Proposal Generation Inputs Study Documentation"). Many within the power system industry have been concerned that providing reserves for wind power causes added wear and tear on the hydropower system, decreasing the lifespan of the hydropower units. With this in mind, researchers have been investigating exactly what the relationship between wind power and hydropower is (Y. Makarov).

Previous research at Oregon State University using correlation analysis had shown that the correlation between wind power and hydropower was less than expected (S. Brosig). This motivated a more in depth study of the relationship between wind power and hydropower. To better understand the relationship, several different types of analysis have been performed. All of the analysis performed for this research attempts to understand the complex relationship between wind power, hydropower, and the rest of the power system.

1.3 Overview of Power System Components

In order for the power system to maintain stability, the power generated must exactly match the power consumed at any given moment in time. This means that if wind power is increasing, either another source of generation must decrease or the load must increase. Several pilot programs are currently in place in the Pacific Northwest to investigate controlling load to essentially provide balancing reserves ("Demand Response and BPA"). While these programs are promising, they are not yet on a scale to meet the needs of the current level of wind penetration in the Pacific Northwest. So it can be concluded that at this time, load is not being used to balance variation in wind power.

However there is another aspect of the power system that must also be considered; power sold to entities outside the balancing authority area of BPA. A balancing authority, such as BPA, is responsible for making sure generation meets load, but it can also sell surplus power to another balancing authority outside of the area it is responsible for. This is done through interchanges; BPA has several interchanges, primarily with California to the south and Canada to the north. Traditionally, these are scheduled on an hourly basis, but BPA and CAISO in California have implemented a pilot program for intra-hour scheduling since 2011 and both plan to implement 15 minute scheduling in the near future ("CAISO Intr-Hour Scheduling Pilot Program, Version 4"). This essentially allows for the interchanges to be used in the same way balancing reserves are used.

Additionally, although hydropower is considered the primary source of reserves, there are other types of power generation within BPA's system. For the purposes of reporting data, BPA refers to the remaining power generation as thermal power, because they all produce power from heating a fuel. But there are many types of power generation that fall under the category of thermal generation, including nuclear, coal, natural gas, and biomass. As stated earlier, nuclear and coal have too slow of ramp rates to be able to provide reserves. But some natural gas and biomass power plants have the ability to provide reserves, depending on the ramp rates of the generators. As shown in Figure 1.5, natural gas, ignoring baseload generators that would not be used for reserves, and biomass account for over 15% of the generating capacity in the Pacific Northwest ("Pacific Northwest Generating Capacity"). Not all of that is within BPA's balancing authority, but it demonstrates that thermal generation is a substantial enough portion of generation in the region to provide balancing reserves, and relieve the hydropower system as necessary.

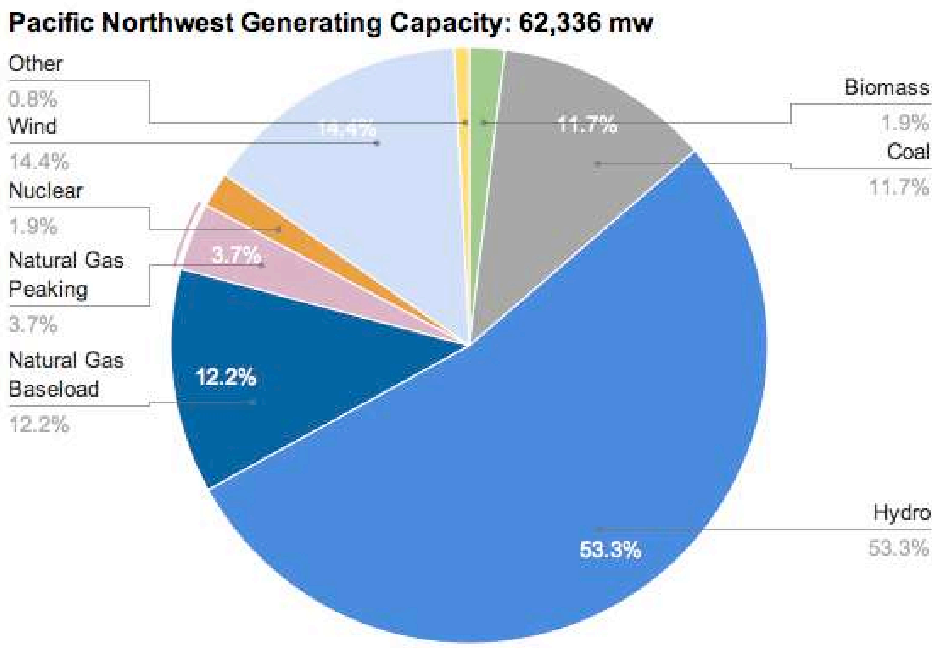

Figure 1.5. Generating capacity in the Pacific Northwest by source (Northwest Power and Conservation Council).

1.4 Scope of Thesis

It is with this knowledge in mind that analysis was performed to determine the relationship between wind power and hydropower, as well as between wind power and interchange power, and between wind power and thermal power. Several types of analysis were performed, including Maximal Information Coefficient analysis, correlation coefficient analysis, and regression analysis. The goal of these studies was to analyze real data such that relationship strength and relationship characteristics could be determined. With this information, it may be possible for future researchers to provide predictive analysis, but the analysis performed for this thesis did not attempt to predict the nature of these relationships in the future.

2 Maximal Information Coefficient Analysis

2.1 Theory of MIC

One type of analysis that seemed promising was to calculate the Maximal Information Coefficient, MIC, a newly developed statistic that could be used to identify relationships between datasets (D.N. Reshef). The benefit of this analysis is that it can identify all types of relationships, compared to most statistical analyses that are primarily appropriate for linear relationships. MIC is based on the idea that if a relationship exists between two variables, then a grid can be drawn on the scatter plot of the two variables that partitions the data to encapsulate that relationship. So to calculate the MIC, a matrix of the maximum mutual information for each grid possibility is created, and then the largest mutual information from this matrix is chosen. This is illustrated in Figure 2.1. MIC gives the relationship strength between two sets of data.

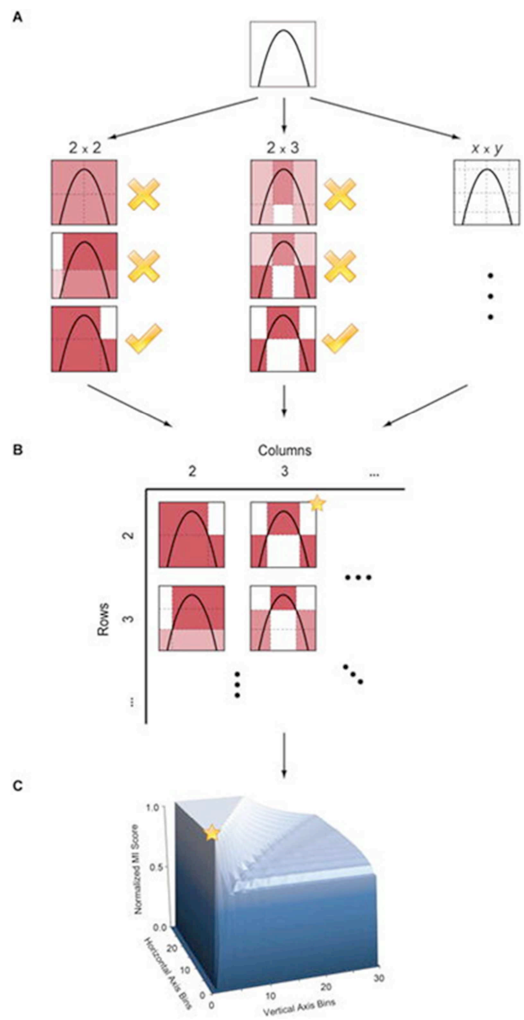

Figure 2.1. A graphical representation of the calculation of MIC (D.N. Reshef).

The mathematical definition of MIC can be described by the following equations. First, for a finite set $D \subset \mathbb{R}^2$ and positive integers, x, y, the maximum mutual information is defined as

$$I^*(D, x, y) = \max I(D|_G) \tag{1}$$

where the maximum is over all grids G with x columns and y rows. Further, the characteristic matrix, $M(D)$, is defined as an infinite matrix with entries

$$M(D)_{x,y} = \frac{I^*(D,x,y)}{\log\ \min\{x,y\}} \tag{2}$$

Finally, the Maximal Information Coefficient, MIC, for a set D of two-variable data with sample size n and grid size less than $B(n)$ is

$$\mathrm{MIC}(D) = \max_{xy<B(n)}\{M(D)_{x,y}\} \tag{3}$$

In addition to MIC, there are a few related statistics that have been developed by the same mathematicians that are collectively referred to as maximal information-based nonparametric exploration (MINE) (D. N. Reshef). These statistics include MAS, which tells the departure from monotonicity, MEV, which defines the closeness to being a function, and MCN, which indicates the complexity.

2.2 Calculating MIC for Wind Power and Hydropower

To determine if this type of statistical analysis would be appropriate for this research, calculations were performed to determine the MIC between wind power and each of the "Big 10" hydropower facilities. The results of these initial studies could then be compared to the correlation coefficient found in previous research on this topic (S. Brosig). All of the data used for this analysis was identical to the data used in the correlation analysis mentioned earlier, performed by a previous OSU graduate student. The power generation data was obtained for each of the "Big 10" hydropower dams operated by the US Army Corps of Engineers and the Bureau of Reclamation, as well as the wind power generated during the same time period, between 2009 and 2011.

The MIC was calculated using a MATLAB toolbox, based on the methodology described in the article that introduced MIC, and summarized above. The toolbox allowed for all MINE statistics to be calculated. While all values were computed, the value of most interest to this research was the MIC, so that it could be directly compared with the correlation coefficient, which is a similar statistic. Both MIC and correlation coefficient determine the relationship strength. MIC can range between 0 and 1, while correlation coefficient can range from -1 to 1. While MIC does not distinguish between positive or negative correlation, the magnitude of the two statistics should be comparable.

To confirm the validity of the MATLAB toolbox being used, several known relationships were tested, such as a linear relationship, a sinusoidal relationship, a parabolic relationship, and a circle. These results directly compared to the MIC values calculated in the original paper (D. N. Reshef). This verified that the MATLAB toolbox worked as expected.

The MIC was calculated for changes in wind power generation to changes in hydropower generation at each of the "Big 10" dams. These values could be directly compared to the correlation coefficient analysis done previously at OSU (S. Brosig). Unfortunately, as shown in Figure 2.2, the results of the MIC calculations were far less than the correlation coefficients.

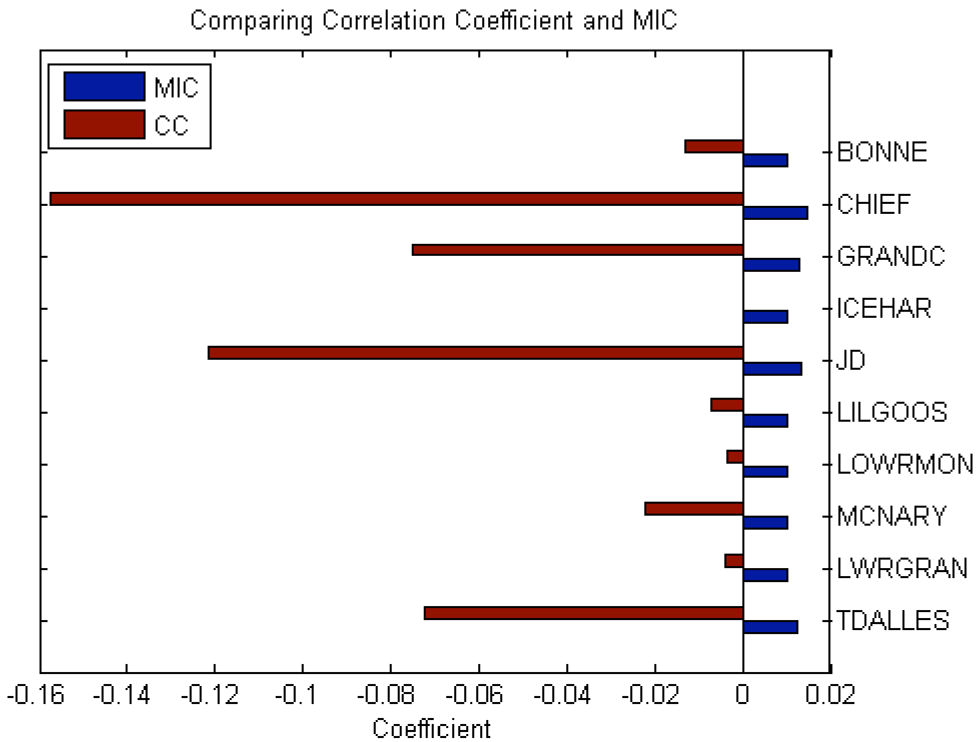

Figure 2.2. Comparing Correlation Coefficient and MIC.

The names and labels used for the “Big 10” dams can be found in Table 2.1.

Table 2.1 Labels and Names for Dams.

Label of Dam	**Name of Dam**
BONNE	Bonneville
CHIEF	Chief Joseph
GRANDC	Grand Coulee
ICEHAR	Ice Harbor
JD	John Day
LILGOOS	Little Goose
LWRMON	Lower Monumental
MCNARY	McNary
LWRGRAN	Lower Granite
TDALLES	The Dalles

In Figure 2.2, the correlation coefficients, indicated in red, vary widely for each dam. It is clear that the values for MIC, shown in blue, were far smaller than the correlation coefficients for each dam. While there is a slight trend between the two statistics, meaning that larger MIC values usually corresponded to larger correlation coefficients and vice versa, there is a significant difference in the scale of the two statistics. There was not a significant difference in MIC for each of the dams, and all the values stayed below 0.02, which indicates very little relationship strength.

There was no clear reason why the MIC values were so low compared to the correlation coefficients. Additionally, the computation time for MIC was significantly higher than for correlation coefficient. While MIC could have had some significant advantages, the method is relatively new, and not well proven. Correlation coefficient analysis, on the other hand, is widely accepted in the academic community. Hopefully further investigation into MIC can result in more fruitful research, but with the finite time allowed to perform this research, it was determined that correlation coefficient analysis was better suited for these studies.

3 Correlation Coefficient

3.1 Theory of Correlation Coefficient

As stated before, correlation analysis is used to determine the strength of a relationship. While it tells the same information as MIC, correlation analysis is most appropriate for linear relationships. For the purposes of this research, correlation coefficients were calculated in MATLAB using a built-in function based on the

Pearson product-moment correlation coefficient, also known as the simple correlation coefficient. This is calculated by the following equation

$$r = \frac{S_{XY}}{S_X S_Y} \quad (4)$$

Where r is the correlation coefficient, S_{XY} is the sample covariance, S_X is the standard deviation of X and S_Y is the standard deviation of Y (G. Shieh). Correlation coefficients can range from -1 to 1, with -1 meaning a negative correlation, 0 meaning no correlation, and 1 meaning positive correlation.

3.2 General Methodology

Studies were performed using correlation analysis, but with a different methodology than the initial studies. Firstly, a different set of data was used; this data was obtained from Bonneville Power Administration, and consists of measurements from SCADA at a 5-minute resolution for wind power generation, hydropower generation, thermal power generation, and interchange power ("BPA Balancing Authority Load & Total Wind, Hydro, Thermal Generation, and Net Interchange Chart & Data, Rolling 7 days"). This data is illustrated in Figure 3.1, showing seven days worth of data for wind power, hydropower, thermal power, and interchange power, as well as the load. Although Figure 3.1 shows data from 2014, the analysis was performed only on data obtained for the time period between January 2007 and December 2013. Secondly, instead of calculating a single coefficient for the entire seven-year period, similar to the previous studies comparing MIC to correlation coefficient, several shorter time periods were used.

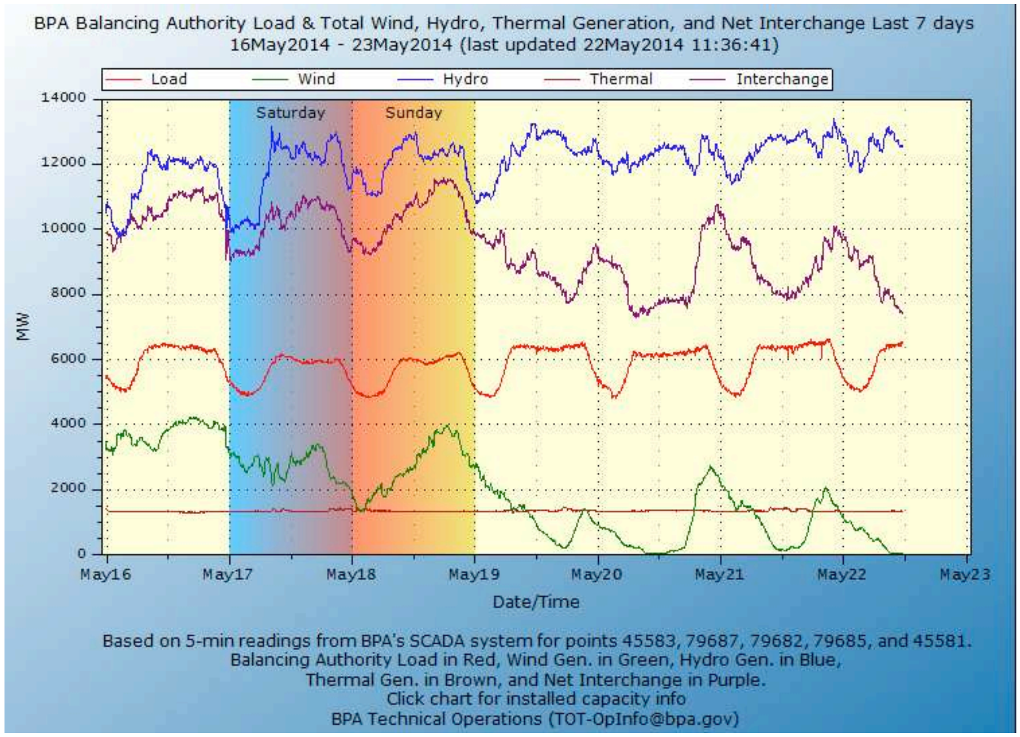

Figure 3.1. Plot of seven days worth of data (from BPA Balancing Authority Load and Total Wind, Hydro, Thermal Generation, and Net Interchange, Near-Real-Time, 2014)

3.3 Calculating Correlation Coefficient by Month

The first study performed used a time period of 1 month, or 30 days, calculating several correlation coefficients for each month. The relationships this study investigated included wind power to hydropower, wind power to interchange power, wind power to thermal power, changes in wind power to changes in hydropower, changes in wind power to changes in interchange power, and changes in wind power to changes in thermal power.

The results of this study clearly indicated that the dynamics of the system have changed over the seven years that were analyzed. Additionally it showed that correlation was not constant throughout a year period. There were some months that had much higher correlation coefficients, and some months with very low values. While these results were encouraging, a higher resolution was desired to better understand the relationships.

3.4 Calculating Correlation Coefficient for 30-Day Sliding Window

The next step was to attempt to get an even clearer picture of the dynamics. Instead of doing a single calculation for each month, a calculation was performed with a sliding window of 30 days, sliding one day at a time. The following figures, Figures 3.2, 3.3, 3.4 and 3.5, display the results of this analysis.

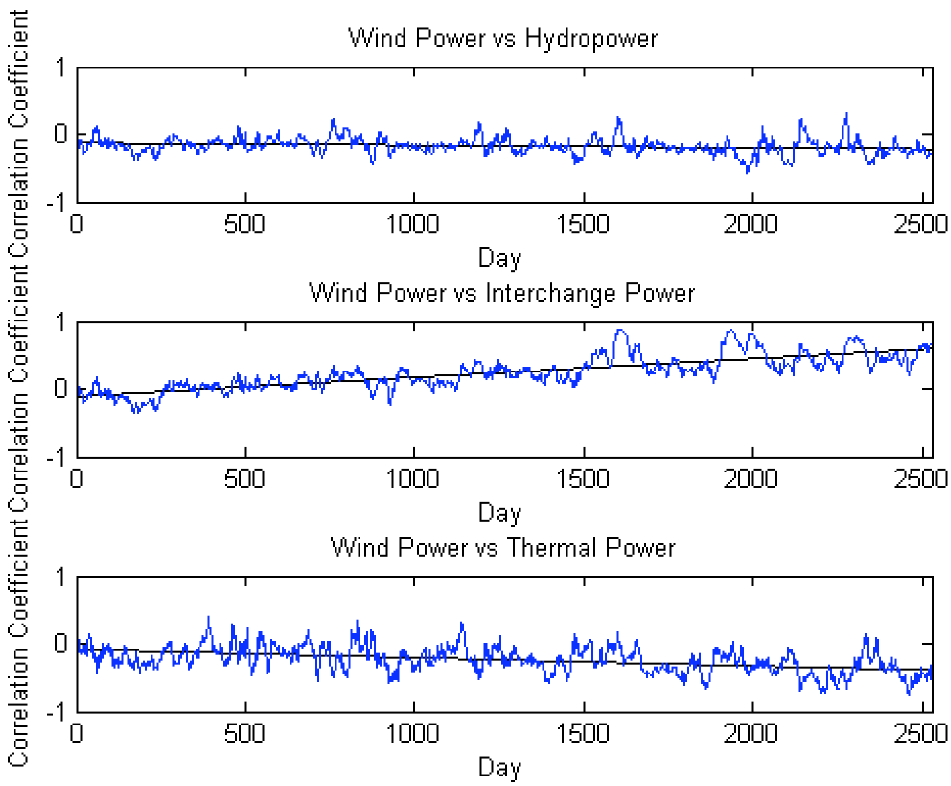

Figure 3.2. Correlation Coefficients for 30-day sliding window for wind power vs hydropower, wind power vs interchange power, and wind power vs thermal power.

Figure 3.2 shows the correlation coefficient for wind power to each of the following: hydropower, interchange power, and thermal power. The plots show seven years of data, with each point on the plot representing the correlation coefficient for 30 days of data, sliding one day at a time. The most interesting of these plots is the middle one, showing the correlation between wind power and interchange power. A trend over the seven-year period is clearly noticeable, with the correlation strength getting stronger as time went on. There is significant variation because wind power varies based on weather conditions, and the load varies seasonally as well. But this analysis clearly shows that more and more wind power is being sent outside of BPA's balancing authority via the interchanges.

Additionally, the bottom plot of Figure 3.2 reveals that the negative correlation between wind power and thermal power has also become stronger. The correlation is not as strong as for wind power to interchange power, but it is larger than expected considering the majority of BPA's thermal power comes from nuclear power.

To more clearly demonstrate the trends shown in Figure 3.2, the plots in Figure 3.3 show the yearly average, yearly maximum, and yearly minimum of the results shown in Figure 3.2. This illustrates the trends, as well as the variation that the correlation coefficients have compared to the average.

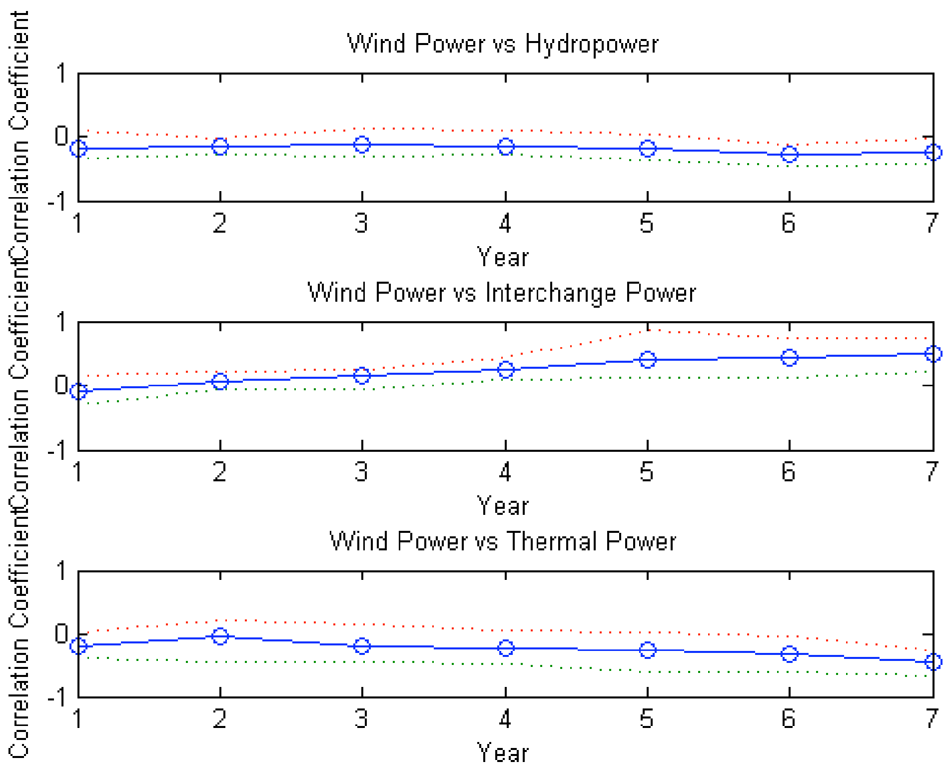

Figure 3.3. Yearly average, yearly maximum, and yearly minimum correlation coefficients for wind power vs hydropower, wind power vs interchange power, and wind power vs thermal power.

It is interesting to note that the top plot of Figure 3.3, showing the correlation between wind power and hydropower, indicates that the correlation has changed very little. This could suggest that hydropower already had very little flexibility to provide reserves for wind power. Additionally, the data used for this analysis included all hydropower within BPA's balancing area. A significant amount of reserves are provided by hydropower, but it is not true that all hydropower is used to provide reserves. As stated earlier, the nameplate capacity of the hydropower system is 22,000 MW, and only about 1,000 MW of reserves are needed by BPA ("BPA

Balancing Reserves Deployed"). That means that a large portion of the hydropower system is operated in such a way that would not be correlated to wind power.

In addition to investigating wind power to each of the other three elements of the power system, it was of interest to determine the relationship between changes in wind power to changes in each of the other three elements of the power system. The analysis was performed based on changes between each five-minute sample. This was done in the same manner as Figures 3.2 and 3.3, calculating a correlation coefficient for a 30-day period of time, and sliding one day at a time. The results are shown in Figure 3.4.

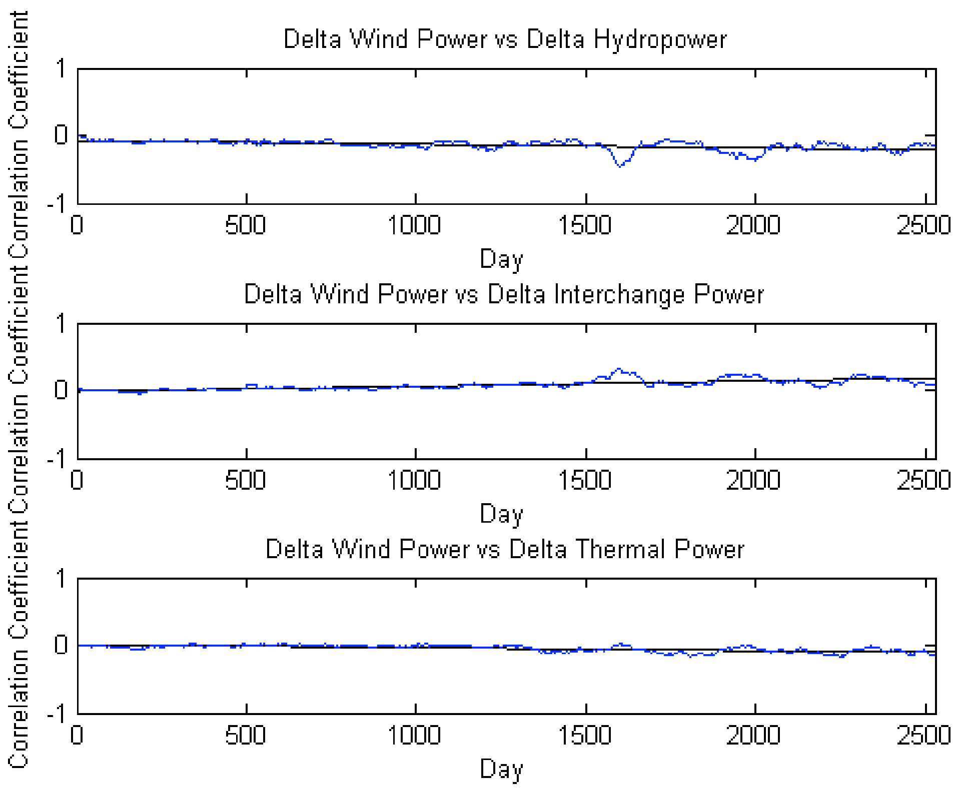

Figure 3.4. Correlation Coefficients for 30-day sliding window for changes in wind power vs changes in hydropower, changes in wind power vs changes in interchange power, and changes in wind power vs changes in thermal power.

Figure 3.4 shows that the correlation coefficients were small, but there are times when the correlation was stronger. There is also an overall trend for stronger correlation as time went on. This is more apparent in Figure 3.5. This is significant because changes in wind power are what require reserves. Again, all of hydropower is not used to provide reserves, so that can be an explanation for why the numbers are small for the top plot. But the overall trend, apparent in Figure 3.5, illustrates that as time went on, changes in wind power were more and more correlated to changes in hydropower. Also apparent in the top plot, the correlation seems to level out by the 6th year, possibly indicating that hydropower's ability to provide reserves is indeed reaching its limit.

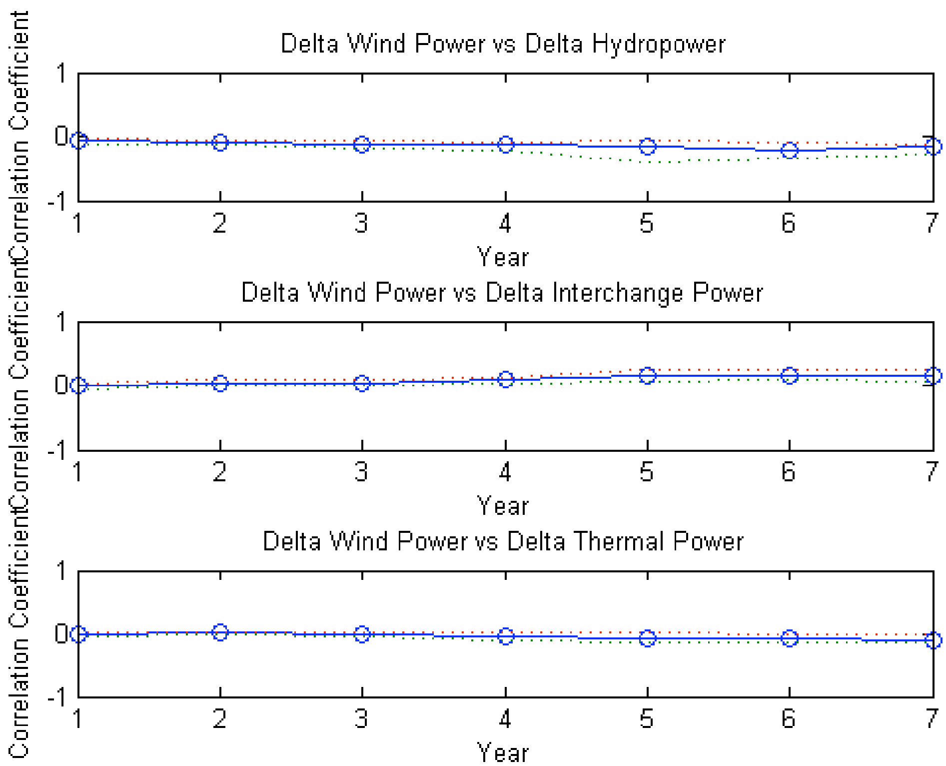

Figure 3.5. Yearly average, yearly maximum, and yearly minimum correlation coefficients for changes in wind power vs hydropower, wind power vs interchange power, and wind power vs thermal power.

The conclusions that can be drawn from Figures 3.2-3.5 can be summarized as follows: as time goes on, the correlation strength increases in all six of the cases investigated. Wind power and interchange power had the strongest correlation, and the largest increase over the 7 years studied. Wind power and hydropower were not extremely correlated, but there was a trend to be more correlated between changes in wind power and changes in hydropower. The small numbers could be because not all of hydropower resources are used for reserves. Additionally, wind power and thermal power are more strongly correlated than anticipated. This could be attributed to the increase in natural gas and biomass in the Pacific Northwest. Further discussion on this phenomenon is addressed later in this thesis.

4 Regression Analysis

4.1 Theory of Regression Analysis

To go one step further in this research, another type of analysis was performed. Regression analysis is a technique that attempts to create a mathematical model that describes the relationship between variables. The simplest type of relationship is a linear relationship, and since the correlation coefficient is most appropriate for linear relationships, this research attempts to create a linear model, which has the form

$$Y = \beta_1 x + \beta_0 \tag{5}$$

Given a set of data, x and y, regression analysis attempts to solve the values of β_1 and β_0 for the line that best fits the data (A. Cottrell). A visual representation is shown in Figure 4.1, where the red line shows a linear regression model for the data shown in blue. This type of analysis not only tells the relationship strength, but also describes the relationship.

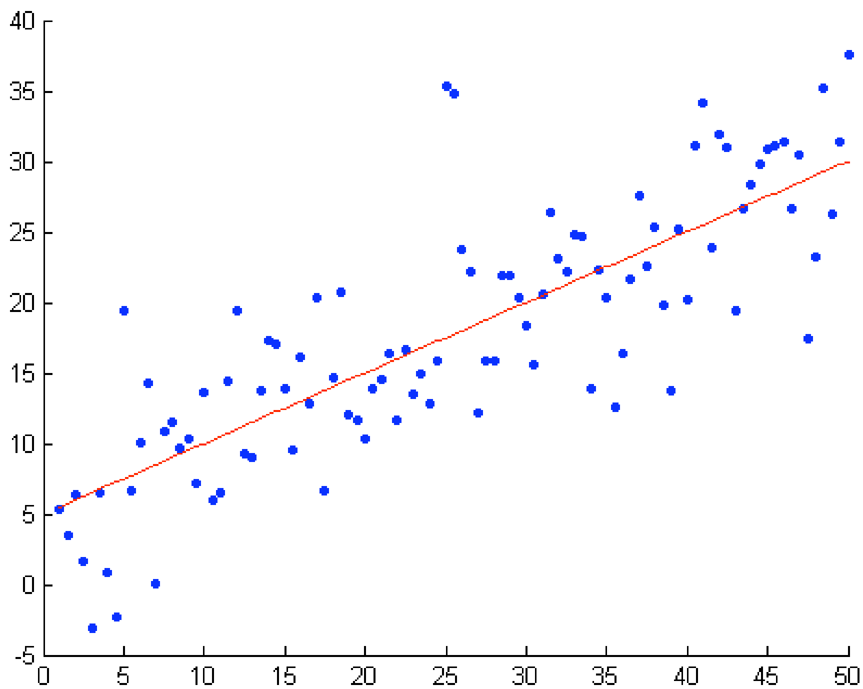

Figure 4.1. Visual representation of regression analysis.

For this research, a built-in function of MATLAB, regress, was used to calculate the values of β_1, β_0, the confidence interval for each of these values, as well as the R^2 value, which tells how well the line fits the data. The R^2 value, sometimes called the coefficient of determination, is not the same as the correlation coefficient. It is defined as the percentage of the variation that is explained by the linear model.

$$R^2 = \frac{\text{explained variation}}{\text{total variation}} \tag{6}$$

Higher R^2 values mean a better fit (A. Cottrell). Additionally, a small confidence interval is desirable because it means that not many other values of β_1 would fit the data as well as the β_1 value returned by the MATLAB function.

4.2 Regression Analysis for 30-Day Sliding Window

Regression analysis was performed for the same six cases used in the correlation coefficient analysis. Using the same data for wind power, hydropower, interchange power, and thermal power obtained from BPA for 2007 to 2013, and using the MATLAB regress function described in the previous section, β_1, the confidence interval, and the R^2 value were calculated using the 30-day sliding window methodology. The relationships are expressed in the following equations.

$$P_{\text{hydro}} = \beta_1 P_{\text{wind}} + \beta_0 \tag{7}$$

$$P_{\text{interchange}} = \beta_1 P_{\text{wind}} + \beta_0 \tag{8}$$

$$P_{\text{thermal}} = \beta_1 P_{\text{wind}} + \beta_0 \tag{9}$$

$$\Delta P_{\text{hydro}} = \beta_1 \Delta P_{\text{wind}} + \beta_0 \tag{10}$$

$$\Delta P_{\text{interchange}} = \beta_1 \Delta P_{\text{wind}} + \beta_0 \tag{11}$$

$$\Delta P_{\text{thermal}} = \beta_1 \Delta P_{\text{wind}} + \beta_0 \tag{12}$$

Firstly, the R^2 value is important to examine because it tells how good the model is. While higher values of R^2 means more of the variation can be explained by the model, for the purposes of this research, a high R^2 value is not expected. The results for R^2, illustrated in Figure 4.2 and Figure 4.3, show that the values of R^2 are meaningful, but are not particularly large.

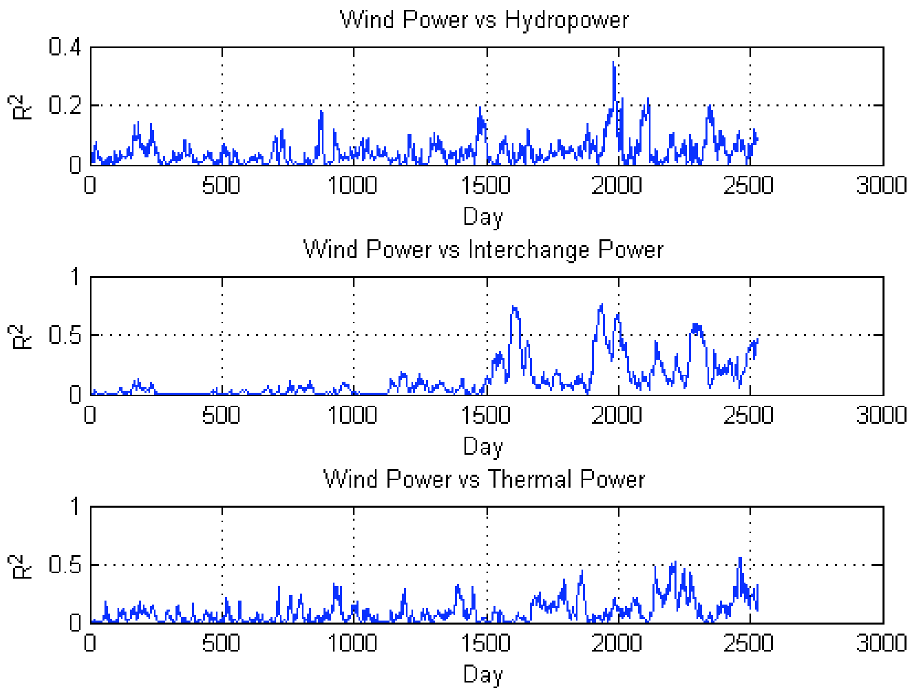

Figure 4.2. $\boldsymbol{R^2}$ values for the regression analysis of wind power to hydropower, wind power to interchange power, and wind power to thermal power.

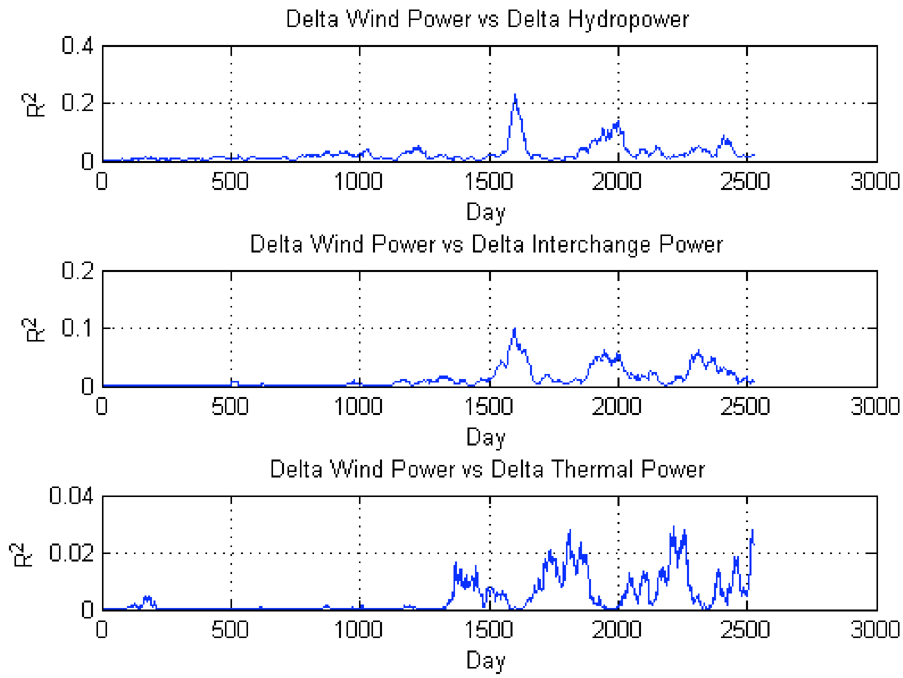

Figure 4.3 $\boldsymbol{R^2}$ values for the regression analysis of changes in wind power to changes in hydropower, changes in wind power to changes in interchange power, and changes in wind power to changes in thermal power.

The R^2 values for this analysis are low because the data encompasses all generation within each category, and reserves are provided by a subset of those generators. Therefore it cannot be expected that all of the generation will be strongly related to wind power. To better understand why the R^2 values are low, it is best to see what the data looks like. Figure 4.4 shows a logarithmic 3-D histogram of one month of data for wind power vs. hydropower, wind power vs. interchange power, and wind power vs. thermal power.

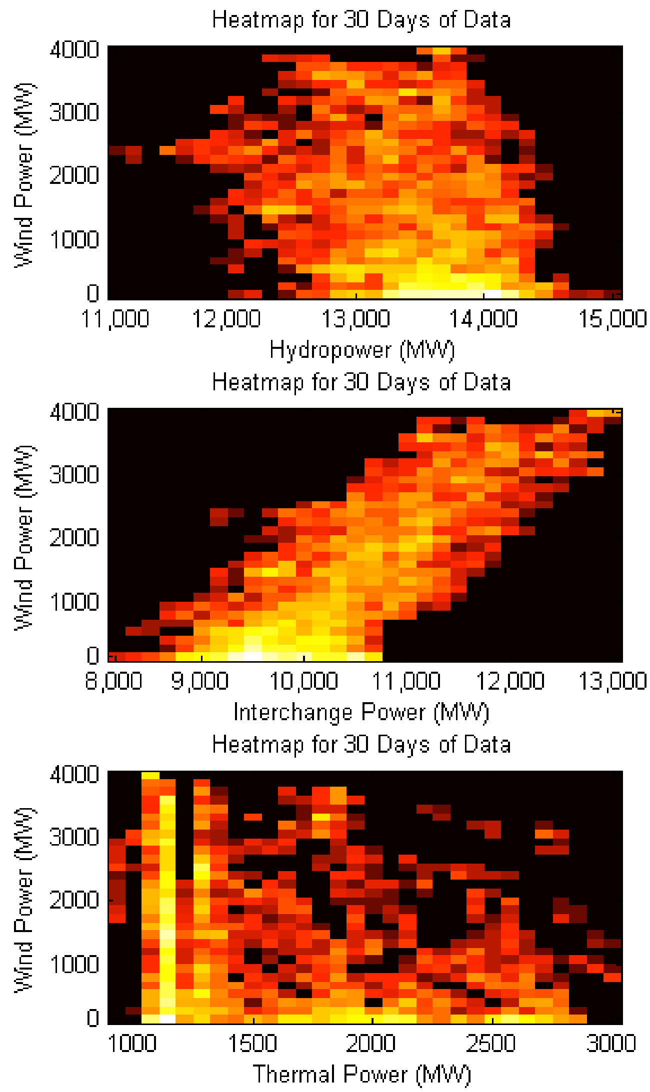

Figure 4.4. A logarithmic 3-D histogram of one month of data for wind power vs. hydropower, wind power vs. interchange power, and wind power vs. thermal power.

Additionally, Figure 4.5 shows a similar plot for change in wind power vs. change in hydropower, change in wind power vs. change in interchange power, and change in wind power vs. change in thermal power. Note that for the plots in Figure 4.5, the center of the plots, where the density is highest, is the origin. This makes sense because for a majority of the month the output power isn't varying significantly.

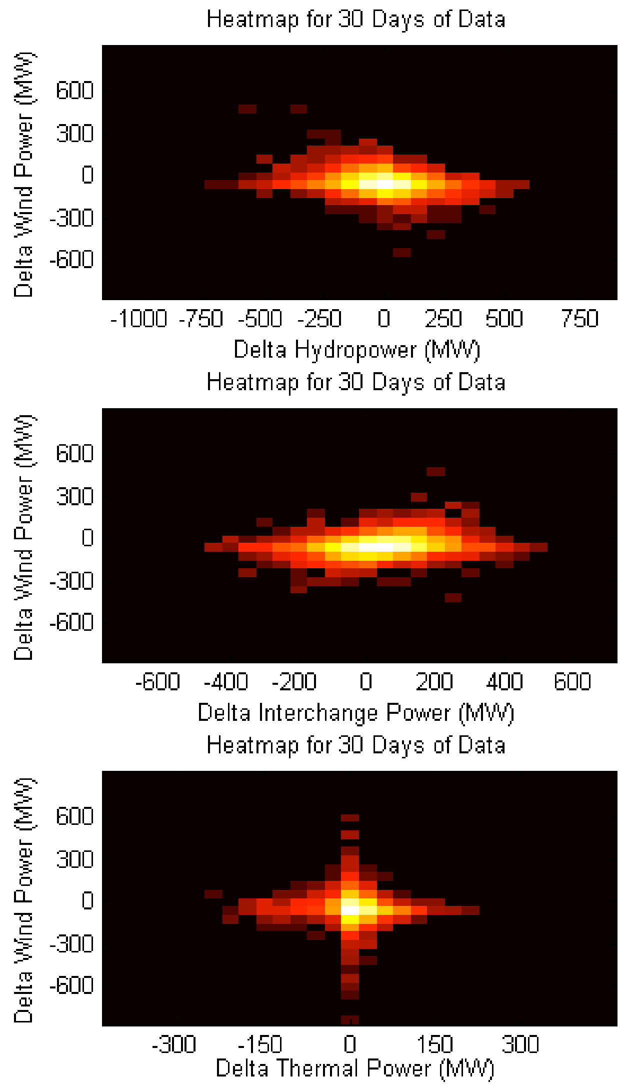

Figure 4.5. A logarithmic 3-D histogram of one month of data for changes in wind power vs. changes in hydropower, changes in wind power vs. changes in interchange power, and changes in wind power vs. changes in thermal power.

By examining Figures 4.4 and 4.5, it is clear that though there are trends to the data, they do not perfectly fit a line. This does not mean that the regression analysis is not still a valid tool in quantifying the relationships though. While the results of the regression analysis will be insightful into the relationships between wind power and the other parts of the power system, this analysis is not meant to create a model that will be predictive of the behavior of the power system. Higher R^2 values are required to use a regression model for prediction purposes. But since this research is meant to better understand the relationship, low values of R^2 are acceptable.

The regression analysis model has the form $Y = \beta_1 x + \beta_0$. The most important part of this model is β_1. This information conveys the slope of the best-fit line for the data. β_0 indicates where the best-fit line crosses the vertical axis. While it is important for the regression analysis to calculate a value for β_0, rather than restricting the line to pass through the origin, it is not crucial in understanding the relationships. Therefore, for the rest of this paper, β, or beta, refers exclusively to β_1.

Figure 4.6 shows the values calculated for beta for the best-fit line for wind power vs. hydropower, wind power vs. interchange power, and wind power vs. thermal power. As before, each point shows the value calculated for 30 days of data, sliding one day at a time. The figure shows that the values of beta started large for all three of the plots, but then quickly decreased, and were small for the rest of the time period under examination. Figure 4.7 shows the beta for changes in wind power vs. changes in hydropower, changes in wind power vs. changes in interchange power, and changes in wind power vs. changes in thermal power. These three plots show a much slower trend, particularly the top two plots. Additionally, the confidence intervals for all six of the plots are very small, so it can be concluded that the values of beta are truly the best fits to the data.

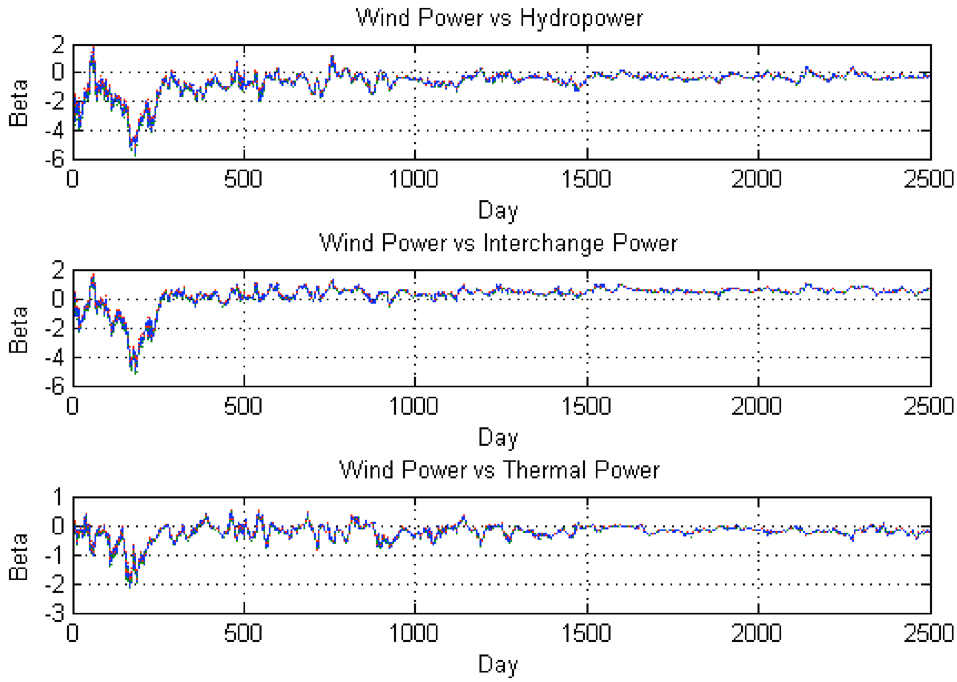

Figure 4.6. Beta values for the regression analysis of wind power to hydropower, wind power to interchange power, and wind power to thermal power.

In Figure 4.7, the plot of the values of beta for changes in wind power to changes in hydropower, the beta values start around -1. This essentially means that an increase of 1 MW of wind power corresponded to a 1 MW decrease of hydropower. As time went on, the beta values decreased, slowly but with a clear trend. By the end of the seven years that were analyzed, the beta was approximately -0.5. This means that for the same 1 MW increase in wind power, only 0.5 MW of hydropower would decrease.

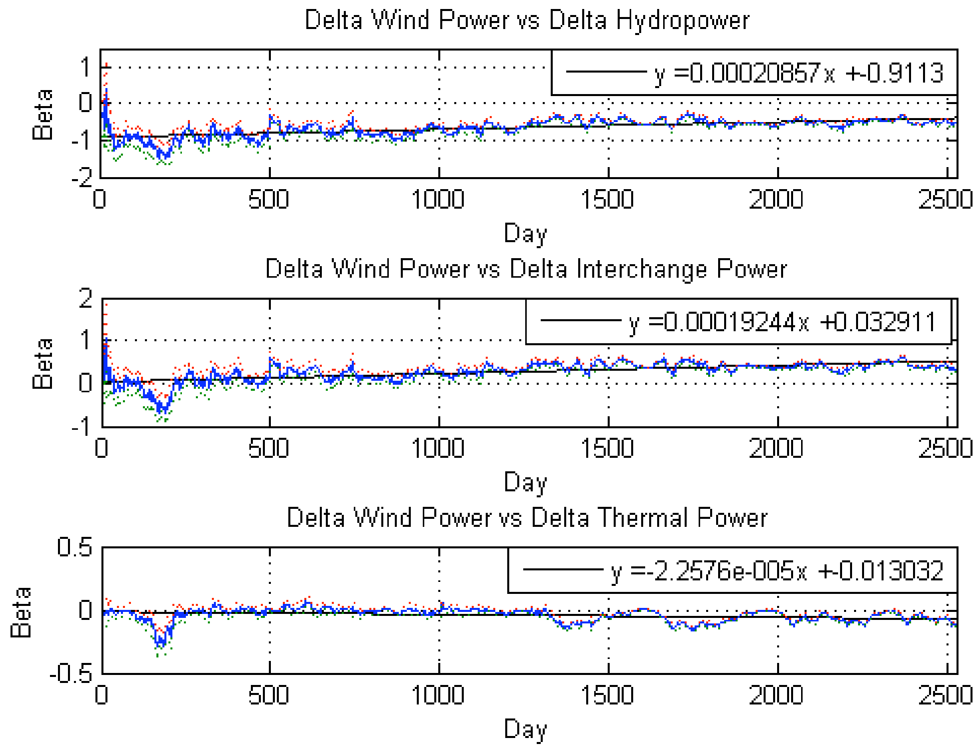

Figure 4.7. Beta values for the regression analysis of changes in wind power to changes in hydropower, changes in wind power to changes in interchange power, and changes in wind power to changes in thermal power.

In the second plot, the beta values were sporadic initially, but mostly remained close to zero. This means that the interchange may have sporadically responded to changes in wind power, but without a clear pattern. Gradually the values for beta increased with time. By the later part of the time period investigated, the beta value was consistently around 0.5. This means that for an increase of 1 MW of wind power, the interchange increased the power it exported outside of BPA's balancing authority by 0.5 MW. This change seems to have occurred around the time that BPA and CAISO implemented its pilot program for intra-hour scheduling.

The bottom plot shows that for the first part of the time analyzed, the beta for thermal power was fairly consistently zero, other than one significant instance. That instance could be explained by the biannual refueling outage of the nuclear facility, Columbia Generating Station, although if this were the case, it would be expected to see a similar shape every other year as well ("Hanford Nuke Plant Restarts After Refueling"). By examining the other two plots, it is clear that the particular time this occurred caused the beta for interchange to be uncharacteristically negative, which likely meant that BPA was importing power. So there may have been other unknown dynamics at play for that time period. Otherwise, the beta for thermal generation was close to zero, meaning thermal generation was not providing any reserves for wind power.

But for the later part of the time period analyzed, the beta value was more frequently non-zero. This could be because of more natural gas plants in the region. As shown in Figure 4.8, there has been well over 1000 MW of natural gas installed between 2007 and 2013 ("Generating Capacity Additions and Retirements"). It could be concluded that natural gas may be beginning to provide reserves.

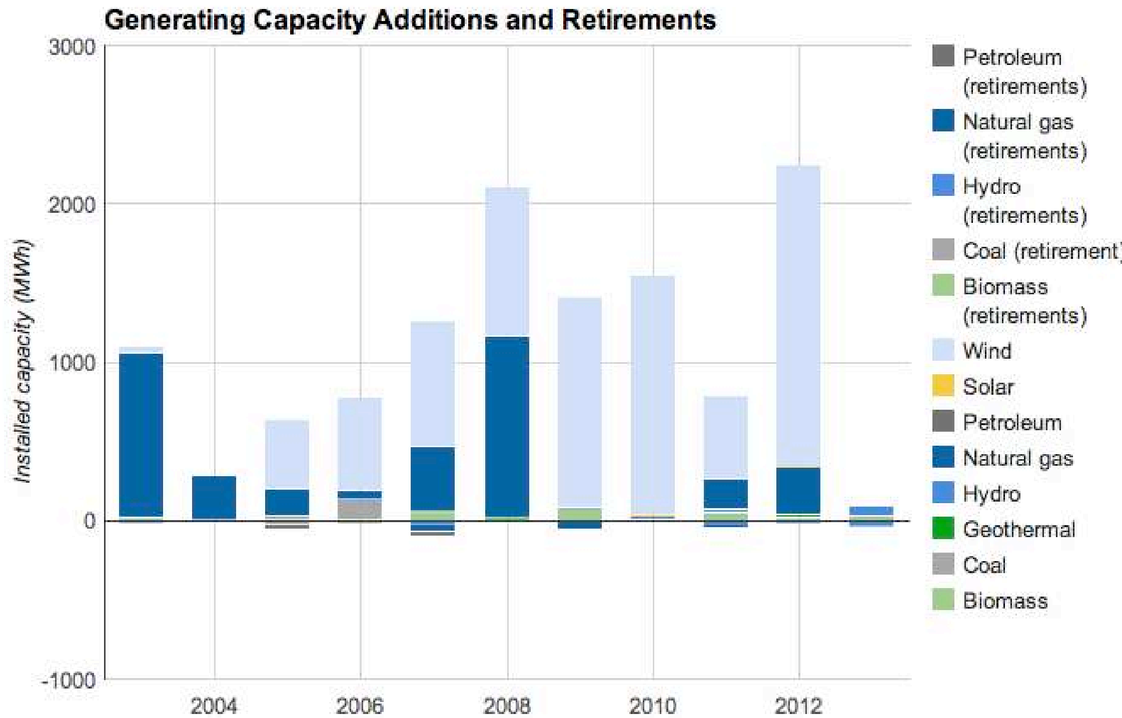

Figure 4.8. Additions and retirements of generation capacity, indicating natural gas installation between 2003 and 2013 (NW Power and Conservation Council)

Another factor that could contribute to the beta for thermal power being non-zero is BPA's Oversupply Protocol ("Seasonal Power Oversupply in 2012"). This policy, originally called Environmental Redispatch, has evolved since 2011 due to continuing litigation. Essentially the policy allows BPA, to varying degrees, to encourage other forms of generation, including all forms of thermal power and wind power, to shut down or reduce their generating output when the hydropower system must produce power during the spring runoff.

There are many nuances and disputes involved in this policy. The hydropower system is constrained when salmon are migrating because the dissolved gas in the river is mandated to maintain within certain levels. In order to maintain certain dissolved gas levels, dams are restricted in how much water can be spilled over the dam. When the water levels are high in the spring, and fish are migrating, the dam operators are forced to send water through the generators, producing power. The problem arises because the load for the region is traditionally lower during spring, particularly at night. The situation is worsened when wind power is producing large amounts of power as well. In order to maintain system stability, all forms of generation other than hydropower are occasionally asked to decrease the power they generate. Wind power owners have been particularly opposed to this policy because they lose tax credits when they reduce their generation. So thermal generators have been relied upon to reduce their power output first, and then wind power.

The Oversupply Mitigation policy has been controversial, and may continue to evolve. But this could be a valid explanation for the beta values in the later part of the third plot in Figure 4.7. Since increasing wind power in these instances causes thermal power to reduce their power output, or shut down all together, it makes sense that these values of beta would be negative. Additionally, the Oversupply Mitigation policy is not used frequently, and for only short periods of time, so it makes sense that though possibly large amounts of thermal generation are shut down, the beta value for 30 days would be small.

4.3 Regression Analysis by Wind Penetration Level

All the analysis so far has calculated the statistics based on time, but what is important about the dynamics of this system is how it relates to new wind power generators being added to the system. Based on Figure 4.9, it is clear that an increase in time corresponds to more and more wind power generation within BPA's balancing authority ("Wind Generation Capacity"). This is the crucial connection that must be made between the results shown previously, and the relationship to wind power. It has been clear so far that the dynamics of the system had been changing with time, but the further conclusion to be drawn is that the dynamics are changing because more wind power is being added to BPA's system.

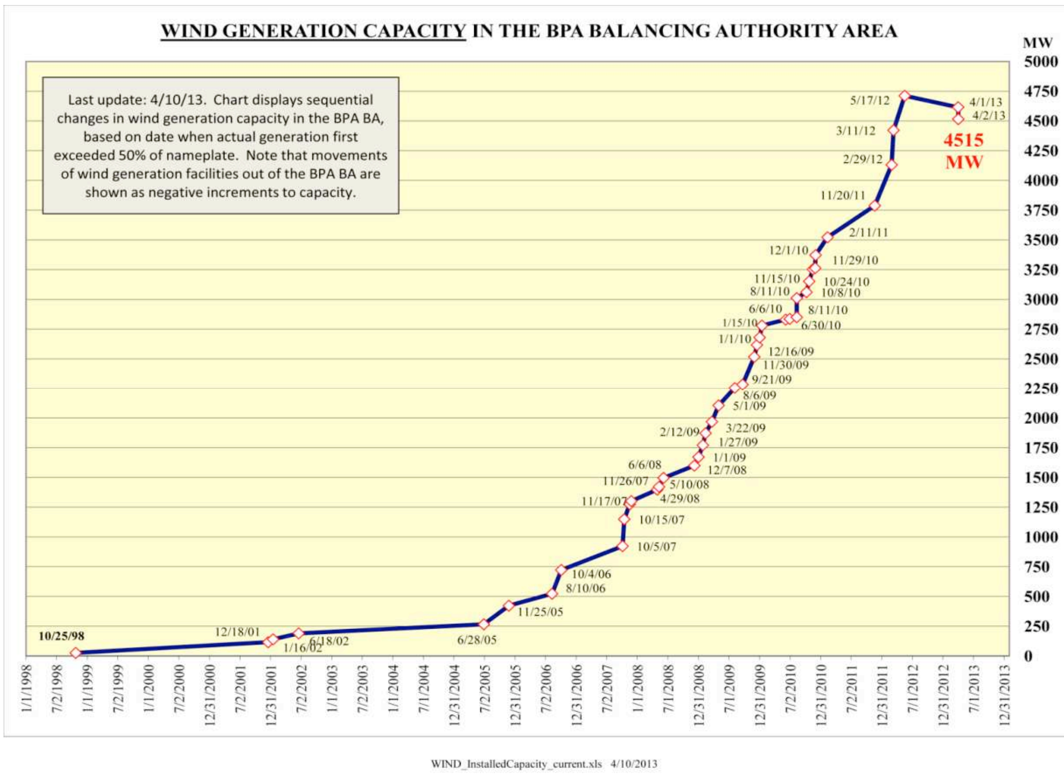

Figure 4.9. Wind generation capacity in the BPA balancing authority area (from Wind Generation Capacity, 2013)

To demonstrate this concept even more clearly, Figure 4.10 shows the results calculated for beta, this time versus the wind penetration level, meaning how much wind power generation is connected to BPA's system. This plot shows a square point for the value of beta calculated for a certain level of wind penetration. The vertical lines represent the confidence interval for each beta calculation. A line is included in blue to demonstrate the trend. Although the line doesn't perfectly fit the values of beta shown, it helps to identify the trend.

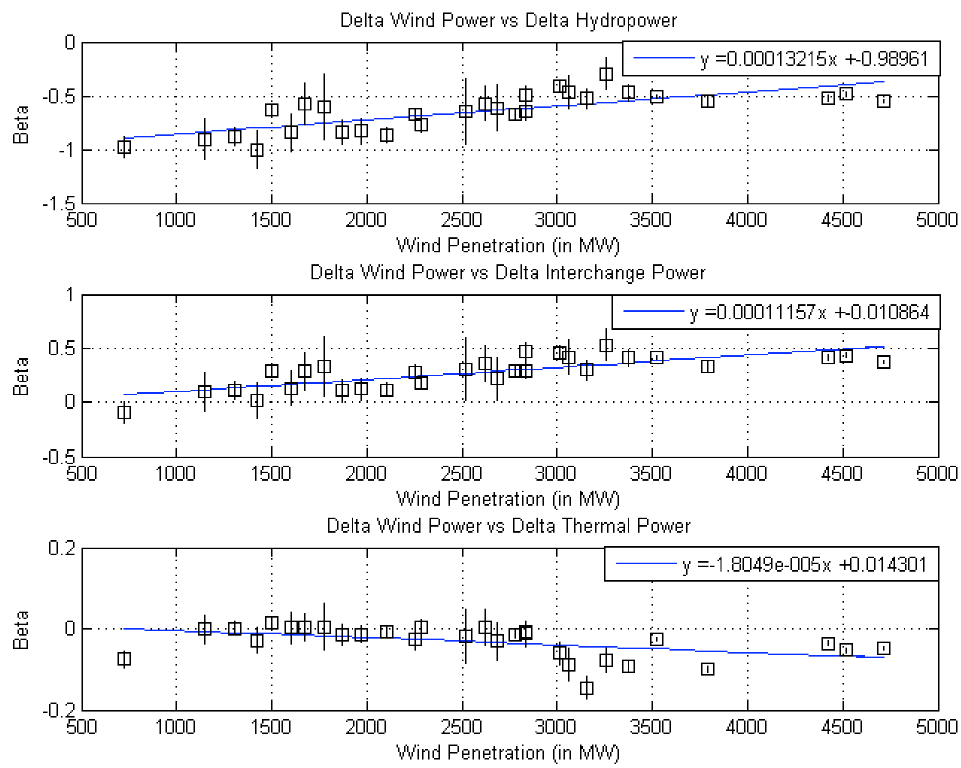

Figure 4.10. Beta values based on levels of wind penetration for the regression analysis of changes in wind power to changes in hydropower, changes in wind power to changes in interchange power, and changes in wind power to changes in thermal power.

Figure 4.10 shows only the changes in wind power to the changes in the other three elements of the power system. This is because Figure 4.6 demonstrated that there was not a noticeable trend to the beta values for wind and hydropower, interchange power, and thermal power. This is not concerning though, because reserves are required because of changes in wind power, so this study is more concerned about the results shown in Figure 4.7 and Figure 4.10.

Similar conclusions can be drawn from Figure 4.10. Firstly, the top plot shows that that beta values were initially around -1. Then as wind penetration increased, the values for beta decreased to around -0.5. In fact for the last few increases in wind penetration, there was not a significant change in the beta calculated for changes in wind power to changes in hydropower. The decrease in beta does not signify that hydropower was being used less to provide reserves; rather it likely suggests that hydropower continued to provide the same MW of reserves, but as more wind power was added to the system, more reserves were required than hydropower alone could supply.

Additionally, the values of beta corresponding to changes in interchange power increased as more wind power generating capacity was added to the system. The mostly likely conclusion for this increase is that since hydropower could no longer solely supply the reserves for wind power, and since a significant amount of the wind power was being purchased by entities outside of BPA's balancing authority, BPA essentially sold the problem outside of it's balancing authority, and used the interchange in the same way reserves are used. For example, if wind power was predicted to ramp significantly over the next 30 minutes, or even over the next hour, then BPA sold that power outside of its balancing authority, and then the interchange power increased correspondingly as the power was exported. By doing this, hydropower and other resources, are not forced to decrease the power they generate.

4.4 Regression Analysis for DC Intertie

The interchanges that BPA has with other entities are primarily AC transmission lines. But there is also a High Voltage DC line, called the Pacific DC intertie, or PDCI, that connects BPA and California, in addition to three AC transmission lines. The PDCI stretches from Celilo, near The Dalles, OR to Sylmar, near Los Angeles, CA ("BPA, PGE, and PacifiCorp bolster California-Oregon Intertie"). In order to determine if the PDCI is used for reserves, data was obtained from BPA for 5-minute net PDCI power for a similar time period, 2008 to 2013 ("Pacific DC Intertie (PDCI) Actual Flows"). The same analysis was performed to determine the beta between changes in wind power to changes in DC interchange power. The results are shown in Figure 4.11.

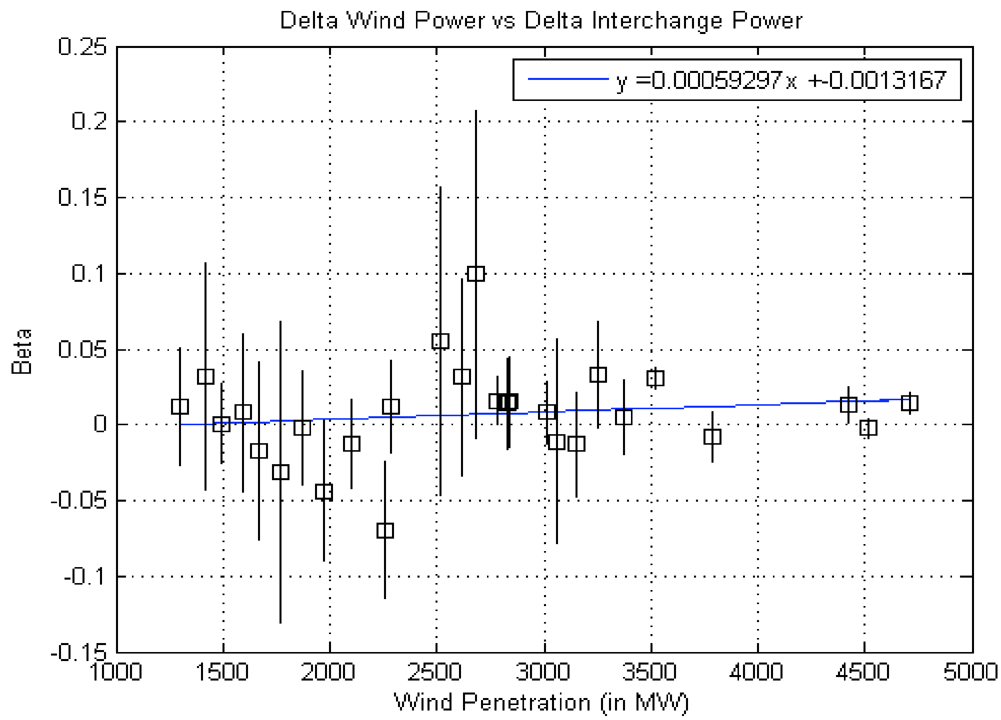

Figure 4.11. Beta values based on levels of wind penetration for the regression analysis of changes in wind power to changes in the DC interchange.

From Figure 4.11 it is apparent that the values of beta calculated for the PDCI were very small, and did not fit a trend line very well. Therefore it can be concluded that the PDCI is not used in the same way reserves are. This makes sense because the PDCI is scheduled on an hourly basis, and not usually based on the power market where excess power is bought and sold. It is usually scheduled to provide large amounts of firm power, which are decided well in advance.

4.5 Regression Analysis for Individual Hydropower Units

To further investigate the dynamics of wind power to hydropower, it was of interest to see if certain hydropower units were more related than others. The data that had been previously used for the MIC analysis consisted of power generated at each of the “Big 10” dams from 2009 to 2011. The data was also available for each individual unit within each dam. This data, along with the wind power generated during the same time period, was used to determine the beta value for wind power and each hydropower unit. Correlation coefficient analysis had already been performed by previous research (S. Brosig).

To understand what a hydropower unit means, Figure 4.12 shows an illustration of a single unit of a hydropower facility ().

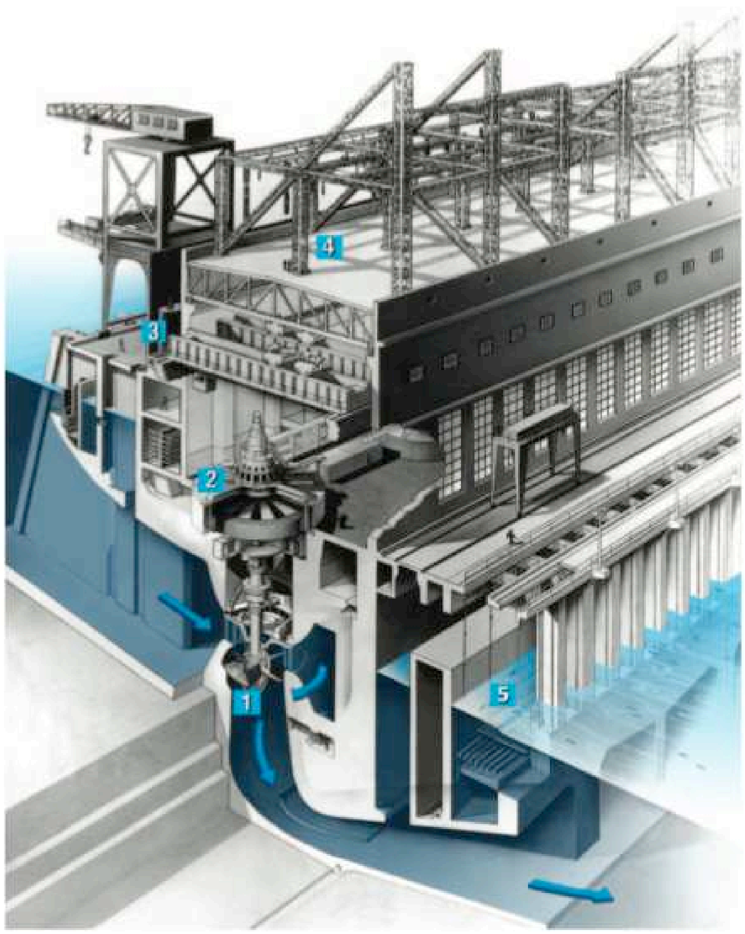

Figure 4.12. Diagram of hydropower facility, showing a single unit (from US Army Corps of Engineers).

Figure 4.12 shows what comprises of a single hydropower unit. In the figure, the labeled components include, 1, the turbine, where water motion is converted to rotational mechanical power, 2, the generator, where mechanical power is converted to electrical power, 3, the transformer, which increases the voltage to the voltage of the transmission line, 4, the switch yard, which directs the power to different transmission lines, and 5, the fish ladder that allows fish to safely travel upstream. There are multiple units at each dam, operated and controlled independently of each other.

Regression analysis was performed in the same manner, calculating a value for beta for a 30-day window, sliding one day at a time. In order to compensate for the drastically different order of magnitude between the nameplate capacities of each unit to the generating capacity of all of wind power, the data was converted into per unit. The data was converted to per unit by dividing each dataset by the respective nameplate capacity. Since wind power capacity changed over the course of this analysis, the data had to be normalized based on the capacity at each data point.

The results revealed that there was not any particular unit or units that had significantly higher values of beta. Figure 4.13 through Figure 4.15 demonstrate a variety of plots that are representative of this analysis. The first plot, Figure 4.13, shows the beta values for unit 19 at Chief Joseph dam. The figure demonstrates that the values of beta varied significantly over the time period examined. The data was only available for two years, so it is difficult to compare these figures to the previous analysis done for all of hydropower. It is clear that this particular unit had high beta values at certain times, but there was not any particular trend to when this unit was strongly related to wind power.

The majority of the time the beta values were negative, but there were several instances where the beta values were positive. This means that when wind power increased, this unit also increased. One possible explanation for this phenomenon is that hydropower provides reserves for the entire power system, not just for wind power. These instances could have been at a time when load increased suddenly, or a baseload generator was taken offline unexpectedly, so this unit had to increase to meet the load. Therefore it would make sense that wind power and this particular unit increased (or decreased) at the same time.

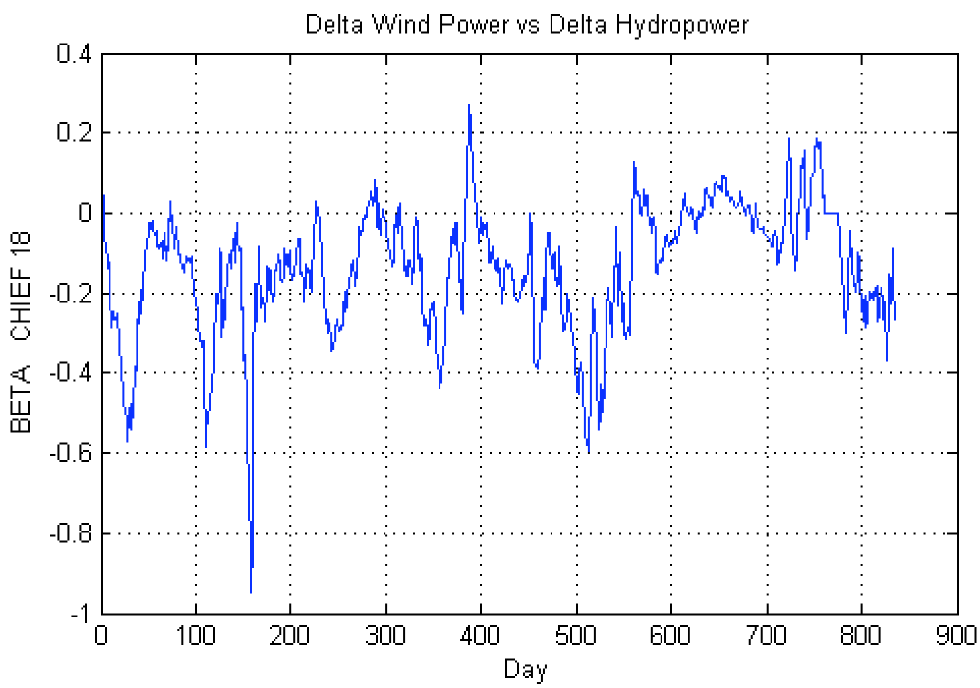

Figure 4.13. Beta values for change in wind power to change in hydropower at Unit 18 at Chief Joseph.

The unit shown in Figure 4.14, Unit 15 at John Day dam, had varying values for beta as well. Comparing Figure 4.13 ad Figure 4.14, it is clear that the units were acting independently of each other. Instances where Unit 18 at Chief Joseph had particularly high values of beta, Unit 15 at John Day did not have particularly high values of beta. This demonstrates that operators use different units at different times to provide reserves. One particular hydropower unit is not being use significantly more than others. And every hydropower unit is not used equally for each event that requires reserves to be deployed.

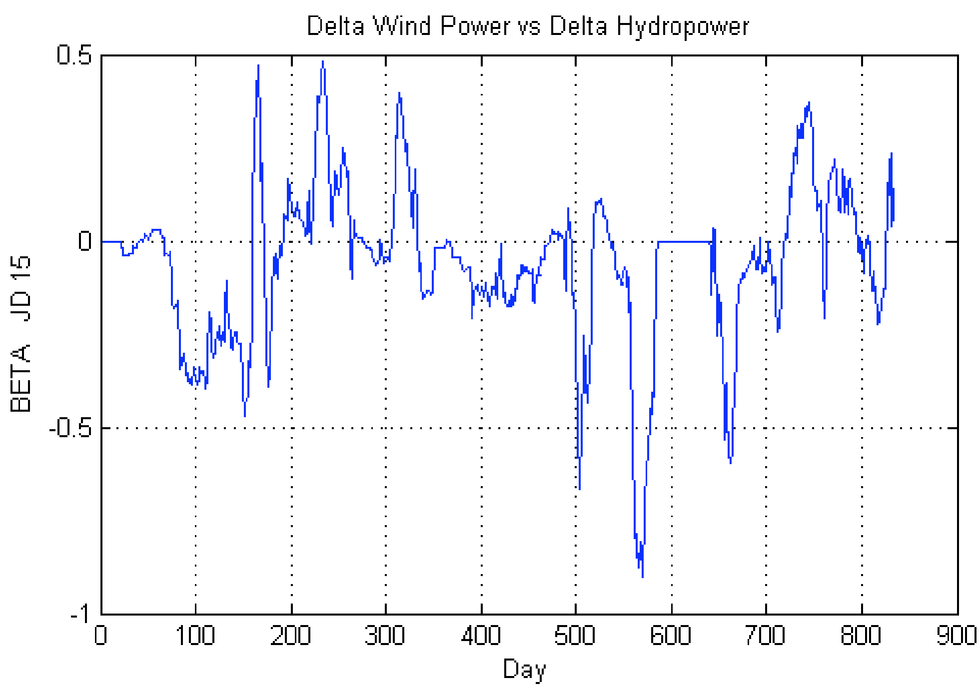

Figure 4.14. Beta values for change in wind power to change in hydropower at Unit 15 at John Day.

Figure 4.15 shows one additional plot for another hydropower unit. This figure shows Unit 2 at The Dalles. Again, this figure demonstrates that the values of beta vary widely for each unit, and there was not a distinguishable pattern to when the beta values were higher. The units were operated independently, and there was not a strong pattern amongst the various units.

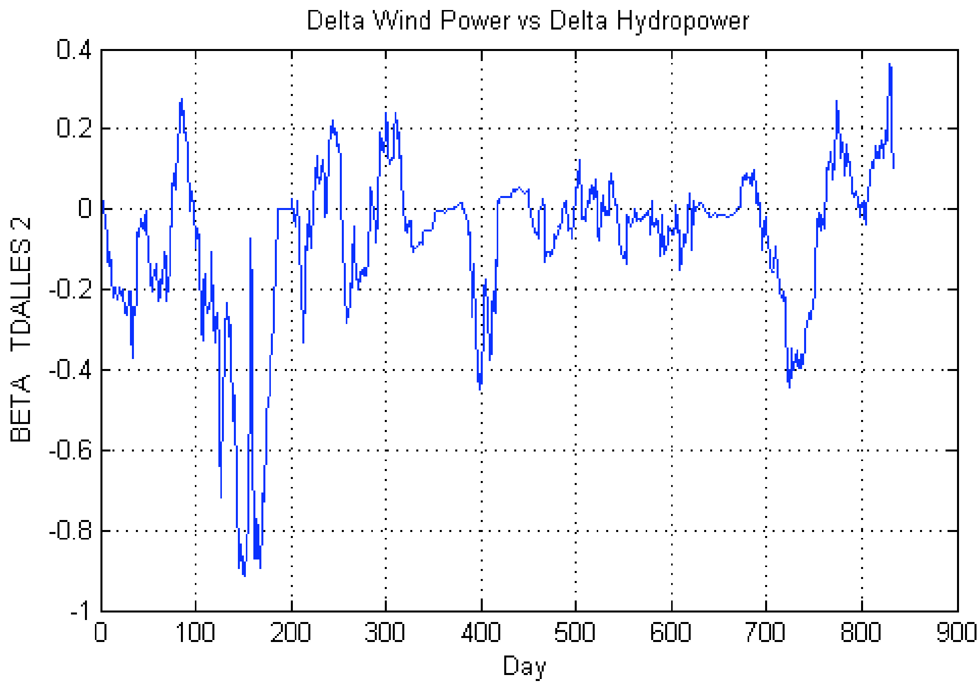

Figure 4.15. Beta values for change in wind power to change in hydropower at Unit 2 at The Dalles.

5 Voltage Stability

5.1 Theory of Voltage Stability

So far this research has examined the relationship between power generated by one source to power generated by another source. But wind power can affect the power system in another way, by impacting the voltage stability. Voltage instability can be the result of the power system not providing enough reactive power support ("Guide to WECC/NERC Planning Standards I.D: Voltage Support and Reactive Power"). There are many ways to improve the voltage stability of a power system, including using transformer load tap changers (LTCs), regulators, synchronous condensers, and static VAR compensators. This equipment is installed as power system studies deem necessary, and each type of equipment has its own benefits and concerns. All of these devices act to keep the voltage within an acceptable range.

But wind power generators tend to worsen voltage stability. When wind power ramps quickly, the voltage can deviate from its normal, stable value. Additionally some of the older types of wind power generators consumed large amounts of reactive power, especially as they generated more real power (S. G. Ghiocel). This makes it harder to maintain voltage stability.

Voltage stability is critical to the power system, so it is important to understand the affect that wind power has on the voltage of the system. If wind power is contributing to voltage instability, then the equipment that has been installed to maintain stability, such as transformer load tap changers, must have to work harder to maintain stability. To investigate this phenomenon, a correlation analysis was performed, but this time the correlation between changes in wind power and changes in voltage were examined.

5.2 Correlating Wind Power to Substation Voltage

The voltage data for this analysis was obtained from BPA for several of the major substations within its system. This data was sampled at 5-minute intervals for April 2013 to April 2014. For several locations, there is a 230 kV and 500 kV substation at the same site, so those are indicated as separate substations. Over this time no new wind power was installed. For this reason, and because one year is a sufficiently short time period, a single correlation coefficient was calculated for wind power to the voltage at each substation, as well as a correlation coefficient for changes in wind power to changes in the voltage at each substation. The results of these calculations are shown in Table 5.1.

Table 5.1. Correlation coefficients for wind power to substation voltages.

Substation	CC	CC (Δ)	Substation	CC	CC(Δ)
Sub 1	-0.492	-0.004	Sub 20	-0.095	-0.001
Sub 2	-0.275	-0.003	Sub 21	-0.094	-0.001
Sub 3	-0.274	-0.002	Sub 22	-0.094	-0.000
Sub 4	-0.234	-0.000	Sub 23	-0.064	-0.007
Sub 5	-0.225	0.003	Sub 24	-0.063	-0.007
Sub 6	-0.198	-0.003	Sub 25	-0.059	0.001
Sub 7	-0.178	0.001	Sub 26	-0.055	0.002
Sub 8	-0.178	0.001	Sub 27	-0.020	-0.007
Sub 9	-0.176	0.004	Sub 28	0.028	-0.001
Sub 10	-0.175	-0.003	Sub 29	0.036	-0.006
Sub 11	-0.163	0.002	Sub 30	0.047	0.001
Sub 12	-0.151	-0.010	Sub 31	0.050	0.001
Sub 13	-0.147	-0.003	Sub 32	0.051	0.000
Sub 14	-0.139	0.001	Sub 33	0.068	-0.004
Sub 15	-0.123	0.001	Sub 34	0.092	0.001
Sub 16	-0.117	-0.006	Sub 35	0.106	0.009
Sub 17	-0.100	-0.006	Sub 36	0.107	-0.003
Sub 18	-0.095	-0.001	Sub 37	0.108	0.013
Sub 19	-0.095	-0.001			

For information security purposes, BPA has requested that the substation names and locations not be disclosed. Therefore, all substations have been given a new name. Table 5.1 shows that the correlation coefficients for wind power to voltage at each substation varied drastically, from -0.492 to 0.108. On the other hand, the correlation coefficients were all very small for changes in wind power to changes in voltage.

The results show that correlation between wind power and voltage at a substation can vary drastically. But when these results are examined in the context of location relative to wind power, these results show a pattern. Figure 5.1 shows the location of many of the wind power projects within BPA's system ("Interactive Map of Wind Projects"). Notice that the majority of the projects, existing, under construction, and proposed, are located in a fairly small area located along the Columbia River, on the border between Oregon and Washington.

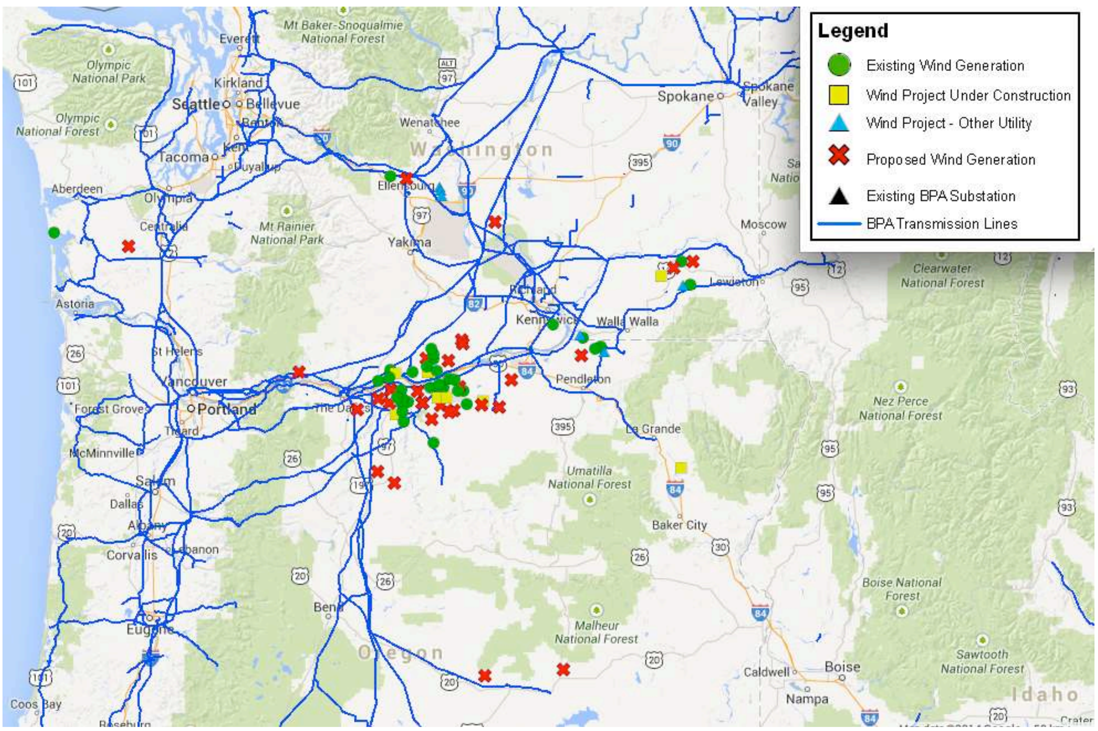

Figure 5.1. Map of wind power sites in Oregon and Washington.

Though the exactly locations of the substations cannot be published here, generalizations can be made about the relative location to the majority of the wind power sites. Figure 5.2 shows the positions of the substations relative to each other. The plot is laid out using standard map directions, meaning up is north, and left is west. But the plot simply orders the substations by direction, and relative distance is not taken into account. For example, Subs 31, 35, 32, 28, 16, and 12 are all close together in the West-East direction, but are spread out significantly in the North-South direction. Additionally, Figure 5.2 does not indicate how these substations are electrically connected. By comparing Figure 5.2 to Figure 5.1, similarities can be recognized, and the reader can get a good idea of the rough location of these substations.

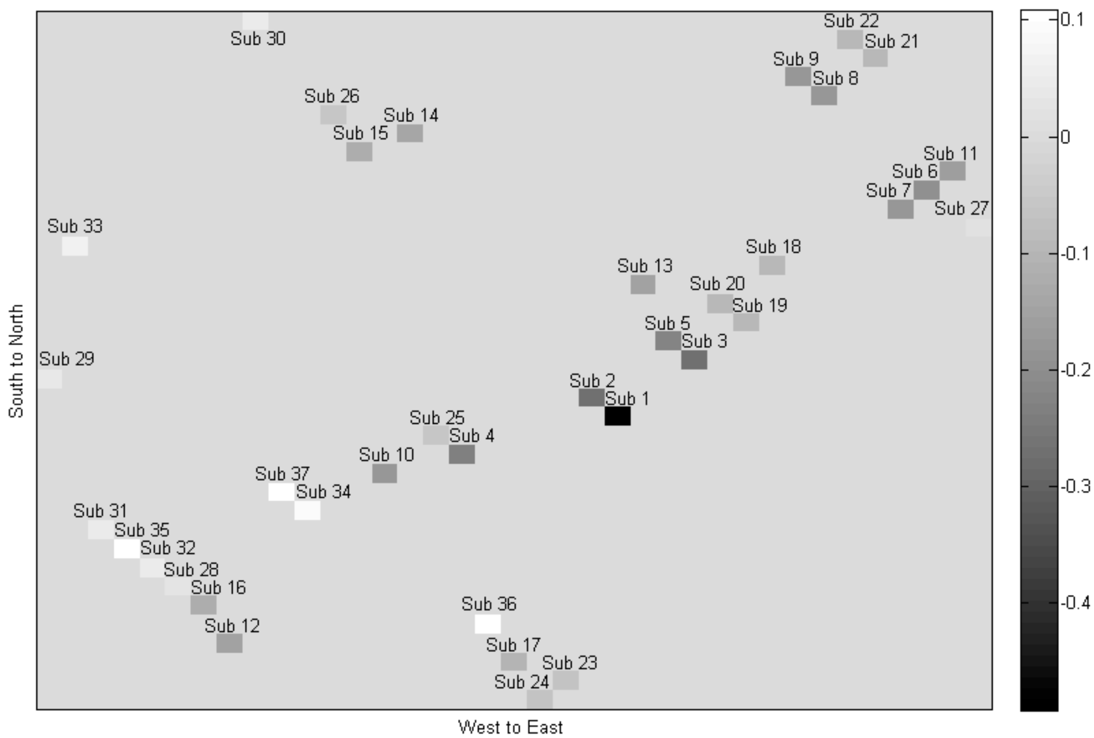

Figure 5.2. Position of substations relative to each other.

The color of each substation corresponds to the strength of the correlation to wind power. The majority of the wind sites are located close to Subs 1, 2, 3, 4, and 5, therefore these substations are indicated with darker shading, for stronger negative correlation. The substations lighter than the background indicate a positive correlation.

The data seems to support the conclusion that substations located closer to wind power sites are more correlated to wind power than substations further away. Most of the substations that are strongly negatively correlated are the point of interconnection to BPA's system for the wind power sites. So it makes sense that these substations are so highly correlated. The remaining substations have fairly low correlation coefficients. All of these substations are located further away from the majority of the wind farms located in the Columbia Gorge.

Another reason that most of the correlation coefficients are small is because there are devices, such as transformer load tap changers and regulators that are installed throughout the system, and are operated to maintain voltage stability. These devices take action when the voltage deviates from its normal value, and correct the problem for all substations downstream of the voltage deviation. Since the substations directly connected to the wind power sites likely do not have devices between the substation and the wind power site, the voltage at those substations will swing when wind power ramps. But there are likely voltage stability devices at these substations that limit the effect on the rest of the system.

The majority of the substations that are positively correlated, indicated by lighter shades, are further away from the wind power sites, and also have reactive power support at the substations. Devices that provide reactive support include capacitor banks, reactor banks, and static VAR compensators. These devices are controlled to maintain voltage stability, and therefore act to increase the voltage when an increase in wind power causes the voltage to decrease. Therefore wind power and the voltages at theses substations would be positively correlated. Subs 24, 32, 35, and 36 are known to have reactive support, and many of the rest of the substations with positive correlation are electrically connected to one or more of these substations.

5.3 Correlating Wind Power to Substation Voltage with a 30-day Sliding Window

To confirm the assumption that one year was a short enough time period to calculate a single correlation coefficient, a similar methodology to all the previous studies was used; a correlation coefficient was calculated for a 30-day window, sliding one day at a time. These results show that there is some variation within a year, but the trends observed based on a single value of correlation coefficient still hold true. To demonstrate this without showing 37 different plots, a handful of substations were chosen to examine closer.

The first substation to examine is Sub 1, shown in Figure 5.3. This substation had the largest correlation coefficient, -0.4925. In Figure 5.3, it is clear that the correlation coefficient was consistently high, with a substantial period of time where the correlation coefficient was -0.8. There is some variation throughout the year, but that can be attributed to the variation of wind power. Sub 1 is located in the midst of the wind power sites, so it makes sense that this substation was the most correlated to wind power.

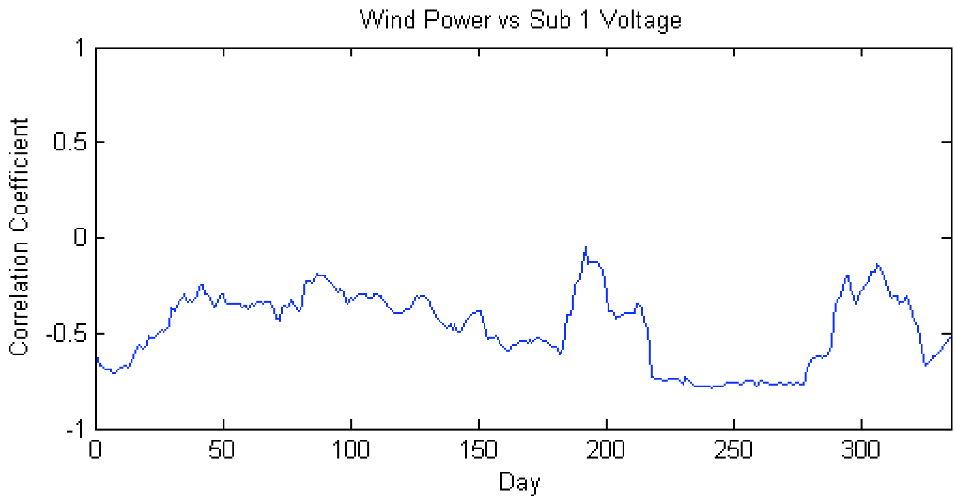

Figure 5.3. Correlation Coefficient for wind power to substation voltage at Sub 1.

Additionally Sub 2 is shown in Figure 5.4, and shows a very similar plot, with a similar shape, but shifted slightly up. Sub 2 is located at the same place as Sub 1, but Sub 1 is the 230 kV substation and Sub 2 is the 500 kV substation.

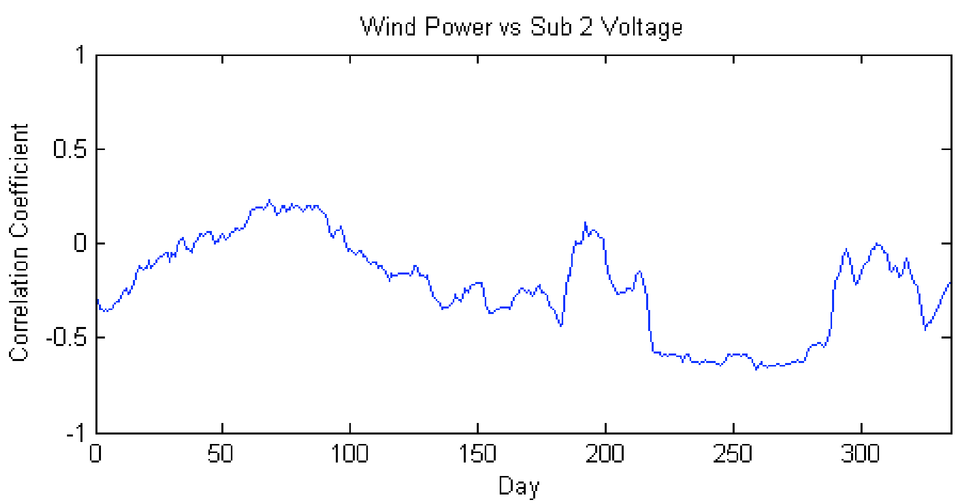

Figure 5.4. Correlation Coefficient for wind power to substation voltage at Sub 2.

The plots shown in Figure 5.3 and Figure 5.4 are interesting because they possibly show the effect of a single tap changer. It is likely that the wind power sites in the area connect to the 230 kV substation, and then the voltage is stepped up through a transformer, possibly one with a tap changer. While there is a similar shape between Figure 5.3 and Figure 5.4, the correlation coefficient shown for Sub 2 is less than for Sub 1.

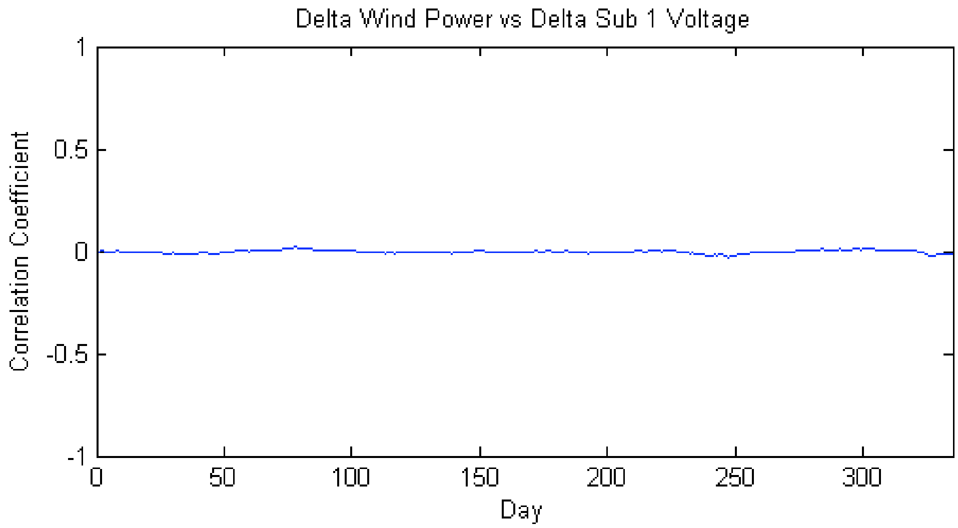

Figure 5.5. Correlation Coefficient for change in wind power to change in substation voltage at Sub 1.

Additionally Figure 5.5 shows the correlation coefficients for change in wind power to change in substation voltage at Sub 1. This plot is representative of all the plots of change in wind power to change in substation voltage. The correlation coefficient was consistently small for the entire year, demonstrating that there is little to no correlation. But the remaining plots show that there is correlation between wind power and substation voltage, to varying degrees, depending on where the substation is located.

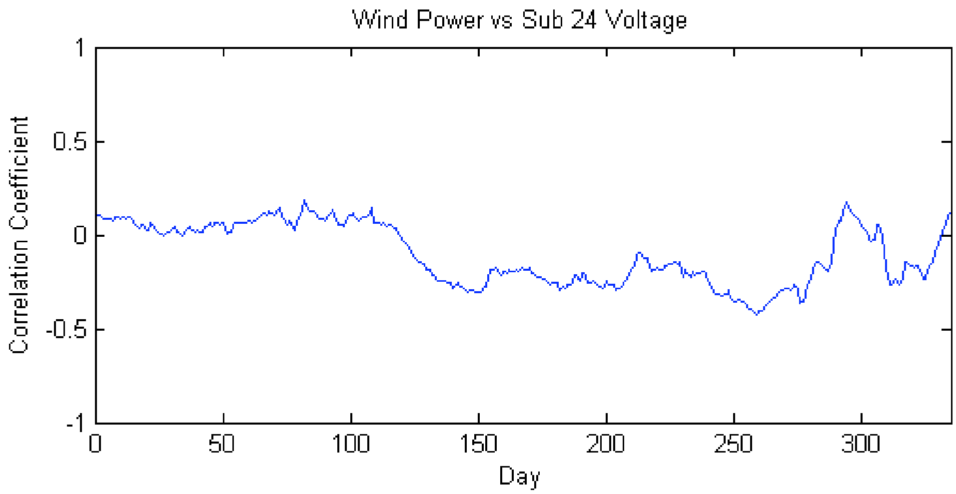

Figure 5.6. Correlation Coefficient for wind power to substation voltage at Sub 24.

Figure 5.6 shows a plot of the correlation coefficients for a year for wind power to substation voltage at Sub 24. This substation is located further south than the majority of wind power, near the Oregon California border. There is also reactive support at this substation. Because this substation is located far away from the majority of the wind power sites, it makes sense that the correlation coefficient is fairly small. The correlation coefficient calculated for the entire year for this substation was -0.063. The plot shown in this figure also demonstrates that this number is representative of the entire year. The reactive support located at this substation explains the portions of the plot that show a positive correlation. This substation is also part of the interchange with California. Since the previous studies have indicated a strong relationship between wind power and the interchanges, it makes sense that at times there was negative correlation as well.

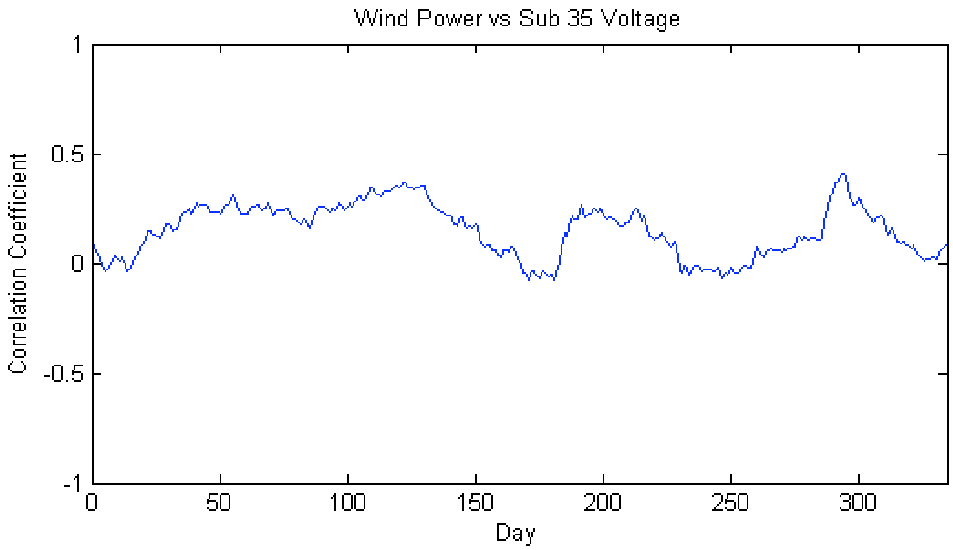

Figure 5.7. Correlation Coefficient for wind power to substation voltage at Sub 35.

Additionally, the plot shown in Figure 5.7, for the correlation coefficient for wind power to substation voltage at Sub 35, shows that the yearly correlation coefficient, 0.106, is representative of the entire year. It is clear that for the majority of the year, the correlation coefficient at this substation was positive, which can be attributed to the reactive support located at this site.

Figures 5.3 to 5.7 indicate that the patterns observed using a single correlation coefficient for the entire year are consistent with the patterns observed using a shorter time window. These plots also demonstrate that while there was slight variation within the year, the correlation coefficient for each substation was fairly consistent.

5.4 Tap Changer Operations

To understand how frequently voltage regulation devices are required to act due to wind power, a study was performed to estimate the number of load tap changer operations that occurred during this time period (April 2103 - April 2014). To isolate wind power from other causes of voltage variation, the only substation that was studied was Sub 1, since it had the highest correlation to wind power. It is not known whether the transformer at Sub 1 has a load tap changer, but to perform this study it is assumed that the transformer at this location does. Load tap changers are not the only way to maintain voltage stability, but by examining the voltage at this substation within the context of load tap changer operations, it gives an idea of how often voltage regulation devices are required to act.

A load tap changer provides voltage regulation by changing the turns ratio of the windings of a transformer. Transformer windings are illustrated in Figure 5.8, with taps that can be changed to maintain the output voltage of the transformer as close to the nominal voltage as possible (D. M. Geibel).

Figure 5.8. Illustration of transformer windings, with taps to change the transformer turns ratio (from ABB).

The standard load tap changer arrangement in North America has a voltage range of ±10%, with steps between taps of approximately 5/8%, leading to 16 steps above and 16 steps below rated voltage (D. M. Geibel). Using this standard, the voltage data for Sub 1 was binned into 33 equally spaced bins for ±10% of the rated voltage, 230 kV. This allowed the voltage data to be quantized. Figure 5.9 shows the voltage quantized into bins of 5/8% of 230 kV.

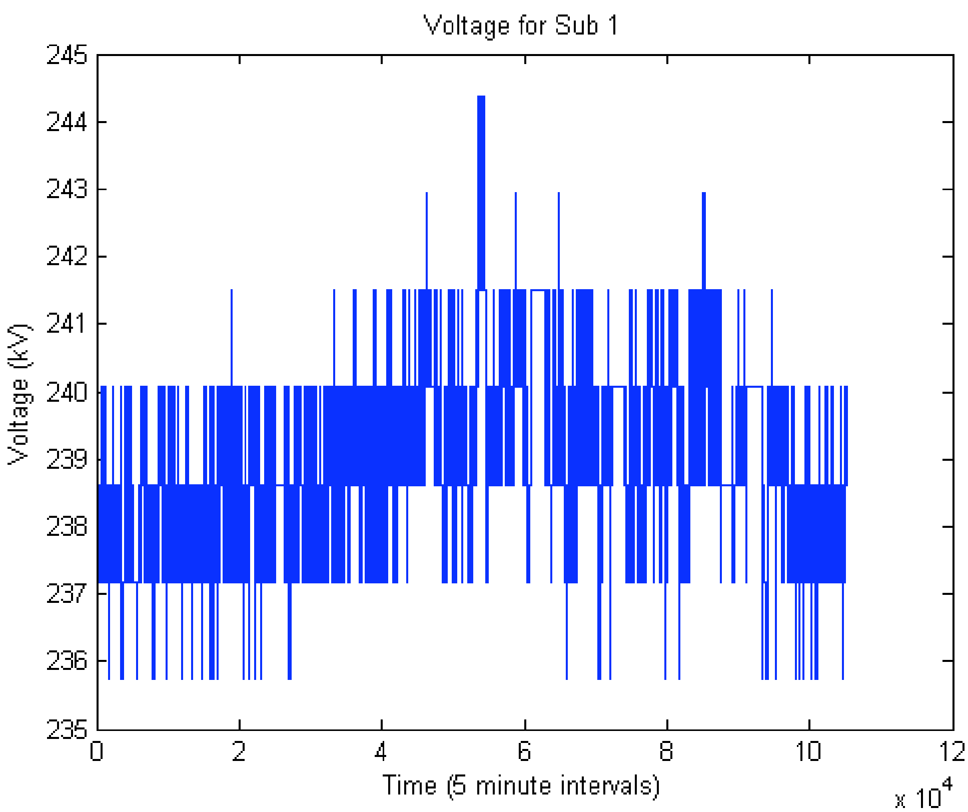

Figure 5.9. Quantized voltage at Sub 1 for one year.

Once the voltage was quantized to discrete values, a MATLAB script counted the number of times the voltage changed from one level to another level. This represents a good approximation of how many times a load tap changer would need to operate in order to maintain the output voltage at a constant value. The number of tap changer operations was calculated to be 8,912 tap changer operations in one year. Load tap changers are typically controlled in such a way to minimize the number of operations, so the number may not necessarily be accurate for a load tap changer at this location. But this approximation is indicative of how frequently the voltage changes at this substation. Since this substation was so strongly correlated to wind power, it can be further concluded that a significant portion of those 8,912 tap changer operations were caused by wind power variability.

For additional insight, ABB, a manufacturer of transformers and load tap changers, provided the chart shown in Figure 5.10 (D. M. Geibel). This indicates that for a load tap changer that is operated 25 times per day, or 9,125 times per year, the load tap changer could operate more than 50 years before requiring an inspection.

		Number of operations				
Operations per day	Operations per year	*15 years*	*20 years*	*30 years*	*40 years*	*50 years*
25	9,125	136,875	182,500	273,750	365,000	456,250
35	12,775	191,625	255,500	383,250	511,000	638,750
45	16,425	246,375	328,500	492,750	657,000	821,250
70	25,550	383,250	511,000	766,500	1,022,000	1,277,500
90	32,850	492,750	657,000	985,500	1,314,000	1,642,500
100	36,500	547,500	730,000	1,095,000	1,460,000	1,825,000
140	51,100	766,500	1,022,000	1,533,000	2,044,000	2,555,000

Inspection at 500,000 operations

Maintenance at 1,000,000 operations

Figure 5.10. Load tap changer maintenance recommendations (from ABB).

This information must be examined critically, because waiting to perform an inspection for 50 years seems highly irresponsible for a utility, but the perspective is still valuable to frame this analysis with realistic values. It therefore seems reasonable that a tap changer at Sub 1 could be operated 8,912 times within a year. It is interesting to note though, that a significant portion of these load tap changer operations could likely be attributed to wind power variability, considering the strong correlation to wind power at this substation.

This analysis made several assumptions, but a reasonable conclusion is that wind power variation causes voltage regulation devices to operate many times a day in order to maintain voltage stability. The voltage variation at this substation cannot be 100% attributed to wind power, but the strong correlation between wind power and the voltage at this substation means that a significant amount of the voltage variation is due to wind power. Additionally, this analysis cannot conclude that a tap changer would truly operate as frequently as approximated, but the voltage variation must be accounted for by a voltage regulation device somewhere, whether located at Sub 1, or some location further away. Therefore it can reasonably be concluded that wind power variability does in fact cause voltage regulation devices to operate more frequently. This analysis also revealed that the number of tap changer operations required at this substation is still within a reasonable level to not cause significant concern about decreasing the lifespan of the load tap changers, at least for a load tap changer manufactured by ABB.

6 Conclusions

This research has examined the relationships between wind power, hydropower, interchange power and thermal power over the past seven years. Multiple types of analysis have demonstrated that the relationships between these power system components have changed significantly within the time period studied. The first analysis performed, MIC, was not particularly insightful into the dynamics of wind power and hydropower though.

The subsequent studies performed using correlation coefficient analysis, with varying time scales, revealed that while the relationship between wind power and hydropower has for the most part remained the same, the relationship between wind power and interchange power has dramatically increased. Additionally the relationship between wind power and thermal power has become stronger.

These results, taken in context with the regression analysis, which revealed similar dynamics, seem to indicate that the relationship between wind power and hydropower has been increasingly strained. The correlation coefficient analysis showed that the correlation only slightly increased between change in wind power and change in hydropower. This means that hydropower did not increase the amount of reserves it supplied for wind power by very much during the seven year period that was examined. This seems to support the conclusions of professionals within the power industry, that hydropower is reaching or has reached its limit for providing reserves. This is further supported by the regression analysis that showed that the beta value for changes in wind power to changes in hydropower decreased from about -1 to -0.5. This means that changes in wind power are no longer fully compensated for by hydropower. Other sources are being relied upon, in addition to hydropower, to provide reserves for wind power.

The analysis also revealed that there were not particular hydropower units that were more heavily relied upon to provide reserves than other units. While all hydropower units did not equally respond to each event that required reserves, all hydropower units were used throughout the time period studied, and no individual unit was used significantly more than the others. There was also no noticeable pattern to which hydropower unit was used for a particular event. This was slightly disappointing, because previous research that designed life-extending control for hydropower units would have benefited significantly if a reliable pattern had been revealed. But the analysis clearly showed that hydropower units were operated independently of each other, and no reasonable pattern was apparent.

The results of these analyses strongly support the conclusion that wind power is increasingly reliant upon the interchanges outside of BPA's balancing authority. This is a significant revelation, because it means that balancing authorities other than BPA must be providing reserves for the wind power located in the Columbia Gorge. The intra-hour scheduling pilot seems to have provided the means for this to occur. It is therefore extremely important for the pilot program to evolve into a more long-term policy. BPA has indicated a desire to continue this program, but it is crucial that the details of the program be solidified so that the interchange can continue to be relied upon to balance variations in wind power generation. This conclusion also reveals that the AC interchanges must be maintained and invested in so that they can continue to support wind power development. If wind power continues to increase, and if the interchange continues to provide transmission for the excess power generation, it is crucial that studies are continued to evaluate the capabilities of the interchanges, and that improvements are made to the system as necessary.

A fairly unexpected conclusion of these studies is that the relationship between wind power and thermal power is continuing to grow stronger. The correlation coefficient between the two forms of generation has increased over the past seven years. The beta value has also increased significantly. At the beginning of the time period studied, there was very little relationship between wind power and thermal power. But by the end of the seven years, there was a significant relationship that cannot be ignored. A strong possible explanation for this relationship is the Oversupply policy that BPA has implemented. Another possibility is the increase in natural gas, and other types of thermal generation with faster ramp rates. Further exploration of this relationship is certainly needed, but it is promising to see that thermal power has been able to react to variations in wind power when necessary.

A final conclusion of this research is that wind power variability has a clear effect on power system voltage stability. The relationship between wind power and substation voltage is strongly related to the location of the substation relative to wind power sites. Substations located close to wind power had a strong relationship to wind power, while substations located further away were less affected by wind power. Additionally, substations with reactive support were positively correlated to wind power, indicating that reactive power support was able to act in a way that opposed voltage swings caused by wind power. Tap changer operations were calculated at a substation closely correlated to wind power, and the results show that voltage regulation is frequently required at this site, but it is within a reasonable number of operations per year.

6.1 Future Work

While the results of this research were extremely informative about the dynamics of the power system, there is still considerable room to investigate further. It would be particularly interesting if the MIC analysis could be explored more fully. The mathematical complexity and long computation time made this analysis too time consuming to be fully appreciated during this research. But further investigation into MIC analysis could be a very promising research topic. It would be particularly interesting to determine the MIC between wind power and interchange power, as well as between wind power and thermal power. This would be valuable to compare with the results for correlation analysis, as well as compare to the magnitudes of the MIC values calculated for hydropower.

Additionally, further research should be done on the relationship between wind power and the interchanges. It would be particularly enlightening to investigate the relationship to transmission outages. More research should be done into the policies of how the interchange is operated. It would also be insightful to investigate how the power system in California is reacting to the large amounts of wind power being imported to its system.

Further analysis into the relationship between wind power and tap changer operations is also strongly recommended. While only one substation was studied for the purposes of this research, it would be fairly easy to expand this analysis to examine more substations. It would be particularly interesting to examine the relationships between the substations. Once the dynamics of these relationships are better understood, it would be interesting to apply life-extending control to the load tap changers. There are already methods employed to preserve the life of a load tap changer, but the research experience of this and previous research perfectly sets up this type of exploration.

Hopefully further research can also be performed to provide predictive analysis for these relationships. Though the nature of the analyses performed for this research made it difficult to create predictive models, there are other types of analysis that can be performed to predict how these relationships may change in the future. There are many unknowns that make this kind of analysis difficult, particularly the ever-evolving political landscape surrounding renewable energy, but a strong predictive analysis would be extremely valuable for this topic.

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