BENEFITS OF SPATIAL SMOOTHING FOR THE INTEGRATION OF WIND POWER

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ABSTRACT

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The stochastic nature of renewables such as wind greatly complicates their integration into power systems. At small levels of penetration the effects of wind integration are hardly noticed. As the penetration grows, the impact is expected to be considerable. Changes will need to be made to the way in which traditional generators are used. Often those generators are forced to run under suboptimal conditions. This can increase cost and also carbon emissions, negating any benefits of renewable energy. This study demonstrates the benefits that can be derived from the use of spatial smoothing. Spatial smoothing involves connecting grids together into larger interconnects and sharing the renewable resources between different regions. It is demonstrated that through spatial smoothing significant decreases can be obtained in the additional costs and other issues associated with wind integration. Additionally, the same theory can be applied to any other intermittent, non-dispatchable renewable resource including solar.

Keywords: Renewable generation, optimization, linear programming, wind, spatial smoothing.

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1.0 INTRODUCTION

The power industry is undergoing a monumental transformation. Since the introduction of electrical power, the basic strategy for growth was always the same. Better efficiency was achieved by constructing larger generators. There was never much concern for the consumption of fossil fuels. Today, there is a lot of pressure to change the old habits. Political, economical and environmental pressures are causing the construction of renewable energy sources at an astounding rate. Most developed countries are even considering a reduction in the number of plants which produce carbon dioxide such as coal plants. As a result of the push to reduce carbon emissions, the nuclear industry is experiencing a sort of renaissance. Yet, expectations for the growth in nuclear power are far surpassed by the growth in renewables such as solar and wind power. Both of which were nearly nonexistent two decades ago.

This is leading to many problems because renewable resources like wind and solar are nondispatchable and intermittent. They are said to be nondispatchable because the operator is not capable of determining when he wants full power out of these sources. If there is no wind or sun, then the wind turbines and solar panels cannot produce any power. The resources are referred to as intermittent because the output power varies as a function of random environmental factors. You never know exactly when the sun will shine or when the wind will blow. Traditional generators of course are also random at times. The difference is that for traditional generators, the random need for downtime is an exception not the norm as it is with wind and solar.

Traditionally, power generators have always been unreliable to a certain degree. Random, unforeseen incidences which take a generator off-line are always possible. At the same time the load is never fully predictable. The solution to these issues has been the use of reserves. Spinning reserve for example involves keeping various generators up and running while not producing power. Alternatively, it could also be generators running at less than full power. In either case those generators are then ready to quickly increase their output power if suddenly there should be a large drop in generation or an increase in load. The problem is that spinning reserve consumes fuel and produces emissions all of the time but is only useful when something goes wrong. The reason that it has always worked is that the amount of power on a system has always been much greater than the systems requirements for spinning reserve.

The situation changes though when traditional generation sources are replaced by the much less reliable renewable resources. With small levels of penetration the problems of renewables can be over seen. As penetration grows the need for additional reserves also grows. One possible criteria for spinning reserve is to insure that the probability that the spinning reserve is insufficient to deal with an unexpected event be less than some fixed value. Wind and solar power is much less predictable than traditional plants. The wind stops temporarily stops blowing quite frequently. A system with a large penetration of wind must account for the probability of mechanical failure of all units as well as the probability of a dip in wind power. The amount of reserves needed to insure that load will be met grows quickly as a function of the wind penetration. Renewable integration can greatly complicate systems opperations [1, 2, 3]. It has even been argued that the benefits of wind power are totally negated when sufficient reserves are used and other effects of wind integration are accounted for. [4].

This paper explores the possibility of using spatial smoothing to decrease the negative affects associated with wind integration. Spatial smoothing refers to the sharing of wind power from different and preferably geographically distant locations. It is hoped that the variability, and thus the unreliability, of wind power will be decreased as a result of this sharing. For example, suppose that there are two cities each with wind power. The wind power in the two cities can not be perfectly correlated. In that case there will be times when city one has no wind but city two does. Making use of that fact and sharing the wind might be beneficial and facilitate system operations, while reducing the need for reserves.

For this study an optimization algorithm was established as described in Chapter 3. The method uses linear programming and finds the optimal solution of allocation of multiple resources having different dynamic characteristics. In other words, it finds the cheapest way of satisfying the load given a specified set of constraints. The stability of the system is not considered directly. Rather it is assumed that the constraints which are given, specifically those related to the dynamics of the system, are sufficient to insure the stability of all solutions. Otherwise, constraints should be modified to achieve that goal.

In this study three different levels of integration are considered. For the smallest interconnection, grids with only a single wind turbine are considered. The optimization method is used to find the best way to schedule generation from wind, coal and gas so as to minimize cost. This is done for each location. Next, five wind turbines in Texas are all assumed to be connected to the same grid. The linearity of the system in terms of costs and constraints on the other generators allows the model to remain unchanged except for the wind part. Any benefits which are observed must therefore result from the spatial smoothing of the wind. The last level of integration involves using ten wind turbines from the Western United States. The goal of this study is to demonstrate the benefits of this integration and sharing of wind resources.

This study uses several assumptions. All of the cost functions and constraints are assumed to be linear. More realistic representations of the system might be achieved using quadratic, piecewise linear, piecewise quadratic or even polynomial cost functions, all of which have been used in the literature [5, 6].

1.1 PROBLEM STATEMENT AND MOTIVATION

This study attempts to answer the following two questions, "How effective is spatial smoothing at decreasing the negative effects caused by renewable integration?" "How do the relative distances and the quantity of wind turbines determine that effectiveness?". It seems reasonable to assume that power curves will be smoothed. But what does that mean in terms of cost, emissions? For this study a generic power grid with four types of generation is modeled, with the goal of quantifying the benefits obtained from using spatial smoothing. This is done by determining the optimum solutions for the allocation of multiple resources having different dynamic characteristics. Such solutions are found with and without spatial smoothing. The benefits can be measured using results from the two optimal solutions. Possible options for the comparison include the wind utilization, the amounts of coal, gas or wind used or any combination there of.

The need to answer the above question is motivated by economic reasons as well as environmental ones. The economic motivation is clear. Integration of wind resources requires additional reserves which increase the cost of operations. Minimizing the need for additional reserves through the use of spatial smoothing could create billions of dollars in saving on a global scale. Similarly, additional reserves means more carbon emissions. The real environmental motivation for spatial smoothing is a result of the economics. At present power from coal is cheaper than power from renewables. Despite the push for renewable power countries like China and even Germany are planning to build more coal plants [7]. The economics are simply too important. If at large penetrations spatial smoothing has significant benefits, then someday it might be the deciding factor economically. It could be the deciding factor in ending the construction of coal plants.

2.0 BACKGROUND

As previously discussed, the integration of wind and solar power into a grid causes difficulties due to the stochastic nature of the resources. A common solution is to use additional reserves to backup the system. That helps to insure that the probability that the system will fail is sufficiently small. The probability can never be zero. There is always a balance between minimizing cost and minimizing the probability of a problem. When the reliability of systems components is decreased, such as is the case when wind turbines replace traditional generators, then the balance is thrown off. In order to maintain the same level of security, it is necessary to employ more reserves. That means spending more money and creating more emissions.

Rather than using coal plants which must be running in order to count as reserves, it is also possible to have quick start generators. The problem is that power from such generators is much more expensive than power from a coal plant. The ideal solution is to have a mix of both coal plants and quick start generators. The model used for this study involves such a scenario. Kennedy et al. have considered the possibility of using distributed diesel generation to balance wind. The cost per kilowatt hour is still more than that associated with power from coal, but the distribution of the generation could be beneficial. Such a distributed generation scheme could be useful in balancing the need for power as the output from wind turbines varies randomly [8]. It could also help to alleviate stresses that wind causes on the transmission grid network. The problem is that such generators when producing power are usually less efficient than coal plants.

The idea of spatial smoothing comes from probability theory. The law of large numbers states that the average of any identically distributed collection of random variables will have a smaller variation than the original variables. For the case of wind turbines, the decrease in the variation of the variables can be seen in Figure 2.1. The histograms for individual wind turbines show that the vast majority of the measurements were either at nearly zero power or at full power output. When the ten turbines are averaged together, the values are much less extreme. Not all of the turbines are giving full power or zero power at the same time. The variation has been decreased which means that the wind power is more consistent. Consequently, it can be dealt with more easily. Thus the connection of many wind turbines produces an output that is more reliable than the output of a single wind turbine. Two assumption are necessary for spatial smoothing. The first is that the output from various wind turbines vary in more than just scale. If the power outputs waveforms from different turbines are distorted versions of each other, then spatial smoothing might be useful. The best situation though is when the waveforms are completely independent. One would expect greater benefits from spatial smoothing when the outputs are more independent.

Bialasiewicz and Muljadi have shown that by connecting multiple wind turbines together flicker and variations in the voltage caused by a single wind turbine can be canceled out [9]. This study attempts to show that spatial smoothing also improves the reliability of the generated power over longer periods of time.

Other studies have been done looking at the possibility of transporting power over large distances. The studies mentioned here consider the issue with respect to the European Union. Giegel et al. have looked at how costs for wind can vary across Europe. They demonstrated

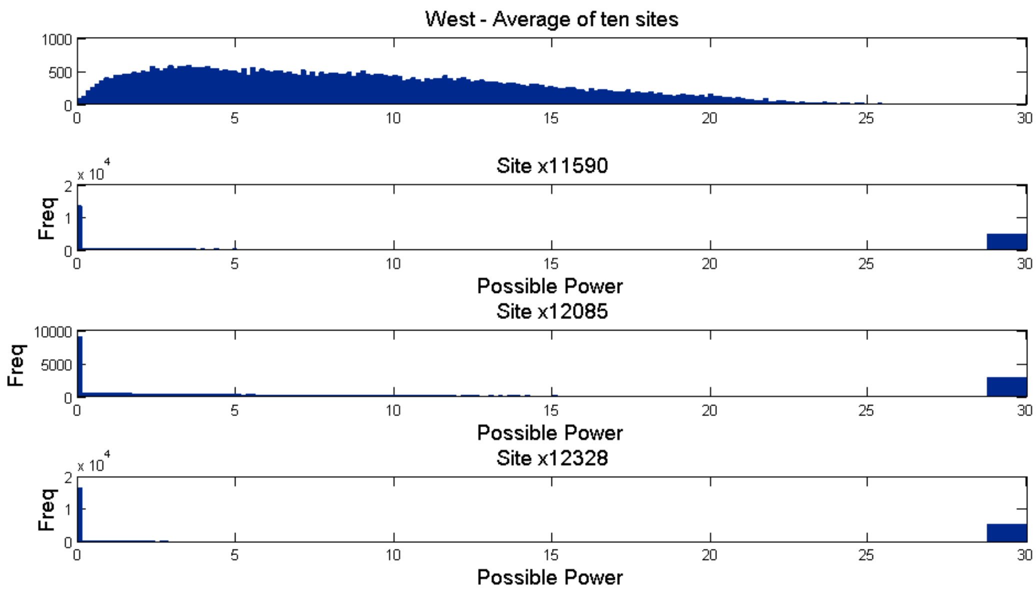

Figure 2.1: Histograms of output values for three wind turbines and for the average of ten turbines.

that in many cases the cheapest wind might come from somewhere else. Specifically they considered the possibility of importing wind power to the continent from the North Sean and the Irish Sea [10] which demonstrates to what extent wind resources can vary and how the costs can be dominated by the regional variations rather than by the costs of transmission. Czisch and Giebel have also presented work demonstrating the possibility of powering Europe and its neighbors completely with renewables. The scenario involves sharing large amounts of power from wind solar, hydro-electric, geothermal and biomass across the entire continent northern Africa, the Middle East and the western part of Russia. The latter article makes use of another sort of smoothing. The authors use smoothing over resources to insure that the demand is always met.

Similar work was done by Warren Katzenstein, a former graduate student at Carnegie Mellon University. His work had three parts. He attempted to characterize the variability of wind. Then he tried to determine the hidden costs that result form wind integration. Those costs being the extra money which must be spent on operating traditional generators in such a way to compensate for wind integration. The last issue that Warren considered was how wind integration can effect emissions. Similar to the hidden costs there are emissions which are caused indirectly by the integration of wind power [11].

The work described in my thesis was presented at the 2010 IEEE PES General Meeting in Minneapolis, Minnesota. The session in which it was presented was titled "Power System Planning and Implementation Committee Main" [12]. Studying spatial smoothing required the determination of the solution of the optimum allocation of multiple resources all having different characteristics. The tool that was chosen for performing this optimization was linear programming.

2.1 LINEAR PROGRAMMING

Linear programming is a powerful tool for finding optimal solutions to a wide range of problems. It is well established in the literature and many solution methods exist [13, 14]. In particular there is a Matlab command, *linprog*, which can be used to solve linear programs. Due to its versatility, linear programming has been used for many applications in the field of power engineering [15, 16, 17]. The standard form of a linear program is given in (2.1).

$$\begin{aligned} \textit{minimize} \qquad & \mathbf{c^T x} \\ \textit{subject to} \qquad & \mathbf{Ax} \leq \mathbf{b} \\ \textit{and} \qquad & \mathbf{x} \geq \mathbf{0} \end{aligned} \tag{2.1}$$

In (2.1) $\mathbf{x}$ is the vector over which the optimization is performed. For the application discussed here $\mathbf{x}$ will be a vector containing the outputs of various generating units at various times. The variable $\mathbf{c}$ is a vector which is associated with the cost of the control strategy given by $\mathbf{x}$. Thus $\mathbf{c^T x}$ is the cost which should be minimized.

In reality a large range of problems can be put into the form of a linear program. Absolute values are not linear, but can nevertheless be represented in linear programming. The equation $|x| \leq d$, for example could be translated as in (2.2).

$$\begin{aligned} |x| \leq d \qquad & \Leftrightarrow \qquad -d \leq x \leq d \\ & \Leftrightarrow \qquad x \leq d \ \ \textit{and} \ \ -x \leq d \end{aligned} \tag{2.2}$$

In a similar fashion any piecewise linear function with a finite number of pieces can be represented in a linear program. Two inequality constraints can also be used to represent an equality constraint. For this study simple linear functions are considered sufficient. This allows for modeling the most significant characteristics of the system. At the same time it means that the size of the system which is being modeled is of no importance. If the system is has a single gas turbine or one thousand the model is the same except for a scaling factor. This turns out to be quite convenient when multiple systems are connected into a larger one.

For this work Matlab and specifically the *linprog* command were used. The *linprog* command allows for the solution of systems which are in standard form or a variety of other forms. Not only are inequality constraints allowed but also there is an option to include equality constraints. Another feature which proved quite useful was the ability to enter arbitrary upper and lower bounds for each variable.

3.0 OPTIMAL CONTROL MODEL

The model that is used in this study involves generation from four different source: nuclear, coal, gas and wind. Nuclear power is considered a baseline load. Such an assumption is reasonable since it is generally much more economical to change the outputs of other types of plants. In the United States for example the output levels of nuclear plants are seldom anything less than the maximum. Coal plants are allowed to vary but the amount of variation is limited. Also, the rate of change is limited. Gas is more expensive than coal but can vary more freely. This creates a trade off between cost and controllability. It is typical in all real applications. Wind is considered to have a relatively low incremental cost, but power can only be generated when the wind is blowing. It is assumed that excess wind can be ignored. Physically, many wind turbines have the ability to change the angle of the blades reducing the amount of power produced.

It is desired that the model be scalable. In other words the model should be able to work for a small power system or for a larger one. That is one justification for the use of linear programming and simple generator models. For example, if wind generation is modeled with a linear cost then the same model holds whether there is only one wind turbine or if there are many.

The model is represented in a normalized fashion. It is fixed so that the highest load is given a value of 1.0. In this way all other power values can be thought of as fractions of the highest maximum load. The limits on the various generators are chosen in such a way to model the grid as it might look a couple of years down the line.

3.1 CONSTRAINTS

Since the optimization method is linear programming all of the constraints must be of a linear nature. Absolute values are also permissible since an absolute value can be represented by a set of linear equations. The constraints on the system can be divided into two types. The first is the set of constraints which limit the output form the generation sources. The second group is the load following constraints.

3.1.1 Generation Constraints

In a linear programming model the set of constraints on the generation fully specify the model of the generators. The model handles dynamics and stability by limiting the operation of generators to regions where questions of stability will never be an issue. The following gives the constraints which were used with respect to each generation source.

Nuclear is fixed at .3. So when the load is maxed out, nuclear will be providing 30% of the systems power. At all other times nuclear will be providing more than 30% of the power. Presently nuclear accounts for only about 20% of the nations electric power; however, with pushes to reduce carbon emissions it is quite possible that in the next decade or so the nations dependence on nuclear power will see significant growth. Since the output from nuclear generation does not change the cost does not affect the solution of the optimal allocation problem. The constraint on the power produced by nuclear each time step is given in (3.1).

$$x_t^{nuclear} = .3, \qquad 1 \leq t \leq 144 \tag{3.1}$$

The model limits the power produced from coal to between .1 and .4. That is significantly less than the present situation in the United States, but could represent a foreseeable future. There is also a limit on the rate of change of the output from coal. Between any two consecutive time steps, over a ten minute period, the output can not change by more than .003. The constraints associated with coal are given in (3.2).

$$\begin{aligned} .1 \leq x_t^{coal} \leq .4, & \qquad 1 \leq t \leq 144 \\ |x_{t+1}^{coal} - x_t^{coal}| \leq .003, & \qquad 1 \leq t \leq 143 \end{aligned} \tag{3.2}$$

Electricity produced from gas is generally more costly than that produced from coal. Nevertheless, gas is still used. That is because gas turbines can be controlled much easier. In other words their outputs can be changed over a larger range and they can change more quickly. Also, when power is only required for a small fraction of the time, as in peaking, then gas turbines can be more cost efficient than coal plants. In the model, gas generation is limited between .05 and .4. The rate of change can be no greater than .03. The drawback is that the cost for gas power is more unit power than the cost for power from coal. This generally the case in practical situations [15]. The constraints on the power from gas are given in (3.3).

$$\begin{aligned} .05 \leq x_t^{gas} \leq .4, & \qquad 1 \leq t \leq 144 \\ |x_{t+1}^{gas} - x_t^{gas}| \leq .03, & \qquad 1 \leq t \leq 143 \end{aligned} \tag{3.3}$$

The last resource to be considered is wind. The maximum possible power from wind at any time, t, is given by the variable w_t. It is assumed that the turbine has the ability to reduce the amount of power as needed. This ability is typically built into wind turbines as a protective measure. When the wind is too strong the efficiency of the turbine can be decreased in order to prevent damage to the system [18]. The constraint on the wind turbines output power is given by (3.4).

$$0 \leq x_t^{wind} \leq w_t, \qquad 1 \leq t \leq 144 \tag{3.4}$$

3.1.2 Load Following Constraints

The load following constraints specify that the total power produced by the generators at any time step must be within a certain tolerance of the load at that time step. In the model we allow a 5% variation in the load. This can be justified by the flexibility of many loads. Any resistive load for example. When less power is produced than is needed the voltage will sag slightly. A lower voltage across a resistive load means that less power is consumed. Thus the load has adapted to the small deviation in the generated power. If the loads are rotating machines the imbalance of power will be balanced by a variation of frequency. This is undesirable but as long as it is limited it causes no major issues [19]. The nature of the load is not considered here. As the present work is only concerned with the basic problem of allocating resources in an efficient manner, simply allowing a small degree of error in the load matching is sufficient. The constraints on load following are given in (3.5).

$$
\begin{aligned}
x_t^{coal} + x_t^{gas} + x_t^{wind} &\geq .95L_t - .3, && 1 \leq t \leq 144 \\
x_t^{coal} + x_t^{gas} + x_t^{wind} &\leq 1.05L_t - .3, && 1 \leq t \leq 144
\end{aligned}
\tag{3.5}
$$

In equations (3.5), .3 is the generation from the nuclear plant. Since the nuclear plants output is constant, representing it by a variable would unnecessarily increase the dimensionality of the problem.

3.2 COST FUNCTION

The cost function in this model attempts to represent the actual cost of power production. To be compatible with linear programming, the cost function must be linear. It is possible to make the cost function piecewise linear but for the purpose of this study simple linear functions was sufficient. It should be noted that any fixed costs can be neglected since they do not affect the optimization.

Like the rest of the model the cost is normalized. We set the cost of power from coal to be one unit cost per unit power. Then the cost for power from gas is set to be two units cost per unit power. So it is twice as expensive as coal. The cost for wind power is set at .1 unit cost per unit power. This may seem strange since in reality wind power is usually more expensive than power from fossil fuels [18]. However the majority of the cost associated with wind power is fixed. The optimization algorithm is only concerned with the incremental cost, the added cost for producing an extra unit of power. That is very small for wind turbines [20]. There is a cost associated with increased wear on the system which in turn increases the required maintenance. That cost is associated with traditional generators as well. With fossil fuels though there is an additional cost for the fuel that must be expended for each additional unit of power that is to be produced. The cost of power from nuclear is of no consequence, because it is fixed. The cost function is given in (3.6).

$$\sum_{t=1}^{144} x_t^{coal} + 2\sum_{t=1}^{144} x_t^{gas} + .1\sum_{t=1}^{144} x_t^{wind} \tag{3.6}$$

3.3 FORMULATING THE PROBLEM FOR LINEAR PROGRAMMING

In order to find solutions to the optimal allocation problem, it was formulated as a linear programming problem and put into Matlab. The Matlab command "linprog" was then used to calculate the solution. The version of the "linprog" command that was used is given in (3.7).

$$x = linprog(f, A, b, [\ ], [\ ], lb, ub) \tag{3.7}$$

Equation 3.7 represents the optimization problem given in (3.8).

$$\begin{aligned} &minimize && \mathbf{f^T x} \\ &subject\ to && \mathbf{Ax} \leq \mathbf{b} \\ &and && \mathbf{lb} \leq \mathbf{x} \leq \mathbf{ub} \end{aligned} \tag{3.8}$$

Where the output, $\mathbf{x}$, is a vector which contains the optimal values of x_t^{coal}, x_t^{gas} and x_t^{wind}. The cost function, given in equation 3.6, is represented by $\mathbf{f^T x}$ where $\mathbf{f}$ is a vector containing the coefficients of the cost function associated with the elements of $\mathbf{x}$. The vectors $\mathbf{lb}$ and $\mathbf{ub}$ are respectively the upper and lower bounds on the variable $\mathbf{x}$. Those bounds are given in equations 3.2, 3.3 and 3.4. The value of w_t is known beforehand for all values of t so it is possible to assign values to lb and ub. The matrix A and the vector b account for the limits on the rates of change of x^{coal} and x^{gas}, given in 3.2 and 3.3, as well as the load following constraints. The absolute values in the rate of change constraints can be removed by replacing each equation with two equations as given in 3.9.

$$\begin{aligned} \left(x_{t+1}^{coal} - x_t^{coal}\right) &\leq .003, & 1 \leq t \leq 143 \\ -\left(x_{t+1}^{coal} - x_t^{coal}\right) &\leq .003, & 1 \leq t \leq 143 \\ \left(x_{t+1}^{gas} - x_t^{gas}\right) &\leq .03, & 1 \leq t \leq 143 \\ -\left(x_{t+1}^{gas} - x_t^{gas}\right) &\leq .03, & 1 \leq t \leq 143 \end{aligned} \tag{3.9}$$

In equation 3.5 L_t is known beforehand so those equations can be combined with 3.9 to get the set of inequalities which form $\mathbf{Ax} \leq \mathbf{b}$ in 3.7.

3.3.1 Utilization

In some ways the model system is set up differently than real systems are. In many cases laws force utilities to buy all of the available wind and solar power. That strategy of course is not sustainable in the long run. Eventually there might be times when the power from renewables on a certain grid could be more than the load. As the renewable resources penetration grows new strategies will be needed, such as simply buying the power which is cheapest. Unfortunately, it can at times be cheaper to keep a thermal unit going at a high output level than to vary the output, even when the total electrical energy output is greater in the first case. That suggests that there may be times when it makes sense to purposefully reduce the outputs from the renewable resources, as our model does.

It is interesting to see how much of the wind power that was available was dropped, and equivalently how much was used. For that purpose we define the utilization in equation 3.10.

$$Utilization = \frac{Total\ Wind\ Power\ Used}{Total\ Wind\ Power\ Available} = \frac{\sum_{t=1}^{144} x_t^{wind}}{\sum_{t=1}^{144} w_t} \tag{3.10}$$

For comparing results with different levels of spatial smoothing it can be useful to compare the values of utilization which are attained. For this study, changes in utilization are the main metric by which results were measured. Other possible metrics include the change in coal, gas or wind used or any combination there of.

3.4 APPROXIMATIONS AND ASSUMPTIONS

This optimization method has several weaknesses. All cost functions and constraints must be linear. With linear functions the most significant components of the costs and constraints can usually be modeled. For a power plant for example the most significant costs will likely be the cost of fuel and the costs of maintenance and staffing. A reasonable approximation for the cost of fuel is given in 3.11.

$$Cost = \left(\frac{units\ cost}{units\ fuel}\right)\left(\frac{units\ fuel}{units\ power}\right)(quantity\ of\ power) + Constant \tag{3.11}$$

Where fuel can often be modeled with the cost per unit output power and the output power per unit fuel both being constant. In addition there is a constant term. Running a power plant at full speed has a cost even when no electrical power is produced. That cost is modeled by the constant term in equation 3.11. Under those assumptions equation 3.11

describes a line. For the purpose of maximization the constant term can be dropped because the optimal solution is not dependent on that term.

The cost of maintenance and staffing could be thought of in two parts. Some of the cost is required regularly regardless of the output level of the plant. Most employees will need to be payed even if the plant is producing a low level of output. These costs are constant and can be ignored in the optimization. Other maintenance costs will be functions of how much power is produced. When the plant is producing more power there will be more stresses and wear on the machinery. A first order approximation to these costs is a linear function. Often in power engineering quadratic cost functions are used [15]. In this study we assume however, that the quadratic component is small and can be neglected.

One place where linear functions have trouble is transmission losses. Assume for example that a transmission line and a load can be modeled by resistor, R_T, and a variable resistor R_L respectively. The power losses, P_T, across the resistive transmission line are given by $P_T = IV = I^2 R_T$. Assuming that the voltage drop in the transmission line is small compared to the voltage of the load, the voltage of the load will be constant. The load resistance can then be modeled as $R_L = cI^{-1}$ for some positive constant c. Which means that the load power can be expressed as $P_L = IV = I^2 R_L = cI$. Solving for the transmission losses as a function of the load power gives equation 3.12.

$$P_T = \frac{R_T}{c} P_L^2 \tag{3.12}$$

Unfortunately, equation 3.12 is quadratic. In control it is common practice to linearize equations around an operating point. That method causes large error in the case of transmission losses because the system operates over a large range of values. Particularly the wind turbines can have an output power of zero. If the losses are linearized around the point zero, the linear equation is uniformly zero. To account for transmission losses in a linear programming algorithm it would be desirable to use piecewise linear functions. Transmission losses also cause a complication in that as the level of integration is changed the network topology must change. In other words the scale invariance would need to be sacrificed in order to adequately represent transmission losses. For this study transmission losses have simply been ignored.

Possibly the most important approximation used for this study is the idea that the wind power and the load are both fully known for the entire day. Optimization is done on a day to day basis and all of the relevant information is assumed to be known at the beginning of the day when the optimization is done. Another effect of calculating optimal solutions are calculated on a daily basis is the fact that large discontinuities can occur at midnight where two independent solutions are joint together. This could be fixed by supplying initial conditions for the optimization. If the previous days solution is known, it provides the needed data. The problem is that solutions would then be suboptimal.

3.5 EXAMPLE OUTPUT

The complete optimization problem is to minimize (3.6) such that (3.1-3.5) are all satisfied. An example output from the optimization algorithm is shown in Figure 3.1.

Figure 3.1 gives a good deal of information about the system. The most obvious observation is that the power from nuclear is constant. Wind on the other hand varies the most. In this particular example wind seems to be providing the majority of the load following capability. Also, the rate of change of the wind power is unlimited in the algorithm. Another important feature of the optimization is that the levels of power produced by the coal and

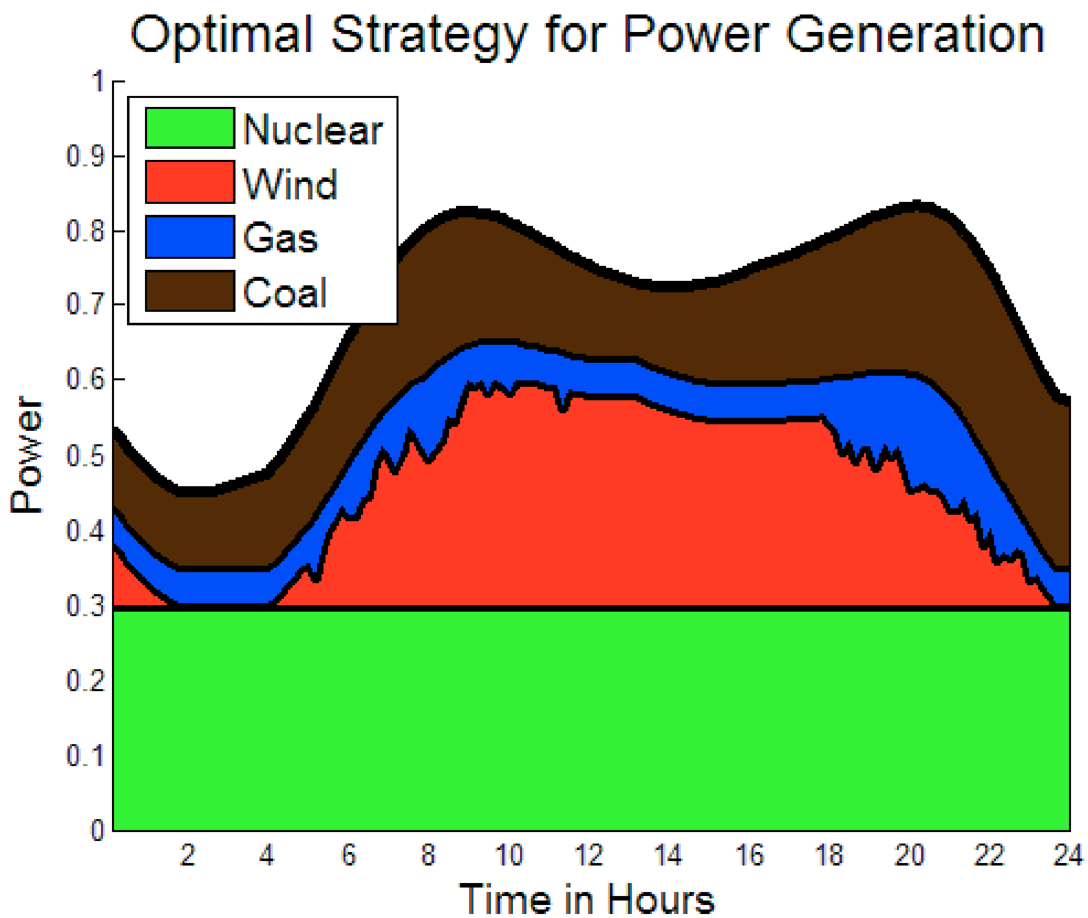

Figure 3.1: A sample output from the optimization algorithm.

gas plants have lower limits. In Figure 3.1 it can be seen that neither the power from coal nor the power from gas ever go to zero.

4.0 DATA

Data for this project comes from many sources. The coefficients used to define the system's model are approximations taken from a broad source of books and publications. In that case the actually values are not as important as the general relationship between the values. For example, gas must be more costly than coal but also more easily controlled. The other two other types of data which were used are the load data and the wind power data. Both are in the form of time series with a sampling period of 10 minutes.

4.1 LOAD DATA

The load data came from the New Hampshire Electric Co-Op [21]. The New Hampshire Electric Co-Op provided data for the last three days of August and the first day of September in 1997. In terms of days of the week the data was from Friday-Monday. The data was given on hourly intervals. In order to reduce the sampling period to the desired 10 minutes the averaging process described in [22], which had been developed for applications related to solar integration. The method in [22] is designed to give a finer sampling resolution while maintaining the average value. Eventually only the data from days one and four, that is Friday and Monday, were used. The curves are shown in Figure 4.1.

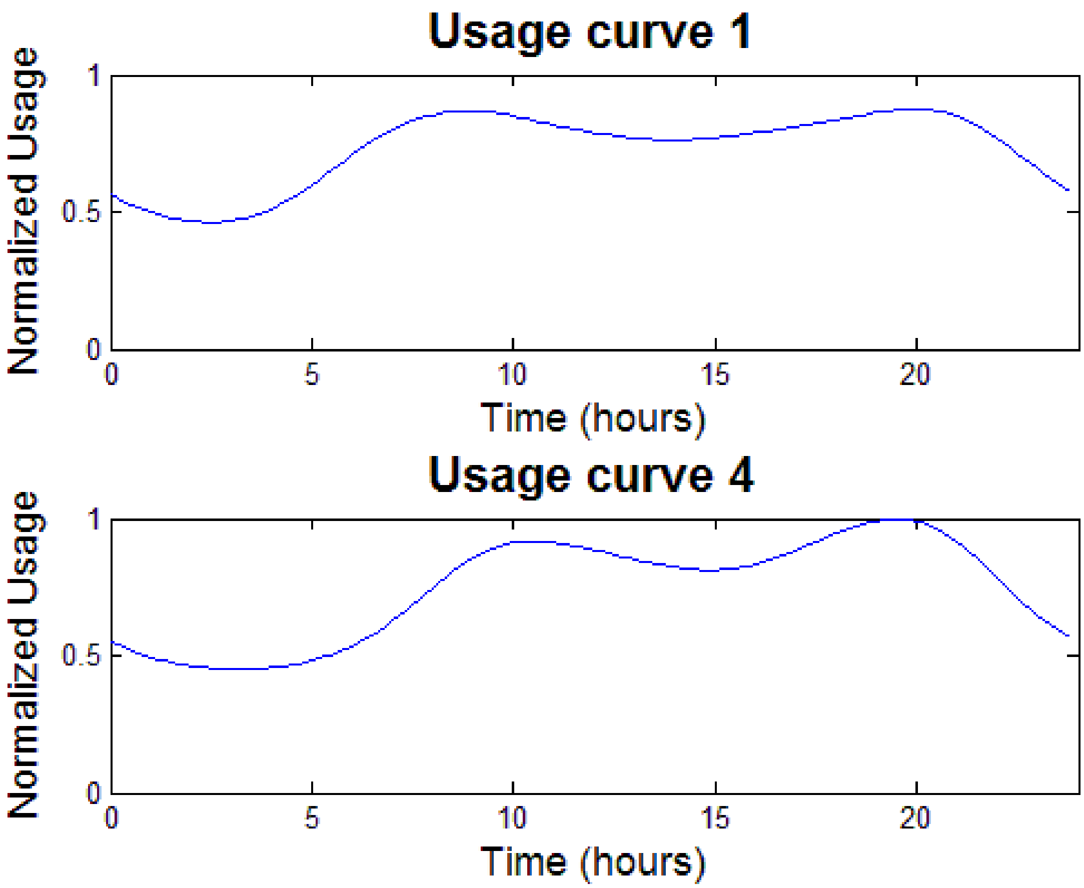

Figure 4.1: Electricity usage for August 29 and September 1, 1997 from the New Hampshire Electric Co-Op [21].

4.2 WIND DATA

For this study the wind data comes from the Western Wind Integration Study (WWIS), which was done in cooperation between 3TIER and the National Renewable Energy Laboratory (NREL). The specific data that was used is the SCORE-lite power output. This data was created using wind speed data and finding the corresponding output powers from theoretical wind turbines. Then to make the data more realistic stochastic variations were added. All of that work was done by 3TIER and NREL, and data is available for hundreds of locations in the western United States [23]. Samples of wind data from January 8, 2006 at two different sites are shown in Figure 4.2.

Spatial smoothing involves sharing wind data. When wind power from ten sights is averaged for January 8, 2006 the result is a waveform with much less variation as shown in Figure 4.3. From Figure 4.2 it is clear that individual sites often have wind power values near zero or full power. In Figure 4.3, on the contrary the wind power stays more or less in the middle range.

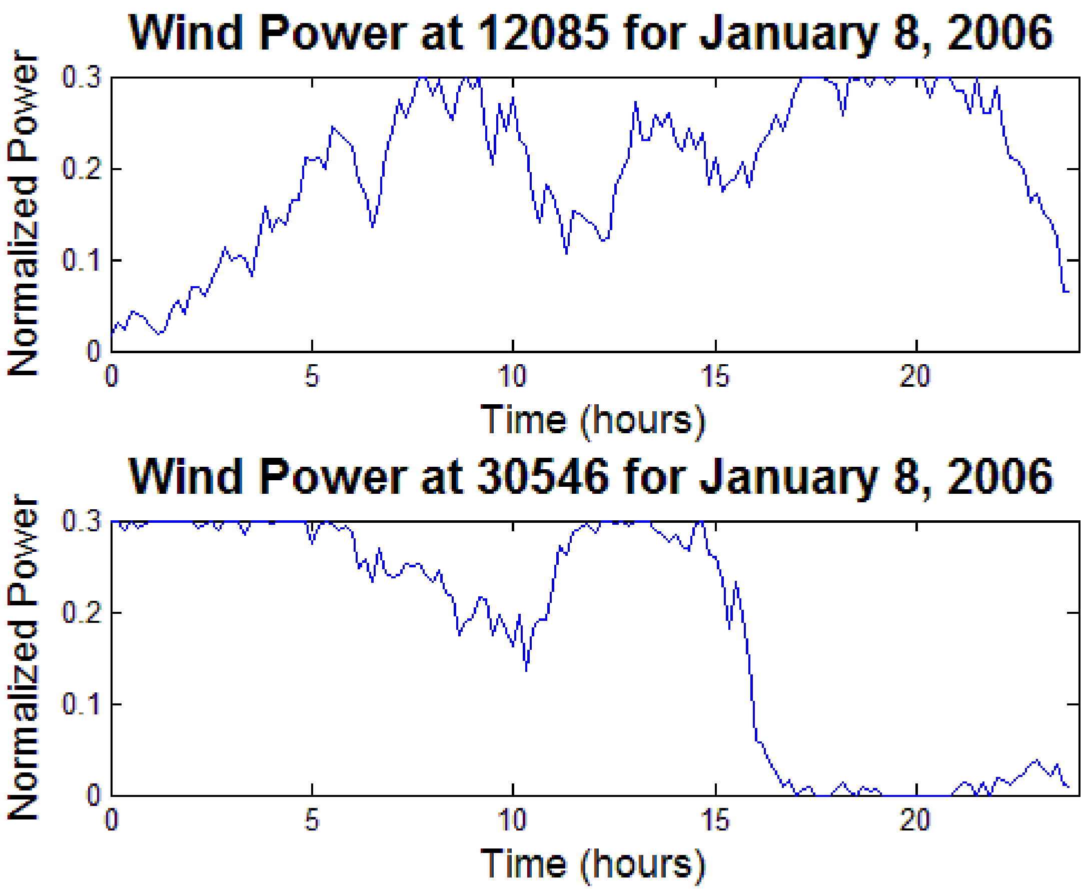

Figure 4.2: Wind power curves from two sites in the West.

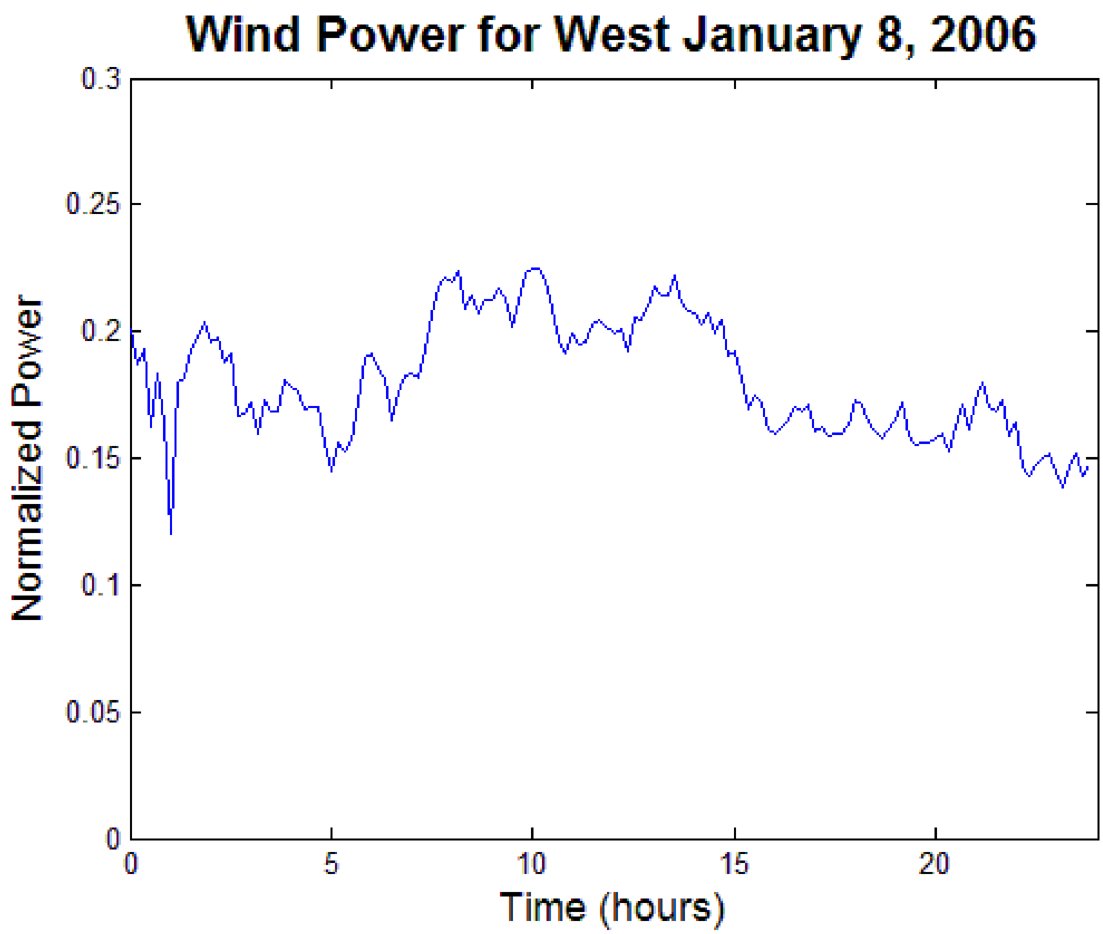

Figure 4.3: Average of the wind in the West.

5.0 RESULTS

This study consists of two parts called Case Study Texas and Case Study West. The two case studies look at different levels of integration and attempt to quantify the benefits of spatial smoothing in the specific contexts.

5.1 CASE STUDY TEXAS

For Case Study Texas a wind farm in Texas was chosen along with five wind turbines from that farm. Data for the output of each turbine during the entire year of 2006 was obtained from the Western Wind Integration Study data sets [23]. Information about the specific wind turbines that were chosen is given in Table 5.1.

The turbines were chosen from the same wind farm in order to demonstrate the effects of spatial smoothing when the geographic diversity is limited. The proximity of the locations included in Case Study Texas, suggests that the power outputs from the turbines could be correlated. Figure 5.1 shows the power from the five sites on January 3, 2006. The waveforms do in fact have similar shapes. All five of the wind turbines produced nearly full power between about 10 AM and 3 PM. Around 5 AM and around 8 PM on the other hand all of the waveforms show half power or less.

Table 5.1: Data for Locations in Case Study Texas

Site Number	Longitude	Latitude	Elevation
66	104.57W	31.54N	1430 m
78	104.51W	31.56N	1320 m
106	104.62W	31.66N	1453 m
211	104.71W	31.88N	1380 m
223	104.71W	31.91N	1393 m

The idea of the case study is to compute the optimal solutions to the problem problem of allocating various resources with and without the spatial smoothing. When spatial smoothing is present it means that all of the wind power is shared between the five locations. Due to the scalability of the model the system can be simulated by averaging the five power waveforms together and running the optimization. The other scenario, when the wind power is not shared, involves running the simulation again with each individual waveform. The results from the individual runs are then averaged together and compared with those for the spatial smoothing case. Wind data was used on a daily basis with each day in the year being used (see Section 4.2). Using the assumption that usage data does not vary much, the same usage curve was used for every day. The entire process was repeated using both of the usage curves (see Section 4.1). The results are shown in Table 5.2. In the table, "Sites in Texas" refers to results collected by testing with individual turbines and averaging the data. The usage curves described in Section 4.1 are listed in the table as "Curve 1" and "Curve 2". The rows entitled "Wind Used", "Coal Used" and "Gas Used" give the amounts of each resource used on average. As explained in Chapter 3, the power levels are all normalized. The utilization

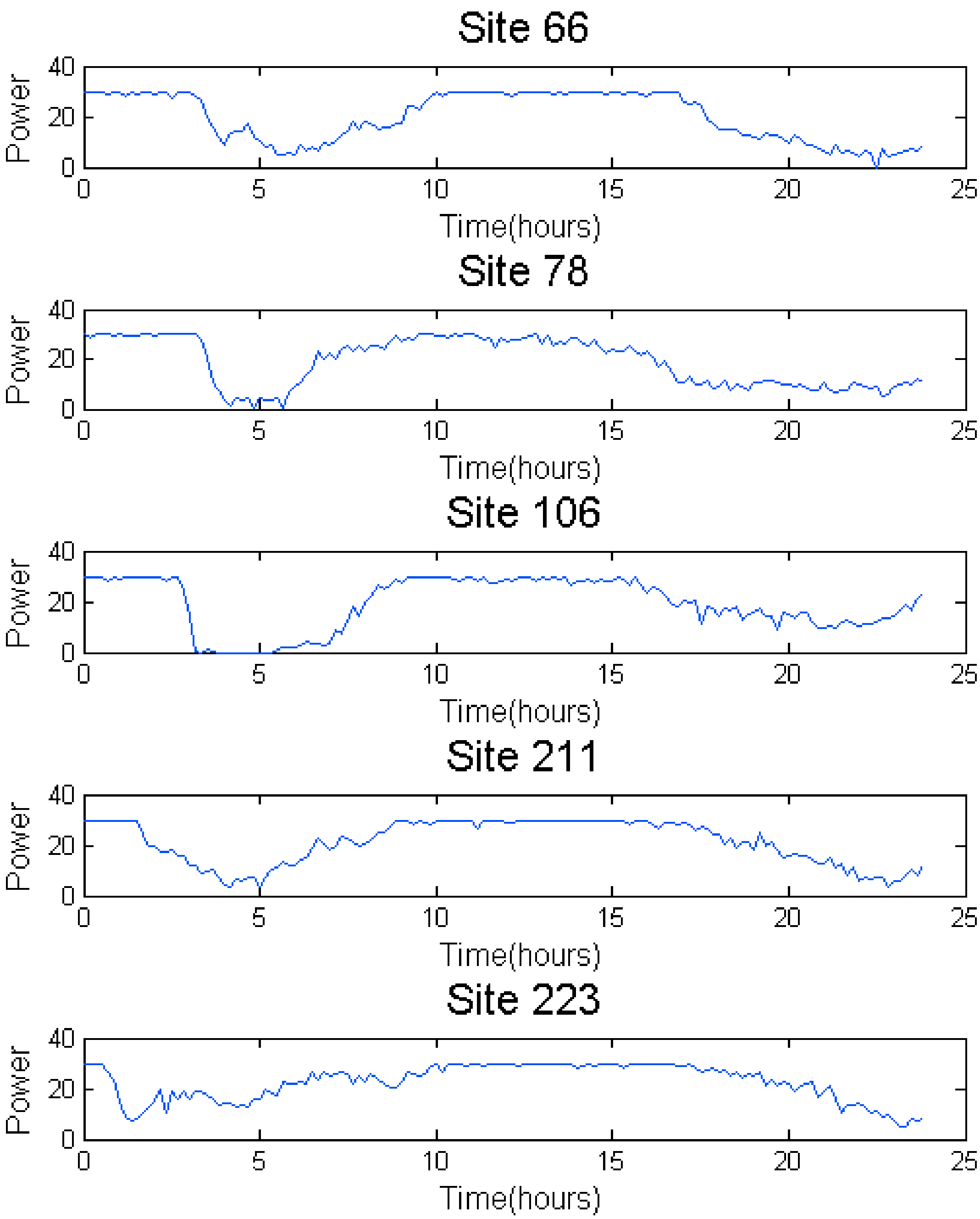

Figure 5.1: Waveforms from the Five Locations in Texas on January 3, 2006.

Table 5.2: Results from Case Study Texas

	Texas		Sites in Texas	
Load Curve	Curve 1	Curve 4	Curve 1	Curve 4
Wind Used	.11828	.10378	.10233	.090152
Coal Used	.30503	.29868	.31071	.30047
Gas Used	.12113	.15157	.1318	.16373
Utilization	.67462	.60248	.63987	.57423

defined in equation 3.10 and given in the last row of Table 5.2 is the fraction of the available wind that was used.

The results show that significant benefits can be gained from just connecting various wind turbines within a small area. For each utilization curve, the amount of wind used and the utilization of the wind are both increased. At the same time the amounts of gas and coal used decreased due to spatial smoothing. By averaging the results from the two load curves, the increase in utilization which is achieved can be calculated to be a 5.19% increase. The average decreases in coal and gas usage are respectively 1.22% and 7.37% respectively. Gas has the higher cost so the fact that it is reduced so much is highly desirable.

5.2 CASE STUDY WEST

Case Study West looks at a larger group of 10 wind turbines. In addition the wind turbines are from various locations spread over the western United States. Figure 5.2 shows the locations of the sites in Case Study Texas in red and the sites in Case Study West in blue.

The locations in Case Study West are much more diverse geographically.

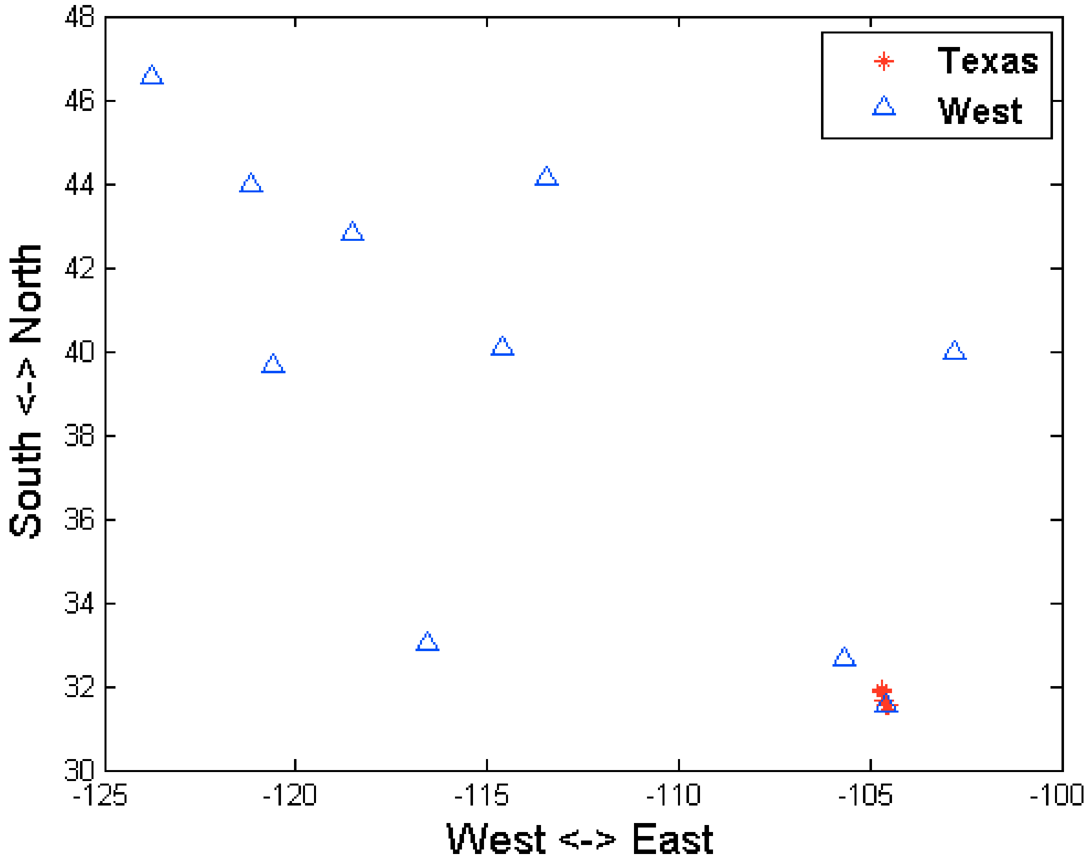

Figure 5.2: Map of Locations in the two Case Studies.

Information, analogous to that given in Table 5.1 for the site in Case Study Texas, is given for sites in Case Study West can in Table 5.3. Now the sites come from eight different states, rather than from just a small portion of Texas.

In Case Study West three levels of integration are tested. As with Case Study Texas, the average of all of the waveforms was computed and used as the input when testing the spatial smoothing case. That corresponds to the column "West" in Table 5.4. Similarly, a set of five sites was randomly chosen and the average of their waveforms was computed. The simulation was run with that average to serve for comparisons with Case Study Texas which

Table 5.3: Data for Locations in Case Study West

State	Site Number	Longitude	Latitude	Elevation
Texas	66	104.57W	31.54N	1430 m
New Mexico	667	105.66W	32.67N	2531 m
California	11590	120.62W	39.66N	1905 m
Colorado	12085	102.77W	39.96N	1312 m
Nevada	12328	114.59W	40.08N	1960 m
Oregon	22823	118.51W	42.79N	1942 m
Oregon	25026	121.17W	43.96N	1256 m
Idaho	25102	113.46W	44.13N	2096 m
Washington	28644	123.74W	46.54N	306 m
California	30546	116.54W	33.03N	1250 m

has the same number of turbines. Those results are found in the column titled “West5”. Finally, the same optimization was also done for each site individually. The results from individual sites were averaged and are given in the column labeled “Sites in West” in Table 5.4.

Table 5.4: Results from Case Study West

	West		West5		Sites in West	
Load Curve	Curve 1	Curve 4	Curve 1	Curve 4	Curve 1	Curve 4
Wind Used	.16982	.14307	.14557	.12295	.09231	.07985
Coal Used	.28063	.29367	.29564	.3002	.31661	.30324
Gas Used	.09183	.11638	.10203	.13073	.13477	.17006
Utilization	.68678	.58886	.68037	.58487	.57304	.50419

Once again in Case Study West, spatial smoothing proves to be beneficial. The quantity of wind utilization is increased by 18.41% when all ten sites are considered. Simultaneously, the amounts of coal and gas needed to produce the power required to supply demand decrease by 7.35% and by 31.7% respectively. The huge drop in the gas usage is of great interest to utilities since the cost of gas is so high. With only five sites sharing their wind resources the gains are still significant. Wind utilization increases by 17.45% while the coal and gas needed decreases by 3.87% and 23.64%.

5.3 COMPARISON

It is tempting to make comparisons by directly compare utilization levels for two different regions, Texas and West5 for example. That is dangerous though. there may be wind

Table 5.5: Summary of the Benefits Observed from the Use of Spatial Smoothing

	Texas	West5	West
Wind Utilization	5.19%	17.45%	18.41%
Coal Used	-1.22%	-3.87%	-7.35%
Gas Used	-7.37%	-23.64%	-31.7%

turbines included in West but not in West5 which produce unusually large amounts of power, and would skew the results. Instead all spatial smoothing results should be compared back to the base case when the turbines are on separate grids. In that way it is certain that any changes which are observed are consequences of spatial smoothing. Table 5.4 gives a summary of the benefits which are observed through the use of spatial smoothing in both case studies.

This study is setup to observe the affects of two variables which were presumed to have an affect on the benefits of spatial smoothing. Those variables are the geographical diversity of the wind turbines involved and the number of turbines involved.

The setups of Texas and West5 were the same in terms of the number of wind turbines. The difference was how the turbines were spread geographically. Figure 5.2 shows the geographical spread for the two case studies. As would be expected Table 5.5 shows that spatial smoothing has significantly more benefits when affected over a much larger region. The benefits observed in West5 are about three times those observed in Texas.

West and West5 differ in number rather than in geographical diversity. It can be seen from Table 5.5 that the utilization increases slightly when the number of sights is doubled. The savings in the quantities of coal and gas which are needed also increased considerably, though neither is doubled. This demonstrates that there is continued potential for added savings by increasing the number of turbines which are involved in the spatial smoothing.

6.0 CONCLUSION

Through simulations and modeling this study has demonstrated the importance of spatial smoothing to facilitate the integration of renewable resources. The results also demonstrate that either increasing the geographic distance between turbines or increasing the number of turbines involved can increase the effects of spatial smoothing. It has been claimed that at higher penetrations renewable integration becomes unpractical or even counter productive [4]. The present work is not able to disprove that arguement but it provides a starting point and suggests that there may be solutions which will allow for the practical implementation of high penetrations of wind power. Specifically, the conclusions that can be drawn from this study is that it can be easier to deal with a collection of wind farms than to deal with each of the wind farms individually, because the output from the collection is smoother than the outputs of the individual farms and that distance and number factor into that relationship.

6.1 THE ISSUE OF POWER TRANSMISSION

The main weakness of this study is that it neglects transmission losses. When comparing Case Study Texas to West5 losses might be the deciding factor. West5 assumes that power can be transmitted with no loss or cost from the state of Washington to Texas. Whether spatial smoothing is beneficial over large regions like the western United States or not could also depend on the transmission infrastructure which is used. A very promising technology known as HVDC, or high voltage direct current, shows great promise for reducing the losses associated with electricity transmission over long distances [24, 25]. By converting AC power to DC power it can be transmitted over longer distances and with less losses. DC transmission is also much more suitable for underwater transmission of any considerable distance. Underwater transmission is important with respect to wind, because often the best wind resources are at sea. Not only are losses decreased but also problems with the power factor can be avoided, meaning that the use of voltage compensators can be avoided. The disadvantage is the need to convert AC power to DC on one end and DC power to AC on the other end. While the conversion losses are not dependent on distance, HVDC is mainly applicable for longer distance applications.

The work of Giebel et al. in 2005 supports the idea that the benefits of spatial smoothing could dominate the increase in transmission losses. They assume a large HVDC connection to help minimize the losses accumulated over hundreds of miles of transmission. With the assumption of such a HVDC connection they even demonstrated that importing electricity into Europe from wind farms in Egypt could be economically advantageous [10]. Their conclusion was solely based on the fact that wind resources are better in Egypt, so the benefits of spatial smoothing are in addition to the economical savings that they observed.

The work of Giebel and others [10, 26] sets up the question of a huge super grid connecting dozens of countries and sharing power. Taking advantage of spatial smoothing as well as smoothing over resources and utilizing efficient HVDC connections could greatly increase the potential for renewable integration. The idea is analogous to that presented in 1817 by David Ricardo in his book *On the Principles of Political Economy and Taxation* [27]. Ricardo's theory is called comparative advantage. During his time many of his countrymen in England were isolationists. Ricardo showed that trading goods is virtually always beneficial for the collection of trade partners. There are of course losses involved with trade which are the cost of shipping the goods. Nevertheless, the comparative advantage gained through trading has dominated the cost of shipping goods. Today, through the use of modern and efficient transportation, almost all products are sold around the world. It could be imagined that as power transmission improves the same could occur with electrical power.

6.2 FUTURE WORK

In the short term my goal is to expand the system model to incorporate transmission and end-user parameters. The resulting system is shown in figure 6.1. The addition of transmission in particular will add a great deal of credibility to results related to spatial smoothing. The additions also make the system much more complete.

Another important improvement of the model is making it do the allocation using prediction. From Figure 2.1 and a comparison of Figure 4.2 to Figure 4.3 it can be imagined that the prediction of wind is easier with spatial smoothing. Since the variance of the wind power is reduced the variance of the error should be reduced at least proportionally. Two distinct options for the wind prediction in the presence of spatial smoothing would be possible. Global prediction of wind resources would provide a single number for the entire grid and have a low variance of the error. Local prediction might work just as well. In the case of local prediction the predictor would lack the benefit of spatial smoothing but the errors from the various regions would cancel each other out and reduce the variance of the global error which is the most important. One possible direction of great utility might be to do a

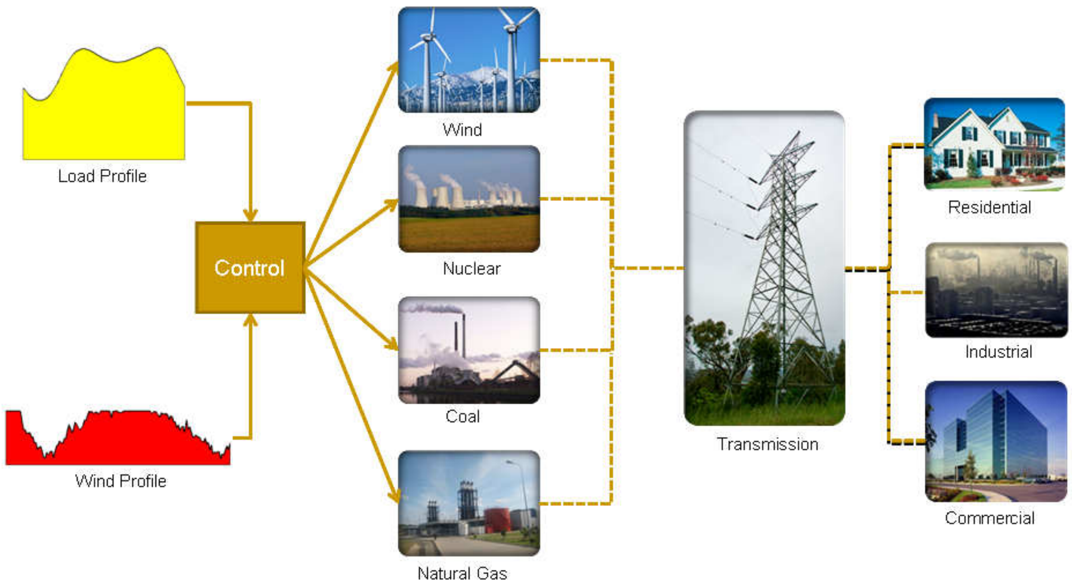

Figure 6.1: Future System Diagram

comparison of global versus local prediction in the context of transmission losses. A better solution might be a global predictor which considers local predictions and the topology of the network to maximize efficiency.

For years meteorologists and physicists have been developing sophisticated models for weather prediction. The most advanced methods involve trillions of calculations and utilize statistical and physical models. Attempting to create better prediction models is unrealistic, and in general some sort of communications should be available so that wind predictions can be obtained from a provider who specializes in such things. For very small applications a basic predictor which uses time series analysis might be more practical than importing predictions. In general though the better option would be to purchase wind predictions from a third party provider. In that case the question of prediction then becomes, "How do we best use the predictions?". Studying such a problem might be a very promising continuation.

To study the problem of using externally provided wind predictions, data which gives predictions and the associated error for various horizons would be of particular interest. Unfortunately all that is generally available is simple time series of actual wind power data. That data does not give any indication of how accurate predictions will be though. Any study of predictions using such data would need to make assumptions about the error that is present in predictions. As a consequence any conclusions of such a study would be highly dependent on the assumptions made and of little practical use.

The study of storage applications is another possible extension of this work. One strategy that is used today is to simply charge storage units during the night when power is cheap and to discharge during the times of peak load. Due to the regularity and predictability of the load, this method works fairly well. With little penetration of renewables, the cost of electricity is mainly dominated by the load. As wind penetration grows this will change and the price of electricity will become ever more dependent on the available wind power. As that happens utilizing storage intelligently will become more important. When the cost of power depends on wind that also implies that wind predictions are needed for optimizing the use of storage.

My eventual goal will be to combine all of the topics discussed here with more realistic models. Adding transmission losses to the work on spatial smoothing is a great advancement. If in addition storage and prediction can be considered then the model starts to look like a practical system. It would be an ideal tool for modeling the grid a couple of years down the line when wind penetration reaches significant levels.

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