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WIND POWER CAPACITY VALUE METRICS AND VARIABILITY:
A STUDY IN NEW ENGLAND

A Dissertation Presented

by

FREDERICK W. LETSON

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
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Mechanical Engineering

WIND POWER PLANT CAPACITY VALUE METRICS AND VARIABILITY: A STUDY IN NEW ENGLAND

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ABSTRACT

WIND POWER CAPACITY VALUE METRICS AND VARIABILITY: A STUDY IN NEW ENGLAND

SEPTEMBER 2015

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Capacity value is the contribution of a power plant to the ability of the power system to meet high demand. As wind power penetration in New England, and worldwide, increases so does the importance of identifying the capacity contribution made by wind power plants. It is critical to accurately characterize the capacity value of these wind power plants and the variability of the capacity value over the long term. This is important in order to avoid the cost of keeping extra power plants operational while still being able to cover the demand for power reliably. This capacity value calculation is particularly interesting because wind power output and demand for electricity are not statistically independent. They are both driven by the weather.

This dissertation describes a model of the New England power system in the presence of increasing wind power penetration, used to achieve three major ends:

1. To evaluate the magnitude of the contribution that wind power would make to resource adequacy in the New England Power system at various levels of penetration (up to 50%).

2. To characterize the inter-annual variability in that contribution

3. To assess various capacity value metrics with regard to their ability to predict the long term capacity value of wind power plants, especially based on limited data

4. To characterize the interaction of wind power plants and energy storage with respect to capacity value

These ends were achieved by completing three studies: a long-term study based on measured wind data, a high-penetration study based on synthesized data, and an investigation of the effect of grid-scale energy storage. While the methods used in these studies are generally applicable, New England is used as a consistent example since many of these phenomena are strongly affected by the regional wind and power system characteristics.

The results of this work show that wind power capacity value is relatively high at low penetration and decreases substantially as penetration increases to 50% and that this is not significantly improved by the inclusion of grid-scale (daily load-shifting) energy storage. Also, the capacity value of this energy storage, considered separately is relatively high, and not strongly dependent on wind energy penetration level. In future power systems with higher wind penetrations than 50% or those relying on longer-term storage (which could be necessary to reach very high levels of renewable penetration), new metrics of capacity value may be necessary to ensure system adequacy

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CHAPTER 1
INTRODUCTION

This dissertation documents an investigation of the effect of wind power plants on the reliability of a power system. The goal was to identify effective metrics for characterizing a wind plant's contribution to reliability using easily available data. These metrics should be useful for system planners making decisions about the adequacy of the generator fleet at some future date, and should be useful to wind developers, siting wind projects.

Bulk power system reliability can be divided into two major parts (Billinton & Allan, 1984):

System Security is the reliability of the power transmission and distribution system. It is a measure of how likely it is that failures in these system will lead to interruptions in electrical service for customers, and how widespread those outages are likely to be.

System Adequacy is the ability of the generator fleet to provide adequate power at all times. This is considered separately from system security. System adequacy is the focus of this study.

The contribution of a power plant to system adequacy is called the *capacity value* of that plant. Capacity value is not an easily-defined quantity like capacity factor. It is dependent on many characteristics of the power plant and the power system of which it is a part. Calculating the capacity value of a *wind* plant is particularly challenging,

because the power available from a wind plant is not statistically independent from power demand; they are both influenced by the weather.

The following definition of terms is included here as a primer for the reader. Readers familiar with the terminology of power system reliability can safely skip to the beginning of Chapter 0.

1.1   Definition of terms

- *Resource adequacy* is the degree to which the existing or planned generation resources meet the current or projected distribution of electrical power demand.
- The *capacity value* (CV) of a generator is a general term for how much a power plant contributes to resource adequacy. This is not to be confused with the capacity factor
- The *capacity factor* of a power plant is a measure of its average power output compared with its maximum power output. This is usually expressed as the fraction:

$$Capacity\ Factor = \frac{Annual\ Energy}{Nameplate\ Capacity * 8760\ hours/year} \qquad \text{1}$$

Capacity factor is a dimensionless quantity, often expressed as a percentage.

The *effective load carrying capacity* (ELCC) of a power plant is a measure of how much that plant contributes to system reliability, compared to a plant with perfect availability (an *ideal plant*). ELCC is a dimensionless quantity, often expressed as a percentage.

- The *loss of load probability* (LOLP) is the probability for a given period of time (typically an hour) that the generation resources will be inadequate to meet the load. X_t is a random variable representing the system capacity at time t, d_t is the electrical demand at time t, and r_t is the contribution of variable renewable (such as wind power) at time t. The renewable contribution is treated as negative demand (and shown on the right side of the inequality) because both the load and the renewable contribution are modeled using historical data, rather than represented by a probability distribution.

$$LOLP = p(X_t < d_t - r_t) \qquad \textbf{2}$$

- The *loss of load expectation* (LOLE) is the long term expectation value, in hours per year, of the amount of time that there will be un-served load. This is required to be 1 day in 10 years or less in North America. LOLE is the industry-standard rigorous metric for resource adequacy. The following equation describes the LOLE calculation.

$$LOLE = \sum_t p(X_t < d_t - r_t) \qquad \textbf{3}$$

- The *forced outage rate* of a power plant is the probability of an unplanned outage of that plant, usually due to mechanical failure

- In this dissertation, the term *wind penetration* is used to mean amount of energy a power system gets from wind power compared to the total system energy consumption. This could be over one year or over a period of years. Except where otherwise specifically noted, penetration will be used to mean this

concept of *energy penetration*. Wind penetrations expressed in this study are the raw fraction of wind energy output over system energy demand, regardless of whether the timing of the wind and the load allow for all energy from the wind power plants to be applied to the load (wind curtailment is not considered in the penetration calculation).

- The *Load-Net-Wind* (LNW) is the time series of system load with the wind power time series subtracted out for each hour. This net load of the load which must be met by the conventional generators of the system.

CHAPTER 2

OVERVIEW OF WIND AND POWER SYSTEMS

This chapter is intended as a primer on issues surrounding wind integration. Many of the topics in this chapter are tangential to the concept of wind power capacity value, and are included here for completeness. Wind integration is the study of large scale issues in the bulk power system relating to the introduction of wind power. Issues surrounding interconnection of wind power (local issues, mostly having to do with voltage control) are excluded entirely.

As a part of plans for the reduction of greenhouse gas emissions, wind power penetration in many countries including the United States is growing rapidly. The benefits of wind include reduced gas and particulate emissions and non-exposure to fuel insecurity and price volatility. The unique attributes of wind power require special attention where power system planning and operations are concerned. The variability of wind power and the fact that wind resource is often located far from electrical load centers create grid issues specific to wind power. These complications will increase in importance as the penetration (the percentage of yearly system energy provided by wind power) increases.

2.1 Power System Planning and Operation

The goals of a power system operator are to provide power to customers as demanded, within certain power quality tolerances, and to do so at a reasonable cost.

These goals have two major implications of relevance to this chapter. First, the system

must be operated such that the total power being consumed by the load and the total

power being generated on the system are equal, or very close to equal, at each moment

in time. This requires that the generator fleet be capable of meeting the maximum

demand, and also that the fleet be capable of *ramping* (changing power output with

time) quickly enough to cover any changes in the load that occur. The system must also

have adequate transmission to deliver all of the power generated to the locations where

it will be consumed (Ackermann, 2012).

The process of matching generation to the load is undertaken on several time

scales. The longest time scale is that of system planning for resource adequacy

discussed above. On a day-to day basis, individual power plants are dispatched

(commanded to run with a certain power output) to cover the load while minimizing

cost and maximizing system reliability.

Figure 1 shows four time scales relevant to power plant dispatch. The longest

time scale is called unit commitment. It is a high-level process to ensure that adequate

generation will be available over the next time period (on the order of days) to meet the

expected load. Plant scheduling generally happens one day ahead of time. The bulk of

power plant dispatch happens during this period in part because many large thermal

plants require several hours of preparation to reach full output. Load following refers to

scheduled intra-hour changes in plant output to follow expected changes in the load.

The shortest time scale of power plant operation is called regulation. Plants responsible

for meeting fluctuations in the load on the time scale of seconds to minutes are

automatically controlled by the system operator to achieve the reaction time required

for high-frequency load matching (Smith, Milligan, DeMeo, & Parsons, 2007).
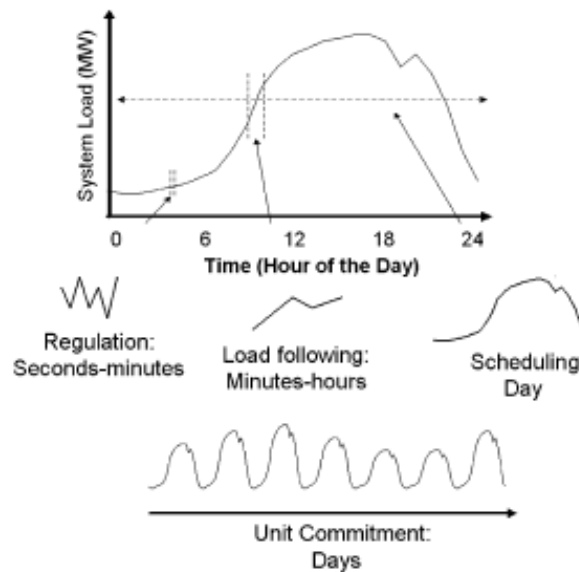
Figure 1 - Time scales of generator fleet operation (Smith et al., 2007)

Successful system operation also requires attention to the transmission system.

Power plants must be dispatched in such a way that no transmission lines are

overloaded, and that voltage at each node in the grid is within its specified range.

2.2   Complications Due to Wind Power

Wind plants are unlike conventional generation in several important ways, two

of which will be discussed here. First, the wind resource varies significantly with

location. This drives the placement of wind power facilities to those areas where the

wind resource is sufficient to produce power economically, and these areas are often far

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from load centers and existing transmission lines. Second, wind power is inherently variable. Rather than power output being controllable within the entire range of operation, as with conventional power plants, wind plant output varies substantially with wind speed. These effects of the nature of the wind resource have important implications for the way wind power must be treated in the power system.

The variability of wind power can have a large effect on the generators providing power regulation to the system. With increasing wind penetration more regulation and load following operations may be required than would otherwise be necessary (with existing generators). In the extreme, this could require the construction of new plants to cover the increased variability in the system. Figure 2 shows two examples of inter-hour variability from different times of the day and year. For hours in which load tends to increase while wind power output is decreasing (or vice versa) the ramping requirements of the other generators on the system are increased.
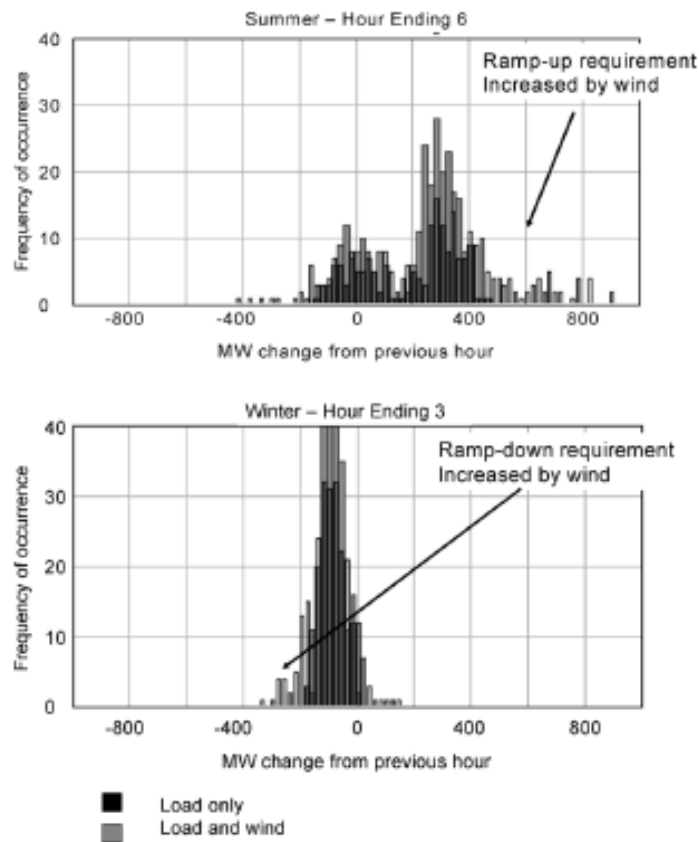
Figure 2 - Inter-hour variability with and without wind power (Smith et al., 2007)

The availability of adequate transmission is key for the development of wind power on a large scale. Remote, variable generation such as wind power can have detrimental effects on voltage if the connection to the rest of the grid is weak. Also, the transmission lines from remote areas of wind generation must have sufficient power capacity to carry the wind power to market. Figure 3 shows a summary of grid issues surrounding wind integration and the time/length scale associated with each. It is of note that the issues associated with large time and length scales tend to be related to power supply, and those with small time/length scales tend to be related to voltage and power quality.

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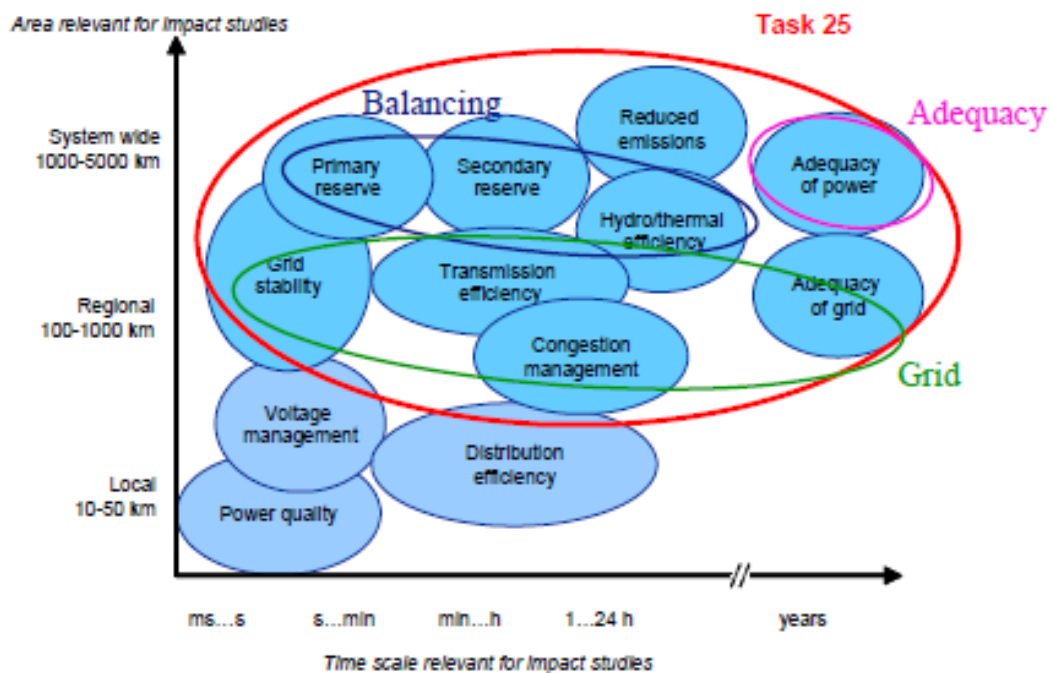
Figure 3 - Time scales of system impact from wind power (Holttinen et al., 2011)

2.3   Geographic Smoothing

The negative effects of increasing wind penetration are exacerbated by the correlation in output of one wind farm to the next. Geographic diversity among wind farms tends to reduce this correlation and to smooth the total wind power output on the system. Figure 4 shows the variability of the wind resource as a function of frequency. Small scale variation (less than one hour in characteristic period), is easily smoothed out with any reasonable geographic diversity in wind plant geography. Larger scale variations (with characteristic periods of hours to days), require plants to be

spread over distances of hundreds or thousands of miles, depending on the speed of the

weather system.

Fig. 2.2   Schematic spectrum of wind speed near the ground estimated
from a study of Van der Hoven (1957).   from Stull 1988
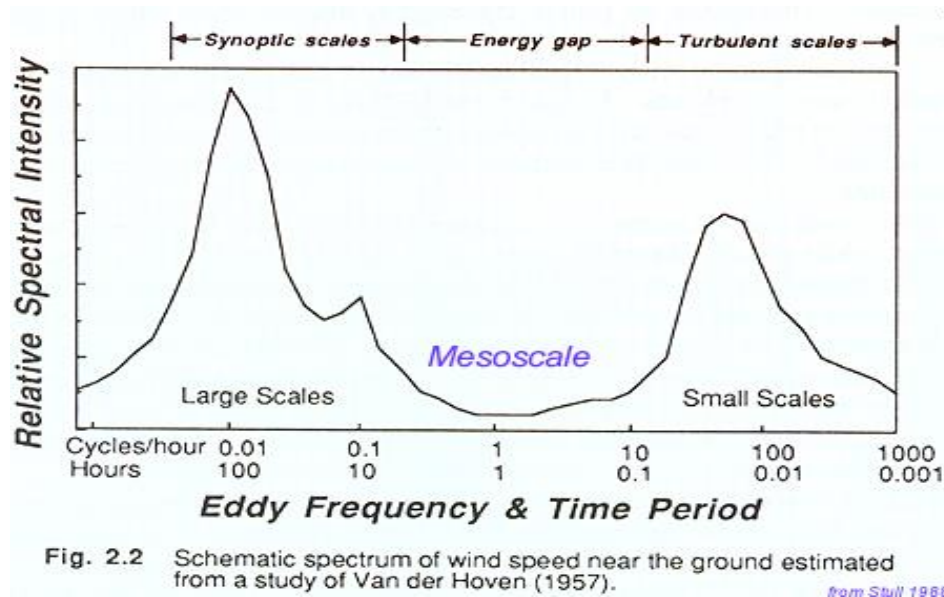
Figure 4 - Time scales of wind variation

Figure 5 is a power duration curve showing the smoothing effect

associated with increasing the region of interest from Denmark and Germany, to all of

the European Union (EU), to the EU and North Africa. It can be seen here that increasing

geographic diversity tends to lower the probability of extremely low or extremely high

outputs. The total wind output from a system with wind power spread out significantly

will tend toward some middling value and rarely reach the extremes.
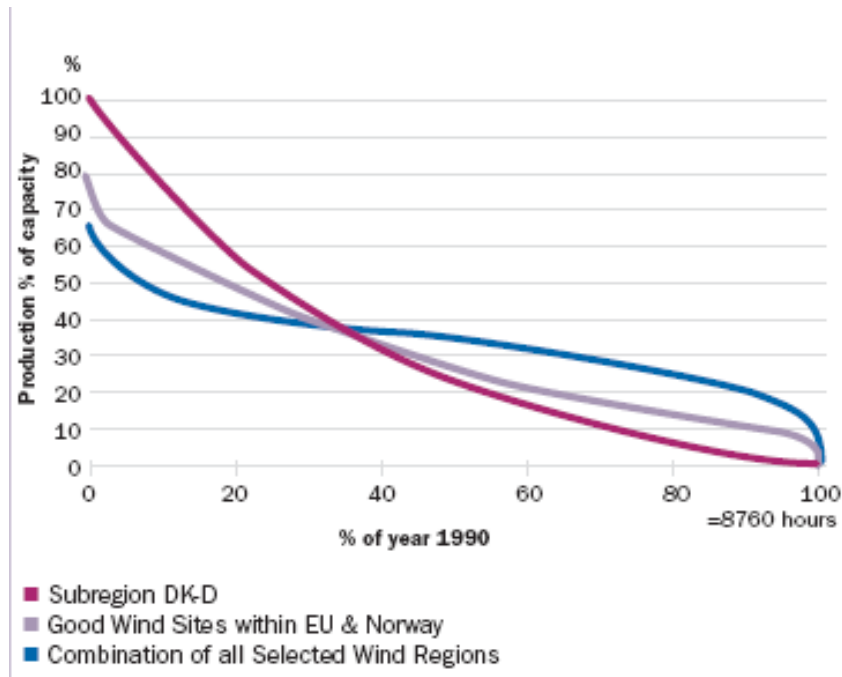
Figure 5 - Smoothing effect on total wind power output (Van Hulle, 2005)

Another concern relating to wind variability is *high-wind cutout events*. These events occur when turbines shut down at high wind speed to protect themselves from high mechanical loads. These events can occur quite suddenly, and, unless the system operator has access to real-time or forecast wind data, can occur without warning. Figures 6 and 7 show a high-wind cutout event in Texas in 2007. The ramp rates of individual wind farms are extreme as they shut down in self-preservation, but the aggregate effect, shown in Figure 7 is much more spread out over time. This allows the rest of the system time to react and balance this change in power.
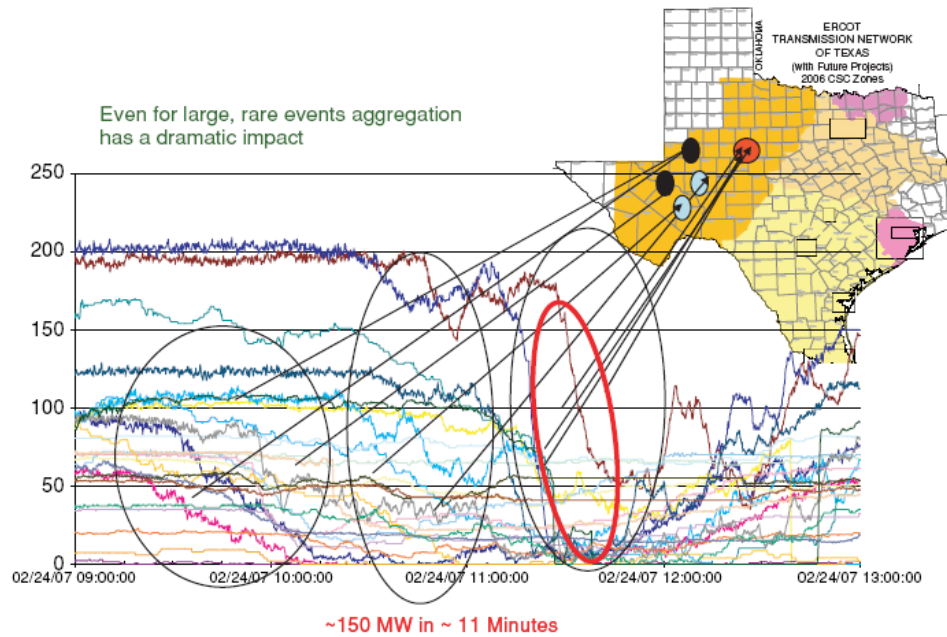
Figure 6 - Effects of a high-speed cut-out event (Michael Milligan & Kirby, 2008). Power is shown in MW
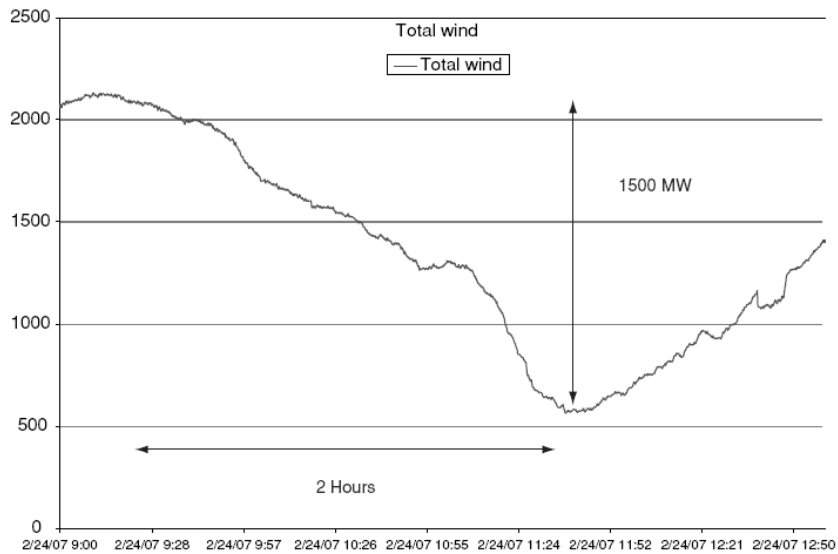
Figure 7 - Aggregate effect of the same cut-out event (Michael Milligan & Kirby, 2008). Power is shown in MW

Quantifying the effects of geographic smoothing on the costs and benefits of

wind power could be an important contribution to wind plant siting decisions and

transmission planning efforts for wind power. Having a ready way to judge the effects of

wind farm siting on grid operation, above and beyond annual energy output of the farm,

could lead to better decisions about the locations in which wind farms are built, and

placement of long-distance transmission built to collect wind power. Operational costs

of wind integration and the value of wind power to the grid both get less favorable as

wind power penetration increases. The effects of geographic smoothing can help to

mitigate these negative effects.

One benefit of geographic diversity of wind power is the decreased cost of

regulation, as discussed in the Geographic Smoothing section above. Less operation of

regulation means higher efficiency and lower cost for the system. Figure 8 shows results

from several studies of the increasing cost of regulation as penetration increases. This

increase in cost is related to the magnitude of the variability in the wind power output

increasing with wind penetration, and becoming a larger contributor to the total

variability of the system. At low penetrations the variability in net load due to wind

power is overshadowed by the variability in the load itself. As penetration increases

wind makes a real contribution to the system variability. This contribution is mitigated

by having geographically diverse wind plants. The less correlated the outputs of the

wind plants on the system are, the smaller the total contribution of wind power to the

total net load variability.
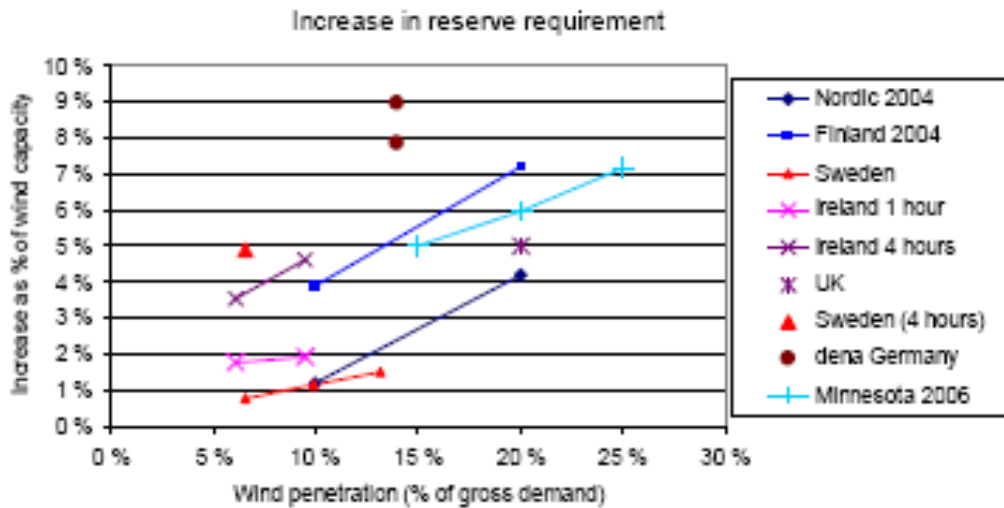
Figure 8 - Operating reserve requirements as a function of wind penetration for various power systems (Smith et al., 2007)

Figure 9 shows the capacity value (called capacity credit, here) of wind energy found in several state and national studies. It can be seen that there is a general trend toward less capacity value of wind power (as a percentage of installed capacity) as wind penetration increases. This indicates that each new wind farm contributes less to the maximum capacity of the power system than the previous one did. This can be explained by a concept called loss of *load expectation (LOLE)*. As defined above in the definition of terms, the LOLE is the expected value, in hours per year that the generation on the system will be inadequate to meet the load. Since the capacity value of a generator is a measure of how much the addition of that generator to the system affects the LOLE. Plants with a high availability, particularly at times of heavy load, will have a high capacity value, since they contribute more to the system's ability to meet

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high demand reliably. A wind plants capacity value is related to the expected plant

output at times when system load is highest. Or, to put it another way, the relationship

between weather (which is a major load driver) and the wind resource at the site has a

major effect on the capacity value of a wind plant at that site.
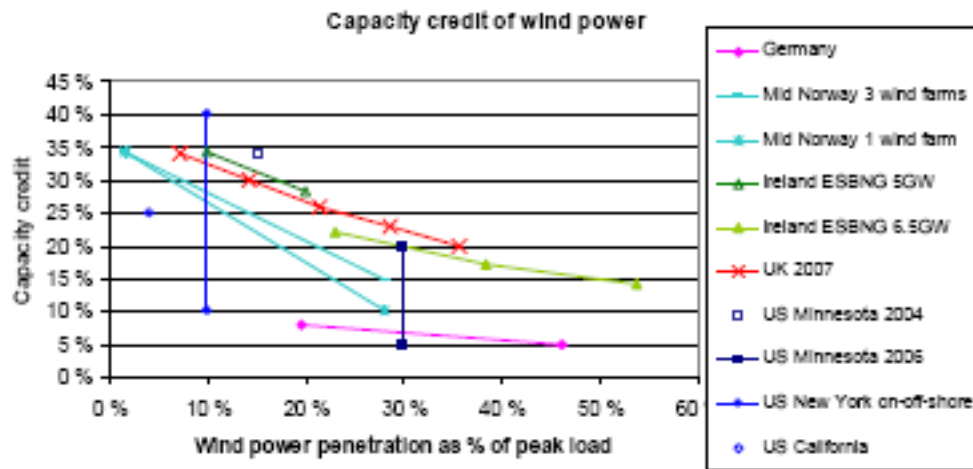
Figure 9 - Capacity value of wind for various power systems (Keane et al., 2011)

As wind penetration on a power system increases, the times of high net load

(load minus wind power output) are shifted away from days where the wind is blowing,

since the system has a comparatively large contribution from wind on those days. The

'problem' days in a system with a high wind penetration will tend to be non-windy days,

and thus the contribution of wind power to reducing LOLE on such a system is low. This

effect is obviously mitigated by geographic smoothing of wind power output. As wind

farms are spread over a wider area, the correlation between their outputs will decrease,

and the probability of non-windy days decreases as the total wind power output

becomes smoother.

CHAPTER 3

CAPACITY VALUE METRICS

Capacity value metrics are used by power system planners to ensure that there will be enough power plants to meet demand at some point in the future. When two or more power plants need to be compared with respect to their contribution to system adequacy, system planners rely on several metrics.

Historically, system adequacy was ensured using a *planning reserve margin*. This is a rule of thumb, based on experience with power system operation, rather than probability theory. A planning reserve margin is the amount by which the total capacity of the generator fleet exceeds the maximum expected demand, as a percentage of expected demand. A typical value for a planning reserve margin might be 15% (Billinton & Allan, 1984). This method does not address the actual reliability of current or future power plants and does not give the user an accurate idea of the probability of an event in which demand exceeds generation capacity.

More probabilistically rigorous methods of examining system adequacy are now preferred (Michael Milligan, 2011).

The following subsections describe the capacity value metrics which are in common use by system operators to identify the capacity value of wind power plants.

3.1 Risk-based Methods

Risk-based methods of ensuring system adequacy are designed to estimate the probability of a low-capacity event and, sometimes, the severity of that event. These methods take into account the reliability of each power plant on the system and some of these methods are applicable to wind power plants.

3.1.1 Loss of Load Expectation and Effective Load Carrying Capability

Loss of Load Expectation (LOLE) is the most rigorous, widespread and trusted measure of system adequacy (Keane et al., 2011) (Billinton, 2001). LOLE is the expectation value (usually measured in hours per year) of the fraction of time for which generation will be inadequate to meet demand. In the United States, the target value for LOLE is 1 day in 10 years (Michael Milligan & Porter, 2006; "NERC Reliability Standards,"). Since this metric is so widespread and will be of central importance to this project, it is described here in higher detail than other metrics.

An LOLE calculation requires the following data an inputs (Holttinen, Bettina Lemström, Meibom, & Bindner, 2007):

1. A demand time series for the period of investigation

2. A wind power time-series for the same period

3. A complete inventory of conventional generation units' capacity and forced outage rates

4. The target reliability level.

Using these four inputs, the LOLE is calculated in three steps (Garver, 1966).

1. *Construct capacity outage probability table (COPT)*

   Given that each generator making up the system has a probability of outage, there is some finite chance, for each hour, the total available generation will be inadequate.

   Starting with the forced outage rate of each power plant in the system, the probability distribution of available generation for any hour is calculated. This system-wide probability distribution is the convolution of the individual probability distribution of available power output for each generator.

2. *Calculate LOLP*

   The Loss of Load Probability (LOLP) is the probability, for each hour of the period, that the generator fleet will be inadequate to meet demand:

$$LOLP = p(X_t < d_t) \hspace{2cm} \textbf{4}$$

   where X_t is a random variable representing the system capacity at time t and d_t is the electrical demand at time t.

3. *Average over the hours in the period of investigation.*

The LOLE is calculated from the LOLP by summing over all hours in the period of investigation and then dividing by the number of years in that period, T.

$$LOLE = \sum_t p(X_t < d_t)/T \qquad \text{5}$$

When using this method, conventional power plants are modeled using a two-state model: they are either operating or they are offline. This two-state model is inappropriate for a wind plant since its output is variable within a range. When a time-varying resource like wind power is included in this reliability model, it is included as a negative load, since there is important information contained in the time history of wind plant output and its relationship to electrical demand. The two are not independent, so it is important to use concurrent load and wind power data in this calculation. Including a contribution from one or more variable, renewable power plants, r_t, the LOLP and LOLE are given by the following equations:

$$LOLP = p(X_t < d_t - r_t) \qquad \text{6}$$

$$LOLE = \sum_t p(X_t < d_t - r_t) \qquad \text{7}$$

In order to find the reliability contribution of a particular power plant, the system is modeled with and without that plant and the resulting change in LOLE is the credited to that plant.

Effective load carrying capability (ELCC) is the most common way of expressing capacity value. The ELCC of a power plant is a comparison between the reliability benefit of adding that plant to the power system and adding a plant with perfect availability. ELCC is useful for comparing the contributions of plant with differing size, reliability and on-peak delivery. ELCC can be used with a wide array of system adequacy metrics, and is generally paired with LOLE (Michael Milligan & Porter, 2006).

For example: a 500MW power plant which, when added to the power system in question, gives the same reliability benefit as a perfectly available 300MW plant, has an ELCC of 300MW or 60%.

An example of ELCC calculation with LOLE is given in Chapter 0.

3.1.2 Expected Unserved Energy

Expected unserved energy (EUE) is a reliability metric very similar to LOLE, but EUE also contains information about the magnitude of capacity shortages, not just their likelihood. The EUE is calculated as follows:

$$EUE = \Delta T \sum_t U(d_t) \qquad \textbf{8}$$

Where $U(d_t)$ is the expectation value of unserved load at time t (Fockens, van Wijk, Turkenburg, & Singh, 1991), (Michael Milligan, 2011).

3.2   Capacity Factor Methods

Some reliability metrics work by examining the average output of a variable generator, such as a wind plant, during some relevant subset of hours in the year. Generally these are hours of high electrical demand, the drivers of LOLE.

3.2.1   Peak Period Method

The Peak period method is a simplified method for determining the capacity value of a variable generator. It is used by many system operators in North America as a standardized metric for crediting renewable generators with a capacity value. This method approximates ELCC by investigating the average output of the proposed plant during certain representative periods; usually periods when power demand is high. For example ISO New England uses summer afternoons and evenings in the fall, winter and spring (Milligan and Porter 2006).

3.2.2   Annual Peak Method

The annual peak method refers to two different capacity value metrics. One is a risk-based metric: examining the change in LOLP during the peak demand hour of the year due to the addition of the plant in question. The other is a capacity factor metric: checking the plant output during the peak hour.

The strength of these metrics is simplicity and transparency. Their weakness is their reliance on a single data point to characterize each year. Since the advent of computerized data analysis, these methods have fallen out of favor.

A metric similar to these was investigated in this study. The average plant output during the top 1% of load hours was used as a predictor of capacity value. This metric is referred to below and the top load hours metric, or TLH.

3.3   Distribution Methods

Distribution methods work by examining the distribution of power demand, and wind power output, rather than a time history. These methods have the advantage of being less sensitive to extreme events than the methods above, but information relating to chronological relationship between wind power output and power demand can be lost.

3.3.1   The Z-Statistic Method

The Z-statistic method centers on the random variable *Z*, defined by the distribution of surplus generation at on-peak times. Z is defined as:

$$Z = \frac{\bar{S}}{\sigma_S} \qquad\qquad \textbf{9}$$

Where $\bar{S}$ is the expectation value of surplus generation, and σ_S is its standard deviation. This random variable is related to LOLP as shown in Figure 10.
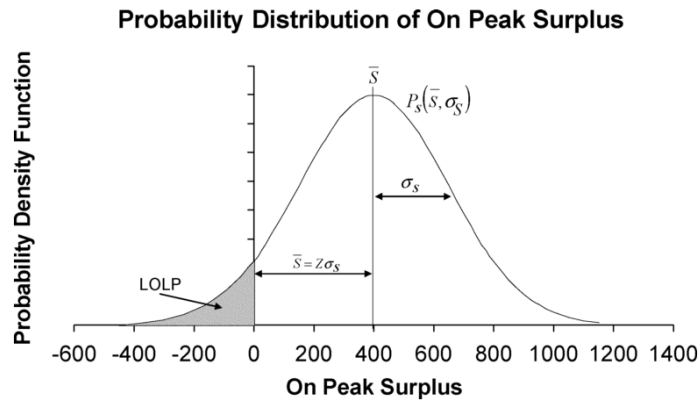
Figure 10 Surplus distribution and the Z- Statistic (Dragoon & Dvortsov, 2006)

By analyzing what is required to hold Z constant during changes to the power system model, one can determine the load carrying capability of a power plant added to the system. If one assumes that the shape of this distribution is unchanged by the addition of a wind plant (the mean and width of the distribution may change), then the Z-statistic method is a valid method for determining the capacity value of that wind plant (Dragoon & Dvortsov, 2006)

3.3.2 Garver's method

Garver's method, also called Garver's approximation, is a graphical approximation method for calculating the capacity value of power plants (Garver, 1966). In order to apply this method to a wind power plant, one must assume that its

distribution of power output is that same at all times. As a result, this method has been rendered obsolete (Dent, Keane, & Bialek, 2010).

3.3.3 Multi-state representation of wind power plants in COPT

Wind power capacity value can be calculated by using the ELCC/LOLE process described above, but instead of including wind power output as a negative load, the wind plant can be represented as a part of the capacity outage probability table (COPT) like any other power plant. While most power plants are represented using a two-state model (the plant is available or it is not), wind power plants can be better represented by a multi-state model. The unconditional cumulative density function for wind plant power output is convolved with the rest of the two-state cumulative density functions for the rest of the generator fleet

Representation of wind power plants in this way fails to address the mutual statistical dependence of wind power output and load, and has fallen out of favor (Keane et al., 2011)

3.3.4 Wind distribution percentile methods

Wind distribution percentile methods are a way of characterizing the 'firm capacity' that a wind power plant provides to the power system. These methods characterize the capacity value of a variable generator by expressing the maximum power output with a given exceedance probability. Usually the power output distribution during peak load hours in considered in this calculation.

For example, the power output which is exceeded by the plant in question 95% of the time (the power output with a 95% exceedance probability), can be used to compare its reliability benefit to one or more other power plants (C.J. Dent, 2010).

This metric is also called the *guaranteed capacity*, and is used some German studies of wind capacity value, such as the DENA study (Bartels et al., 2006).

3.3.5   Mont Carlo methods

If the joint probability distribution of wind power output and load is known, a long time series of wind power data can be synthesized which reflect the complex inter-relationship between these two quantities. These Monte Carlo methods are sometimes used in operational studies of grid integration of wind power. The difficulty of using these methods is the results can only be as accurate as the characterization of wind and load that one uses as a starting point (Michael Milligan & Porter, 2006) (Ensslin, Milligan, Holttinen, O'Malley, & Keane, 2008). The difficulty of assessing this relationship is central to the problem of estimating wind power capacity value.

3.4   Capacity value metric summary papers

The following is a list of papers which summarize the metrics used to calculate the capacity value of wind power plants, dating back to 2006. The metrics outlined in each of these papers is listed also. The intention of including this list here is to show how widespread the use of a few major metrics is, and to support the idea that the

above list of metrics represents a reasonably exhaustive account of the metrics used in the literature.

- Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning, (Michael Milligan, 2011)

  - Reserve margin, LOLP, LOLE (recommended),

- Capacity Value of Wind Power, IEEE transactions on power systems (Keane et al., 2011)

  - LOLE, ELCC, Garver's method

- Impacts of large amounts of wind power on design and operation of power systems, results of IEA collaboration (Holttinen et al., 2011)

  - LOLP, ELCC

- Capacity value of wind power: summary(O'Malley, Milligan, Holttinen, Dent, & Keane, 2010)

  - LOLE, LOLP, ELCC

- Simplified Methods for Renewable Generation Capacity Credit Calculation: A Critical Review (C.J. Dent, 2010)
  - Annual peak method, Garver's method, Z-method, wind distribution percentile methods, peak period methods.

- Capacity Value of Wind Power: Calculation and Data Requirements (B. U. C. D. Hasche, Keane, Engineering, & O'Malley, 2009)

  - LOLE, Garver's method

- Comparison of capacity credit calculation methods for conventional power plants and wind power (Amelin, 2009)

  - LOLP, ELCC, Garver's method, Guaranteed capacity

- Wind capacity credit in the United States (M. Milligan & Porter, 2008)

  - ELCC, LOLE, Peak period methods, wind distribution percentile methods

- Current methods to calculate capacity credit of wind power, IEA collaboration (Ensslin et al., 2008)

  - ELCC, LOLE, EUE, Monte Carlo methods

- The capacity value of wind in the united states: Methods and implementation (Michael Milligan & Porter, 2006)

  - ELCC,EUE, LOLP, LOLE, Peak period methods, Garver's method, Monte Carlo methods

3.5   Wind Integration Studies

Wind Integration Studies are in-depth studies of the effects of the addition of wind power to a particular power system. They are usually undertaken by system operators in order to predict what measures will be necessary to accommodate more wind power coming online, and what benefits the system will see from the addition of wind power (Keane et al., 2011).

The Eastern Wind Integration and Transmission Study (EWITS) is a study that was finished in 2009. It is a study of the effects and requirements of getting 20% of electrical energy from wind power in the eastern United States. One of the major components of the study is a large amount of synthesized wind data for thousands of sites in the Eastern US. The data set for each site contains a wind speed time series for the years 2004, 2005 and 2006, as well as a time series of power output for a theoretical wind farm at the site, based on a simple plant model (Corbus et al., 2010). This synthesized wind speed and wind power output data is publicly available and forms the basis for much of the analysis in this project.

The EWITS study analyzes the Eastern Interconnection. Figure 11 shows the interconnections overseen by the North American Electricity Reliability Corporation (NERC).
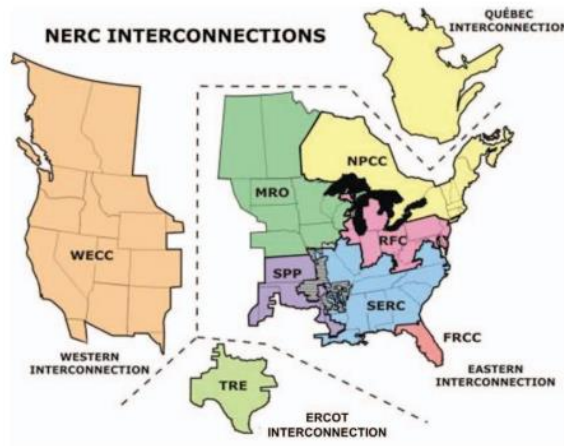
Figure 11 - The NERC Synchronous Interconnections (Corbus et al., 2010)

The EWITS study addresses the capacity value of the wind farms in its data set

using the ELCC/LOLE method. Some results of this capacity value study are shown in

Figure 12.
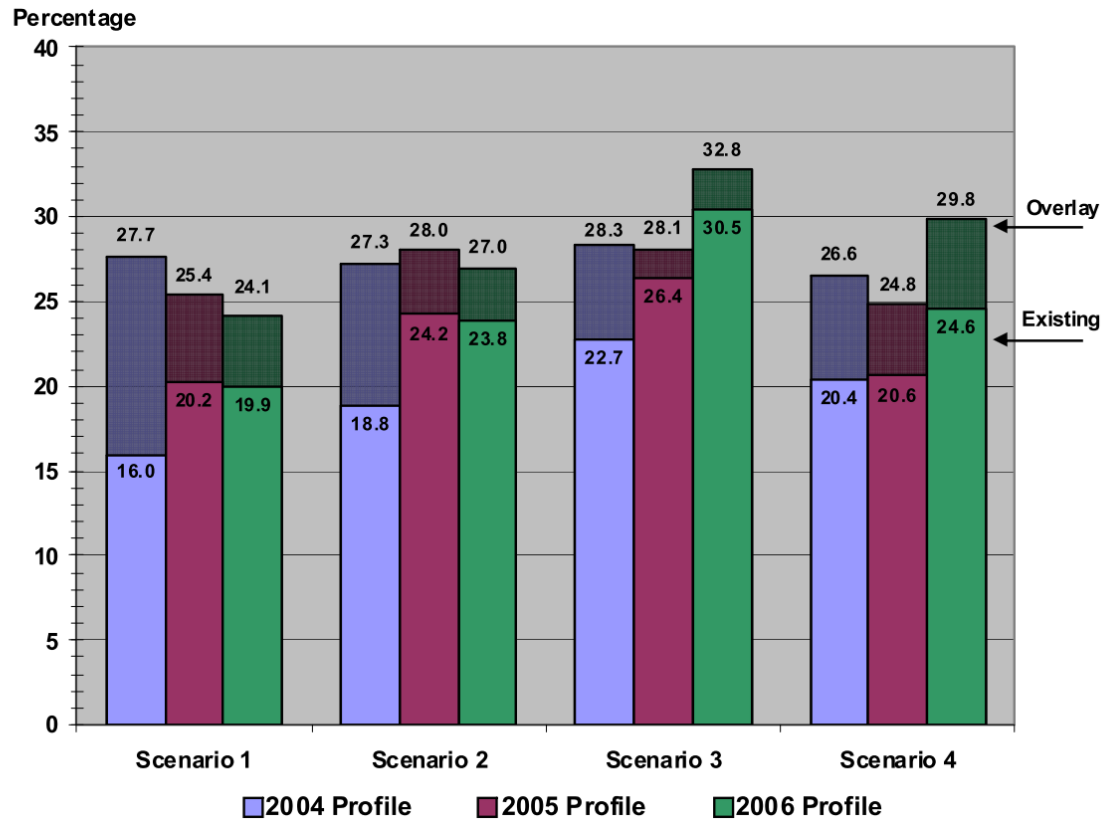
Figure 12 - EWITS capacity value results

The four scenarios shown in Figure 12 refer to four different sets of wind farms chosen as plausible build-outs of future wind power in the eastern U.S. These four scenarios are described as follows:

- Scenario 1

    o Penetration 20%

    o High capacity factor sites, on shore

- Scenario 2

    o Penetration 20%

    o Hybrid with offshore

- Scenario 3

- o   Penetration 20%

- o   Local, with aggressive offshore

- Scenario 4

  - o   Penetration 30%

  - o   Aggressive and on- and off-shore

Penetration percentages in the EWITS study are power percentages: total

nameplate capacity vs. maximum system load. The shaded area at the top of each bar

represents capacity value lost to transmission constraints in scenarios with less

transmission capacity. The capacity value results in the EWITS study vary less year-to-

year than similar results from other studies. This could be the result of a study area that

is particularly geographically large, with a large number of wind farms represented.

Scenarios 3 and 4, which have aggressive offshore development, have less geographic

diversity among wind farms and more inter-annual variability in capacity value results.

The New England Wind Integration Study (NEWIS) (Clark, Jordan, Miller, & Piwko, 2010) uses
largely the same data synthesis model as the EWITS study, but with a higher time resolution.
Capacity value investigations are done using the ELCC/LOLE method in the NEWIS. Figure 13
shows the capacity value results across several scenarios, with an increasing proportion of
offshore sites moving from left to right. One can see that scenarios with more offshore wind
have higher capacity values and more inter-annual variability in capacity value.

Figure 14 and Figure 15 are from the New York and Minnesota Wind Integration

Studies, respectively. They show the sensitivity of capacity value metrics to the

particular year of data used. In the New York study, the system in 2002 has a much

higher LOLE and gets much more reliability benefit from each wind power scenario than

the same system in the year 2001. Investigating data from 2003 in the Minnesota Study

would lead one to believe that wind power plants had a much higher ELCC than doing

the same investigation in 2005.
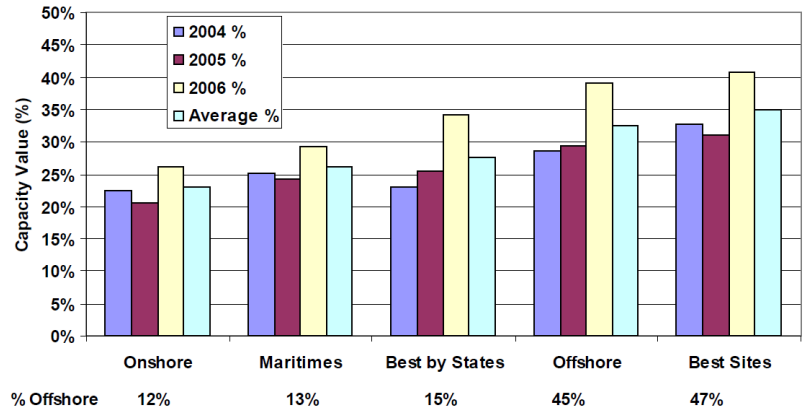
Figure 13 - NEWIS capacity value results 14% penetration
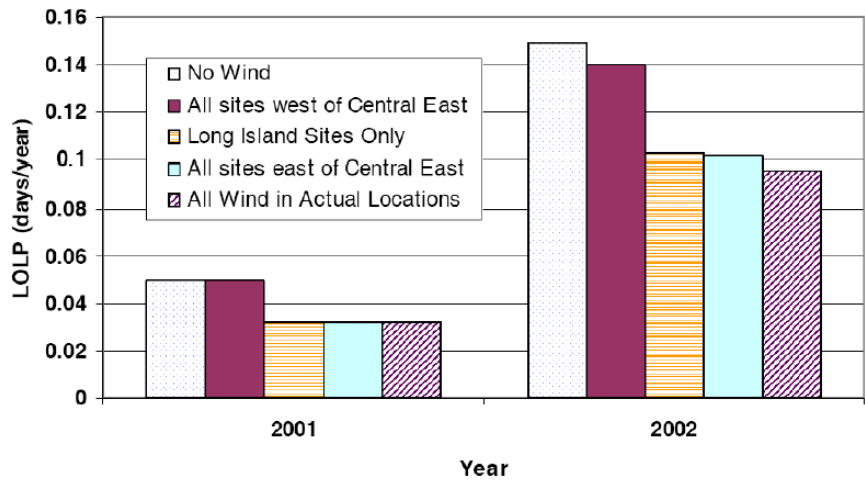
Figure 14 Change in LOLP due to the addition of wind power plants (Clark, Jordan, Miller, & Piwko, 2005)
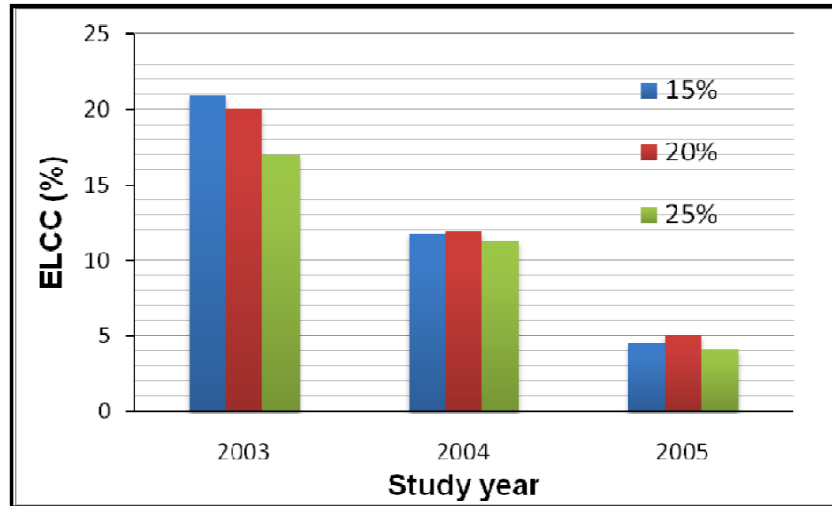
Figure 15 - ELCC of Wind power plants, by year (Zavadil, 2005)

In 2005 and 2006, a planning study was done of the German power system:

Planning of the grid integration of wind energy in Germany onshore and offshore up to

the year 2020 also known as the DENA study. This study addresses the capacity value of

wind in Germany using a firm capacity metric. It is not a major part of the study, but

investigators found the guaranteed capacity associated with wind power plants to be

between 5 and 8% of nameplate capacity, depending on wind penetration (Bartels et al.,

2006).

In 2011 an Irish study was conducted on the amount of data required to perform

an accurate assessment of the capacity value of a wind plant (B. Hasche, Keane, &

O'Malley, 2011). This study used ELCC/LOLE as its metric for capacity value. The major

conclusion of the study is that four or five years of concurrent wind and load data are

required for a stable and reliable capacity value calculation. Figure 16 shows the

decrease in ELCC variability as the number of years of data used in the calculation

increases.
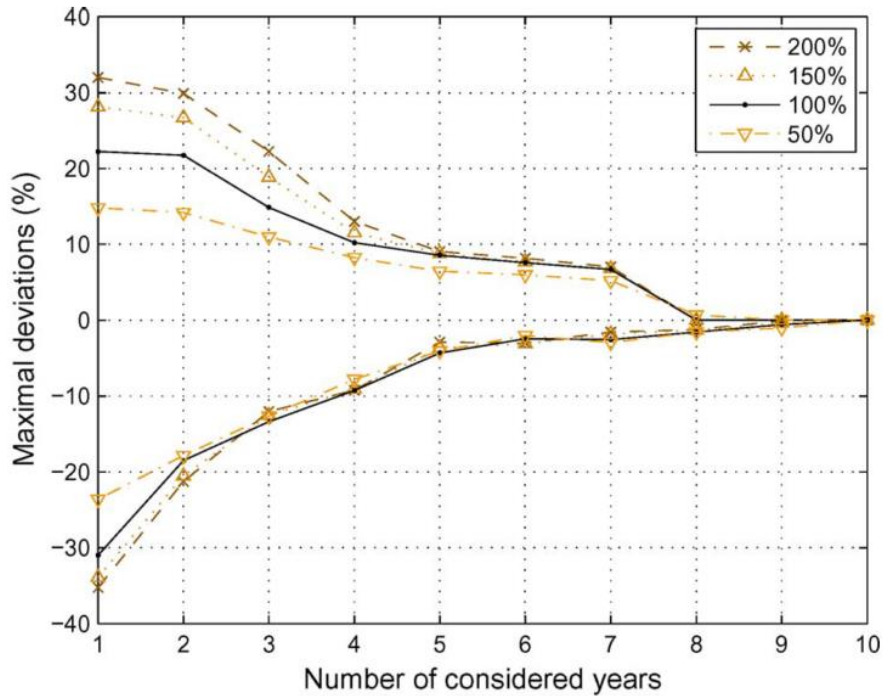
**Figure 16 - Variability in ELCC calculation as a function of number of years considered (B.
Hasche et al., 2011)**

In a 2011 study of the Texas power system (ERCOT), The integration of very high

penetrations of wind and solar power was investigated (Denholm & Hand, 2011). The

focus was on the grid flexibility and storage infrastructure required to operate with

variable renewable generators supplying 80% of system energy. The following three

figures are from this NREL 80% renewables study. They relate to wind and solar

penetration and curtailment, as they relate to storage and grid flexibility. Figure 17

Shows wind curtailment as a function of wind penetration for various levels of grid

flexibility. Grid flexibility is a measure of the fraction of power plants which are not "must run" baseload plants, and whose output may be varied to follow the load-net-wind. At 50% wind penetration, 80% grid flexibility results in a 45% curtailment of wind energy. In the same wind scenario, a 100% flexible grid (zero must-run plants) results in only a 7% curtailment of wind energy output.
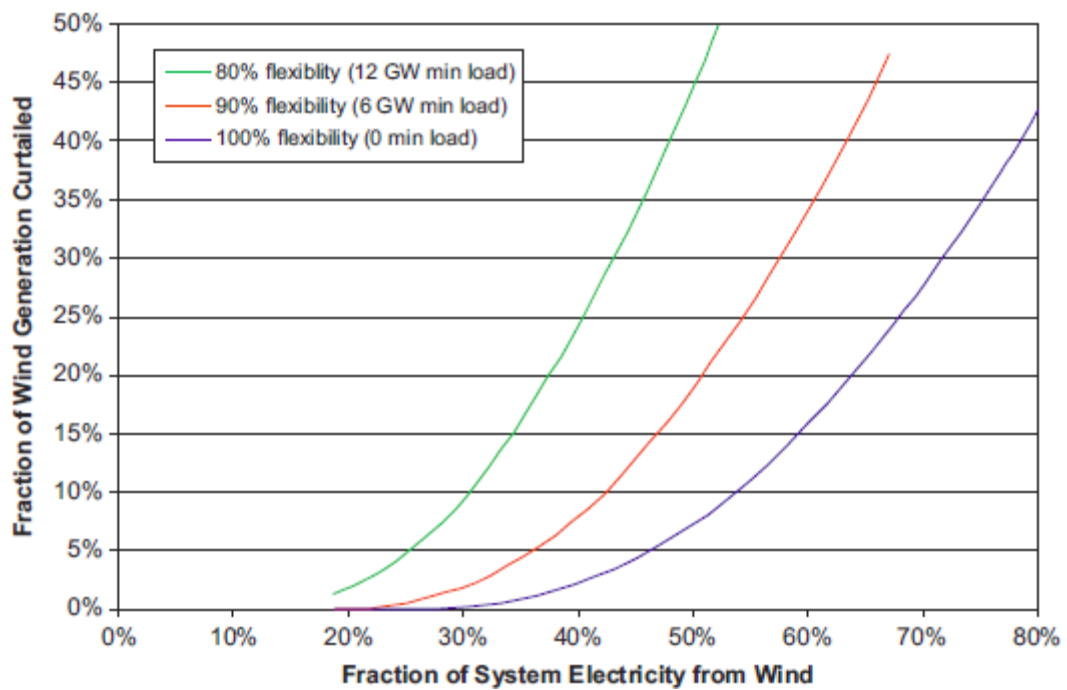
Figure 17 – Wind Curtailment and Grid Flexibility (Denholm & Hand, 2011)

Figure 18 shows an analysis of variable renewable energy curtailment with various mixes of wind and solar energy, and 100% grid flexibility. Generation mixes with a high proportion of wind and with some solar contribution fare the best in terms of curtailment. The high-solar scenarios suffer from the geographic concentration of the solar plants. The '0/100' curve here is the same at the '100% flexibility' curve in Figure 17.
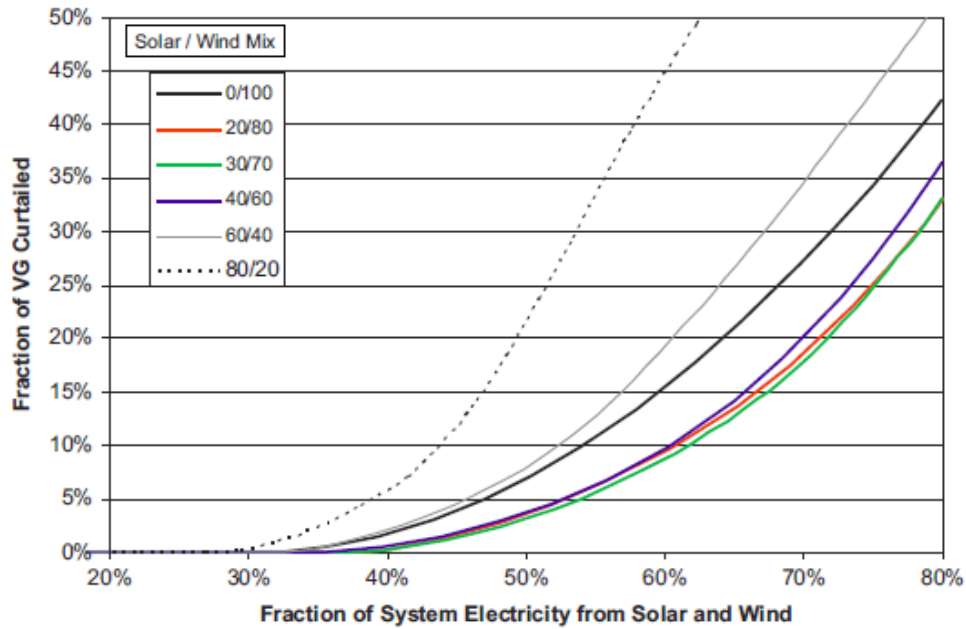
Figure 18 – Wind and Solar Curtailment by Proportion of Energy from Each (Denholm &

Hand, 2011)

Figure 19 shows the effects of storage on curtailment in the 30/70 solar/wind

scenario. The 'No Storage' curve here is the same as the 30/70 curve in Figure 18.

Storage power capacity is to the average system load and various durations are

investigated. The first 4 hours of storage capacity have the greatest impact, lowering

curtailment at 80% penetration from 32% to 18%. The addition of the final 12 hours of

storage (from 12 to 24 hours) only mitigates 2 percentage points of curtailment.
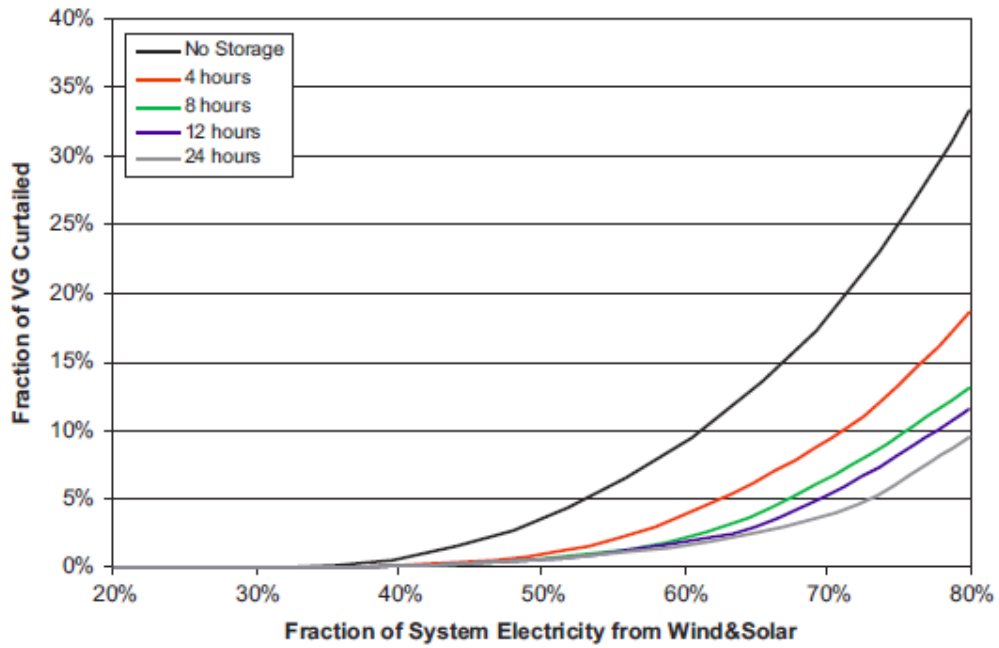
Figure 19 – Wind and Solar Curtailment by Storage Duration (Denholm & Hand, 2011)

Storage and Curtailment are investigated in Chapter 0 of this dissertation.

Comparisons to these ERCOT results are made in the conclusion. The following section

deals with a major motivator to the adoption of wind power in power systems: avoided

emissions.

CHAPTER 4

WIND POWER AND AVOIDED EMISSIONS

Avoided emissions are a primary benefit that wind power provides to the

operation of power systems. The energy produced by wind power plants offsets the

energy that needs to be produced by conventional generators, reducing fuel use and

thereby, emissions (Ackermann, 2012). This chapter summarizes the results of some

wind integrations studies with respect to avoided emissions, and estimates the effects

of wind penetrations up to 50% in New England on emissions. This overview focuses

primarily in carbon emissions.

In 2004, a climate change study was conducted at Princeton, *Stabilization*

Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies

(Pacala & Socolow, 2004). This study originated the often-cited idea of climate

stabilization wedges. The concept of these wedges is the in order to stabilize CO_2 in the

atmosphere at 500 ppm (the target identified in (Wigley, Richels, & Edmonds, 1996))

several strategies must be employed simultaneously, each contributing to lowering

carbon emissions over the next 50 years toward a rate consistent with 500ppm CO_2.

Each of these wedges, shown in Figure 20 corresponds to 1 Gigaton of carbon in

2054. The wedges are a way of comparing the effort required to meet this 500 ppm

target with different mixes of currently-available technology. The top plot shows the

difference between 'business as usual' (BAU) and the 500 ppm stabilization curve

identified by (Wigley et al., 1996). The bottom plot shows how the stabilization wedges

each contribute to moving carbon emissions toward the target WRE500 curve.
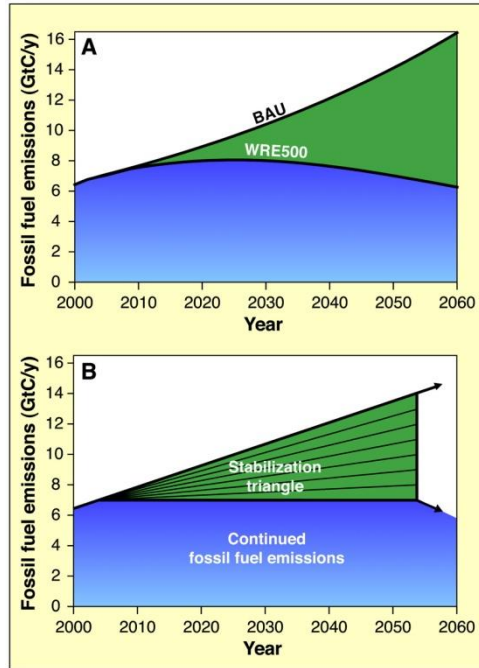
Figure 20 - Climate stabilization wedges (Pacala & Socolow, 2004)

The caption for Figure 20 from (Pacala & Socolow, 2004) is included here for

clarity:

(A) The top curve is a representative BAU emissions path for global carbon emissions as CO2 from fossil fuel combustion and cement manufacture: 1.5% per year growth starting from 7.0 GtC/year in 2004. The bottom curve is a CO2 emissions path consistent with atmospheric CO2 stabilization at 500 ppm by 2125 akin to the Wigley, Richels, and Edmonds (WRE) family of stabilization curves described in (Wigley et al., 1996), modified as described in Section 1 of the SOM text. The bottom curve assumes an ocean uptake calculated with the High-Latitude Exchange Interior Diffusion Advection (HILDA) ocean model (Shaffer & Sarmiento, 1995) and a constant net land uptake of 0.5 GtC/year (Section 1 of the SOM text). The area between the two curves represents the avoided carbon emissions required for stabilization. (B) Idealization of (A): A stabilization triangle of avoided emissions (green) and allowed emissions (blue). The allowed emissions are fixed at 7 GtC/year beginning in 2004. The stabilization triangle is divided into seven wedges, each of which reaches 1 GtC/year in 2054. With linear growth, the total avoided emissions per wedge is 25 GtC, and the total area of the stabilization triangle is 175 GtC. The arrow at the bottom right of the stabilization triangle points downward to emphasize that fossil fuel emissions must decline substantially below 7 GtC/year after 2054 to achieve stabilization at 500 ppm.

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Wind power (replacing coal) is included on a list of 15 technologies, 7 of which

would be required to hold carbon emissions stable for 50 years. One 'wedge' worth of

wind power consists of 2000 GW of installed capacity, at a 33% capacity factor. This

framework is included here to provide a context for the importance of reducing

greenhouse gas emissions in New England.

4.1   Avoided Emissions in the EWITS Study

The Eastern Wind Integration and Transmission Study (EWTIS) is described above

in Section 0. In the EWITS study, 4 wind power build-out scenarios were modelled.

Three with 20% wind penetration and one (Scenario 4) with 30% penetration (As noted

above, penetrations in the EWITS study are power penetrations). The first three

scenarios are distinguished from one-another by the geographical distribution of the

wind power plants. Figure 21 (Table 1 from the EWITS study) shows the installed

capacity for each scenario

TABLE 1. TOTAL AND OFFSHORE WIND IN THE SCENARIOS								
Region	Scenario 1 20% High Capacity Factor, Onshore		Scenario 2 20% Hybrid with Offshore		Scenario 3 20% Local, Aggressive Offshore		Scenario 4 30% Aggressive On- and Offshore	
	TOTAL (MW)	Offshore (MW)	Total (MW)	Offshore (MW)	Total (MW)	Offshore (MW)	Total (MW)	Offshore (MW)
MISO/ MAPP[a]	94,808		69,444		46,255		95,046	
SPP	91,843		86,666		50,958		94,576	
TVA	1,247		1,247		1,247		1,247	
SERC	1,009		5,009	4,000	5,009	4,000	5,009	4,000
PJM	22,669		33,192	5,000	78,736	39,780	93,736	54,780
NYISO	7,742		16,507	2,620	23,167	9,280	23,167	9.280
ISO-NE	4,291		13,837	5,000	24,927	11,040	24,927	11,040
TOTAL	223,609	0	225,902	16,620	230,299	64,100	337,708	79,100

Figure 21 - EWITS Wind Scenarios (Corbus et al., 2010)

Figure 22 shows the CO_2 emissions avoided in each of the four wind power scenarios the rightmost 'Carbon Sensitivity' scenario inlcudes a carbon pricing scheme which changes the order in which conventional power plants are dispatched, favoring lower emissions plants.
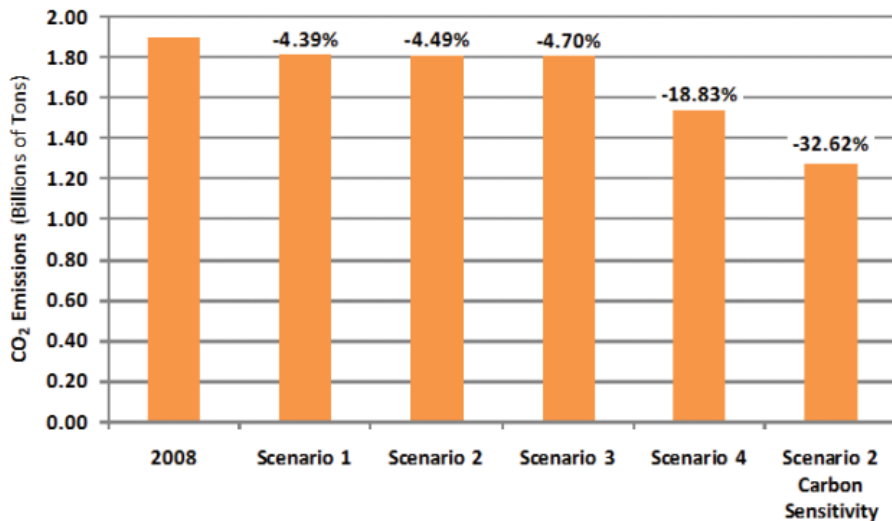
Figure 22 - Avoided CO_2 emissions in EWITS (Corbus et al., 2010)

Table 1 shows the emissions reduction and the wind penetration level for each scenario. The *Ratio* for each scenario is the ratio of these two percentages. These percentages and their ratio are the metrics for emissions reduction that are used in this chapter to characterize the effect of wind power penetration. The small variations in avoided emissions among the first three scenarios are due to the timing of wind power production and its effect on the dispatch of fossil plants. The time series of wind power output is different in each scenario, so the fossil energy which is being displaced may come from different power plants. The large increase in avoided emissions in scenario 4 is due to the displacement of some energy from carbon-intensive baseload plants. One might make the simplistic assumption that avoided emissions would be proportional to wind energy production, since each kWh of wind energy displaces a similar amount of energy that would otherwise have been produced at a fossil plant. In fact, the avoided emission from a kWh of wind power varies as a function *which* fossil plant is reducing its output.

Table 1 - EWITS scenario emissions reduction

	EWTIS scenarios			
	1	2	3	4
Penetration [%]	20	20	20	30
Carbon reduction [%]	4.39	4.49	4.7	18.83
Ratio []	0.22	0.22	0.24	0.63

4.2 Avoided Emissions in the NEWIS Study

The New England Wind Integration Study (NEWIS) is described above in Section 0. The NEWIS investigates emissions reduction in several wind power build-out scenarios. Figure 23 shows total emissions of oxides of nitrogen (NO_X), oxides of sulfur (SO_X), and carbon dioxide (CO_2).
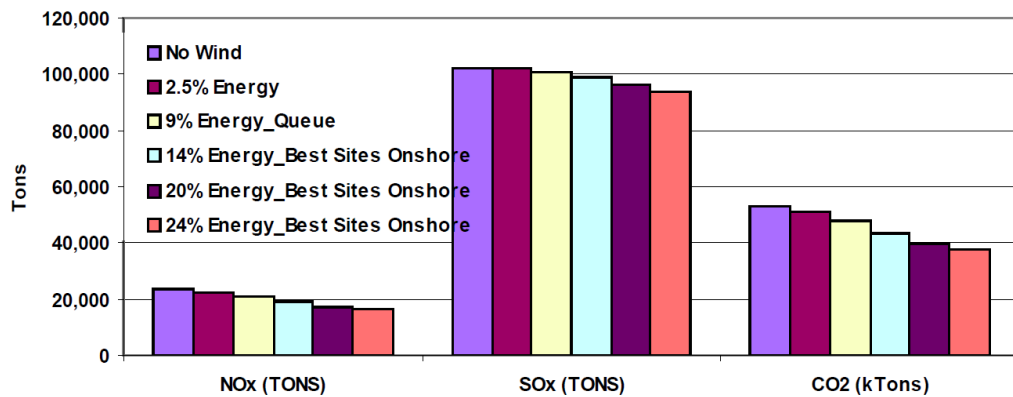
Figure 23 - NEWIS total Emissions by Scenario

Figure 24 Show the emissions reduction rate per MWh of wind energy, in each scenario. It is notable that the CO_2 reduction rate is relatively consistent across all scenarios, but the SO_X reduction rate increases with wind penetration. This is due to the reductions in coal plant output in the higher penetration scenario.
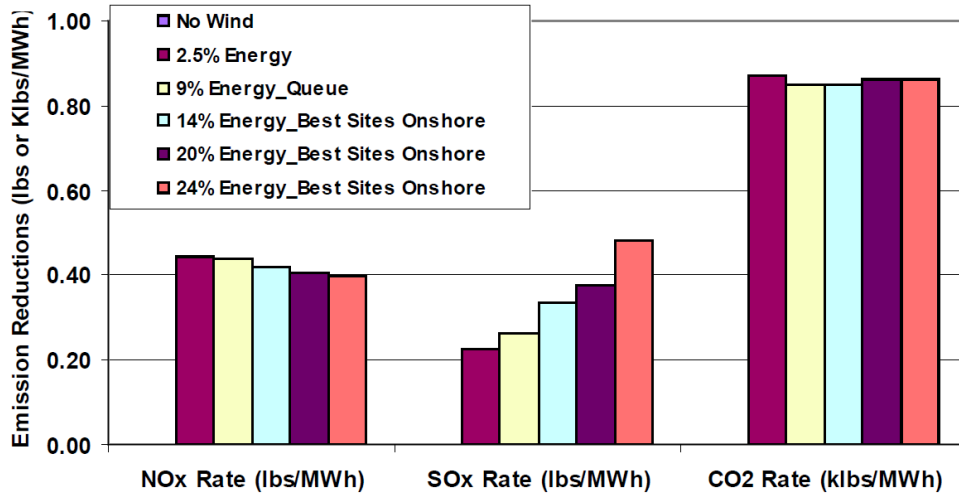
Figure 24 - NEWIS emissions reduction per MWh of wind power

Figure 25 and Figure 26 show power plant dispatch during a week in April in the 14% and 24% scenarios, respectively. These figures show a much greater reduction in the energy output of coal plants during the week in question, for the higher-penetration scenario. This explains the increasing SO_X reduction rate as wind penetration increases.
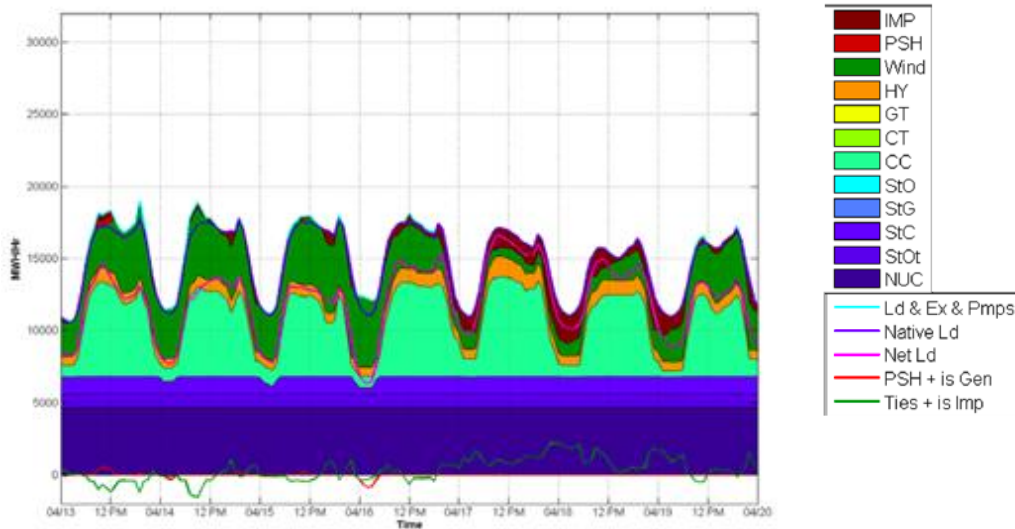
Figure 25 - NEWIS power plant dispatch, 14% Energy Best Sites Onshore
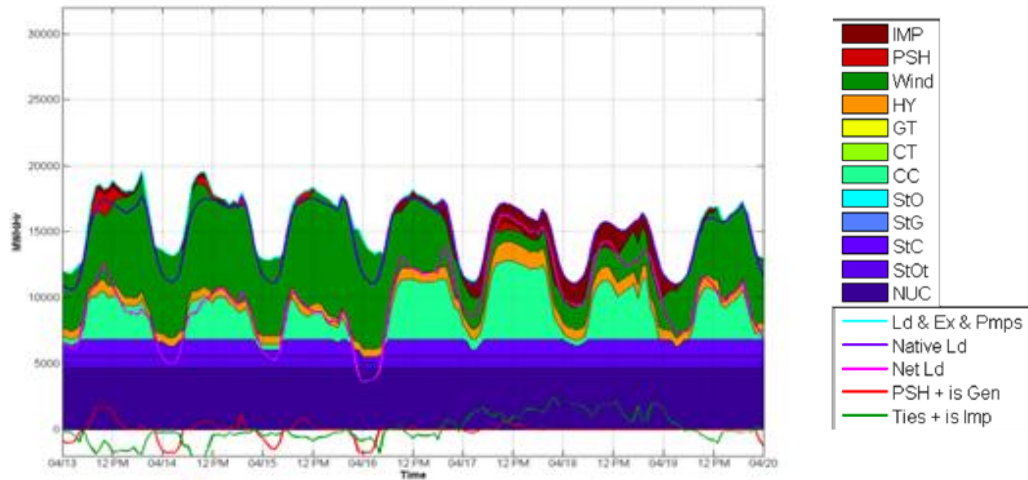
Figure 26 - NEWIS power plant dispatch, 24% Energy Best Sites Onshore

Table 2 shows the emissions reduction percentage and the wind power penetration percentage for each scenario. It is noteworthy that the ratio of CO_2 reduction percentage to wind penetration percentage is greater than one for all scenarios; the percentage of CO_2 emissions avoided is *greater* than the percentage of energy generated by wind power. This is possible because of the large fraction of energy that is produced by nuclear and hydro power in New England. Since the energy that is displaced is entirely from fossil fuel plants, and the total system CO_2 emissions rate (kTons per MWh) is reduced by the presence of nuclear and hydro plants, this result is possible.

Table 2 – NEWIS scenario emissions reduction

	NEWIS Scenarios					
Penetration [%]	0	2.5	9	14	20	24
kTons Carbon	52.69	51.15	47.69	43.08	39.62	37.31
Carbon reduction [%]	0.00	2.92	9.49	18.25	24.82	29.20
Ratio []	-	1.17	1.05	1.30	1.24	1.22

The next two figures are from ISO New England's 2013 Electric Generator Air Emissions Report (ISO-NE, 2014b). Figure 27 shows the energy generated in New England in 2004 and 2013, by fuel type. Taken together, hydro and nuclear power produced 33% of energy in 2004, and 39% in 2013. This is enough to substantially affect the system wide CO_2 rate. Wind power grew from 0% to 2% of annual energy during this period.
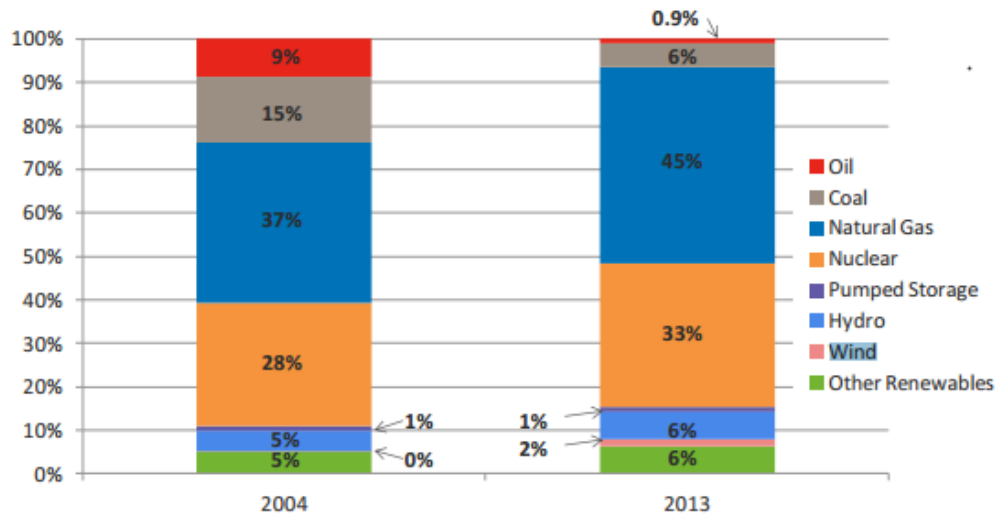
Figure 27 – New England energy generation by fuel type: 2004 and 2013 (ISO-NE, 2014a)

Figure 28 (Table 1-1 in the Air Emissions Report) shows the 2012 and 2013 emissions and emissions rates.

Annual System Emissions					
	2012 Emissions (kTons)	2013 Emissions (kTons)	Total Emissions % Change	2012 Emission Rate (lb/MWh)	2013 Emission Rate (lb/MWh)	Emission Rate % Change
NO_x	20.32	20.32	0.0	0.35	0.36	2.9
SO_2	16.61	18.04	8.6	0.28	0.32	14.3
CO_2	41,975	40,901	-2.6	719	730	1.5

Figure 28 - 2012 and 2013 New England system emissions and rates

4.3   Avoided Emissions and the Hull Offshore Wind Project

In a 2008 MIT study, the emissions benefits of a proposed offshore wind farm in

Hull, Massachusetts were investigated (Rached, 2008). Figure 29 shows the

methodology used. This method assumes that the wind plant output is small compared

to the system load, and does not change the mix of power plants dispatched in any

given hour. Power plant emissions are based on hourly data reported to the EPA. The

marginal power plant (the one whose output would be offset by energy produced by the

Hull wind plant) is identified be recognizing load-following behavior in its output time

series. The avoided emissions are then calculated for each hour based on the predicted

energy output from the Hull Offshore Wind Project and the emissions characteristics of

the marginal fossil fuel plant.
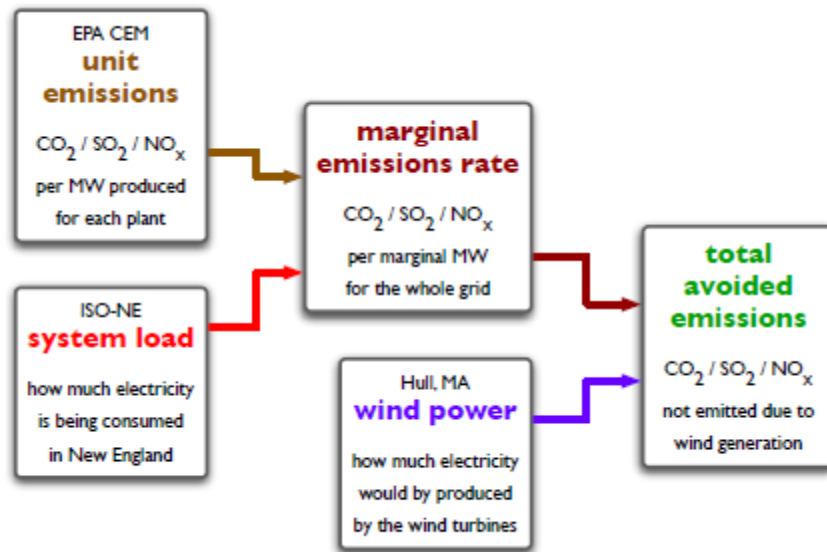
Figure 29 – Hull Study methodology

Figure 30 show a table of avoided emissions for the Hull Project, based on three scenarios: high, medium and low wind. These scenarios correspond to 0.28, 0.31 and 0.36 capacity factory for the wind plant respectively.

CO_2	Avoided Emissions $\left[\frac{\text{tonnes } CO_2 \text{ avoided}}{\text{installed MW} \cdot \text{year}}\right]$	Δ
High Wind	2,280	15.70 %
Med. Wind	1,970	-
Low Wind	1,780	-9.62 %

SO_2	Avoided Emissions $\left[\frac{\text{kg } SO_2 \text{ avoided}}{\text{installed MW} \cdot \text{year}}\right]$	Δ
High Wind	4,030	15.90 %
Med. Wind	3,480	-
Low Wind	3,140	-9.66 %

NO_x	Avoided Emissions $\left[\frac{\text{kg } NO_x \text{ avoided}}{\text{installed MW} \cdot \text{year}}\right]$	Δ
High Wind	1,730	16.00 %
Med. Wind	1,490	-
Low Wind	1,350	-9.57 %

Figure 30 – Hull Avoided emissions

Figure 31 shows the range of avoided emissions for the Hull Offshore project over a period of years, and for the three representative high, medium and low wind years. The avoided emissions are split up seasonally for each year. It is interesting to note that the avoided NO_x and SO_x emissions for 2004 2005 and 2006 are lower due to the effect of the Clean Air Act on the Generator Fleet. Also, the largest share of avoided emissions occurs in the winter, even thou the highest loads occur in the summer.
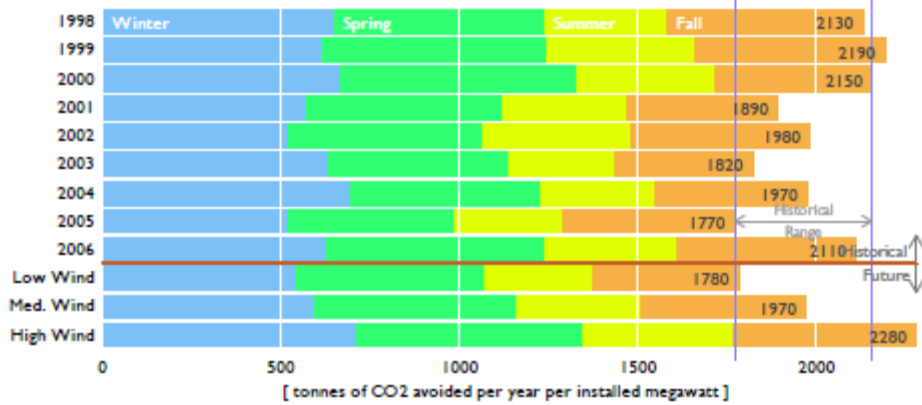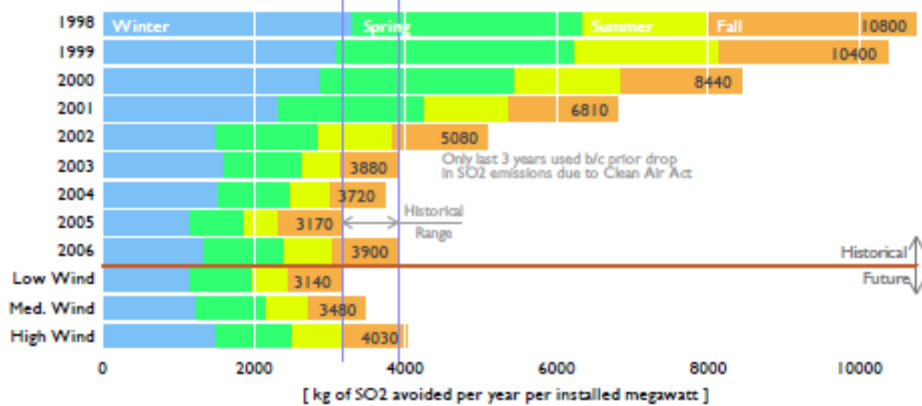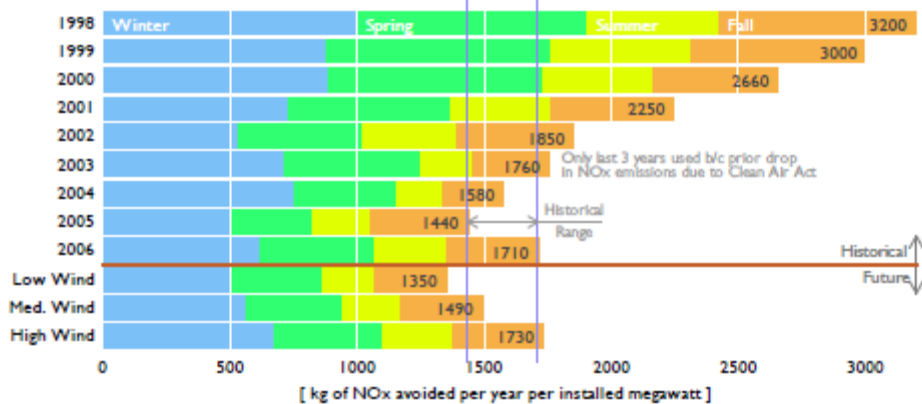
Figure 31 – Range of Annual avoided emissions for the Hull Project

4.4   Regional Variations in Avoided Emissions

A 2013 study from the University of Washington, Seattle investigated the emissions effect of placing a 1 MW wind turbine at various places in the United States. This study used the EWITS wind data and information about regional power plant mixes and dispatch to evaluate the regional variation in avoided emissions (Siler-Evans, Azevedo, Morgan, & Apt, 2013).

Figure 32 shows the dollar value of the marginal emissions of the ERCOT power system, at various system output levels. These dollar values are an estimate of the social, health, and environmental damage done by the various pollutants. The marginal emissions rate at low power output is high because the base load plant which are on the margin at this power level are coal plants which are CO_2 and SO_2 intensive. The plants which are on the margin at 40 GW have the lowest marginal impact, and the peaking plants which are called upon to cover loads above 40 GW have a higher impact. Wind power output at times when the system load is near 40 GW will have a smaller effect on emissions than at times when it would be displacing energy from plants with higher emissions. This effect is important when predicting the avoided emissions at various wind penetration levels. The energy being displaced by wind may be from a different fuel type depending on the marginal power plants at the times in question.
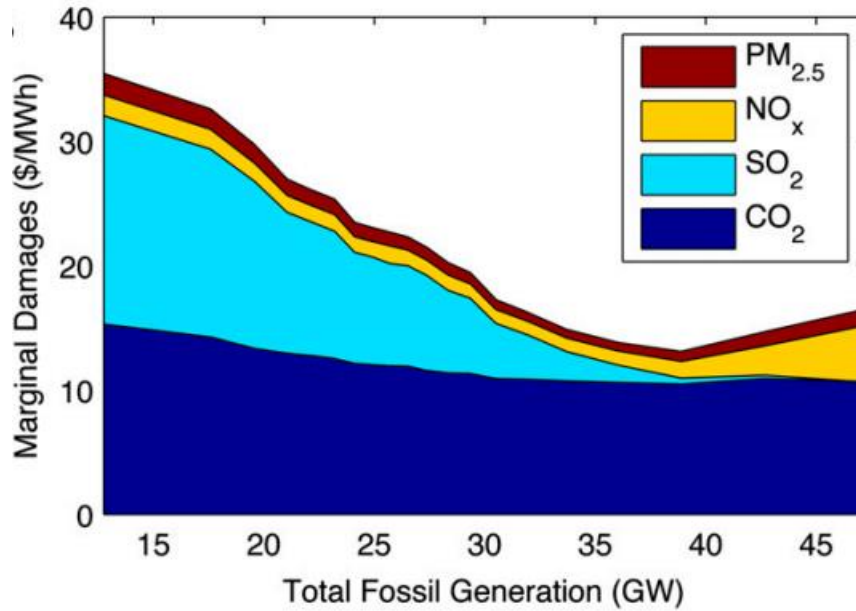
Figure 32 - Marginal damages from electricity generation, ERCOT (Siler-Evans et al., 2013)

Figure 33 is a map of the locational results for this geographic study. This map shows that a wind turbine in the northern and central United States would have a larger effect on CO_2 emissions than one located elsewhere. This is due to the combination of factors. The excellent wind resource in this region leads to more energy production and the conventional generation displaced by that energy production are more carbon intense than those in other regions. The CO_2 emissions avoided in New England are comparatively small. While the wind resource in New England is fairly good, the energy produced by wind plants in this region tends to displace natural gas energy, which has a smaller carbon effect.
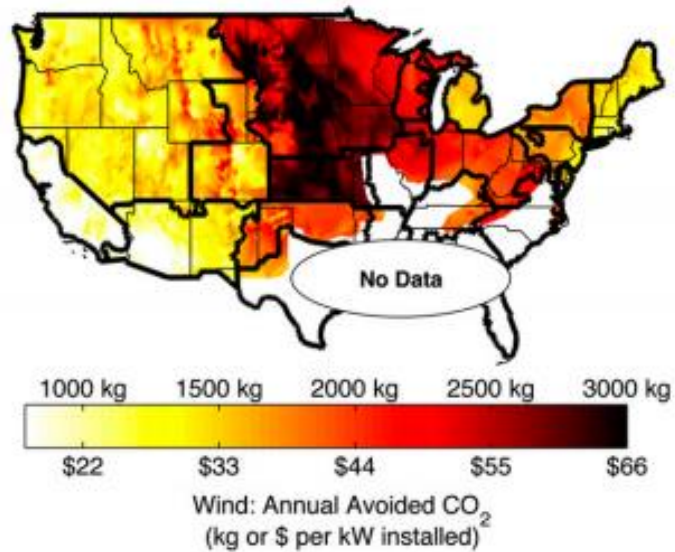
Figure 33 - Avoided CO$_2$ emissions from a wind power plant, by location (Siler-Evans et al., 2013)

This substantial variation in carbon displacement performance across the United States indicates that avoided emissions results from outside of New England are poor predictors of carbon effects in New England. The emission results from the NEWIS are likely to be the most relevant to this study of wind power in New England. The results of the NEWIS can be considered representative of emissions performance of wind power in New England with penetrations perhaps as high as 30%. At higher penetrations, the nature of the generator fleet required to cover the load-net-wind might be quite different, and have different emissions characteristics.

CHAPTER 5

AN ILLUSTRATIVE EXAMPLE OF AN ELCC CALCULATION USING LOLE

Since LOLE and ELCC calculations are central to this project, a concrete example of these calculations will be helpful. The following is an example of wind plant capacity value capacity value calculation using ELCC and LOLE. Figure 34 shows the structure of an ELCC calculation using LOLE as reliability metric.
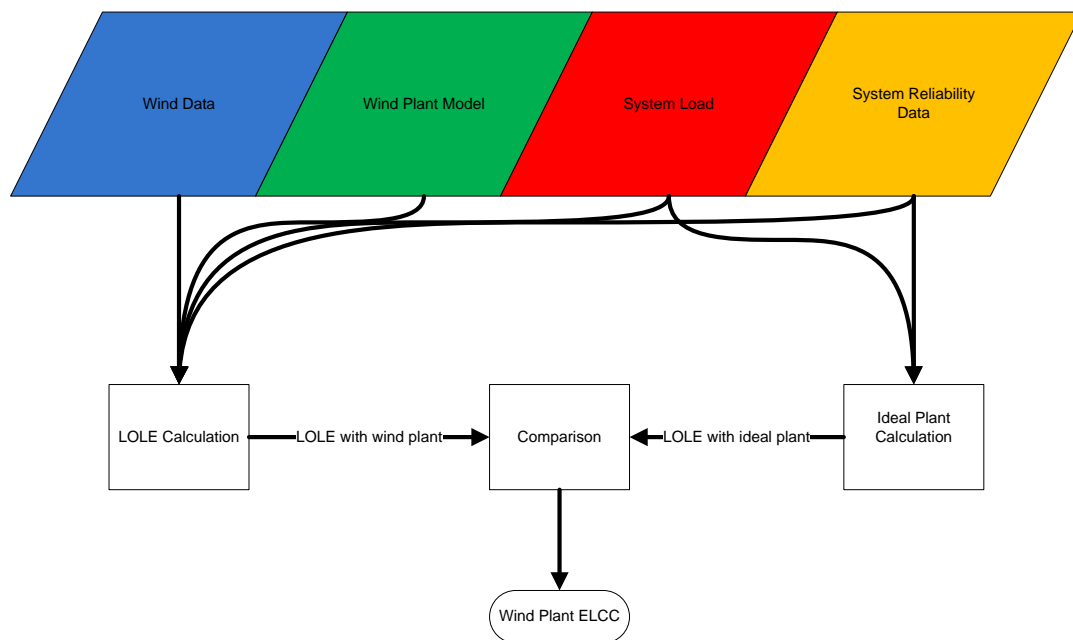
Figure 34 - Data flow in an ELCC calculation with LOLE

5.1   Model Input Data

This section describes the data used in this example to assess the capacity value of the many EWITS data sites in New England.
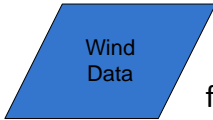
The wind data used in these calculations are synthesized data from the EWITS study. These data (described in greater detail below in section 0) are the results of a mesoscale atmospheric model, with boundary conditions set by historical measurements. Data from 2004, 2005, and 2006 were used for all of the EWITS sites in New England.
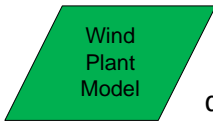
Wind farm power output is provided as part of the EWITS data. These power data were calculated by AWS Truepower using a composite power curve based on the IEC class of each individual site. Array and electrical losses are considered. These data were provided in 10-minute intervals and needed to be combined into hourly averages to fit the hourly system load data.
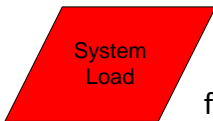
Historical system load data were provided by ISO New England for the years 2004, 2005, and 2006. Since this project is a study of New England system adequacy, only the total New England load is considered. It is important to note that these load data are concurrent with the wind data being used. This is important because wind and electrical demand are both driven by weather, and are not independent of one another. Transmission between the sub-areas of the New England region is assumed to be adequate to move power to where it is consumed. The time series of system load data is shown in Figure 35. One can see that the highest loads occur generally in the summer. The same data are shown in a duration curve (ordered by magnitude rather than time), in Figure 36. Displaying the data this way emphasizes the important fact that the highest loads occur for only a small fraction of the time.

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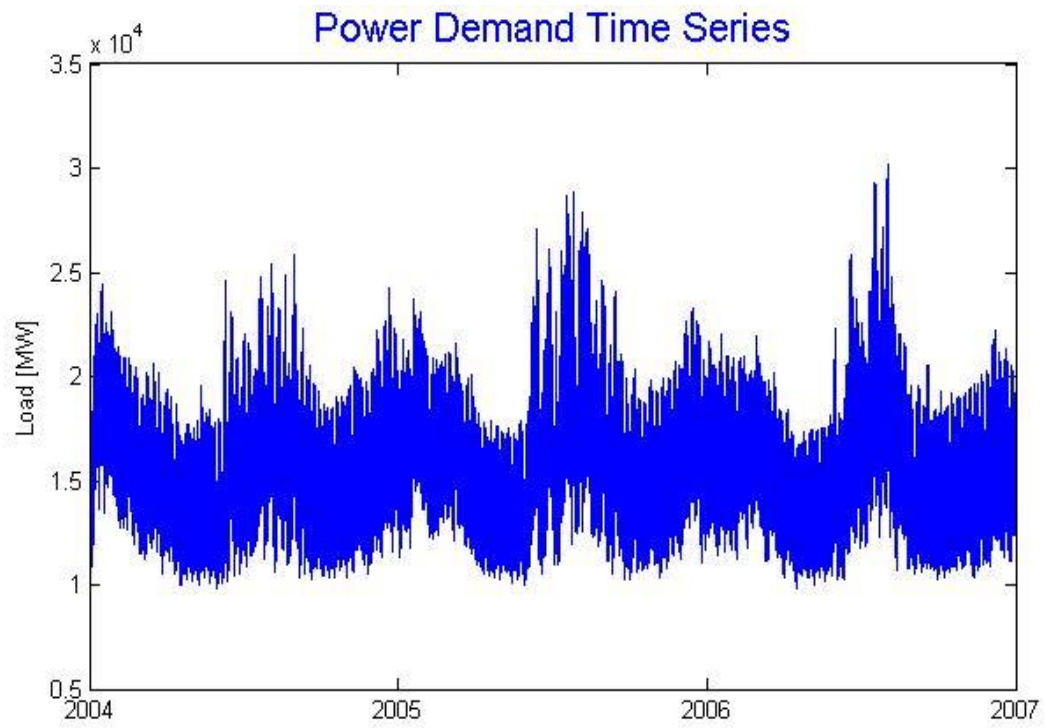
Figure 35 - System load time series
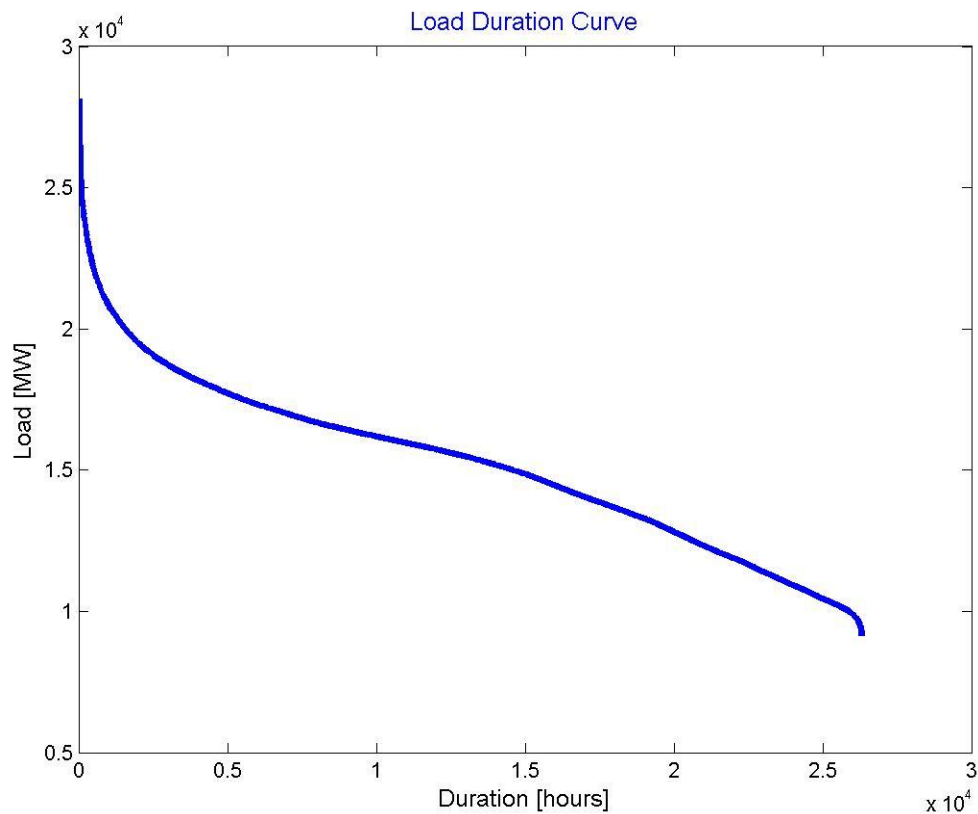
Figure 36 – System load duration curve

System
Reliability
Data

In order to calculate the LOLP for each hour of the three years
used in this calculation, a function was constructed that gives the
probability of inadequate generation as a function of demand: the Cumulative Density
Function (CDF) of available power. This is a function of the size of each power plant on
the system and its reliability. Since reliability information about the individual power
plants are not publicly available, industry averages for each technology type were used.
There are 696 power plants in New England. The mix of plant technologies is shown in
Figure 37.

Current Generation Capacity Mix 2011
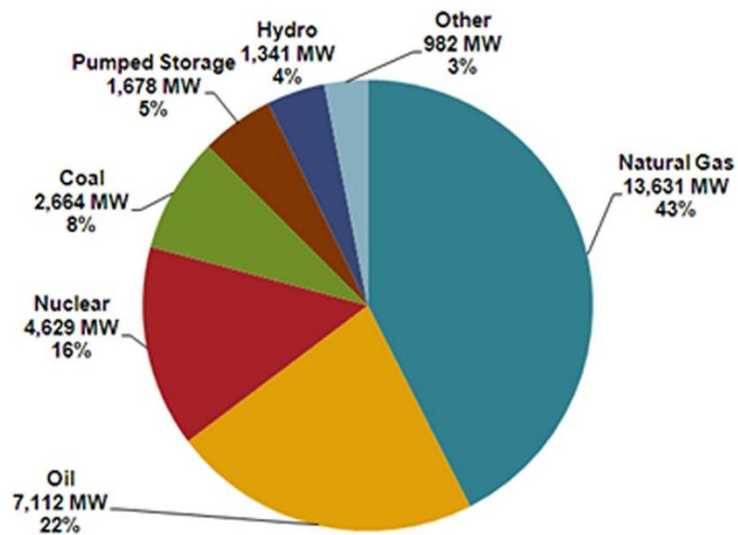
Figure 37 - New England generation mix

For the purpose of constructing the CDF of available power, a CDF of the power available from each power plant was assumed, based on the plant's capacity and the industry-wide average forced outage rate for plants with its fuel type. The total-system CDF was calculated by taking the convolution of the individual power plant CDFs (Billinton & Allan, 1984). The CDF of available power is shown in Figure 38. This CDF serves as the reliability model for the entire power system. It gives the probability of un-served load as a function of the hourly demand.
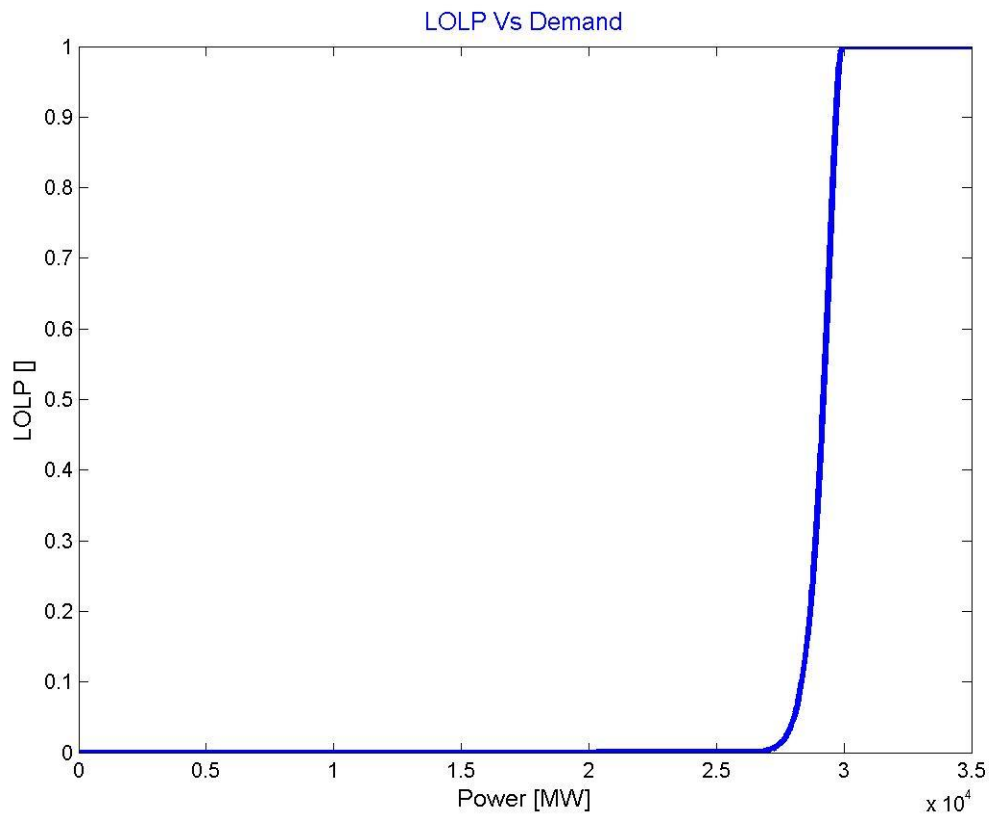
Figure 38 - Probability of un-served load vs power demand

The base-system LOLE was calculated by calculating the LOLP for each hour in the data set. The demand for that hour is combined with the CDF of available power to arrive at the LOLP for that hour. The average LOLP is the LOLE, shown in this equation. There is the number of years of data used. *T* is not usually included since it is generally assumed that one year of data is used.

$$LOLE = \sum_t p(X_t < d_t - r_t)/T \qquad \textbf{10}$$

Figure 39 shows a histogram of power demand plotted against the same CDF One can see that the value of the CDF is very close to zero for power demand up to

about 27 GW, and rises steeply before 30 GW. Almost all of the contribution to LOLE

happens during the relatively rare events in this interval.
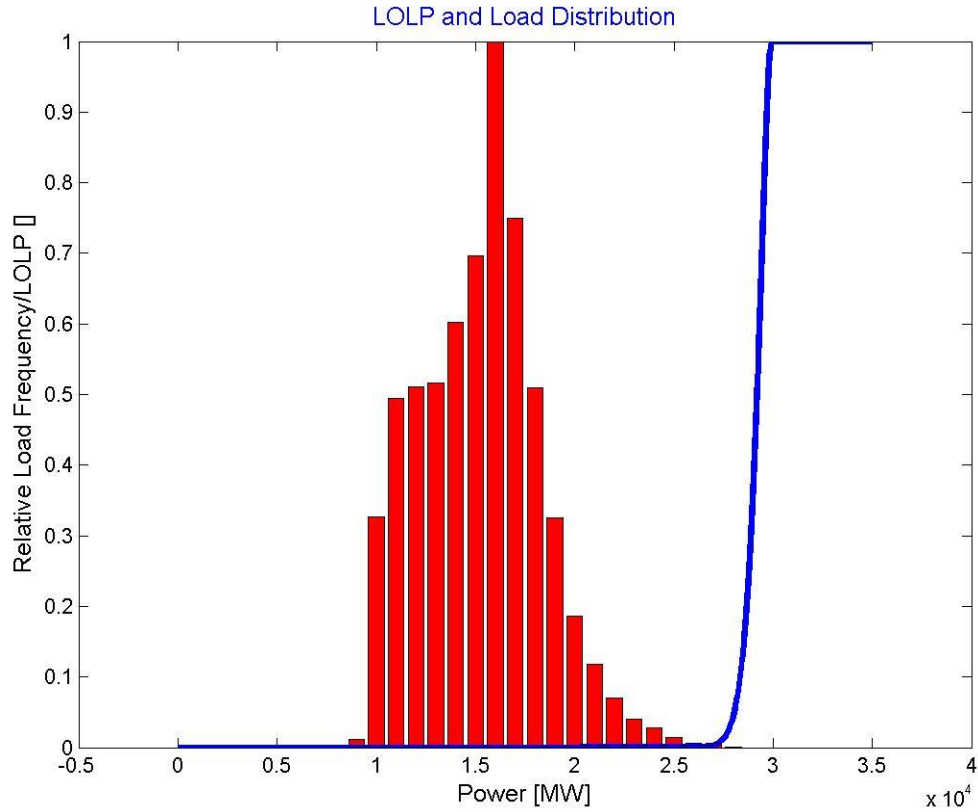
Figure 39 CDF of available power with system load distribution

The ELCC of each of the theoretical wind plant in the EWITS data set was

calculated by subtracting its power output from the 3 years of system load data and

recalculating the LOLE. This change in LOLE was compared to the change in LOLE from

the addition of ideal power plants of several sizes, to find the ideal plant that made an

equivalent reliability contribution. The size of this ideal plant, as a percentage of the

nameplate capacity of the wind plant in question is the ELCC of that wind plant. The

ELCC of each of the EWITS wind farms in New England is shown in Figure 40, separated

by region. ELCC is plotted against capacity factor, to show how the reliability

contribution of each wind plant compares to its energy contribution.
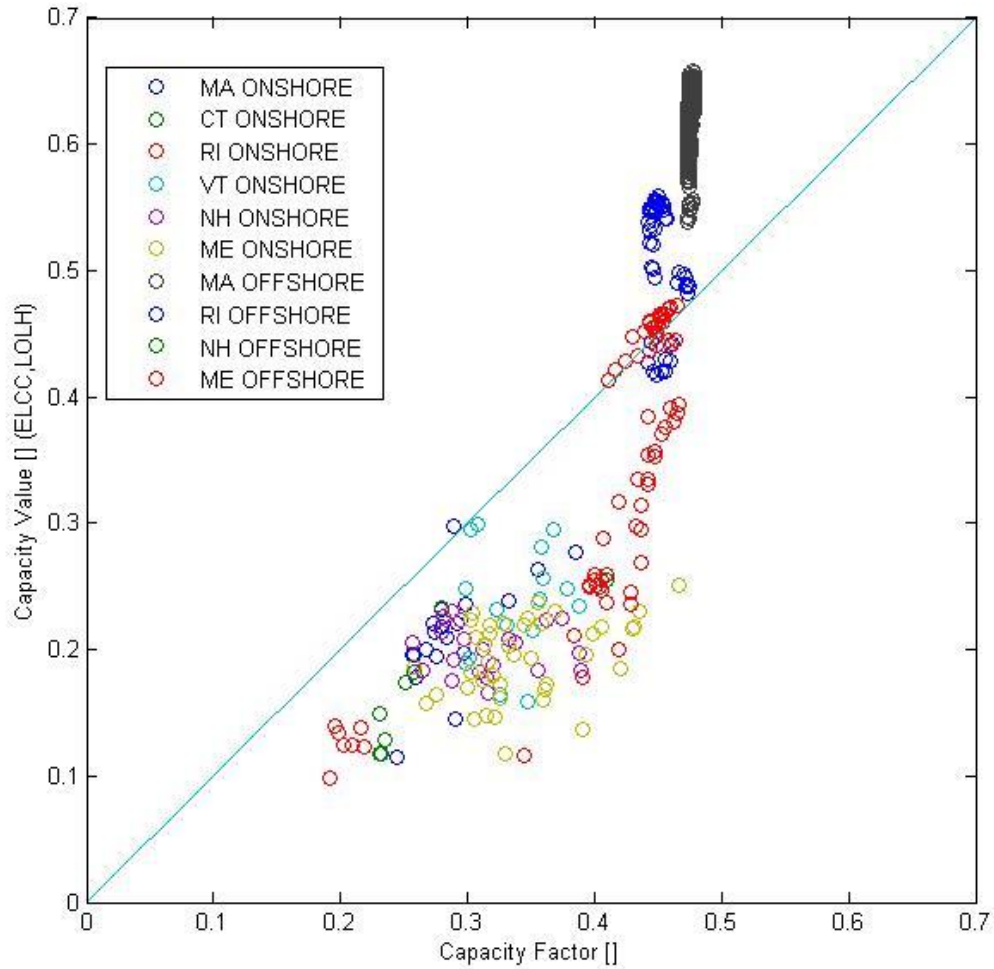
Figure 40 - ELCC vs. capacity factor

One can see in Figure 40 that many of the offshore sites have a very high ELCC, up to about 68%. It is very hard to believe that any wind plant would have such a high capacity value. Since the ELCC is based on the performance of each wind plant during the several peak hours of the three years of data used, the metric is very sensitive to the peculiarities of the years used in its calculation. Using a different period of time in the

calculation could lead to a substantially different ELCC result. An investigation of this

problem is described in the next section.

5.2   Long-term investigation

In order to be sure that we have characterized the real long-term capacity value

of a wind plant, many years of wind and load data would need to be used in the ELCC

calculation. Such volume of data is often unavailable at a wind project site, so it is

desirable to find a reliable capacity value metric with less stringent data requirements.

The following describes an initial investigation of the inter-annual variability of capacity

value.

Two sets of wind data were found of at least ten years in length, both from the

National Atmospheric and Oceanic Administration's (NOAA's) National Data Buoy

Center. These two sites are the buoy, B44013, and the platform, Buzm3. These two sites

are shown in Figure 41. They are outlined in purple on the map.
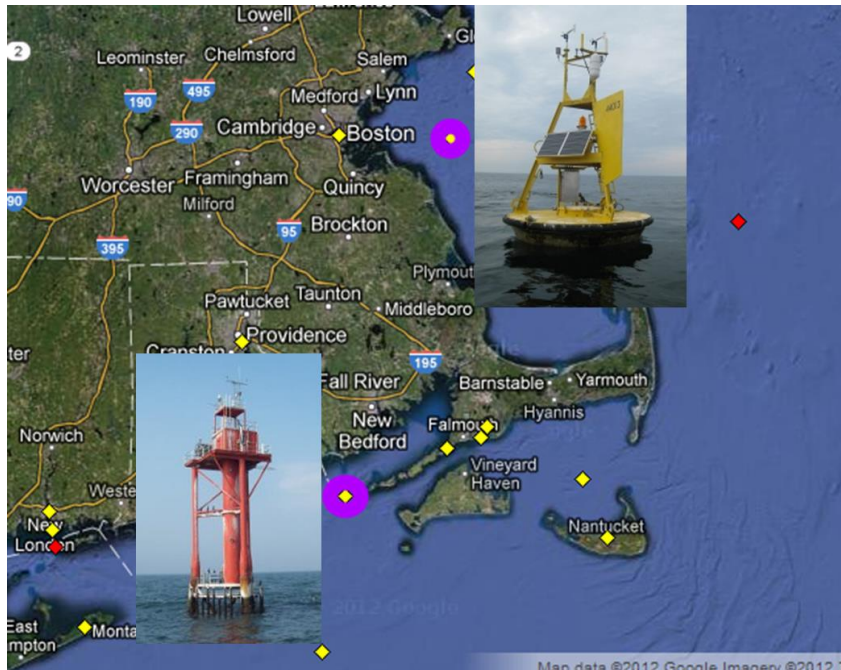
Figure 41 - Long term wind data sites (photographs from (NDBC))

A simple wind plant model was developed for this investigation. This model is designed to produce results similar to the model used by AWS Truepower to produce the EWITS data. A piecewise curve was fit to a set of wind speed and power data from a few offshore sites in the EWTIS set. Gaussian scattering was added to produce a spread similar to the EWTIS data. This curve and a simulation with scatter are shown in Figure 42 and Figure 43. The EWITS data are shown in blue, and my reverse-engineered model results are shown in red.
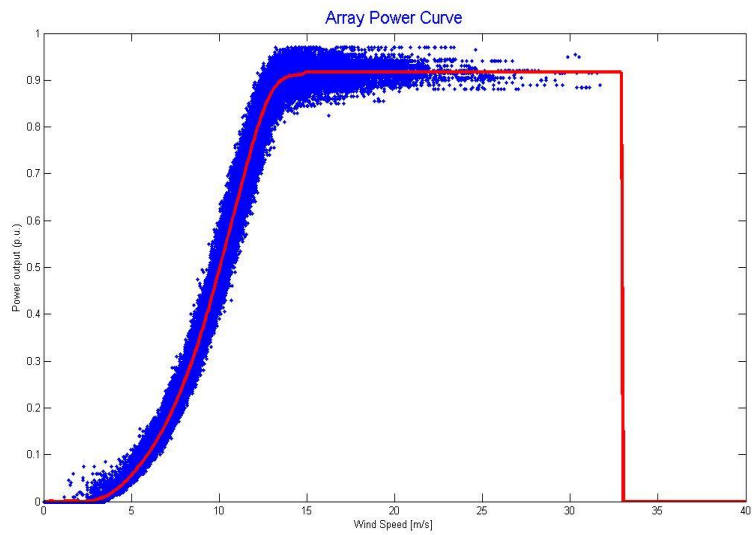
Figure 42 - Curve fit to EWITS offshore wind farm power curve
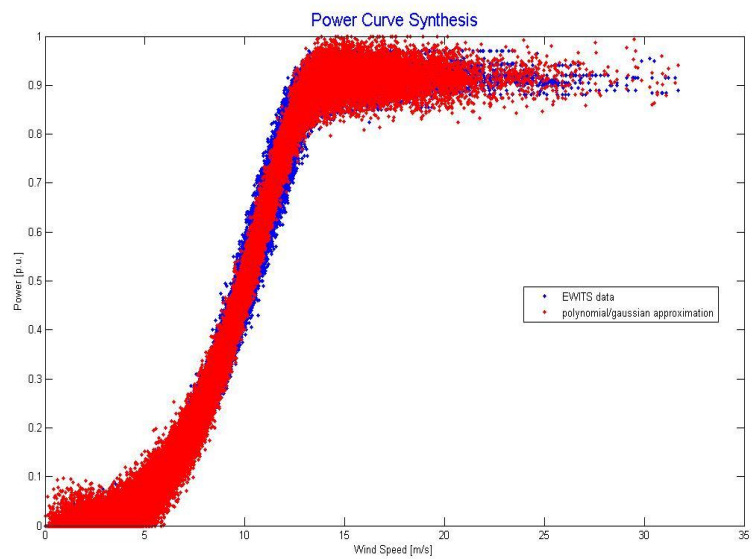
Figure 43 - Power curve with Gaussian scatter

This wind plant model was applied to the wind speed data from each of the two long-term sites to produce a power output time series for a theoretical wind farm at each site. After de-trending 11 years of system load data concurrent with the wind data available from these sites, an ELCC calculation was performed for each year, for each

site. The capacity value results are shown in Figure 44.
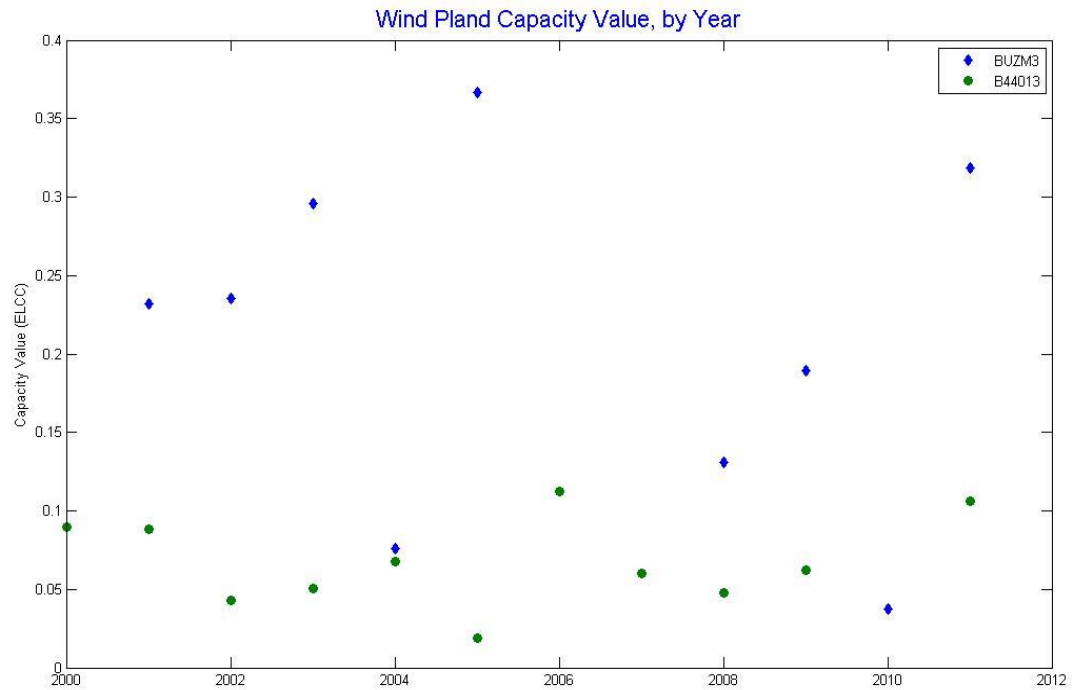
Figure 44 – ELCC by year

It is plain that the ELCC/LOLE metric is highly sensitive to the year of data that was used in its calculation. ELCC values for Buzm3 vary between 0.05 and 0.37, depending on the year. The fact that the LOLE each year is dominated by a few peak hours means that the statistical uncertainty in the ELCC calculation based on a single year is large. This presents a double problem. It is difficult to know the long-term average capacity value of a wind power plant based on one year (or a few years) of data. Additionally, even given the long-term average capacity value of a wind plant, its actual behavior will be quite variable year-to-year, and very hard to predict in advance.

It is proposed that the *long-term average ELCC* of a wind plant should be taken as its actual capacity value, and any proposed capacity value metric should be judged by its ability to approximate this long term value. Chapter 0 describes an effort to compare 4 capacity value metrics in this fashion, and to characterize the inter-annual variability of wind power plants, particularly in New England.

CHAPTER 6

THE INTER-ANNUAL VARIABILITY OF WIND POWER CAPACITY VALUE

This chapter describes a study of capacity value metrics and the inter-annual variability of wind power capacity value, using the New England power system as an example. Characterizing the variability in wind power capacity value is critical for system planning in systems with increasing wind penetration. This chapter includes two investigations: a long-term investigation and a high penetration investigation.

The long term-investigation, described in Section 0, investigates the capacity value of a few wind plants over several years. These calculations are based on measure data, and are designed to identify how many years of data are necessary for each metric to produce a consistent result.

The high-penetration investigation, described in Section 0, uses synthesized data representing a large number of wind power plants in New England to identify trends in capacity value results related to wind penetration level.

6.1   Capacity Value Metrics used in this Study

A subset of the capacity value metrics described in Chapter 0 were used for this investigation. They were chosen based on their applicability to wind power, ease of use, and effectiveness with limited data. The following four capacity value metrics were

compared in terms of their accuracy at predicting the long-term capacity value of wind power plants and their volatility year-to-year.

1. **Effective Load Carrying Capability** (ELCC) is the metric by which other metrics were judged. It is described in detail in Section 0.

2. The ISO New England **Peak Period Method** (ISONE) is described in Section 0. It is based on average power plant performance during hours which tend to have high load.

3. The **Annual Peak Method** (TLH) is described in Section 0. It was applied in this study using the 1% of hours with the highest load each year.

4. The **Linear Fit Method** (LINFIT) is a novel method developed during this investigation. It is intended to predict wind plant performance during a small number of peak hours based on data from a much larger number of similar hours. Being a novel method, it is not described in Chapter 0. It is described instead in the following section.

6.1.1 The Linear Fit Method

In choosing a metric with which to approximate capacity value of a variable resource such as wind power, there is a trade-off to be managed. Metrics such as ISO New England's peak period method include plant performance during a significant fraction of the year. The inclusion of this much data reduces the statistical variability of the metric result year-to-year, but this large subset of the data includes many hours

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during which demand is not especially high. Including these hours in the capacity value estimate may not be appropriate. This may lead to inaccurate estimates of capacity value.

The annual peak method might be based on one hour or several hours of system load and plant output data. Characterizing the performance of the plant during these critical hours is the goal of a capacity value calculation, but basing the metric on so few hours of data leads to a high statistical variability and a large importance placed on which year or years of data are chosen for the calculation.

A novel method for the prediction of wind plant capacity value was investigated in this study. This method uses wind plant performance during a significant fraction of the year to predict performance at peak times. The method, herein referred to as the *linear fit method*, consists of dividing a concurrent wind power and load time series into a large number of load bins. The size of each of these load bins was chosen such that they each contain an equal number of hours of data. The mean power output of the wind plant in each of these bins was calculated.

A linear least-squares fit is made to the top several bin means. This linear equation is intended to characterize the varying behavior of the plant in question with respect to load during times of high load.

This linear fit is used to estimate the average plant performance during the times of peak load.

In this study the following parameters were chosen for this method:

- The wind power output and load time series was divided evenly into 100 bins by load

- The top 10 bins were used in producing the linear fit.

- This linear fit was used to predict average performance during the top 1% of load hours

  This metric is referred to below as the linear fit method or LINFIT.

  Figure 45 shows visualization of this method as used this study. It shows the mean wind power output for a wind plant at Thompson Island for each percentile bin of load. The thick black line shows the linear fit to the top 10% of load hours. This linear fit is used to predict the wind plant performance during the top 1% of load hours. Power output is given on a per unit (p.u.) basis: as a fraction of the plant's nameplate capacity.
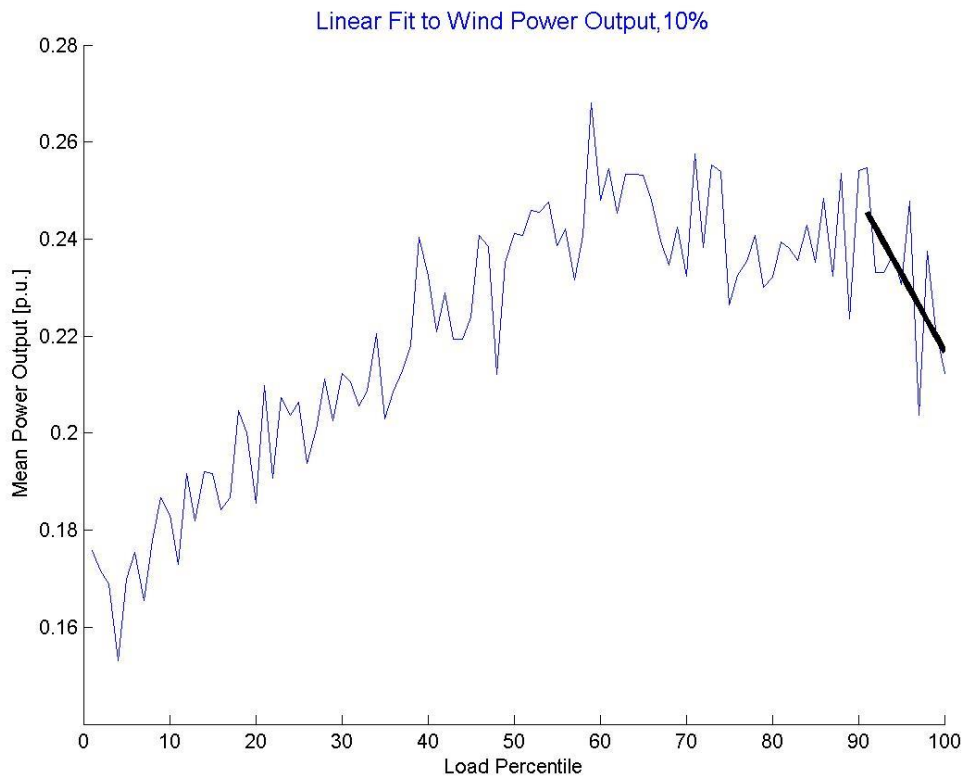
Figure 45 - Linear Fit Method Example

6.2 Comparing and evaluating capacity value metrics

In order to compare the effectiveness of various wind power metrics, a comparison framework was developed based on how well each capacity value metric approximates the long-term ELCC for any site.

Taking the long-term ELCC to be the target value for any capacity value estimate, a diagnostic variable, R, was used as a simple indicator of the accuracy of any capacity value metric given the years of data used.

$$R = \frac{CV(metric, years\ of\ data)}{ELCC_{long\ term}} \qquad \textbf{11}$$

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Values of R close to unity indicate an effective metric. High values indicate an overestimation. Low values indicate an underestimation.

When judging the fitness of a capacity value metric, that metric is applied to several subsets of the input data, each with the same number of years. The statistics of the various R values produced by this process are the primary indicators of the effectiveness of the metric. The mean squared error of these R results is an indicator of the accuracy of the metric. The standard deviation of the values is a measure of the variability within the set of results.

In order to model power system reliability in this project many simplifying assumptions were made. Several of the more important assumptions are detailed here.

- **Wind power plants have 100% mechanical availability**. Since the variability of wind power output due to wind variations is large compared to the effect of mechanical failure, and in order to treat wind plants simply in LOLE calculations, mechanical unavailability of wind power plants was not modelled. This is common in capacity value studies of variable, renewable generation (Michael Milligan, 2011).

- **Power Transmission is unconstrained**. This project is a study of system adequacy. The intent was to characterize the effect of wind power plant on the adequacy of the New England generator fleet. Modelling transmission constraints and transmission failures is outside the scope of this project.

- **Energy Storage is not included in the model**. For simplicity, existing energy storage within New England was excluded from system operation. A power system with 50% wind penetration would need to include a large amount of energy storage in order to avoid curtailment. Study of the effect of this level of storage is left for the analysis in Chapter 0.

- **Scheduled power plant outages (routine maintenance) are not considered**. All load events in this study which have a system adequacy impact occur in the summer months. Power scheduled power plant maintenance can be conducted at times of the year in which they will not have an impact on system adequacy.

- **Seasonal variations in thermal and hydro power plant output are excluded**. Since the summer months account for all of the times of interest to system adequacy, the summer power rating for all thermal power plants was used in all cases. Energy constraint of hydro power plant due to seasonal variations in water flow was also not considered.

The following two sections describe the use of this fitness framework in two contexts. Section 0 describes a long-term study based on measured data from several sites to characterize the behavior of each capacity value metric with various lengths of input data. Section 0 describes a high-penetration study based on synthesized data from

a large number of sites to investigate the changes in capacity value and its variability in systems with high wind penetration.

6.3   Long-Term Capacity Value Study

A long-term study was undertaken to characterize the efficacy of various capacity value metrics at predicting the long term capacity value (ELCC) of a wind power facility based on limited data. The goal was to investigate the behavior of these capacity value metrics as a function of the number of years of wind power output and load data used.

Measured wind data from several sites in Massachusetts were used to produce wind power output time series.

6.3.1   Wind Data

The wind data used in this study were measured data from seven sites in Massachusetts, shown in Figure 46. The wind data were taken during the years 2000 to 2010.
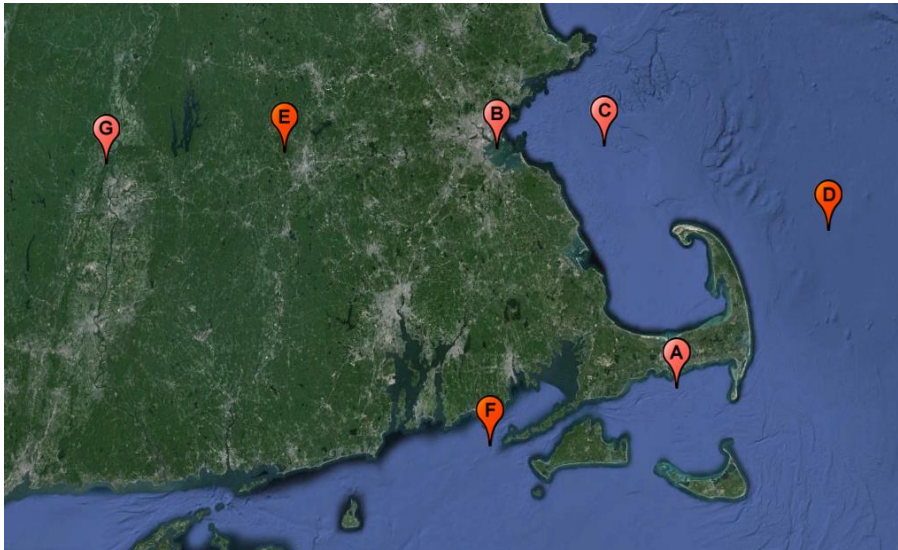
Figure 46 - Long-Term Wind Data Sites

The sites used are maintained by two organizations: The Wind Energy Center at
the University of Massachusetts, Amherst (WEC), and the National Data Buoy Center
(NDBC). These organizations are responsible for the maintenance of the wind
monitoring equipment at these sites and for making the data available to the public. The
organization responsible for each site is listed below in Table 3 under *Source*. The *Height*
column gives the height of the highest wind speed sensor at each site, in meters. Data
are available from (NDBC) and (WEC).

In order to accurately characterize the system adequacy contribution of a wind
plant during any given year, the plant output during peak load hours must be known.
Toward that end, years of data from these long-term sites were only used when there is
at least 90% data availability during the top 1% of load hours. That is, if there are not
wind data available for at least 79 hours out of the 88 hours with the highest load during

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each year, that year was excluded from the analysis for that site. The number of years

which passed this quality test for each site is listed below in Table 3 under *Good Years*.

Table 3 – Long-Term Wind Data Sites

Site Name	Map Letter	Good Years	Height [m]	Source
Bishop & Clerks	A	7	15	WEC
Thompson Island	B	9	39	WEC
Buoy 44013	C	11	5	NDBC
Buoy 44018	D	7	5	NDBC
Paxton	E	7	78	WEC
Buzm3	F	9	24.8	NDBC
Mt Tom	G	7	37	WEC

6.3.2   Analysis

The measured wind speed time series for each site was used to produce a wind

power output time series for that site. This transformation consists of two steps:

applying wind shear to get a hub-height wind speed, and applying a power curve to get

power output.

The log law for wind shear was used with a surface roughness length appropriate

to each site. Each wind speed time series was transformed to represent a wind speed

time series at 100 m. The log law is described in (Manwell, McGowan, & Rogers, 2010).

Figure 47 shows the power curve used to produce wind power output from the

hub-height wind speed time series. It is a composite power curve designed to represent

a wind farm rather than a single turbine. Due to array losses, intra-farm electrical losses,

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and the improbability of all turbines producing at rated power at the same time, wind

plant power output in this model is never 100% of the rated power. This power curve is

the same curve used in the EWITS study data synthesis that is used in the following

chapter.
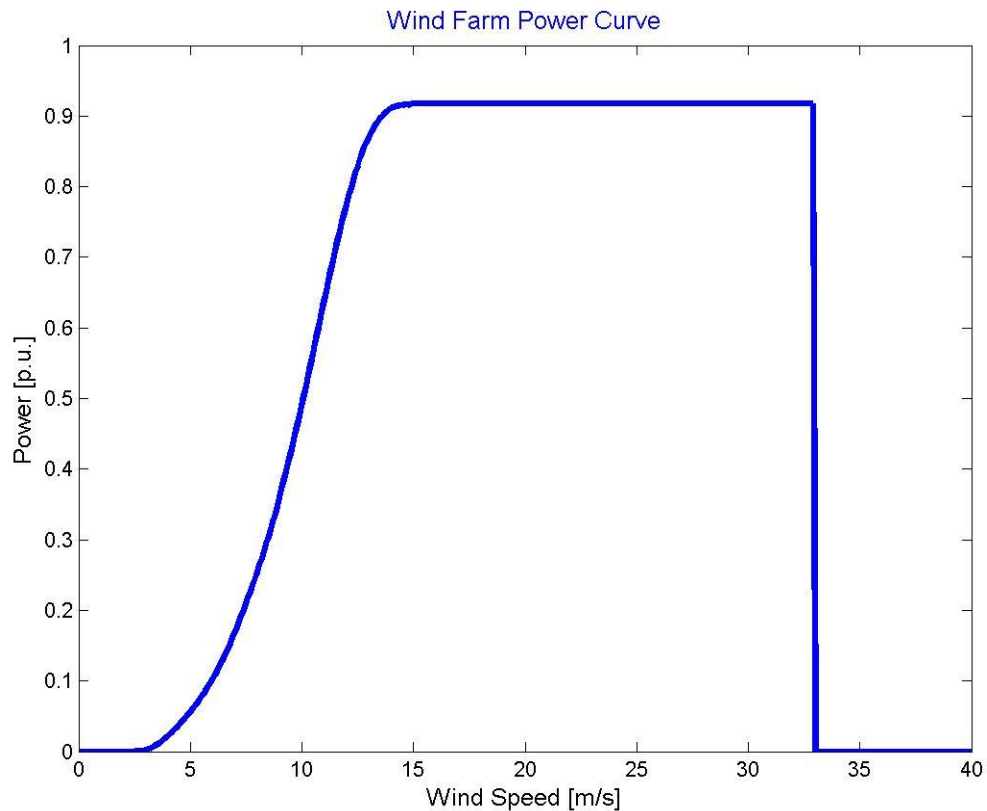
Figure 47 - Wind Farm Power Curve

These wind speed time series are used in conjunction with concurrent system

load data to carry out capacity value calculations using each capacity value metric.

In order to investigate the effect of the number of years of data used in a capacity value

calculation on the accuracy and variability of the result, the data from each site was

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divided into several subsets. Each subset consisted of an integral number of years of data. As an example of this subsetting and analysis, Figure 48 shows the results of a set of these calculations for a single site (Thompson Island) organized by the number of years of data used. Each blue circle represents an ELCC calculation based on a number of years of data, N, indicated by its position along the x axis. The horizontal black line represents the long-term ELCC value for the Thompson Island site. This figure shows the nature of the convergence of ELCC calculations as N increases. Using 1 year of data, ELCC values range from 0.07 to 0.48. Using 4 years of data, this interval has decreased to 0.21 to 0.33: a much tighter interval around the long-term value of 0.26.
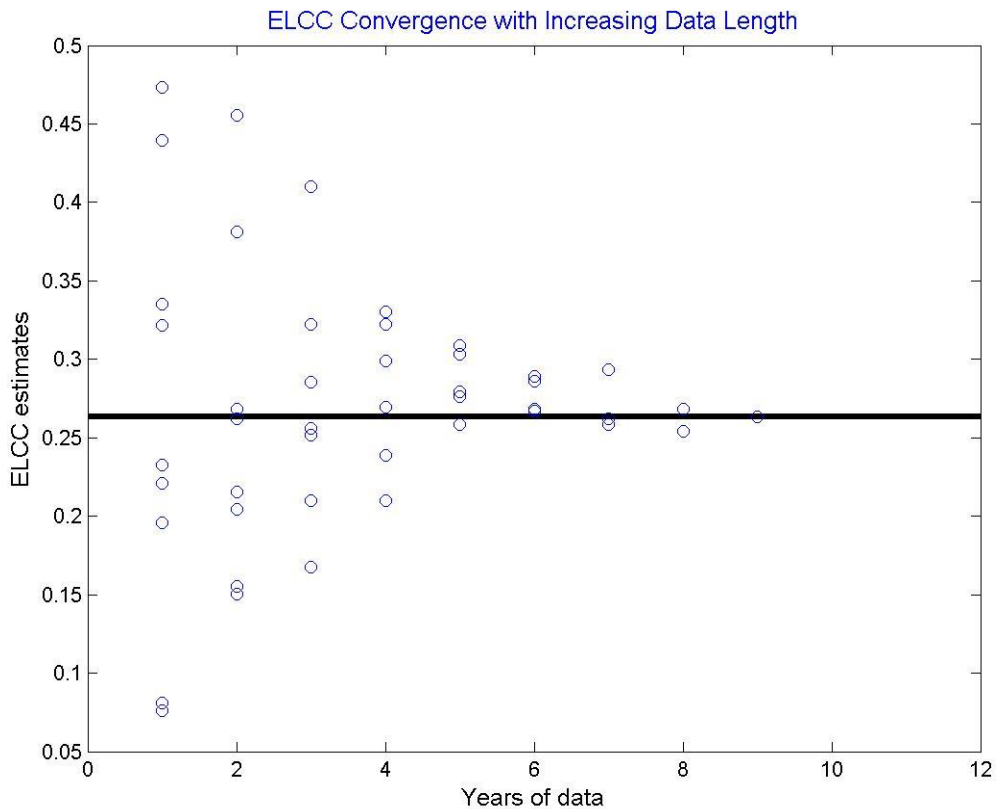
Figure 48 - ELCC Calculation for each Subset of Data by Number of Years of Data Used

The following section shows the results of a set of calculations which compare the accuracy and variability of the various capacity value metrics with respect to N.

6.3.3   Results of Long-Term Capacity Value Study

This section describes the results of the long-term capacity value study for each metric across all sites. These results reflect the effectiveness of each capacity value metric as a function of the number of years of data used. The results given here are limited to N=7 years since all the sites studied have at least that much data available.

The mean squared errors of the R values for each capacity value metric were calculated as a function of N. These mean squared errors indicate the accuracy of each metric given the number of years of data used as an input. Figure 49 shows the results of this accuracy calculation. The ISO New England peak period metric (ISONE, in green), has a much higher mean squared error for all N than the other metrics. This is due to the inclusion of many hours of off-peak wind power output in the calculation.

Of the remaining three metrics the short-term ELCC calculation (shown in dark blue) has relatively high mean-squared error for low N, due to the volatility of a metric which includes so few hours, and converges to very low error at high N. The remaining two metrics have fairly consistent accuracy for all N investigated.
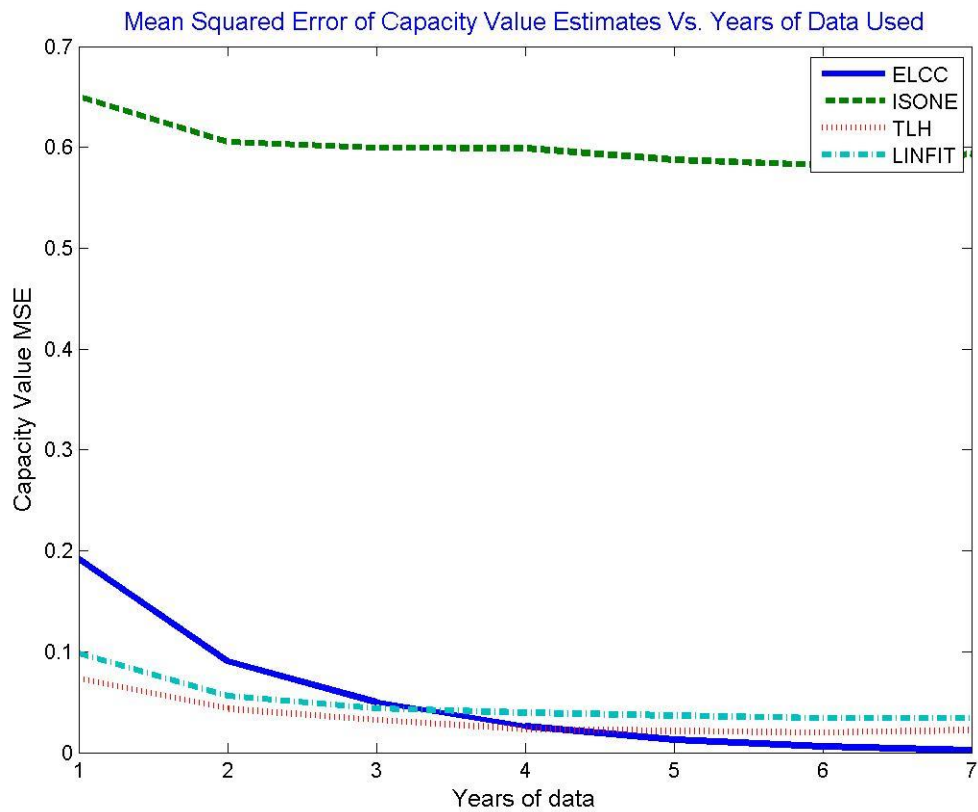
Figure 49 - Mean Squared Error of R Metric

Figure 50 shows the standard deviation of R with increasing N, as a measure of volatility. It shows that the ISO New England method does lead to consistent results, with variability similar to the TLH and LINFIT methods. The ELCC method has the highest variability for N<5 years.
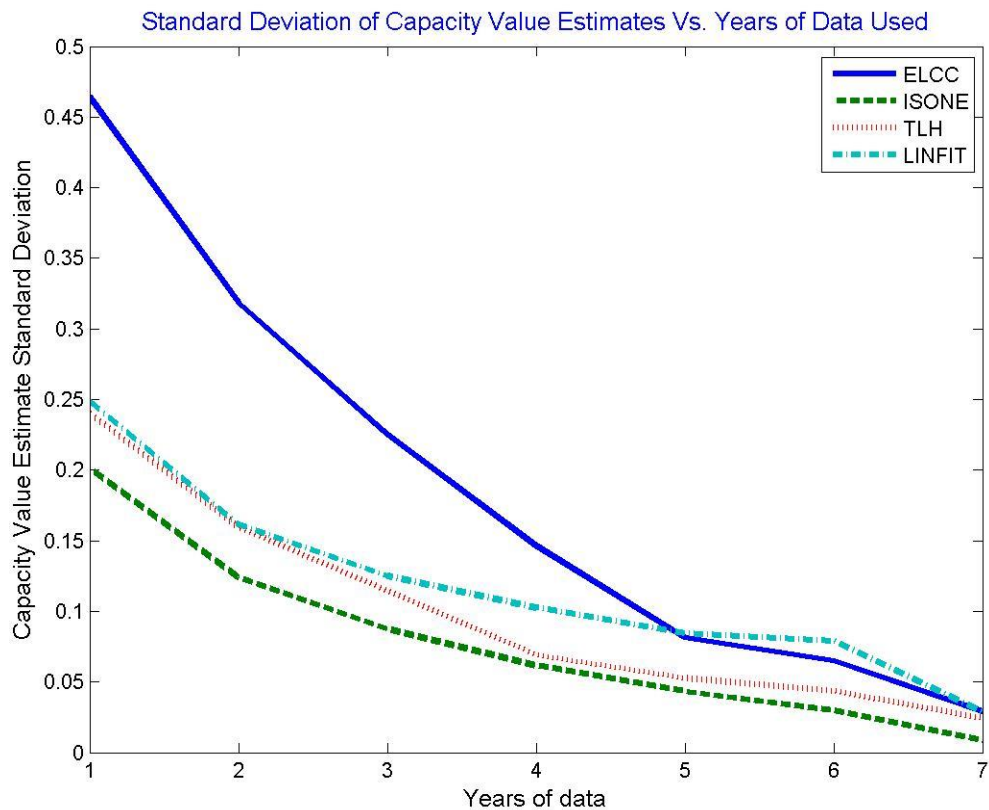
Figure 50 - Standard Deviation of R Metric

In conclusion, there is a general trade-off between the low volatility of methods which use a large fraction of the time series to calculate capacity value (e.g. ISONE), and the higher accuracy of methods which concentrate on the highest load hours (e.g. ELCC and TLH). It's fairly clear from its performance in this study that the ISONE metric is not accurate enough for its low volatility to be of much help. In the above scenarios, the TLH method has the best overall performance among the metrics studied, especially for N<4 years. For N> 4 years, short-term ELCC (naturally) becomes the best predictor of long-term ELCC.

The following section describes a study of these 4 metrics and their effectiveness under conditions of increasing wind penetration.

6.4   High-Penetration Capacity Value Study

A high-wind-power-penetration study of capacity value and capacity value metrics was undertaken to evaluate the way that capacity value and the inter-annual variability of capacity value change and wind power makes up a larger and larger part of the generator fleet. A large number of wind power sites were needed to reach the target of 50% penetration of wind power by energy. Synthesized data from the EWTIS study (Corbus et al., 2010) were used for this purpose.

6.4.1   EWITS data

The Eastern Wind Integration and Transmission Study (EWITS) is a study that was finished in 2009. It is a study of the effects and requirements of getting 20% of electrical energy from wind power in the eastern United States. As mentioned in Section 0, one of the major components of the study is a large amount of synthesized wind data for thousands of sites in the Eastern US. The data set for each site contains a wind speed time series for the years 2004, 2005 and 2006, as well as a time series of power output for a theoretical wind farm at the site, based on a simple plant model. This synthesized wind speed and wind power output data is publicly available (NREL).

These synthesized data are available for 696 sites in New England both on- and offshore. The locations of these sites are shown in Figure 51, color coded by capacity factor. These data are the results of a mesoscale atmospheric model, with boundary conditions set by historical measurements. Data from all three years were used in this capacity value investigation for all of the EWITS sites in New England.
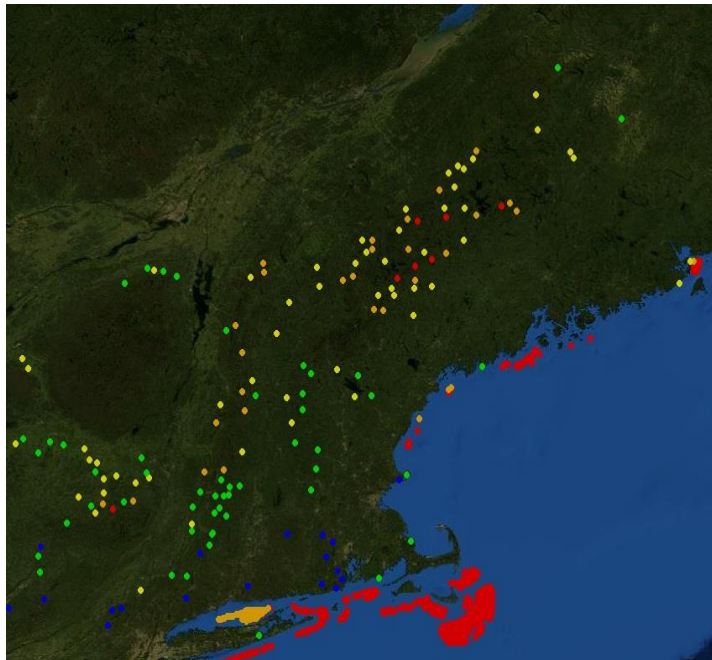
Figure 51 - The EWITS sites in New England (NREL)

6.4.2 Wind Power Build-Out Scenarios

For clarity and concision in this analysis, the EWITS sites were grouped into five sets, herein referred to as *quintiles*. Each quintile includes wind plants whose total energy output is 10% of the system load over the three years for which data are available.

The wind plants were grouped by capacity factor, with the highest capacity factor sites in Quintile 1, and the lowest in Quintile 5. A result, the wind plants in higher-numbered quintiles have a higher total nameplate capacity in order to produce the same total energy. Statistics for each of these quintiles are shown in Table 4.

Table 4 - Wind Quintile Characteristics

Quintile	1	2	3	4	5
Capacity Factor	0.48	0.47	0.47	0.44	0.34
Nameplate Capacity [MW]	3360	3340	3360	3922.1	4457.1

Increasing wind penetration was modeled by adding each quintile to the system, one after another, starting with quintile 1. Figure 52 shows the load-net-wind (the power demand for each our minus the wind power output for that hour) for a week of October 2004. The top curve is the total demand, and each lower curve represents the addition of another 10% wind power. By the time 50% wind penetration is reached the daily and weekly load shapes have been altered significantly.
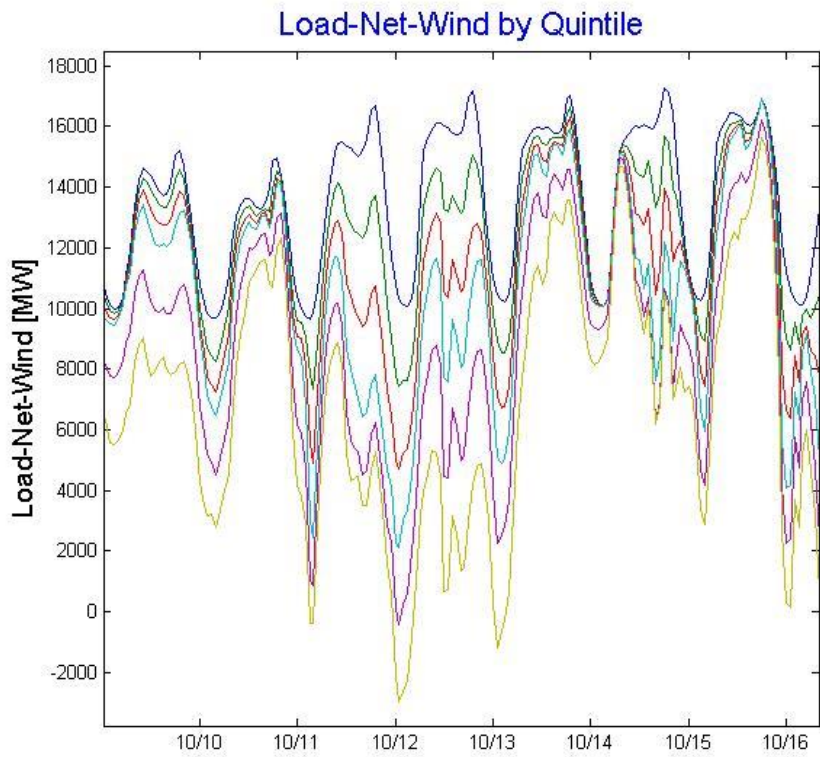
Figure 52 - Load-net-wind time series, by quintile

Figure 53 shows the average energy output of each quintile by month. Each quintile has the same annual shape: more output in the winter and less in the summer. The first three quintiles are dominated by offshore sites, and have very similar monthly averages.
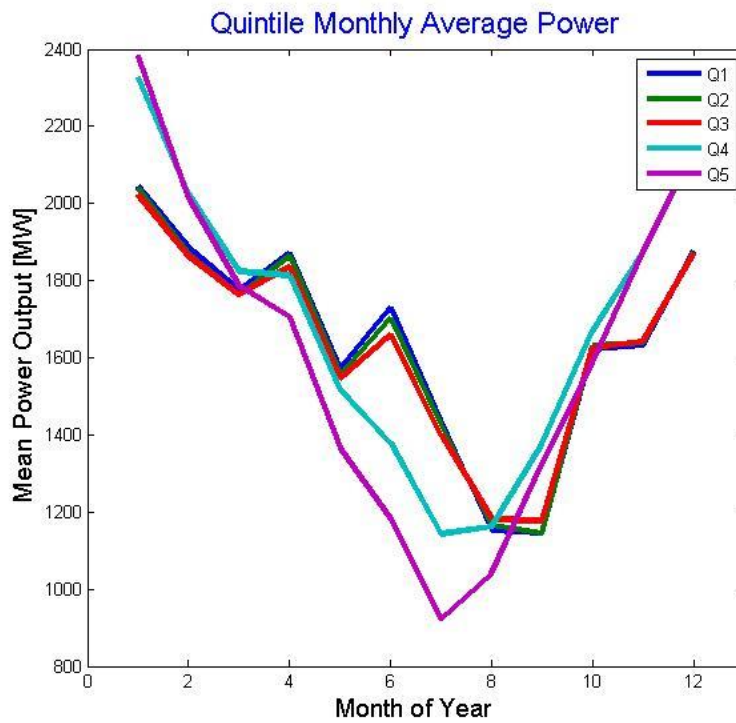
Figure 53 - Wind power monthly average output, by Quintile

Figure 54 shows the diurnal average output for each quintile. Again, the offshore sites in quintiles 1, 2 and 3 are clustered tightly together. Quintiles 4 and 5 show a lower afternoon output and a much higher output in the early morning.
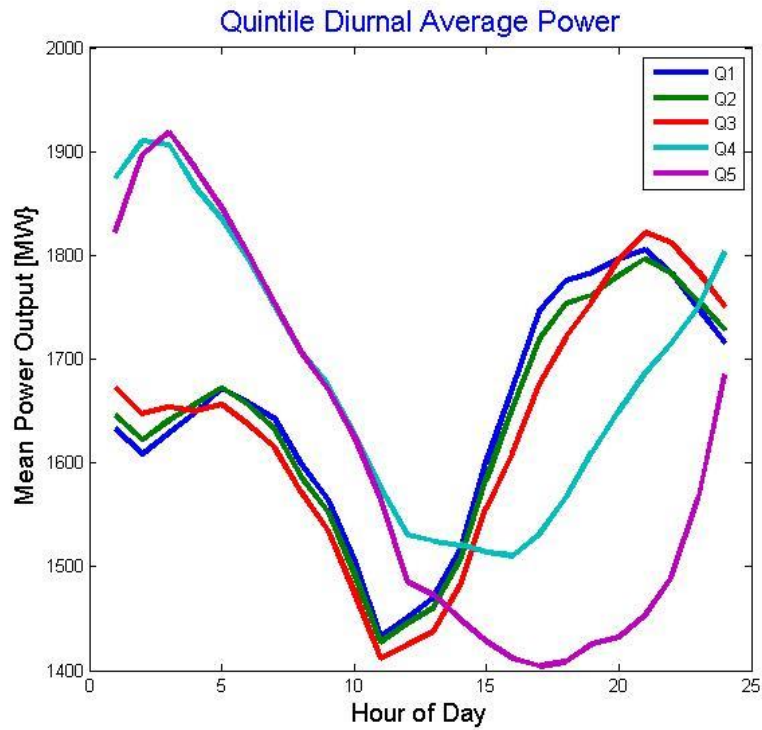
Figure 54 - Wind power diurnal average output, by Quintile

As the wind penetration in the power system increases the variability of load-net-wind also tends to increase. Figure 55 shows the trend in the standard deviation of load-net-wind with increasing penetration. The total variability almost doubles between 0% and 50% penetration.
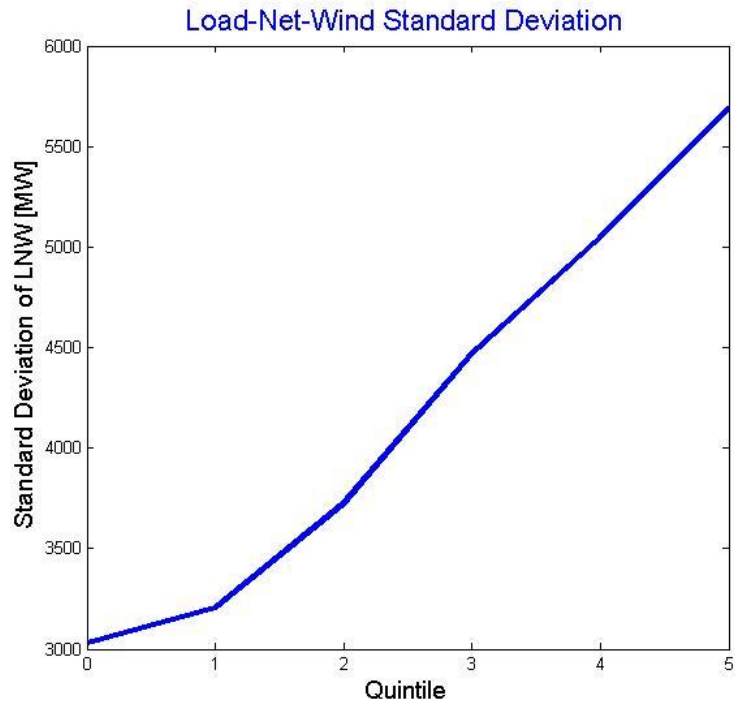
Figure 55 - Load-net-wind standard deviation, vs Quintile

This framework of 5 quintiles up to 50% energy was used to study the effect of increasing penetration of the capacity value of wind power: both its magnitude and its inter-annual variability.

6.4.3 Load Net Wind Calculation

Each quintile of wind plants was added to the power system sequentially, to represent increasing penetration of wind power. After the first, the reliability contribution of each quintile was modelled using the system load minus the power output of the previous quintiles in place of the system load in capacity value calculations. This is analogous to the $(d_t - r_t)$ expression in Equations

91

As discussed previously, this difference is referred to as the *load-net-wind* or *LNW*. Figure 56 shows the duration curves the total system load of load-net-wind for each quintile. The fact that the curves close together in the highest load hours and they spread out as load decreases indicates that the wind plants make a relatively small contribution at times of high demand.
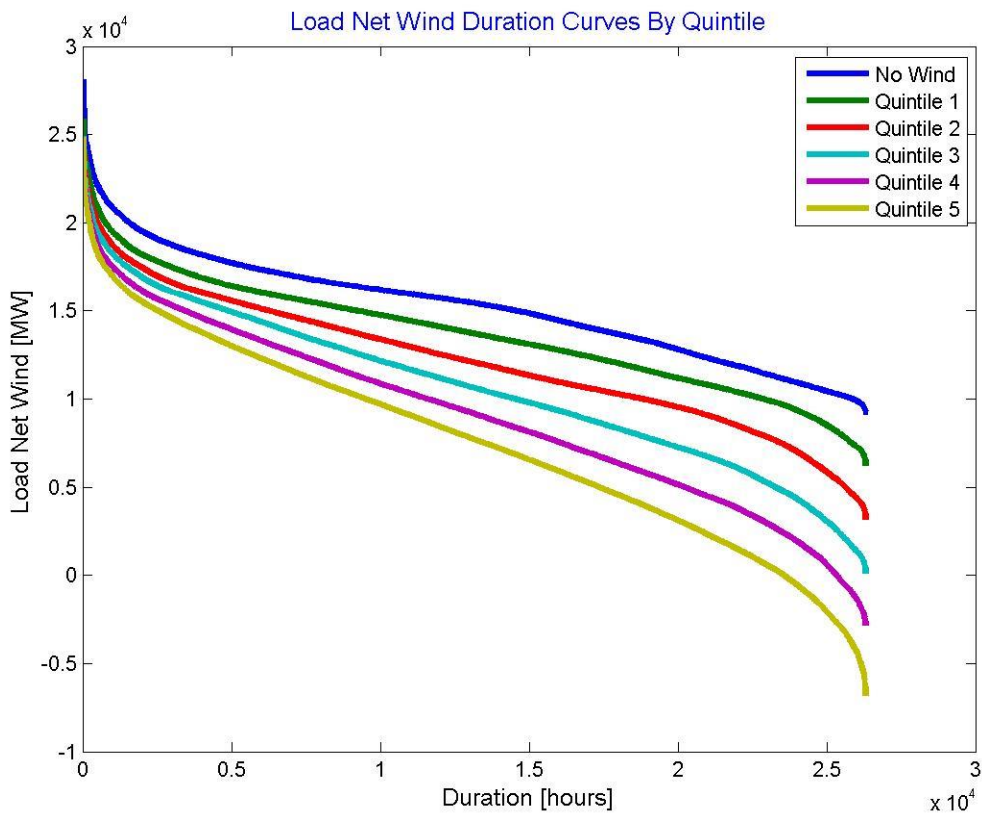
Figure 56 - Load-Net-Wind Duration Curves

Figure 58 gives a series of charts each displaying the mean LNW for each month of the year and each hour of the day. Each chart represents a level of wind penetration starting at 0% and increasing to 50%. The hours in the year with the highest mean load (summer afternoons) have a relatively small change in LNW with increasing penetration.

Winter evenings, another time of relatively high load, show substantial decrease in LNW as penetration increases.

Figure 57 - Mean Load by Time of Year shows the mean system load for each month of the year, for each hour of the day. It is a larger copy of the upper-left chart in Figure 58 (the others are shown smaller to keep them on one page for easier comparison). The load is highest on summer afternoons, with relatively high loads on winter evenings. As wind penetration increases, the LNW decreases generally, while remaining high on those summer afternoons. The addition of wind power is affecting these peak times less than most other times. It can be seen that the winter evening peaks are substantially reduced by to time 50% penetration is reached in the lower-right chart of Figure 58.
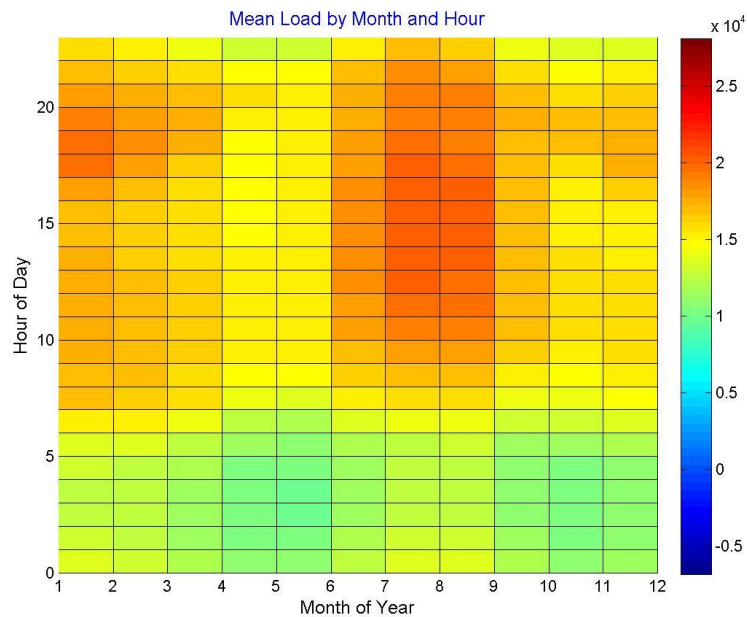
Figure 57 - Mean Load by Time of Year
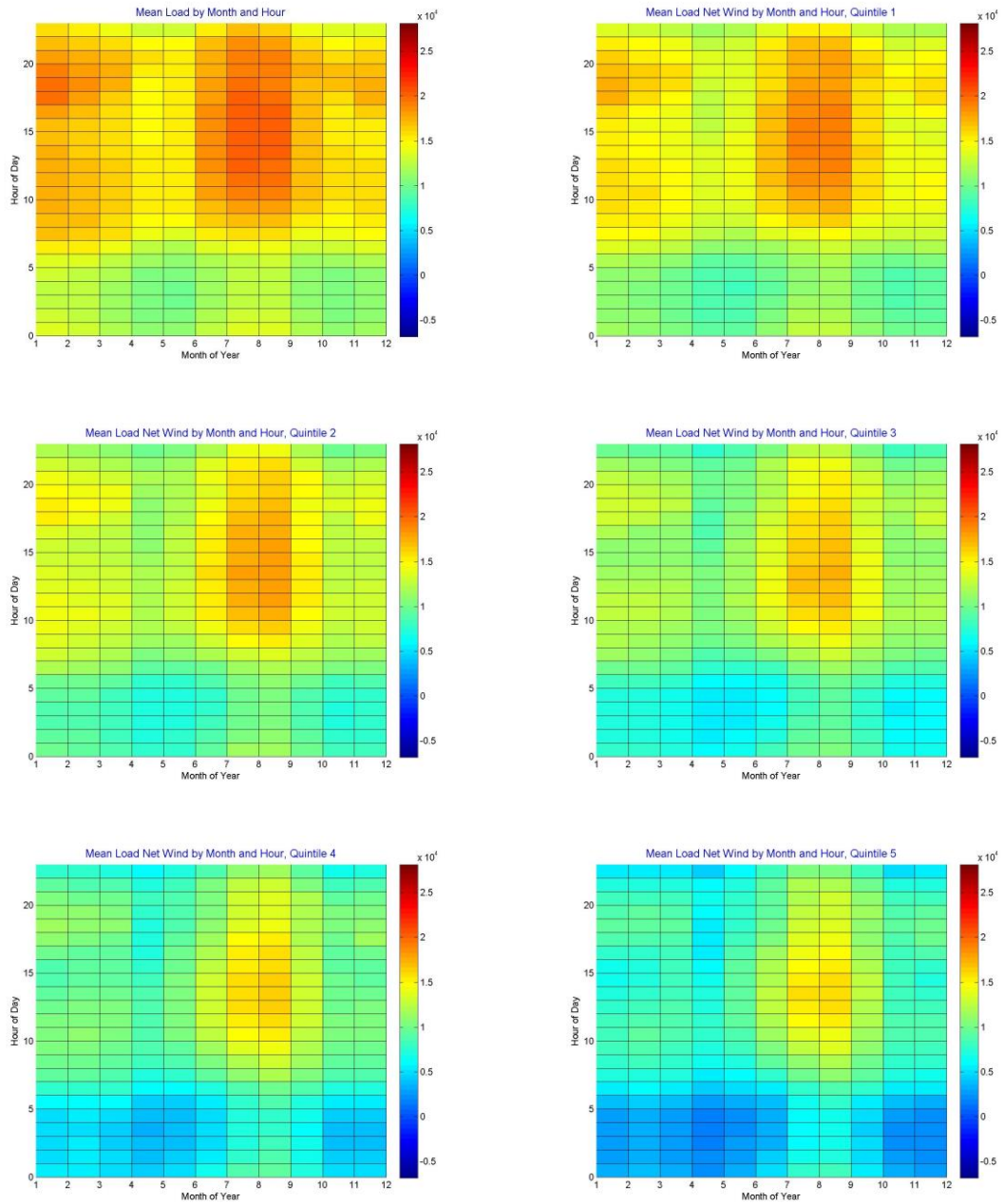
Figure 58 - Mean Load-Net-Wind by Time of Year

6.4.4 Results of High-Penetration Capacity Value Study

Figure 59 shows the capacity value of each quintile of wind plants. The solid,

blue *Increasing Penetration* line represent the capacity value of each quintile on a power

system that includes the lower numbered quintiles (for example, the ELCC of Quintile 3 is calculated using a power system model which already includes the contribution from Quintiles 1 & 2). The dotted, green *Zero Penetration* line represents the capacity value of each quintile of wind plants on a power system with no other contribution from wind power.

Both of the analyses shown in Figure 59 present a strong downward trend in capacity value in the higher numbered. This can only mean that the wind plants in Quintiles 4 and 5 have poorer performance at times of high load. In the Increasing Penetration analysis, there is an additional effect. The substantial presence of wind previously added to the system tends to shift the times of high net load away from windy days, meaning that the newly added plants will tend to make smaller reliability contributions. The remainder of the analysis described in this section reflects the scenarios with increasing penetration.
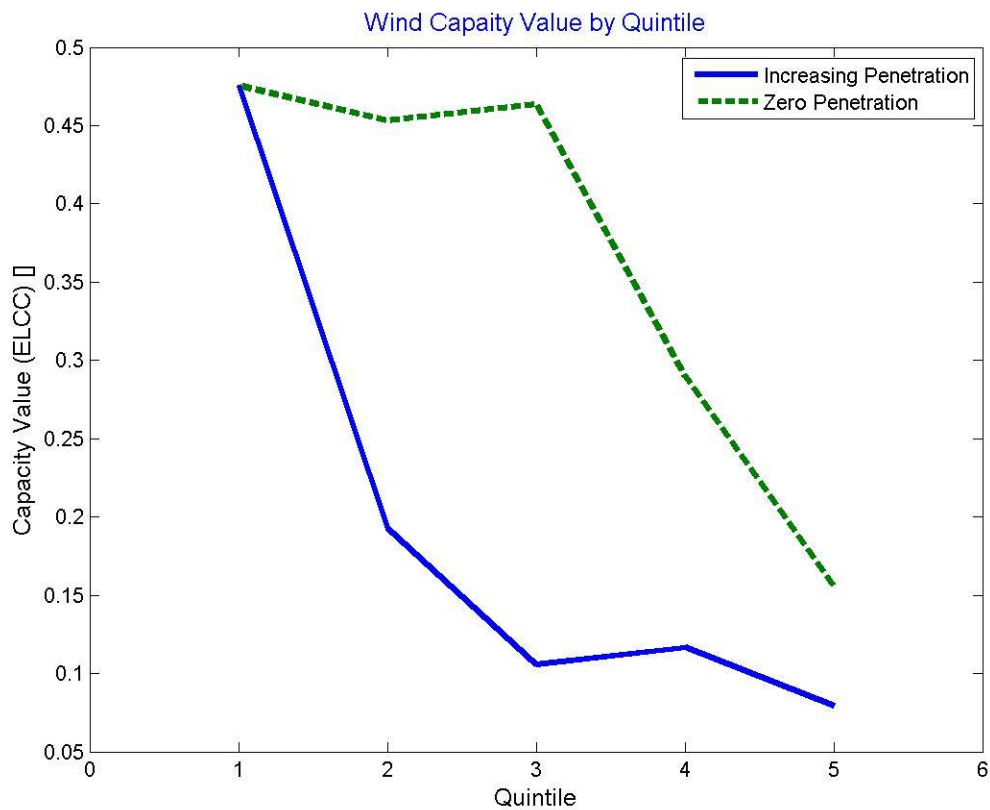
Figure 59 - Capacity Value by Quintile

R, in this high-penetration study was calculated by comparing one-year

estimates of capacity value to the ELCC value based on all three years of data available.

Figure 60 shows the standard deviation of R for the four metrics, as a measure of each

metric's variability as a function of penetration. The variability seems to be highest for

quintiles 2 and 3. The fact that standard deviation is low for quintiles 1, 4 and 5 suggests

that this variability is not strongly influenced by the degree of wind penetration. The

fact that the standard deviation of R for ELCC is sometimes near or above one implies

that the annual capacity value for these wind plants often varies by *100%* of its long

term value from year to year. 18.4 GW of wind make up the 50% energy scenario. With

an average ELCC of 19%, that's equivalent to 3.4 GW of perfect capacity (in an average

year). This means that the year-to year variability in the capacity contribution of this

fleet of wind plants is about 3.4 GW, or 12% of the maximum system load.
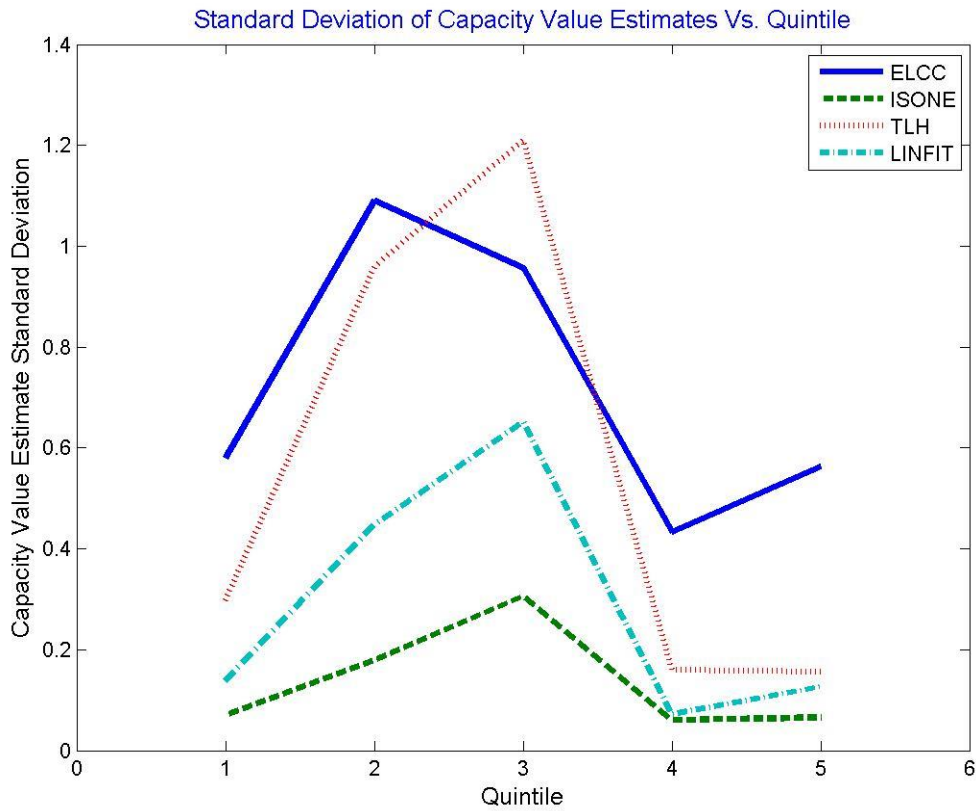
Figure 60 - Standard Deviation of Capacity Value Estimates, By Quintile

Figure 61 shows the mean squared error for each metric and quintile. Quintile 3

has the worst accuracy, especially with the ISO New England Metric. The accuracy of

capacity value estimation does not seem to increase or decrease monotonically with

wind penetration.
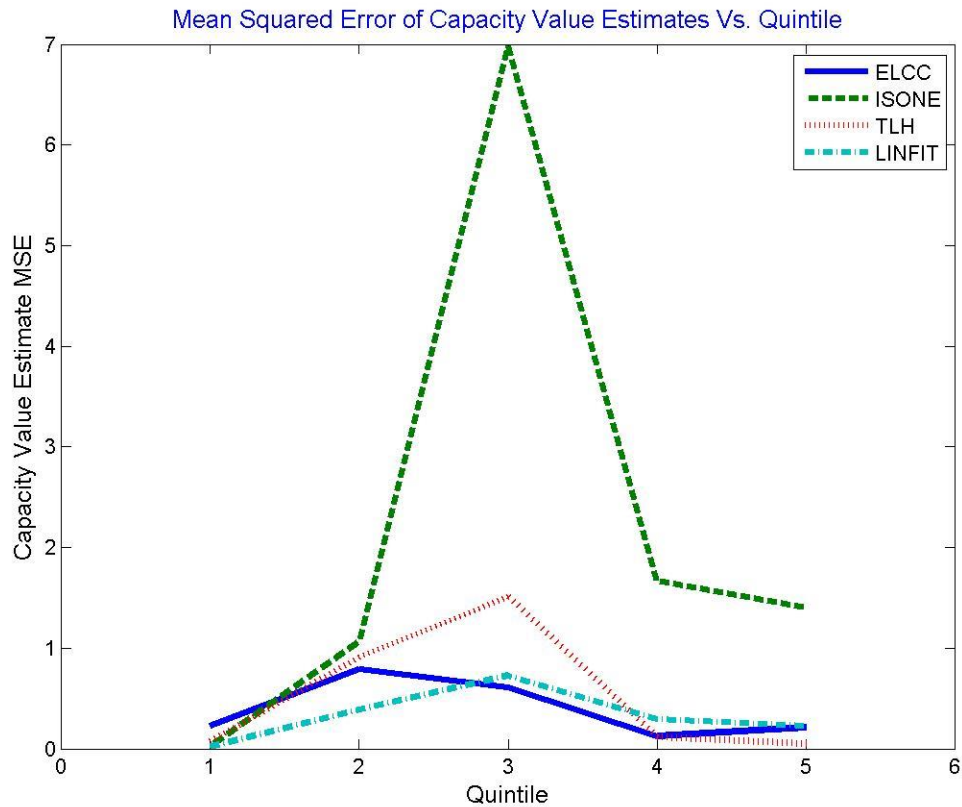
Figure 61 - Mean Squared Error of Capacity Value Estimates, By Quintile

The increased variability and decreased accuracy of all metrics in the middle

quintiles is likely due to the variability of the particular wind farms making up those

quintiles, rather than any generalizable effects around 30% wind penetration.

This section detailed a study of the capacity value of a large number of

theoretical wind farms in New England. This investigation characterized the

effectiveness of two existing capacity value metrics and two novel metrics at

approximating the long-term ELCC of wind power plants based on limited data. These

metrics were also evaluated at wind energy penetrations of up to 50%. It was

demonstrated that the capacity value of wind power plants decreases severely by 50%

penetration of wind power. It was found that capacity value estimation accuracy and variability are not strongly affected by the level of wind penetration in the power system. In the long term study, the ISO New England metric displayed the poorest performance. The ELCC metric performed well for long data sets. The linear fit method and the top load hours method performed relatively well for short data sets.

The metrics which relied on small amounts of on-peak wind power output data (ELCC and TLH) had good accuracy at predicting the long-term ELCC, but had higher variability between years. The ISONE metric which uses a large fraction of the time series, with equal weight, was less sensitive to annual fluctuations, but did a poor job of accurately predicting the long-term ELCC. The LINFIT method did as well as any method in accuracy, and was second only to the ISONE method in reducing inter-annual variability.

CHAPTER 7

WIND POWER CAPACITY VALUE AND ENERGY STORAGE

This chapter presents a study of the New England power system with wind

power penetration increasing to 50%. Additionally, the power system was modelled

with and without energy storage sufficient to mitigate wind curtailment at times of low

power demand and high wind power output. Table 5 shows the occurrence of

curtailment for each of the 5 wind power scenarios from Chapter 0. Wind curtailment

begins occurring at 40% penetration, and by 50% penetration, a significant amount of

wind energy is being lost to curtailment. Due to the timing of wind power output, some

available energy cannot be used to serve the load. This lost energy will not offset fossil

fuel consumption, and reduces the value of the wind power plants.

Table 5 - Wind Curtailment by Penetration

Wind Penetration []	10%	20%	30%	40%	50%
Total Energy from Wind [MWh]	3.6E+08	3.2E+08	2.8E+08	2.39E+08	1.99E+08
Wind Curtailment [MWh]	0	0	0	999268.9	6009257
Percent of Wind Energy Curtailed [%]	0.00%	0.00%	0.00%	0.42%	3.02%

In order to operate the power system at 50% wind penetration without

curtailment of wind power output, some grid scale energy storage is required. In this

project, storage was modelled in a simple, technology agnostic fashion. 'Storage' here

could refer to and mechanism by which the load could be shifted within a day. This

could be accomplished by means of actual energy storage, such as pumped hydro or

compressed air energy storage. It could refer of demand response or other load

deferment. Various benefits of storage to a power system are discussed in Section 0

Research into the operation of power systems with significant storage is a large and active field, with many avenues of investigation. In this dissertation, storage is investigated for its effect on peak load shape (and thus, LOLE), and on wind power curtailment.

7.1   Power System Modelling

This aim of this project was to assess the effects of the addition of a large amount of wind power and energy storage to the New England power system on the adequacy of that system. Several aspects of the power system needed to be modelled:

1. The load on the power system

2. A large number of wind power plants

3. The conventional generator fleet

4. Energy storage for daily load shifting

These models are based on the existing New England power system. When historical data were used, these data were taken from the years 2004, 2005 and 2006. Concurrent wind and load data were used to preserve the statistical relationship between these phenomena. Five wind power build-out scenarios were considered: one each at 10%, 20%, 30%, 40% and 50% penetration.

Capacity value in this study was assigned using ELCC, with LOLE as a system adequacy metric. The following sections describe the details of the various data and models used in this project.

7.1.1 System Load

Historical hourly load data from the New England power system were used. These are hourly data from the years 2004, 2005 and 2006. These data are available to the public at the ISO New England website (ISO-NE, 2014b). These years were chosen to coincide with the EWITS wind data, described below.

It may be useful to understand the size of the New England power system. The maximum annual energy output occurred in 2005 and was 136,335 GWh. The maximum hourly demand occurred in 2006 and was 28,130 MW.

7.1.2 The Conventional Generator Fleet

Using the characteristics of the current conventional generators on the power system in New England, a capacity outage probability table (COPT) was constructed. This process consisted of finding the probability of inadequate generation (the *loss of load probability, or LOLP*) as a function of demand, based on capacity and the forced outage rate of each power plant. The process of building a COPT is described in (Garver, 1966).

For each wind power penetration scenario, an appropriate COPT was used, such that the initial loss of load expectation for the system was close to 1 day in 10 years.

This was done by retiring of power plants to reflect a plausible future generator fleet (as wind plants are added to the system, the number of conventional power plants required to maintain system adequacy will decrease).

An expanded explanation of the system adequacy calculations used in this project is included in Appendix A.

7.1.3 Wind Power Output

Wind power output data in this part if the study are taken form the EWITS data described in Section 0. These synthesized data are used to create plausible wind power build-out scenarios up to 50% penetration. The same wind power scenarios that were used in Chapter 0 were also used here.

7.1.4 Energy Storage

The primary benefit of storage on high-wind-penetration power systems (meaning 40-50% penetration) is the reduction of wind curtailment (Ackermann, 2012). Storage has the greatest impact on system performance when it is operated to address the net system demands rather than paired to increase the effectiveness on any one technology, such as wind or nuclear power (Holttinen et al., 2009).

Storage operation can be of benefit to the system on several timescales, depending on the energy capacity available. In decreasing order of energy capacity, here are several time scales of interest to power system operation (Ackerman, 2012).

- **Long-term seasonal storage** shifts load from peak seasons to off peak seasons this requires weeks or months' worth on energy capacity and might be accomplished by large, conventional hydro plants.

- **Daily time-shifting** storage operation serves to reduce daily peaks by shifting demand to off peak hours. This requires several hours' worth of energy capacity.

- **Management of uncertainty**: this mode of storage operation requires about 6 hours of energy capacity. It is the use of storage to mitigate errors in wind and load forecasting.

- **Transmission curtailment reduction** is the operation of storage to reduce curtailment of wind plants due to transmission constraints.

- **Reduction of short-term fluctuations:** seconds to minutes of storage, operated to support power quality

- **Grid frequency support**: approximately 1 hour of storage, operated to control grid frequency at times of power mismatch.

The time scale of interest for this study is daily load-shifting. This is the longest time scale of load shifting feasible with technology available in New England.

While the analysis in the project is storage-technology agnostic, a short summary of storage technologies appropriate to this application may interest the reader. Figure 62 shows the time and power scales offered by many different storage technologies. Pumped hydro and compressed-air energy storage could provide the energy and power requirements of daily load shifting in New England. Some batteries also approach the size required. It may make sense to include hydrogen as an energy storage method, based on its versatility. Hydrogen can be used as a fuel or stored over the long term and converted back into electricity.
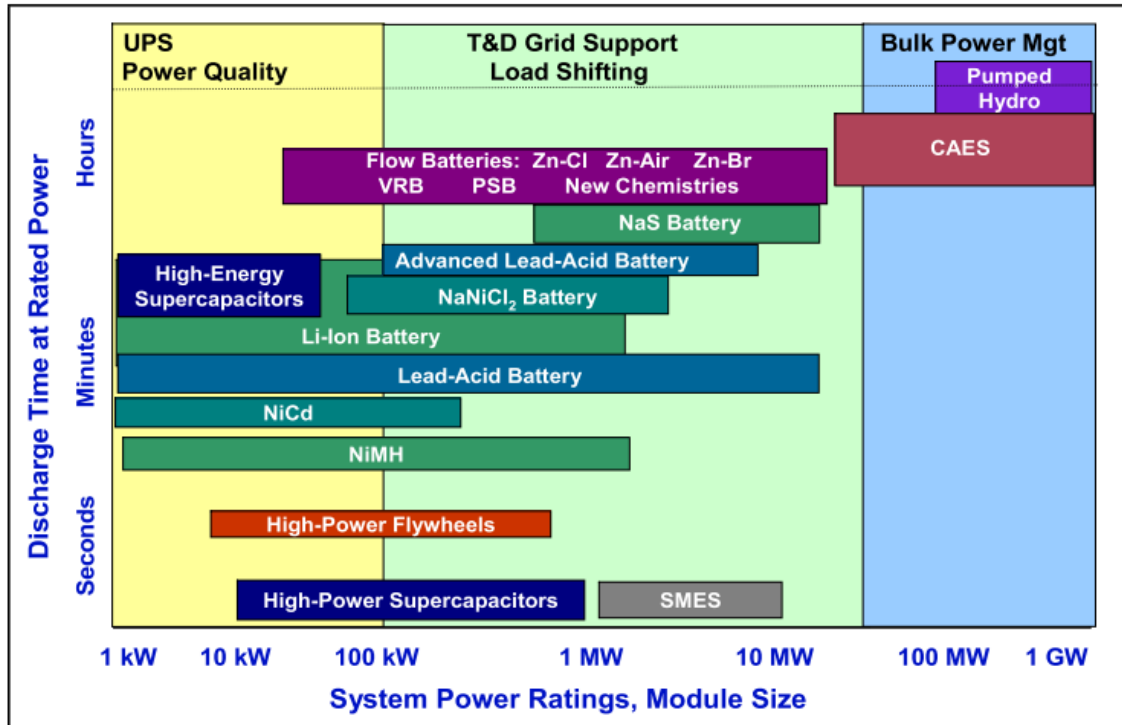
Figure 62 – Storage technologies and their capacities (Eckroad & Gyuk, 2003)

Of interest for this application are:

- Round trip efficiency

- Power capacity

- Energy Capacity

- Cost

7.1.5 Pumped storage

Pumped Hydro energy storage stores energy by pumping water from a lower reservoir to an upper reservoir during off-peak times and extracting that potential energy with turbines during times of peak demand. Pumped storage is by far the most common type of grid-scale energy storage in use today. There are approximately 1600

MW of pumped storage in the New England power system today, and about 22 GW

nationwide. Expansion of this storage resource is limited by the availability of

appropriate sites. Round-trip efficiency (energy produced/energy consumed) of pumped

hydro plants is in the range of 80 to 85% (Eckroad & Gyuk, 2003).

7.1.6 Batteries

Lead acid batteries are another storage technology with a long service history.

There are also newer battery technologies which may be suitable for grid-scale

application, including: lithium-ion batteries and Sodium Sulfur batteries. While these

batteries vary widely in cost and specific energy (kWh/kg), each technology delivers a

round-trip efficiency of around 80%. Battery Storage facilities could be built with size on

the order of megawatts (Hittinger, Whitacre, & Apt, 2012).

7.1.7 Demand Response

Demand Response is a system which allows energy consumption to be deferred

from one time period to another, in order to ease the operation of the power system.

Typically, this is accomplished by agreements between industrial energy consumers and

the system operator. The consumer receives power at a lower cost, and is expected to

reduce consumption during times of high demand, when instructed to do so. There are

currently about 2400 MW of demand-response resources in New England (ISO-NE,

2014b).

While it is not a storage technology, demand response is included here because is serves a similar function: lowering peak demand by moving energy consumption to off-peak time periods. With the assumption that this deferral of consumption does not result in a net increase in energy consumption, demand response can be represented in the power system model as storage with a round-trip efficiency of 100%.

7.1.8   Compressed Air Energy Storage (CAES)

Compressed air energy storage functions by pumping air into large reservoirs (usually underground cavities) and releasing it through turbines to produce energy, or using the compressed air as an input to a gas turbine generator to increase its fuel efficiency. Compressed air energy storage facilities might be built with power capacities of tens or hundreds of MWs (Hadjipaschalis, Poullikkas, & Efthimiou, 2009) and round-trip efficiencies of 25 to 70% (Eckroad & Gyuk, 2003).

7.1.9   Hydrogen Energy Storage

Energy could be stored on a grid scale in the form of hydrogen. Hydrogen is produced by electrolysis and converted back to electricity using fuel cells. While less cost and energy efficient than batteries, hydrogen as a storage medium has the advantage that it could be used for a fuel rather than only being converted directly back into electricity for the grid. Also, with hydrogen storage systems, power capacity is largely independent of energy capacity.

Round trip efficiency for hydrogen energy storage is about 32% (Barton & Infield, 2004)

7.1.10 Storage Algorithm

The storage algorithm used in this study is one which acts on the load-net-wind (LNW) in each scenario to limit the maximum load during each day by shifting demand to the lowest demand hours in that day. The algorithm assumes perfect knowledge of the LNW 24 hours in advance. Figure 63 Shows and example of storage operation during one week of July 2004. The data shown are for the 50% wind penetration scenario. One can see that the LNW falls below zero at times. These are times when total wind power output is greater that the system load. The algorithm acts to flatten each daily peak and lowers the maximum load each day as low as is possible within its energy and power constraints. The storage is refilled during periods of low demand and raises the daily minimum as far as possible within its power and energy constraints. This operation will serve to reduce wind curtailment in high-wind-penetration scenarios.
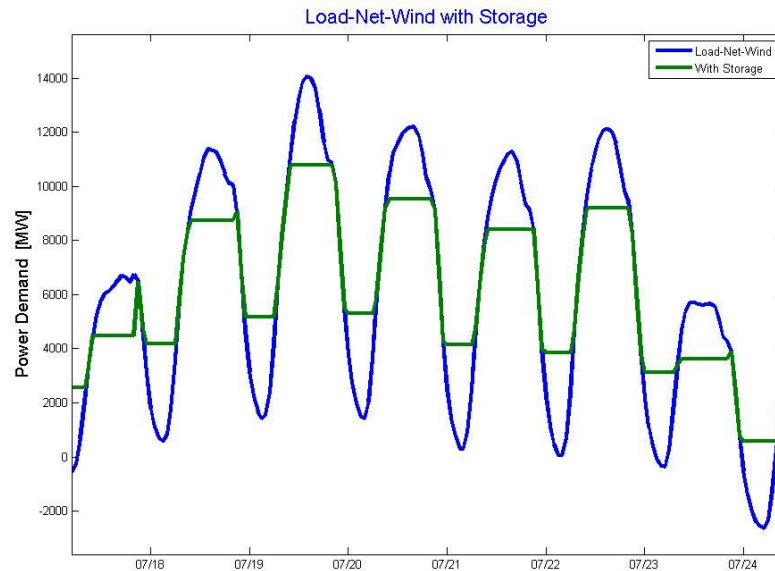
Figure 63 - Load Net Wind and Storage Operation

The following section details the simplifying assumptions made for the development of the power system model

7.2 Wind Power and Storage Build-out Scenarios

Wind Power and Storage additions to the power system are considered independently. The intention was to identify the individual contributions of these systems rather than their combined effect.

7.2.1 Wind Power Scenarios

This power system study with storage uses the same wind power build-out scenarios used in Chapter 0: Wind power plants sufficient to provide 50% of the annual load were divided in to 5 quintiles by capacity factor. These quintiles were added to the

power system sequentially resulting in 5 scenarios from 10% penetration to 50%

penetration. These scenarios are described in more detail in Section 0.

7.2.2   Storage scenarios

Two storage scenarios were defined based on mitigating high peak loads and

wind curtailment in the two highest-penetration scenarios. Storage operation was

modelled for Quintiles 4 and 5 with a range of storage power capacity and energy

capacity. Figure 64 and

Figure 65 show the effects of including various amounts of storage in the power

system with 40% wind penetration. To go with this wind power scenario, a storage

scenario of 3000 MW power capacity and 4 hours' worth of energy capacity (12,000

MWh) was chosen. This amount of storage is enough to reduce wind curtailment to near

zero, and to reduce LOLE to near the minimum achievable with daily load-shifting

storage in this wind scenario.
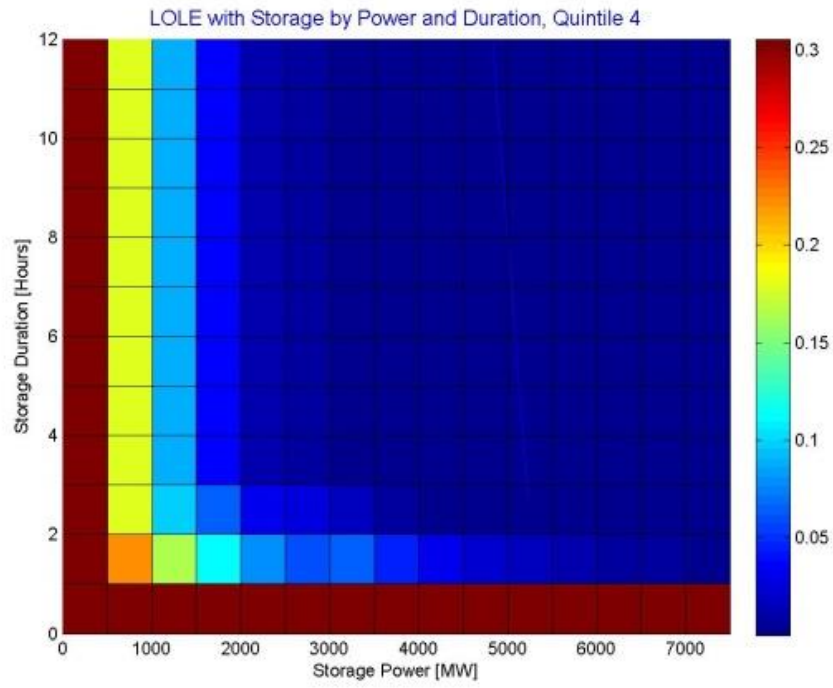
Figure 64- Effect of Storage on LOLE, Quintile 4
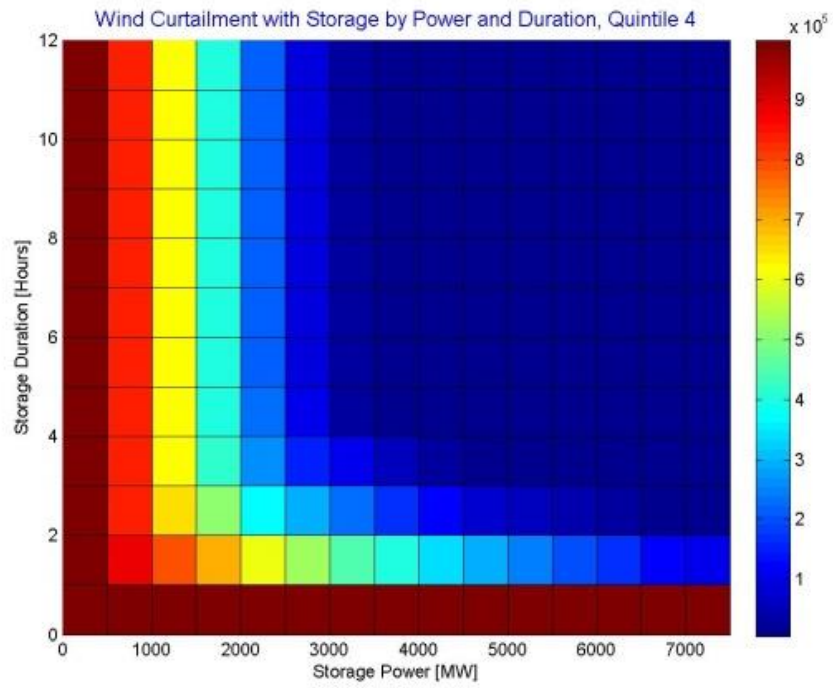
Figure 65- Effect of Storage on Wind Curtailment, Quintile 4

Figure 66 and

Figure 67 show the effects of various amount of storage on LOLE and wind

curtailment. The storage scenario chosen to fit this level of wind penetration has 6000

MW of power capacity and 6 hours of energy capacity. These figures show that most of

the wind curtailment avoidance and reliability benefit achievable by daily load-shifting

storage is reached by this level of storage.
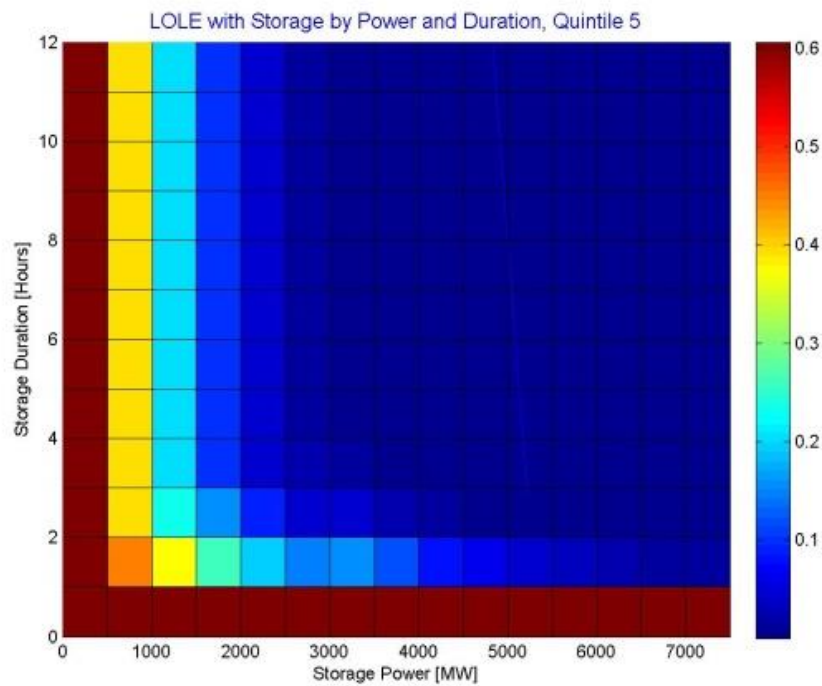
Figure 66- Effect of Storage on LOLE, Quintile 5
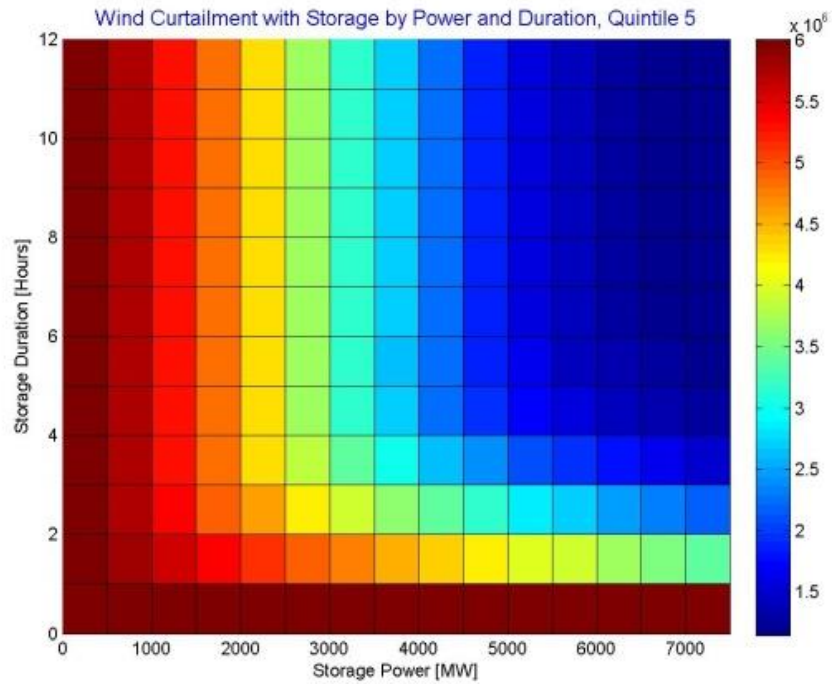
Figure 67- Effect of Storage on Wind Curtailment, Quintile 5

Table 6 shows the three storage scenarios used in this study. Each scenario is
characterized by its maximum power output and its total energy capacity. Storage
duration is the number of hours that the storage system can be run at full power before
exhausting its stored energy supply. This is included as an intuitive description of the
size of the system.

Table 6 - Storage Scenarios

Scenario	Storage Power [MW]	Storage Duration [Hours]	Storage Energy [MWh]
Scenario 0	0	0	0
Scenario 1	3000	4	12000
Scenario 2	6000	6	36000

As will be discussed in the next section, reliability (LOLE) calculations were done for each level of wind penetration with each storage scenario. The capacity value (ELCC) of each storage scenario and was calculated in conjunction with each wind scenario. That is: the two storage scenarios developed above (together with the zero-storage scenario) were each combined with the 6 wind scenarios described in Section 6.4.2

Wind Power Build-Out Scenarios (5 Quintiles and the zero-wind scenario), for a total of 18 combinations. This allowed the calculation of the reliability benefit to adding wind or storage under various conditions by comparing scenarios with and without the system (wind or storage) in question, while holding the rest of the system equal.

7.3   Results of Storage Study

As stated above, the capacity value of additions of wind plants and energy storage to the power system were considered separately. The capacity value of any new system addition can be heavily dependent on the system to which it is being added. It is of interest to investigate the way in which the capacity value of storage changes with increasing wind penetration, and the dependence of wind plant capacity value on the level of storage available.

The capacity value of each storage scenario was calculated by comparing the LOLE of each wind scenario with no storage to the LOLE of the same wind scenario with storage included. Similarly, the capacity value of each wind quintile was calculated by comparing the LOLE of the system with and without that quintile included, with storage kept constant.

Figure 68 shows the capacity value (ELCC) of each wind and storage scenario.

The blue and green lines at the top represent the capacity value of storage scenarios 1

and 2 respectively, as a function of wind penetration. Storage Scenario 2 has higher

ELCC because it represents 6 hours' worth of storage instead of 4. The ELCC of the

storage scenarios is not strongly affected by wind penetration but does increase slightly

with increasing wind power.
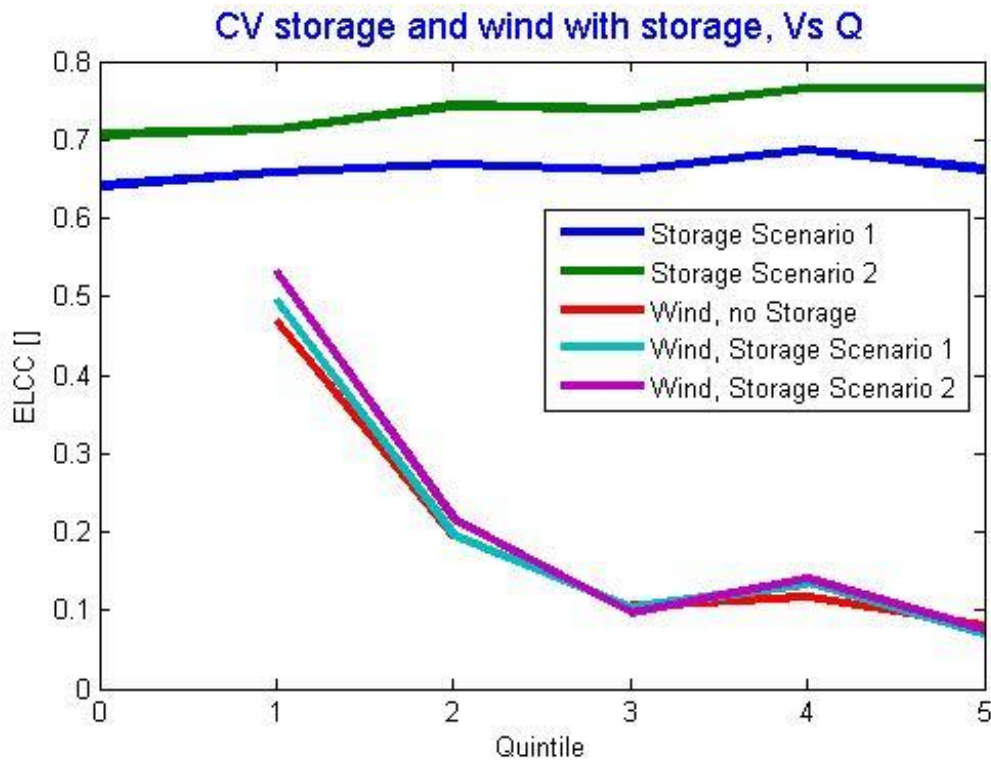
Figure 68 - Capacity Values of Wind and Storage with Increasing Wind

Penetration

The lower three curves in

Figure 68 represent the capacity value of each quintile of wind as they are added sequentially to the system. It can be seen here that the presence of storage has a small positive effect on wind power ELCC for most quintiles. Capacity value tends to decrease as wind penetration increases. This decrease is due to a combination of reasons. Some of the dominant effects are listed here:

- The lower numbered quintiles have the highest capacity factor sites. These sites have higher energy production generally and tend to have better performance at times of high load.

- The lower numbered quintiles contain mostly offshore sites. These sites have relatively good power output on summer afternoons. Inland sites in New England tend to have poor performance at these times.

- As wind penetration increases, the hours which have the largest effect on LOLE change. Hours which have high wind power output region-wide have a lower load-net-wind, and thus a low LOLP. The hours which still have high LOLP in the higher-penetration scenarios will tend to correspond with lower performance from the wind plants being added to the system.

It may be surprising that the presence of storage has such a small effect of the ELCC of wind plants in this study. This counter-intuitive result is explained by a couple of observations. The days in the three year period of this study which contain the highest loads tend to have poor performance in the high-numbered quintiles *for the entire day*. This means that even in the presence of storage, the addition to the power system of

these wind plants has a small effect on system adequacy. The limited energy capacity, and the method of operation of the daily, load-shifting storage investigated in this study does not allow for wind energy produced days before the annual peak hours to be applied to those peaks.

Figure 69 shows the effect of wind and storage on load-net-wind in the highest wind scenarios. It can be seen here that the addition of the fifth quintile has a substantial effect on the total energy required of the conventional generator fleet over the three year period, but a much smaller effect during the peak load hours (at the far left of the figure).The red and cyan curves show the system LNW with no storage. The difference between these two curves represents the effect of adding the fifth wind quintile to a system with no storage. The blue and green curves show the system LNW with storage (storage scenario 2). The difference between these two curves represents the effect of adding the fifth wind quintile to a system including storage.
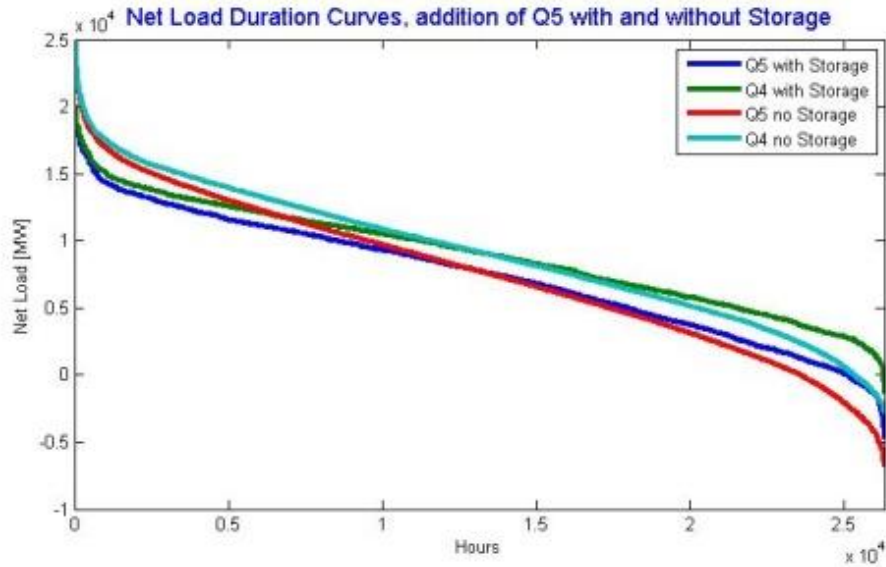
Figure 69 - Load-Net-Wind Duration Curves

Figure 70 shows the same curves as Figure 69, but shows only the top 100 hours of the three-year period of the study. It is clear that the addition of the fifth quintile of wind here has a small effect on LNW in the presence or absence of storage, but the storage itself has a relatively large effect at either wind penetration level. This result is consistent with the ELCC summaries in

Figure 68.
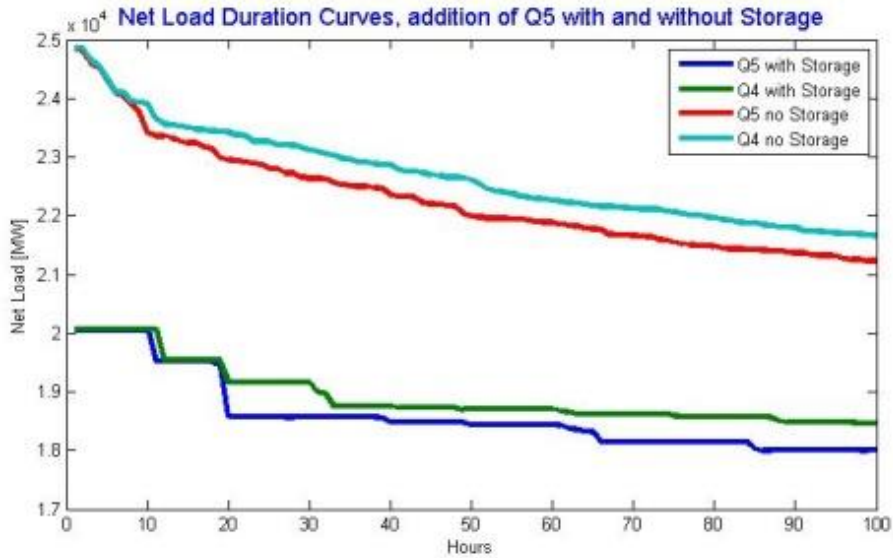
Figure 70 - Load-Net-Wind Duration Curves, Peak Hours

7.4   Summary

An investigation was performed of the New England power system with wind

penetrations of up to 50% and some daily load-shifting energy storage. The capacity

values calculated for the first wind plants added to the power system in this study were

relatively high because these plants were at offshore sites with high energy production

and excellent power output during hot summer afternoons when the demand for

electricity was high. As penetration was increased the wind plants being added tended

to be onshore sites with poorer performance especially during these peak hours. The

capacity values calculated for these sites were substantially lower. This and other effects

resulted in a drastic decrease in wind power capacity value as penetration approached

50%. Wind power capacity values were near 50% at low penetration and decreased to

near 10% at higher penetration. The ELCC of daily load shifting storage tended to be between 65% and 85%, increasing slightly with increasing wind power build-out. The inclusion of energy storage had a small, positive effect on wind power capacity value at all levels of penetration.

7.5   Long-Term Storage and Higher Wind Penetrations (up to 100%, and above)

This section is a conceptual exercise demonstrating the storage levels required to run a power system with a small conventional generator fleet and a large amount of wind power. These simulations were done without regard to capacity value, simply to calculate the storage power and energy that would be required to run the New England power system at various wind penetrations with only a given amount of conventional generation capacity. Wind penetrations between 50% and 200% were investigated in this way. Penetrations above 100% indicate that the total available energy from wind power over the course of a year is larger than the total energy demand. These scenarios necessarily include some curtailment of wind (or some alternative use of this extra energy, such as producing hydrogen for fuel).

Operating the power system in these scenarios requires storage on a longer time scale than the daily load-shifting storage modelled earlier in this chapter. The long–term storage algorithm used here takes a load-net-wind time series and restricts the maximum load to a given value, without constraints on storage power or energy capacity. The algorithm logs the energy stored and used by the storage system and finds the storage power and energy that are required to maintain the maximum net load at

the given value. This is not an optimization. There may be much smaller amounts of storage that could achieve similar results. This algorithm simply calculates the amount of storage required the keep the load ceiling at a given level.
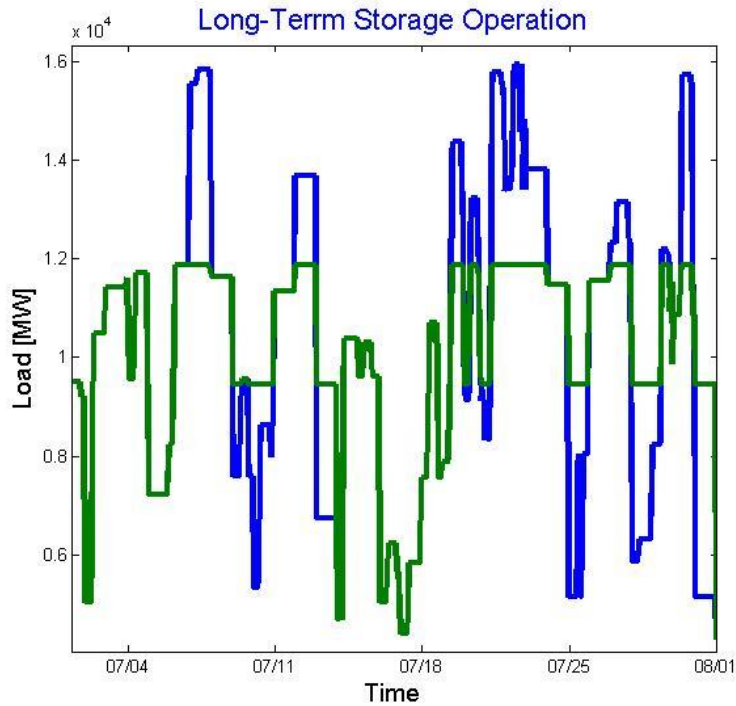
Figure 71 - Long Term Storage Operation, 50% Penetration

Figure 71 shows the operation of long-term storage on a load-net wind time series at 50% penetration, in blue. The net load after storage operation is shown in green. The storage algorithm has restricted to maximum net load to 12 GW (down from 16 GW).

Figure 72 represents the storage capacities required to restrict the maximum net load to various values from 15.8 GW down to 12 GW. It can be seen that the amount of

storage power and duration required increase fairly linearly as the power ceiling is

lowered.
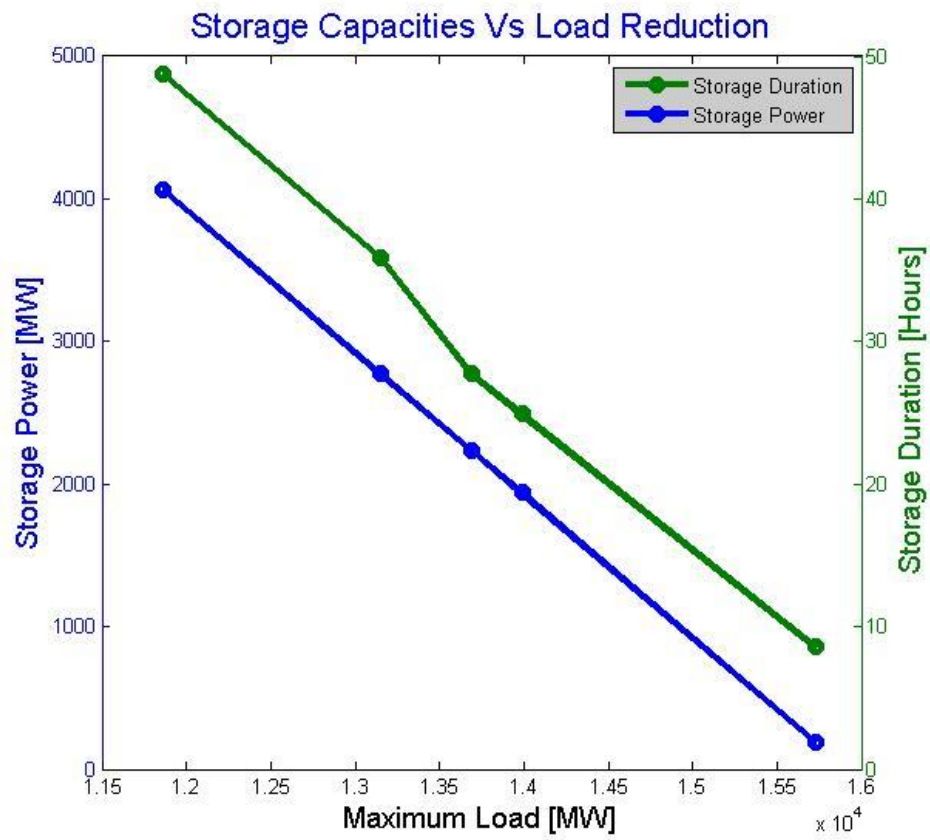
Figure 72 - Long-Term Storage Capacities, 50% penetration
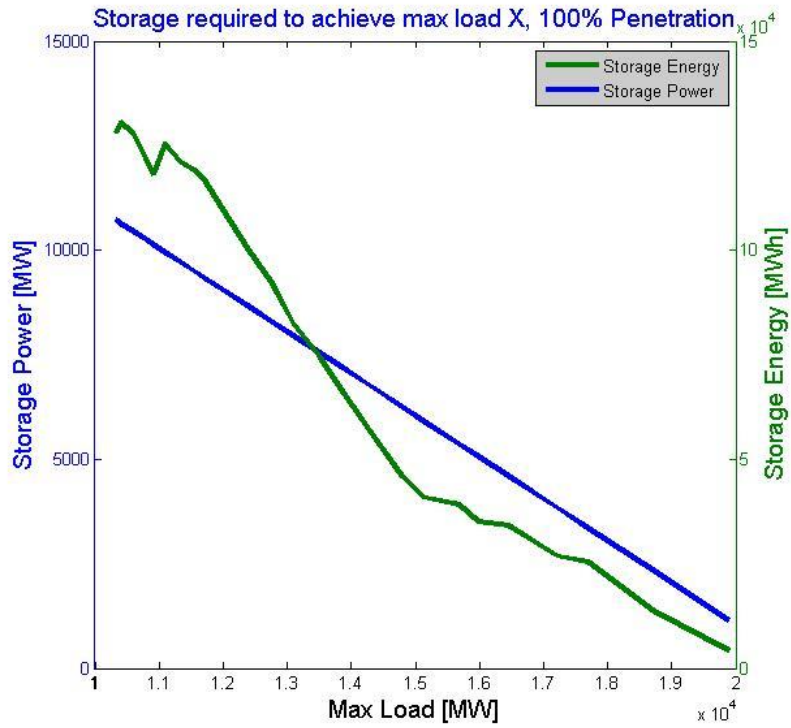
Figure 73 - Long-Term Storage Capacities, 100% Penetration

Figure 73 and Figure 74 show the results for this algorithm operating at wind penetrations of 100% and above. It is important to note here that the efficiency of this theoretical storage system is assumed to be perfect. To the extent that there are energy losses in any real wind-only system, energy from wind will need to exceed energy supplied to the load in order provide for those losses.

Figure 73 Shows the power and energy requirements to achieve a ceiling as low as 10 GW. The right-hand axis now shows storage energy rather than duration as in

Figure 72. This is why the green curve is less linear. Figure 74 shows the amount

of storage required to run a system at various wind penetrations with a net power

ceiling of *zero*. This is the condition under which *no other generators are required*. 100%

wind penetration entails nearly all of the EWITS sites being included in the wind power

output time series. To simulate wind penetrations higher than this the total wind time

series is simply scaled up by scalar multiplication. It can be seen in Figure 74 that the

storage power required decreases linearly with wind penetration. This is due to the

height of the maximum of the load-net-wind time series decreasing as the wind power

time series is scaled up. The required storage energy decreases quickly for wind

penetrations up to around 140% and then begins to level off. The storage power and

energy required to run a wind-only system with 150% wind penetration are

approximately 20 GW and 700 GWh respectively .This corresponds to 35 hours of

storage, and a power capacity 71% of the maximum system load. This is much more

than the larger storage scenario from the previous section, designed to accommodate

50% wind penetration (6 GW and 36 GWh).
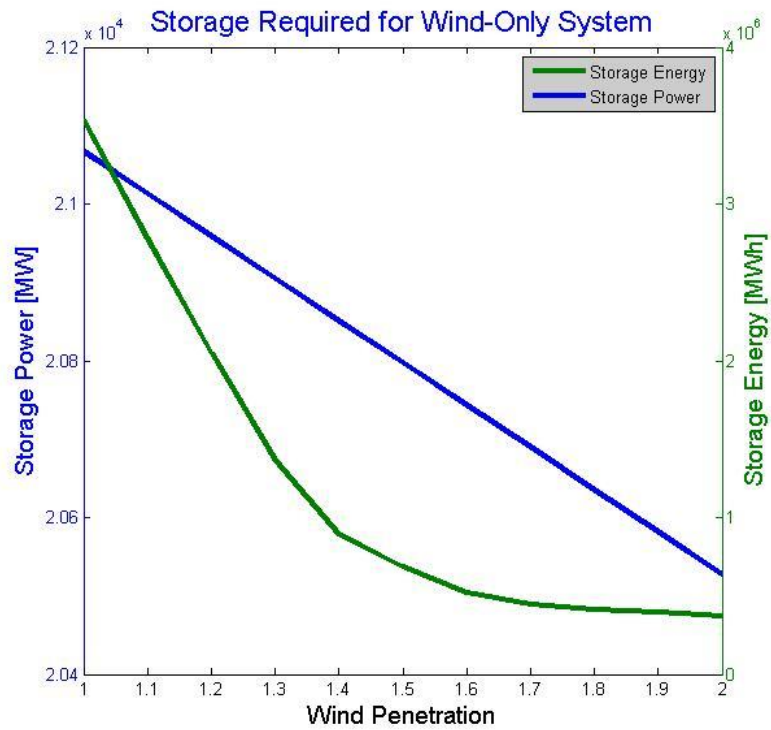
Figure 74 - Long-Term Storage Capacities for Wind-Only System, 100% - 200% Penetration

The meaning of capacity value in scenarios such as these less clear than in the lower penetration situations described in earlier sections. In the absence of conventional generators, the entire system can be energy constrained. This means that the capacity value of storage and wind generation are harder to separate here, than at lower penetrations.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

This study consisted of modelling the New England power system with wind

penetrations increasing to 50%. This was undertaken to estimate the capacity value of

wind power plants under these conditions, and the variability of that capacity value

year-over-year.

Four capacity value metrics were compared in two similar but separate

investigations: a long-term study and a high-wind-penetration study. These four metrics

were compared in their accuracy at estimating long term capacity value based on

limited data and at the inter-annual variability of their estimates.

The long-term study of the capacity value of a few wind power plants, based on

measured data was conducted to investigate the long term characteristics of capacity

value calculations. All metrics increased in accuracy as the length of data used to inform

them was increased. The ISO New England metric was found to be by far the least

accurate at estimating capacity value (but had the lowest variability). The ELCC metric

outperformed all other metrics when it was given four or more years of data to work

with. The Top Load Hours metric and the Linear Fit method performed similarly to one-

another, and were the most accurate metrics when applied to three or fewer years of

data. The large inter-annual variability of wind power CV has two important converse

implications.

1. It is hard to estimate the long-term value of capacity value of a prospective plant based on the one or two years of wind data that might be taken to characterize the wind resource at a site

2. Even if one knows the long term average capacity value for a wind plant or a group of wind plants, the actual capacity performance of these plants may vary widely from year to year, making reliability difficult to achieve.

The high-penetration study investigated the effectiveness of the same four metrics as wind penetrations increased to 50%. This study was based on synthesized wind power output data from the EWITS study. Capacity values ranged from 0.47 for the lowest at low penetration down to 0.08 at 50% penetration. This decrease in capacity value was explained by two main factors:

1. The lower capacity factor wind sites added to the system later in the process tended to be onshore sites with poor summer output.

2. At higher penetration, the high LOLP hours which dominate the ELCC/LOLE calculation were shifted toward times when it was not windy, region-wide.

The penetration level was not a strong predictor of the variability of capacity value metrics.

The effect of storage on this system model was investigated by including a simple, technology-agnostic, daily load-shifting storage model. The capacity value of the wind power plants and the energy storage were considered independently as both were added to the system in increasing amounts. The storage was found to have an ELCC of 65% to 85% of its nameplate capacity, with a tendency to increase slightly in value as

wind penetration increased. The presence of storage had a small, positive effect on wind plant capacity value across all penetration levels.

Wind curtailment at 50% penetration in the absence of storage was found to be about 3%. This number is slightly less than half of the 7% curtailment at 50% wind penetration reported in (Denholm & Hand, 2011). This can be attributed to differences in the temporal alignment of wind and load in New England as opposed to ERCOT (influenced by the large fraction of offshore wind in the EWITS scenarios used in this dissertation). Storage scenarios used in the ERCOT study had larger power capacity, and similar duration to the storage scenarios investigated above, in Chapter 0. Benefits to wind curtailment at 50% penetration were similar. Changes in peak load and effects on LOLE were not investigated in the ERCOT study.

Energy storage has the capacity to change the load shape and reduce LOLE, but in systems with very high penetration of variable renewable energy and large-scale storage, a new framework may be required to ensure system adequacy and to credit those system components with their capacity value in a way that is clear, fair and effective. Energy storage systems obviously do not provide net energy, and only provide capacity value when they are in the presence of generators.

In power systems which include very high wind penetration (above 50%) or similar penetrations of other variable, renewable energy, system adequacy calculations may need to take a different form. The ELCC calculation, based on LOLE, is not well-equipped to handle systems with generators whose output varies hour-to hour, especially if the variability is not independent of the load (as is the case with wind and

solar). With high wind penetration the mechanical availability of wind power plants becomes a factor. Considering wind power output as 'negative load' in these situations does not address this concern.

A framework for ensuring system adequacy in systems with a very high penetration of variable renewable generation should do the following:

1. Characterize system adequacy in power systems with little or no conventional generation

2. Consider system flexibility, as in (Denholm & Hand, 2011), whether that is the ability of the conventional generator fleet to cover fluctuations in net load, or the capacity of storage to accomplish this

3. Identify risks associated with the inter-annual variability of the capacity value of variable renewable generation

4. Credit storage systems and generators appropriately for their capacity contributions

5. Take into account the mechanical availability of renewable generators

In future renewable-heavy power systems, new challenges and opportunities will arise. High penetrations of multiple, diverse variable renewable sources will be easier to integrate than wind alone (Denholm & Hand, 2011).In their planning and operation, very high-penetration power systems may grow to resemble large-scale versions of hybrid power systems (McGowan & Manwell, 1999) more than conventional power grids. Use of electrical energy to run vehicles (either electric vehicles, or with some electrically produced fuel (Morgan, 2013)), can change the characteristics of electricity

consumption and add flexibility to the grid. As fossil fuel plants are phased out, the

functions that renewables must perform on the grid will increase. Studies of system

adequacy will need to remain up-to-date to be effective as the way we produce and

consume electricity changes.

BIBLIOGRAPHY

Ackermann, T. (2012). *Wind power in power systems* (Vol. 140). Hoboken, NJ: Wiley.

Amelin, M. (2009). Comparison of capacity credit calculation methods for conventional power plants and wind power. *Power Systems, IEEE Transactions on, 24*(2), 685-691.

Bartels, M., Gatzen, C., Peek, M., Schulz, W., Wissen, R., Jansen, A., . . . Grebe, E. (2006). Planning of the grid integration of wind energy in Germany onshore and offshore up to the year 2020. *International journal of global energy issues, 25*(3), 257-275.

Barton, J. P., & Infield, D. G. (2004). Energy storage and its use with intermittent renewable energy. *Energy Conversion, IEEE Transactions on, 19*(2), 441-448.

Billinton, R. (2001). Bibliography on the application of probability methods in power system reliability evaluation 1996-1999. *IEEE transactions on power systems, 16*(4).

Billinton, R., & Allan, R. N. (1984). *Reliability evaluation of power systems*: Pitman Advanced Publishing Program.

C.J. Dent, M., IEEE, A. Keane, Member, IEEE and J.W. Bialek, Senior Member, IEEE. (2010). Simplified Methods for Renewable Generation Capacity Credit Calculation: A Critical Review.

Clark, K., Jordan, G. A., Miller, N. W., & Piwko, R. J. (2005). The effects of integrating wind power on transmission system planning, reliability, and operations, Report on Phase 2. *GE Energy*.

Clark, K., Jordan, G. A., Miller, N. W., & Piwko, R. J. (2010). New England Wind Integration Study: Holyoke, Massachusetts: ISO New England Inc.

Corbus, D., King, J., Mousseau, T., Zavadil, R., Heath, B., Hecker, L., . . . Hunt, R. (2010). Eastern wind integration and transmission study. *NREL (http://www. nrel. gov/docs/fy09osti/46505. pd f), CP-550-46505*.

Denholm, P., & Hand, M. (2011). Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. *Energy Policy, 39*(3), 1817-1830.

Dent, C., Keane, A., & Bialek, J. W. (2010). *Simplified methods for renewable generation capacity credit calculation: A critical review.* Paper presented at the Power and Energy Society General Meeting, 2010 IEEE.

Dragoon, K., & Dvortsov, V. (2006). Z-method for power system resource adequacy applications. *Power Systems, IEEE Transactions on, 21*(2), 982-988.

Eckroad, S., & Gyuk, I. (2003). EPRI-DOE handbook of energy storage for transmission & distribution applications. *Electric Power Research Institute, Inc*.

Ensslin, C., Milligan, M., Holttinen, H., O'Malley, M., & Keane, A. (2008). *Current methods to calculate capacity credit of wind power, IEA collaboration.* Paper presented at the Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE.

Fockens, S., van Wijk, A., Turkenburg, W., & Singh, C. (1991). A concise method for calculating expected unserved energy in generating system reliability analysis. *Power Systems, IEEE Transactions on, 6*(3), 1085-1091.

Garver, L. L. (1966). Effective load carrying capability of generating units. *Power Apparatus and Systems, IEEE Transactions on*(8), 910-919.

Hadjipaschalis, I., Poullikkas, A., & Efthimiou, V. (2009). Overview of current and future energy storage technologies for electric power applications. *Renewable and Sustainable Energy Reviews, 13*(6), 1513-1522.

Hasche, B., Keane, A., & O'Malley, M. (2011). Capacity value of wind power, calculation, and data requirements: the irish power system case. *Power Systems, IEEE Transactions on, 26*(1), 420-430.

Hasche, B. U. C. D., Keane, A. U. C. D., School of Electrical,, Engineering, E. M., & O'Malley, M. U. C. D. (2009). Capacity Value of Wind Power: Calculation and Data Requirements. *IEEE transactions on power systems*.

Hittinger, E., Whitacre, J., & Apt, J. (2012). What properties of grid energy storage are most valuable? *Journal of Power Sources, 206*, 436-449.

Holttinen, H., Bettina Lemström, V., Meibom, F. P., & Bindner, H. (2007). Design and operation of power systems with large amounts of wind power. *State-of-the-art report. VTT (Espoo))(= VTT Working Papers, 82). URL: http://www. ieawind. org/AnnexXXV/Publications W, 82*.

Holttinen, H., Meibom, P., Orths, A., Lange, B., O'Malley, M., Tande, J. O., . . . Strbac, G. (2011). Impacts of large amounts of wind power on design and operation of power systems, results of IEA collaboration. *Wind Energy, 14*(2), 179-192.

Holttinen, H., Meibom, P., Orths, A., Van Hulle, F., Lange, B., O'Malley, M., . . . Ummels, B. C. (2009). *Design and operation of power systems with large amounts of wind power: Final report, Phase one 2006-08, IEA WIND Task 25*: VTT.

ISO-NE. (2014a). 2013 ISO New England Electric Generator Air Emissions Report. Retrieved from: http://www.iso-ne.com/static-assets/documents/2014/12/2013_emissions_report_final.pdf

ISO-NE. (2014b). ISO New England Website. from http://www.iso-ne.com/

Keane, A., Milligan, M., Dent, C. J., Hasche, B., D'Annunzio, C., Dragoon, K., . . . O'Malley, M. (2011). Capacity Value of Wind Power. *Power Systems, IEEE Transactions on, 26*(2), 564-572.

Manwell, J. F., McGowan, J. G., & Rogers, A. L. (2010). *Wind energy explained: theory, design and application*: John Wiley & Sons.

McGowan, J., & Manwell, J. (1999). Hybrid wind/PV/diesel system experiences. *Renewable Energy, 16*(1), 928-933.

Milligan, M. (2011). Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning. Retrieved from: www.nerc.com

Milligan, M., & Kirby, B. (2008). The impact of balancing area size and ramping requirements on wind integration. *Wind Engineering, 32*(4), 379-398.

Milligan, M., & Porter, K. (2006). The capacity value of wind in the united states: Methods and implementation. *The Electricity Journal, 19*(2), 91-99.

Milligan, M., & Porter, K. (2008). *Wind capacity credit in the United States.* Paper presented at the 2008 IEEE Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century.

Morgan, E. R. (2013). *Techno-economic feasibility study of ammonia plants powered by offshore wind.* University of Massachusetts, Amherst, (January 1, 2013). Doctoral Dissertations Available from Proquest. Paper AAI3556272.

http://scholarworks.umass.edu/dissertations/AAI3556272.

NDBC. National Data Buoy Center Website. from http://www.ndbc.noaa.gov/

NREL. Eastern Wind Dataset.   Retrieved January, 2015, from http://www.nrel.gov/electricity/transmission/eastern_wind_methodology.html

O'Malley, M., Milligan, M. R., Holttinen, H., Dent, C., & Keane, A. (2010). *Capacity value of wind power: summary.* Paper presented at the Paper presented at the 9th International Workshop on Large-Scale Integration of Wind Power into Power Systems, 18-19 October 2010 Québec, Canada.

Pacala, S., & Socolow, R. (2004). Stabilization wedges: solving the climate problem for the next 50 years with current technologies. *Science, 305*(5686), 968-972.

Rached, T. (2008). *Communicating complexity and informing decision-makers: challenges in the data and computation of environmental benefits of renewable energy.* Massachusetts Institute of Technology.

Shaffer, G., & Sarmiento, J. L. (1995). Biogeochemical cycling in the global ocean: 1. A new, analytical model with continuous vertical resolution and high-latitude dynamics. *Journal of Geophysical Research: Oceans (1978–2012), 100*(C2), 2659-2672.

Siler-Evans, K., Azevedo, I. L., Morgan, M. G., & Apt, J. (2013). Regional variations in the health, environmental, and climate benefits of wind and solar generation. *Proceedings of the National Academy of Sciences, 110*(29), 11768-11773.

Smith, J. C., Milligan, M. R., DeMeo, E. A., & Parsons, B. (2007). Utility wind integration and operating impact state of the art. *Power Systems, IEEE Transactions on, 22*(3), 900-908.

Van Hulle, F. (2005). LARGE SCALE INTEGRATION OF WIND ENERGY IN THE EUROPEAN POWER SUPPLY: analysis, issues and recommendations. EWEA.

WEC. Wind Energy Center Resource Data. from http://www.umass.edu/windenergy/resourcedata

Wigley, T. M., Richels, R., & Edmonds, J. A. (1996). Economic and environmental choices in the stabilization of atmospheric CO2 concentrations. *Nature, 379*, 240 - 243.

Zavadil, R. (2005). Minnesota Public Utilities Commission Statewide Wind Integration Study. http://www.uwig.org/windrpt_vol%201.pdf: NYSERDA.