Chapter 17
A Review of Large-Scale Wind Integration Studies in the United States

1. Introduction

This chapter reviews eleven major quantitative regional and national wind integration studies from the U.S. Each of these is summarized and compared with regard to their data sources, methods and conclusions. We place particular emphasis on the operational impacts of wind integration and changes in reserve requirements necessary to maintain system reliability, as well as the statistical challenges associated with developing and analyzing time-series wind power profiles. Based on comparisons among these studies, we suggest areas where improvements in methods are warranted in future studies, and areas where additional research is needed to facilitate future improvements in wind integration studies.

To our knowledge, this is only the second broad review of industrial wind integration studies. The first, by Holttinen et al. (2011), focused primarily on European studies completed before 2007. Since that time a number of large and important studies have been published, which have a number of improvements (as well as some areas that still need improvement); we review these. This review also takes a more detailed look at the statistical challenges associated with wind integration studies, suggesting several directions for methodological improvements and future research.

We review eleven U.S. integration studies published since 2005. These include the U.S. Department of Energy (DOE)'s national "20% Wind by 2030" report (U.S. DOE 2008), two DOE-sponsored follow-up studies covering the eastern (EnerNex 2011) and western United States (GE Energy 2010) and a recent national study by the U.S. National Renewable Energy Laboratory (NREL) (NREL 2012). We also review seven state and regional studies covering New York (GE Energy 2005a; NYISO 2010), Texas (GE Energy 2008), Minnesota (EnerNex 2006), California (KEMA 2010), Nebraska (EnerNex et al. 2010) and the South-central U.S. (Charles River Associates 2010).

While the specific research questions addressed by these studies differ, they generally fall into three broad categories. The first category is the assessment of potential wind resources. These assessments frequently included the determination of when, where and how much wind could be harvested within a given region as well as the creation of net load (load power minus wind power) profiles for the study period. Some studies also calculated other metrics of wind potential such as regional variations in capacity factor or effective load carrying capacity (ELCC), a measure of wind's ability to contribute to meeting peak demand (Keane et al. 2011).

The second broad category focuses on the effects of wind (and in some cases solar) integration on operational procedures and resources. As part of the assessment of the effect of wind on operational procedures, almost all of the reviewed studies estimated the amount of power balancing resources (reserves) required to maintain adequate reliability.

Third, some studies also assessed infrastructure adequacy, looking at the need for and the effect of new investments in transmission, generation, and control/storage technology. Most of these studies also estimated the financial costs of operational changes and infrastructure investments.

Unfortunately, integration studies do not use uniformly consistent terminology when discussing reserve requirements and integration costs. The terminology describing short-term balancing reserves is particularly inconsistent, reflecting both new challenges associated with increased net load variability and also current regional differences in reserve requirements and practices. In most balancing areas, sub-hourly balancing typically involves a combination of sub-hourly dispatch adjustments (often referred to as "load following") and automatic adjustments via Automatic Generation Control (AGC) systems. However, the language used to describe this short-term balancing process is not consistent across studies. For example, several of the studies used the term "regulating reserves" to describe any balancing that occurs on sub-hourly time scales while others used this term exclusively in reference to fast adjustments made in response to AGC signals.

To avoid this potential confusion, we use the terms "regulation" and "regulating reserves" exclusively to refer to adjustments made in response to the AGC system and use "balancing reserves" to refer to all sub-hourly load/wind following reserves inclusive of regulating reserves. A third category of reserves, contingency reserves, must be available to compensate for unexpected plant failures; most studies reported that wind integration did not increase the need for contingency reserves. The system costs resulting from large-scale wind integration come primarily from increased balancing costs (the costs of procuring larger reserve margins, increased plant ramping, etc.) and the costs of additional investments in grid infrastructure. As observed in (Holttinen et al. 2011) only in a few cases did the studies also describe the financial benefits, in terms of fuel costs or emissions reductions, of wind integration.

Conducting large-scale wind integration studies involves massive data collection and modeling efforts. While each study selected data and modeling methods based on its specific objectives, there were common patterns in the data and methods that illustrate the challenges of large-scale wind integration studies as well as the opportunities for scientific advances going forward. Section 2.1 of this chapter discusses the various approaches to wind and net load data collection. Once data were obtained from the data collection and modeling processes, most of the studies performed detailed statistical analysis on the resulting data. Section 2.2 reviews the various statistical approaches to characterizing net load variability in some detail. Section 2.3 discusses the power system modeling methods used to assess the operational and grid stability aspects of wind integration.

Because different studies approached their questions in different ways, their conclusions were also diverse. Section 3 of this chapter highlights the specific research questions raised in each study and the particular methods used to address them. In Section 4 we quantitatively compare the key conclusions from the studies. Because operational issues are a common theme across a majority of the studies, this comparison focuses particularly on the suggested operating policy changes and the estimates of additional reserves requirements needed to support wind integration at varying penetration levels. Section 5 provides our conclusions from this review, and suggests several topic areas where methodological improvements and additional research are needed to facilitate greater insight from future integration studies.

2. Data and Methods for Wind Integration Studies

Wind integration studies generally follow a similar format. After defining a set of research questions, wind data are collected for a set of potentially viable plant locations using a combination of meteorological models, anemometer measurements and historical wind farm output. Next, since both wind and load can have correlated seasonal and weather-related components, historical load data are collected for the same time period. From these synchronized datasets (see Section 2.1) time-series net load data are typically calculated. Wind and load data then are used in a variety of statistical analyses and power system modeling tools, which are used to assess the costs (and, in a few cases, benefits) of wind integration.

When used well, this process can provide valuable insight into the operational effects of large scale wind integration, which can facilitate effective investment and policy planning. However, some statistical and modeling methods may lead to misleading conclusions, and eventually sub-optimal planning outcomes. For example, assuming that wind and load are uncorrelated, or that wind forecast errors are distributed according to Gaussian distributions could lead to an underestimation of balancing resource requirements. Additionally, modeling the transmission system such that power flows can be directed could lead to an underestimation in transmission needs. This section provides an overview and analysis of the data sources, statistical methods, and modeling tools used in large-scale integration studies. In several places, we compare methods to empirical data to understand the strength and limitations of particular approaches.

2.1. Sources of Wind and Load Data

Gathering representative data for potential future wind farms is one the most significant challenges to a successful wind integration study. Three types of wind data were used in the reviewed studies: historical wind plant output data, wind speed measurements from anemometers or LIDAR systems, and mesoscale numerical weather prediction (NWP) model data. Data from each of these sources offer trade-offs in terms of quality, time resolution, generalizability and availability.

Data availability is particularly challenging because historical wind plant performance data are almost always proprietary. Efforts to release data more openly substantially advance wind integration research. For example, NREL's efforts to publish much of the data behind their EWITS (EnerNex 2011) and WWSIS (GE Energy 2010) studies, as well as BPAs publication of historical 5-minute wind power production (BPA 2013), are particularly admirable. On the other hand, the U.S. Federal Energy Regulatory Commission recently declined to obligate transmission system operators to share data from "Variable Energy Resources" with other entities (FERC 2012), a setback to data availability.

2.1.1. Historical wind plant data

Historical data from existing wind farms give an accurate picture of the statistical properties of real plant production, including the effects of wind variability and the effects of curtailment. High sample rate (1-minute or faster) data make it possible to more accurately model the effects of wind on balancing reserves. Of course, historical wind production data are limited to sites that have existing wind plants. Due to the spatially and temporally specific nature of the wind, results from a few plants are not easily generalizable, except in the important area of understanding the general character of the ratio of fast to slow variations in wind (Apt 2007). In addition, wind farms in many locations are frequently curtailed (required to operate at less than full capacity) for reliability reasons, making the data from these hours non-representative.

2.1.2. Empirical wind speed data

An alternative to gathering wind plant power production data is to gather wind speed data and translate speeds into power. Anemometer or LIDAR wind speed measurements are gathered at most current and planned wind farm locations, but are costly to obtain for other locations at wind turbine hub-height elevations. In the U.S., large quantities of data gathered 10 meters above ground level are publically available (see, e.g., ncdc.noaa.gov), but accurately estimating wind speeds at hub height from 10 m data is potentially unreliable because of its reliance on assumptions about atmospheric stability and surface roughness.

Even if wind speed data are available they need to be converted into wind power data. While it is straightforward to convolve time-series wind speed data with a manufacturer's power curve, the results may not accurately reflect the production from actual wind farms (see Figure 2.2). An anemometer measures wind speeds at a single point in space, whereas a plant produces power based on many speed vectors across the farm. Also wind turbines create shadowing that is not easily modeled. Given these challenges, there is need for more research to develop speed-to-power translation methods based on the statistical characteristics of wind farm power production data. The EWITS and WWSIS studies (EnerNex 2011; GE Energy 2010) are notable for providing detail and validation on the methods used for speed-to-power translation (Pennock 2012; Potter et al. 2008).

2.1.3. Data from Numerical Weather Prediction models

The final alternative is to generate data for potential wind farm locations using mesoscale numerical weather prediction (NWP) models, calibrated with weather data (wind speeds, temperatures, etc.) from a historical time period, using a process known as data assimilation (e.g.,(Stauffer and Seaman 1994)). Because of the ability to generate data for wind farms at any on- or off-shore location, almost all of the studies used NWP models in some form. A majority of the U.S. studies (Charles River Associates 2010; EnerNex 2011; EnerNex et al. 2010; GE Energy 2005a, 2008; NYISO 2010; U.S. DOE 2008) used data from the commercial firms AWS Truepower (formerly AWS TrueWind) and 3Tier. Mesoscale models have the advantage of producing wind speed data for locations without the need for costly anemometer installations. However, NWP data must be used cautiously. A number of studies have shown that mesoscale models under-estimate the high-frequency variability in wind speed data (e.g., (Skamarock 2004)). In a few cases, this difference has been noted in detailed literature about the generation of wind datasets (EWEA 2009; Potter et al. 2008), but it is relatively uncommon for wind integration studies to address the under-estimation of short-term wind variability in any depth.

To illustrate this reduction in high-frequency variance, we calculated the average power spectral density (PSD) for the wind speed data released with the EWITS and WWSIS studies. To do so, we computed the PSD using a fast Fourier transform (FFT) of the 10-minute data for 100 randomly selected EWITS and WWSIS sites, and averaged the spectral power at each frequency over all 100 sites. Since the PSD of wind speed data generally follow the Kolmogorov spectrum ($PSD \propto f^{-5/3}$) for frequencies in the inertial subrange (Pope 2000) (in our case for $f >$ $(1/24$ hrs)) we show the data before and after dividing the PSD by $f^{-5/3}$ (see Figure 17.1). The results show that at frequencies greater than $5\text{x}10^{-4}$ Hz (periods of 30 minutes or shorter) data from the model have almost an order-of-magnitude less spectral power in wind speeds than in observed wind data. While this reduced variability is particularly notable for wind speed data, the effect on wind plant power variability is somewhat less than that implied by Figure 17.1, since (as previously mentioned) wind farm production is the average of many wind speed vectors convolved with a particular turbine's power curve. Katzenstein et al. (Katzenstein et al. 2010) show that increasing the number of turbines/wind farms does reduce the high-frequency variability. In their study, the spectrum from 20 wind farms was proportional to $f^{-2.56}$.

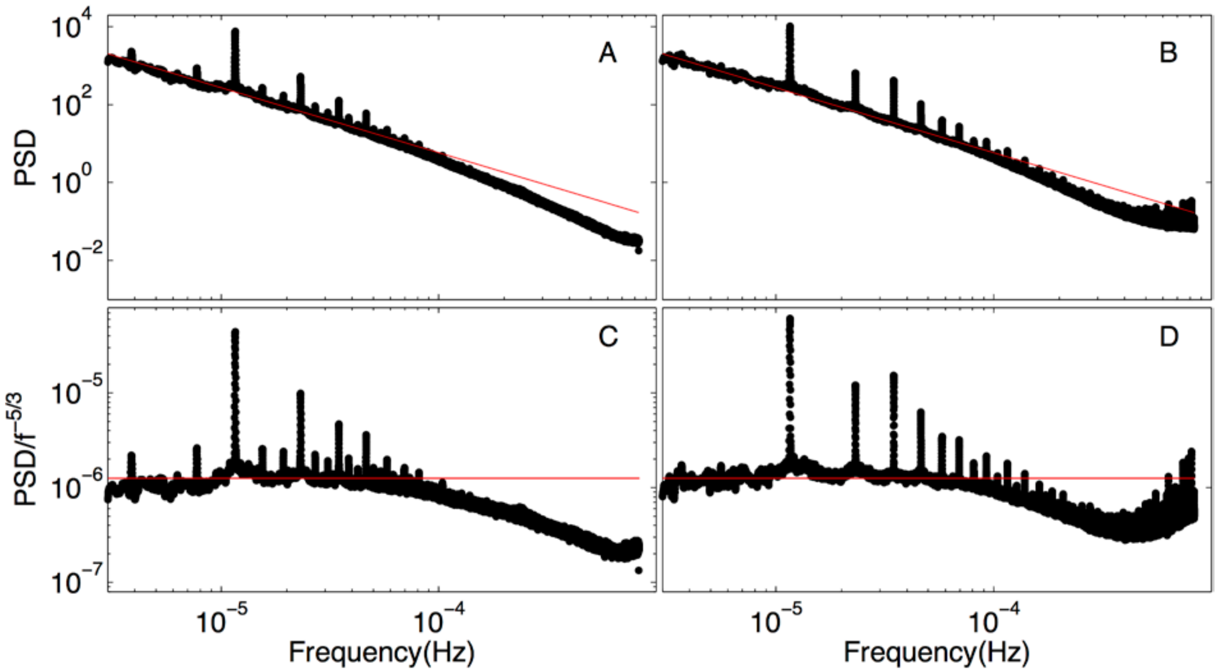

Figure 17.1. Average power spectral density of 10-minute wind speed data generated for the WWSIS (GE Energy 2010) (left) and EWITS (EnerNex 2011) (right) studies. Panels A and B show the data with lines showing the Kolmogorov spectrum ($f^{-5/3}$). Panels C and D show the same data after dividing by ($f^{-5/3}$). Note that the EWITS graphs come from the updated dataset posted in June 2012. The original dataset (Brower 2009) showed less PSD at higher frequencies.

To the extent that reduced wind speed variability affects wind power variability, this reduced PSD could have an effect on conclusions regarding grid reliability and integration costs. The costs of variability come from a combination of increased requirements for regulation, load following and unit commitment. Since unit commitment occurs over longer time scales (one-three hour time intervals), this reduced variability is unlikely to substantially effect unit commitment cost estimates. However, estimates of load following and regulation requirements (balancing reserves) are likely to be at least somewhat affected by this phenomenon. In order to correct for this issue in the WWSIS dataset, Potter et al. (2008) used empirical data from several power plants to develop stochastic power curves with added variability; to our knowledge, this is the only reviewed study that did so. It is possible that the method used in (Potter et al. 2008) was an over-correction, since (Milligan et al. 2012) reported that data resulting from this method include more high-frequency variability than they found in historical plant data.

Another challenge in the production of representative mesoscale data is stitching together data from many shorter model runs in a way that does not produce discontinuity along the seams. Problems with seams were observed in the public WWSIS (Lew 2009) and EWITS datasets, and in the latter case, ultimately corrected (Pennock 2012).

Finally, NWP models are computationally intensive and limited in spatial and temporal resolution. The NWP models used in the earliest wind integration studies had a spatial resolution of 8 to 10 km and a 60 minute sampling rate (see, e.g., (GE Energy 2005a, 2008)). More recent NWP models produce output with 2 km resolution and a 10-minute sampling frequency (see, e.g., (EnerNex 2011; GE Energy 2010)). Wind data sampled at a rate of only a few (or one) samples per hour are useful for some applications, such as unit commitment modeling and capacity value estimation, but are insufficient for estimating the effect of higher frequency variability on balancing reserves.

For this reason, several studies supplemented NWP model data with minute-by-minute or even second-by-second, historical plant output data to create hybrid, minute-by-minute data sets (EnerNex 2011; GE Energy 2005a, 2008, 2010). The hybridization process involves extracting de-trended variability from historical plant data and adding the resulting time series to the NWP outputs. While this approach was used in several of the studies to estimate balancing reserves requirements, none of the studies (perhaps due to the non-public nature of power plant data) provide detailed validation of the statistical properties of the hybrid high-resolution data. Validation of hybrid data is crucial since historical wind data tend to be limited in geographic scope, coming from a single wind plant (GE Energy 2005a) or small number of wind facilities in a limited geographical region (EnerNex 2011; GE Energy 2008). An alternative to combining the model data with plant data, proposed in (Rose and Apt 2012), is to synthesize data using frequency-domain statistical methods.

2.1.4. Combining wind and load data

Because wind and load are both closely connected to weather more generally, most of the studies reviewed collected load data (P_d) from the same time period as the wind data (P_w), and subtracted them to create a net load (P_n) profile for each time point k, as shown in Eq. (17.1).

$$P_n[k] = P_d[k] - P_w[k], \forall k \tag{17.1}$$

The net load profile provides a reasonably accurate profile of the variability of the wind/load combination, with the caveat that it does not capture the effect of wind turbine pitch control systems, which are increasingly being employed to reduce variability (Xie et al. 2011). In order to examine future scenarios, historical load data are typically scaled based on the expected load in the study year.

2.2. Statistical Analysis of Wind and Net Load data

Once produced, wind and net load time-series data are a source of useful information, when appropriate statistical methods are used to analyze them. Understanding the variability of wind and net load, as well as wind-power forecast data on different timescales provides some insight into the reliability effects of large-scale wind integration.

The most common statistical method, used in almost all of the reviewed studies, is to measure statistical properties of changes in wind or net load over different time intervals (typically ten-minute or one-hour intervals). Step changes are typically calculated by assembling a discrete time-series of power (wind or net load) data, $P[k]$ (with a total of K observations), and then computing differences, $\Delta P[k]$, according to Eq. (17.2).

$$\Delta P[k] = P[k] - P[k-1], \forall k \in \{2...K\} \qquad (17.2)$$

Many of the studies computed the standard deviation of $\Delta P[k]$ and draw conclusions based on this measure (e.g. (EnerNex 2011; GE Energy 2005a, 2010; NYISO 2010)). However, the standard deviation does not necessarily convey information about the frequency of low-probability, dramatic changes in wind or net load, which are the primary reliability risks – the main reason that reserves are required.

Using the standard deviation as a measure of variability is a valid assumption if step changes, $\Delta P[k]$, or forecast errors are distributed according to a Gaussian probability density function. However, as noted in (Hodge and Milligan 2011; Holttinen et al. 2008) and illustrated here and in chapter 9, wind data do not follow Gaussian distributions. To illustrate the difference between the Gaussian distribution and wind data, we compared the statistical properties of wind power data to Gaussian probability density functions (PDFs). To do so we measured the 10-minute changes $\Delta P[k]$ in wind power production using Eq. (17.2) for three data sets. The empirical probability density function for $\Delta P[k]$ was computed by counting the number of intervals k for which

$$x - 0.05 \leq \frac{\Delta P[k]}{P_{cap}} \leq x + 0.05 \qquad (17.3)$$

for all x in the set $\{-1,-0.99,...,0.99,1\}$. The resulting counts were scaled to give a total probability mass of one, which resulted in an empirical probability density function for each dataset. Comparable Gaussian probability density functions were determined by computing the mean and standard deviation of the time-series $\Delta P[k]$.

This calculation was performed for three distinct datasets. The first was the output from all 10 GW of wind generation operating in the Bonneville Power Authority (BPA) area in 2010; the second was power output from a 300 MW wind farm in the central U.S. (Plant A) over one year; and the third was power output from a 120 MW wind farm also in the central U.S. (Plant B) over two months. The BPA dataset reflects the combined power production from many wind plants, and thus includes substantial spatial averaging. In all three cases, the tails of the empirical distributions show far greater probability density than one would expect from the fitted Gaussian distributions (see Figure 17.2). For the BPA dataset, we repeated the Gaussian/empirical comparison for the difference between the 24 hour-ahead wind power production forecast. Again, the data show vastly greater weight in the tails than one would expect from Gaussian statistics.

In order to understand how probability densities translate into actual probabilities and step-change occurrence frequencies, Figure 17.3 shows the complimentary cumulative distribution function (CCDF) of $|\Delta P[k]|$ for the 5-minute step changes in the BPA dataset and the equivalent Gaussian cumulative distribution. The CCDF for the absolute value of a zero mean random variable x, such as $\Delta P[k]$, if it is Gaussian distributed, is:

$$\Pr(|x| \geq X) = 2\big(1 - \Pr(x < X)\big), \text{ for } X \geq 0 \tag{17.4}$$

where $\Pr(x < X)$ is the standard cumulative distribution function (CDF) for x. The results in Figure 17.3 illustrate the dramatic extent to which the Gaussian function underestimates the frequency of extreme events.

To further illustrate the difference between Gaussian and observed wind data, we generated a 30-day time series using a mean-reverting Gaussian random walk stochastic process, with the same 5-minute step change standard deviation. The random walk parameters were chosen to produce roughly the same capacity factor as that of the BPA data, and the output was not allowed to go below zero, nor above the maximum from the BPA data. As shown in Figure 17.4(A), the empirical wind data show substantially faster ramp rates over longer time periods than the synthesized data. For comparison purposes, we also show two randomly selected samples of wind power data from the EWITS and WWSIS studies in Figure 17.4(B). While the studies have somewhat reduced high frequency variability, the differences are less clear, relative to purely Gaussian data.

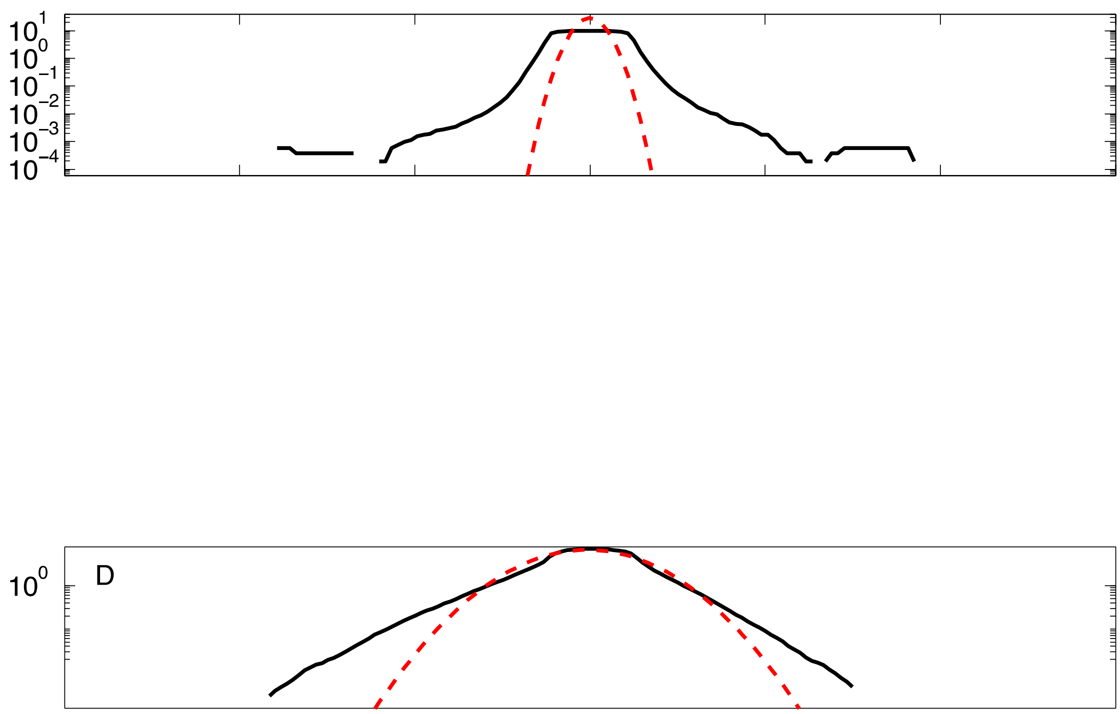

Figure 17.2. Comparison of empirical and fitted Gaussian probability density functions of wind power step changes (A-C) and forecast errors (D). Panels A shows 5-minute step changes from the aggregated wind production in BPA [BPA 2013]. Panels B and C show 10-minute step-change data from a 300 (B) and a 120 (C) MW wind plant. Panel D shows the distribution of wind power forecast errors for the BPA data.

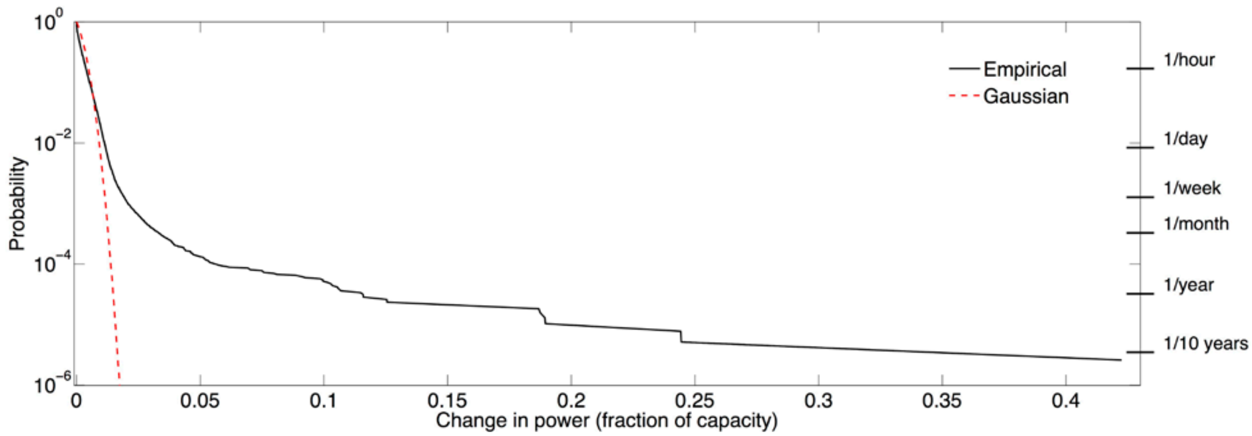

Figure 17.3. The probability (CCDF) of absolute 5-minute step changes that are at least as large as the value on the x axis; based on data from BPA and a Gaussian distribution fit to the data [BPA 2013].

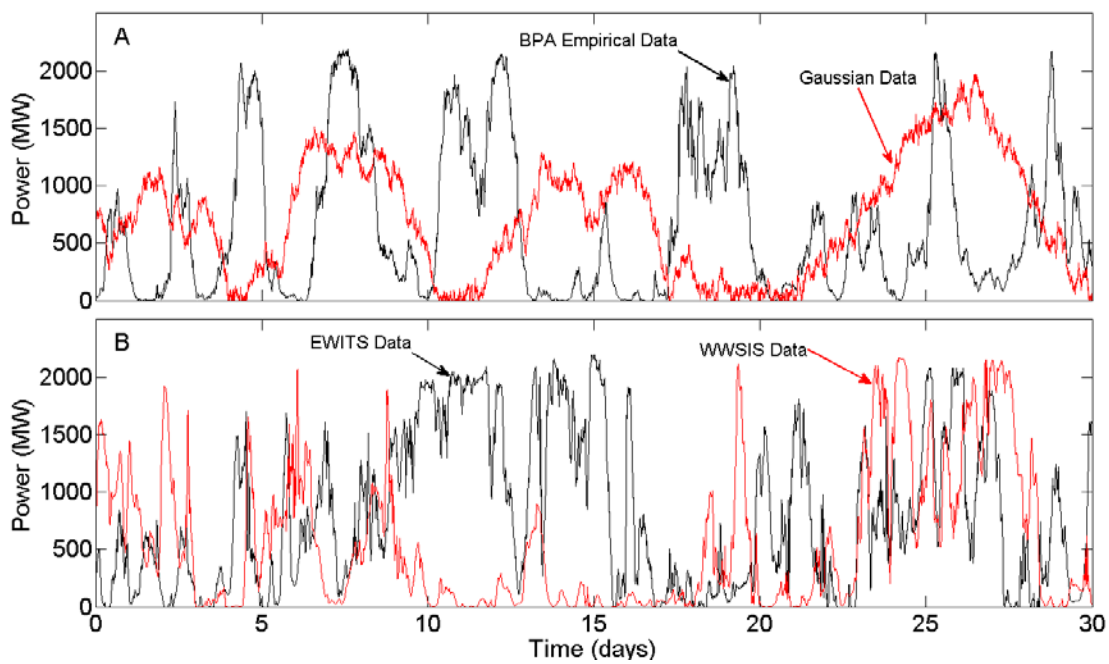

Figure 17.4. Panel A compares the power production of wind farms in BPA to synthesized data generated from a Gaussian random process, with the same standard deviation in step changes. Panel B shows two randomly selected wind power time series' from the WWSIS and EWITS mesoscale data.

While load deviations are not as extreme as wind deviations, the heavy-tailed nature of wind data will cause net-load data to be heavy-tailed for high wind penetration scenarios. A few of the more recent studies (Charles River Associates 2010; GE Energy 2008, 2010) noted the heavy-tailed nature of these step-changes, but most did not.

In spite of the divergence between the Gaussian statistics and wind data, many of the studies in this review establish reserves rules based on the standard deviation (σ) of wind or net load variability. Because the reliability effects of wind production depend critically on the severity and frequency of relatively low-probability events, these statistical differences are very likely to have an effect on conclusions in these studies.

The Gaussian assumption reflects, in part, existing regulatory requirements. NERC requirements for reserves margin, for example, explicitly state that errors within 2σ of expected load variation must be covered without the use of contingency reserves (GE Energy 2010), despite the fact that load step changes also have heavy-tailed distributions. Holttinen et al. (2008) also studied the use of the standard deviation to estimate regulation requirements, arguing that scheduling balancing reserves to cover 2σ - 6σ of net load variability would provide sufficient reliability, however they do not substantiate this claim with reliability modeling.

The SPP study (Charles River Associates 2010) is commendable for estimating reserve requirements without an implicit Gaussian assumption. Rather than using standard deviations of wind or net load for their estimates, they compute the 95 and 5 percentile step change magnitudes to establish up- and down-regulation requirements. A similar approach is suggested in the ERCOT study (GE Energy 2008). The data presented in this section suggest that future studies should explicitly quantify the magnitude of low-probability ramp events for which reserves are needed, rather than basing the estimations on standard deviations.

Another statistical technique found in several studies (EnerNex 2006, 2011; EnerNex et al. 2010), and suggested in (Holttinen et al. 2008), is to develop a combined standard deviation of wind and load by adding the variance (σ^2) of the wind and load step change data, and using the combined variance to represent that of the net load. This technique is valid only if there are no correlations between wind and load, and if the statistics of each are Gaussian, neither of which is accurate.

A much better approach is to compute net load data using equation (17.1) and then compute the sizes of the extreme changes (i.e., the 1 and 99, or 0.1 and 99.9, percentile values for $\Delta P[k]$). While such extreme values seem to be low probability, a 99.9 percentile 5-minute step change will occur once every 3.5 days – a relatively frequent event. Effective planning for low-probability events could reduce the risk of reliability problems due to wind integration, and may allow wind power to be integrated with less curtailment (an increasingly common problem in many U.S. regions, e.g., (Dillan 2013; Gu et al. 2011)).

2.3. Power System Modeling Methods

One of the most important functions of wind integration studies is to determine the capacity of the existing transmission and generation infrastructure to support a proposed quantity or configuration of wind power production, while keeping grid reliability at or above a specified level. Examining step change frequencies in net load can provide some insight into grid reliability, but a detailed understanding of the costs and effects of wind integration, as well as the relative benefits of technologies like grid-scale storage, requires at least some power system modeling.

While there are many ways in which wind generation might affect grid reliability, we can roughly divide these effects into two broad categories. The first is electrical effects on the transmission system that might result in equipment damage, trigger instability or cascading blackouts. Examples of electrical analyses include voltage stability analysis (Vittal et al. 2010), fault ride-through analysis (Seman et al. 2006) and contingency analysis. Since detailed engineering studies of these issues are often performed on a site-by-site basis for individual wind farms, only a few of the reviewed studies (e.g., (Charles River Associates 2010)) include detailed electrical systems analysis. The second type of analysis is of imbalances between supply and demand, and the resources needed to maintain this balance.

2.3.1. An overview of power system models

Power system operators (including independent system operators, balancing authorities, regional transmission authorities, and vertically integrated utilities) must monitor the balance between supply and demand on a second-by-second basis, because of the physics of the system and dearth of electricity storage. When this balance is not maintained the result is that generators in the system speed up or slow down according to the differential equation known as the swing equation:

$$P_m = P_e + D\omega + M\frac{d\omega}{dt} \qquad (17.5)$$

where ω is the rotational speed of the generator, P_m is the mechanical power input to a generator, P_e is the electrical power output of a generator, D is a damping constant that includes friction in the rotating machinery, and M is an inertia constant (Sauer and Pai 1997). When $P_m \neq P_e$ machine speeds (ω) deviate from nominal, causing the frequency of AC voltages to deviate from nominal (50 or 60 Hz). The challenge of power system operations is to maintain the balance between P_m and P_e, while keeping network flows and voltages within limits. The challenge of power system modeling is to accurately capture the many methods used by system operators to solve this problem.

The ways in which variable energy resources (VER) affect grid reliability and the methods used by system operators to maintain reliability differ along different time scales. Ideally, one would use the same grid model, accurately capturing both generator dynamics and power flows, to estimate the effects across all time scales. However, the most sophisticated power system models (dynamic/transient generator models coupled to non-linear transmission network models) are generally too complicated to support analysis covering longer time scales. Even if detailed, fine-grained generator simulations could be run with sufficient computational speed, the results could still be misleading due to the large number of parameters, many of which are not accurately known *a priori*. Therefore different types of models are needed to understand the behavior of power grids along different time scales. The types of models, the times scales on which they typically operate, and the degree to which they address transmission and/or generation effects is summarized in Figure 17.5. These model types are then discussed separately in Sections 2.3.2 through 2.3.7.

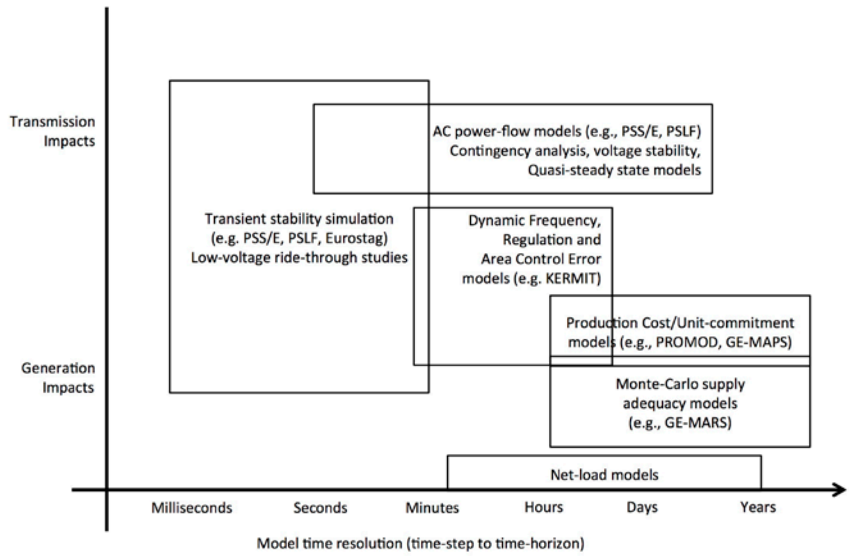

Figure 17.5. An illustration of the time resolution and scope of different types of power system models used in wind (and solar) integration studies.

2.3.2. The simple net load model

The simplest model used in many integration studies is, as previously discussed, the net load model in equation (17.1). A net load profile gives a rough estimate of how quickly generator power production (P_m) will need to ramp in order to maintain the balance between P_m and P_e.

The net load model has some significant limitations, particularly for short time-scale analysis. The first challenge is to obtain accurate wind and load data, with variability at the right time scales. A second challenge comes from the fact that the balance between supply and demand does not need to perfectly balance perfectly at every instant within a given area. The inertia and damping in rotating machines, M and D in equation (17.5), in addition to automatic generator controls, have the effect of averaging frequency deviations across time scales. If one were to estimate that reserves or load-following resources needed to be procured to follow the fastest observed change in net load, one might over-estimate the costs of wind integration. As previously discussed, most of the studies do not look at the worst case changes, but rather use the standard deviation of the step changes in wind, load and/or net load to estimate the amount of regulating reserves that would be required to balance supply and demand. This may indicate that additional balancing resources, beyond those projected in these studies, will eventually be required to mitigate large changes in wind production. Finally, net load models do not represent the transmission system, and thus cannot account for the ability of an operator to quickly exchange power with neighboring operators. When one area has a momentary surplus, power is exported to neighboring areas, and visa-versa. In the U.S. NERC regulates the accuracy with which utilities maintain their internal supply-demand balance through their balancing control performance standards, known as CPS1 and CPS2 (NERC 2011).

2.3.3. Quasi-steady-state network models

An improvement on the net load model that allows one to understand the effect of wind on the transmission system is to explicitly model power flows between locations over a sequence of time intervals. Assuming that one can estimate the load, generation, and wind power at each node, for a sequence of time periods, this type of quasi-steady-state (QSS) simulation can be used to model regional effects of wind plants on power flows. QSS models were used in several of the studies, including (GE Energy 2005a, 2010).

The most accurate QSS models estimate both load and generation for time intervals and use these values as inputs to an AC power flow model. DC models can be a reasonable approximation, if voltages or power losses are not important to the outcome. In (U.S. DOE 2008) power flows were modeled assuming that power flows on individual transmission lines are fully controllable. This is not an accurate representation of real power networks, except for the rare case of flow-controlled transmission lines (e.g., FACTS devices). Since few such lines exist, AC power flow QSS models are substantially more accurate.

However, even the most accurate QSS models have limitations. Estimating which power plants are likely to be operating at what levels for particular time intervals requires production cost modeling (see Section 2.3.4) and capturing second-by-second variations in frequency requires a dynamic model (see Section 2.3.6).

2.3.4. Production cost simulation models

Estimating the hourly (or sub-hourly) state of power plants, with various fuel types and costs, for plausible wind penetration scenarios is both important and difficult. Most of the recent wind integration studies use "Production Cost Simulation" (PCS) software for this purpose. Most of the studies used proprietary PCS tools such as GE MAPS (Charles River Associates 2010; GE Energy 2005a, 2008, 2010), Ventyx PROMOD (EnerNex 2006, 2011), or Global Energy's PROSYM (EWEA 2009). The most sophisticated of these model generator ramp rates, startup/shutdown costs, and transmission limits (typically using the DC power flow model). One study (EWEA 2009) used a research PCS tool, WILMAR (Weber et al. 2009), which was specifically designed for wind integration studies. Each of these tools uses a unit-commitment generator cost model. The most sophisticated models (e.g., PROMOD) solve for power flows and account for transmission constraints.

The evolution of production cost simulations is evident in these studies. The NREL 2030 study (U.S. DOE 2008) used an internally developed PCS model, with detailed cost data for a large area (the whole of the Eastern U.S.), but (as noted previously) a transportation model of electrical flows. The newer studies include substantial detail regarding generator and transmission constraints. Since most of the newer studies used PCS models for 1-3 years of data, with 1-3 hour time increments, the results provide reasonable estimates of the effect of wind power on dispatch and unit commitment costs. Because the time-scales for unit commitment calculations are somewhat longer, the reduced higher-frequency variance found in mesoscale data (Sec. 2.1) should have little effect on unit commitment calculations.

One area in which PCS technology is rapidly evolving (for both PCS and the industrial unit commitment systems that PCS simulates) is the ability to deal with the stochastic nature of renewable generation. The science of stochastic unit commitment is rapidly maturing (see, e.g., (Takriti et al. 1996; Wu et al. 2007)), and there is increasing evidence that effective use of this technology can reduce wind integration costs (Madaeni and Sioshansi 2013). As stochastic methods are effectively adopted in the PCS software used in integration studies, future studies are likely to provide more detailed insight into the benefits, costs and challenges of wind integration.

2.3.5. Supply-adequacy reliability modeling

One of the critical responsibilities of a system operator is to ensure that there is sufficient generation capacity to supply load during future periods of high demand, for many years into the future. The most common standard for supply adequacy is to ensure that there are sufficient supply resources to reasonably expect that shortages will occur not more frequently than one day in 10 years (or not more than 2.4 hours of shortage per year) (NERC 2009).

The most common method for determining the adequacy of a given supply portfolio is to use Monte-Carlo simulation for time intervals (typically one-hour) to determine the annual probability of a supply shortage (Billinton and Jonnavithula 1997; Ghajar and Billinton 1988). Many of the reviewed integration studies used commercial Monte-Carlo models (most commonly GE-MARS, see (EnerNex 2006, 2011; GE Energy 2005a, 2010)) to estimate the effect of wind on supply adequacy. One of the weaknesses in GE-MARS is the limited ability to account for transmission constraints within the model. As with WindDS (U.S. DOE 2008), GE-MARS uses a transportation model of the transmission network (see (EnerNex 2011), p.90). Technology for composite transmission and generation adequacy is relatively mature in the research literature (Billinton and Li 1994), but was not, to our knowledge, employed in any of the integration studies reviewed here.

One the most important reasons for supply adequacy analysis in wind integration studies is to establish rules for setting the capacity credit due to wind plants, since many system operators provide wind plants with financial payments based on their contributions to system adequacy. Since this is a subject of ongoing research (Hasche et al. 2011; Keane et al. 2011), methods for establishing capacity credits varied from one study to another. One particular challenge for setting capacity payments, discussed in chapters 11 and 12, is that, because of the potential for substantial variations in wind speeds from one year to the next (Katzenstein et al. 2010), at least 4-5 years of data are needed to establish accurate estimates of ELCC (Hasche et al. 2011). Also, the siting of renewables and transmission can have a dramatic effect on the capacity value of a wind plant. The EWITS study (EnerNex 2011), for example, found that expanded transmission increased the capacity contribution of wind by approximately 50% (from 16% to 24% of nameplate capacity) by enabling capacity that is not required for resource adequacy in one area to contribute to resource adequacy in another area. This conclusion differed from that of the WWSIS study (GE Energy 2010), which argued that resources outside of a given capacity market should not be considered when determining resource adequacy.

2.3.6. Power system dynamics

The power system modeling methods in Sections 2.3.1-2.3.5 make the assumption, at least implicitly, that there is no imbalance between supply and demand and that voltages in the network are nominal. In reality, momentary imbalances between supply and demand cause small fluctuations in node voltages and small deviations in frequency, which are governed by equation (17.5). Both of these phenomena can, in extreme cases, trigger instabilities in the system, potentially resulting in large blackouts. It is therefore difficult to make confident conclusions about phenomena that occur along short time scales (seconds to minutes) using the steady-state models described above. Since unit commitment and system adequacy are long-time-scale calculations, dynamic models are largely unnecessary for these issues. However, power system stability calculations and estimating the effect of wind on balancing (particularly regulating) reserve requirements depend critically on short time-scale phenomena. While detailed non-linear, transient power system models and one-second data are probably not always required in wind integration studies, there is need for model validation in order to quantify the uncertainty associated with simpler models.

The CEC study (KEMA 2010) presented an illustrative alternative to the net load and QSS modeling approaches to estimating balancing reserve requirements. In (KEMA 2010) researchers developed a composite dynamic model of generators in each of four areas, which together form the U.S. Western Interconnection (known as KERMIT). Each area model captured the empirically-estimated behavior of generators in that area, using a version of equation (17.5). A simplified transmission model was used to connect the four areas. Because KERMIT was substantially more tractable than a fully dynamic model with detailed representation of every generator, it was possible to simulate many different scenarios and estimate the regulating and load-following reserve requirements for several high-penetration renewables scenarios. Because of the explicit way that system dynamics were captured in KERMIT, the CEC study could differentiate between the behavior of fast-ramping storage resources, and slower-ramping fossil fuel plants. As a result the study was able to draw important quantitative conclusions about the economic value of fast-ramping storage. To our knowledge this is the only wind integration study to use dynamic modeling to estimate reserve requirements. While some of the modeling assumptions in KERMIT limit the policy conclusions that can be drawn from the model outputs, using dynamic models to understand the effects of wind is an important area for research (e.g. (Mackin et al. 2013; Wang and McCalley 2013)), which should be incorporated into future integration studies.

3. Summary of studies

In Sections 3.1 to 3.11, we summarize the eleven studies (ordered chronologically) reviewed in this chapter. For ease of comparison among the studies, each summary follows a standard template. The first paragraph states when and by whom the study was conducted, the wind penetration levels assessed (in terms the percent of total energy that is generated by wind annually), and the major research questions that the study addresses. The second paragraph focuses on the study scenarios and the key assumptions about the scenarios, such as changes to the transmission system, changes to the non-wind generating portfolio and changes in market operations and balancing authority size. The third paragraph describes the development of wind and net load profiles used in the study while the fourth paragraph describes the analytical methods employed by the study. The fifth paragraph presents the study’s key findings, with particularly emphasis on changes in reserve requirements. In several cases we add a sixth paragraph discussing notable methodological innovations or challenges associated with each study.

Following the description of the individual studies, Table 1 summarizes the source of the wind data used in each study, the sample rate for this data, the statistical methodology for characterizing the distribution of changes in wind/net load, as well as the power production and power-flow models used to represent the electric systems for each study.

3.1. New York (NYSERDA) 2005

In 2005, GE conducted a study for the New York Independent System Operator (NYISO) and New York State Research and Development Authority (NYSERDA) that modeled 3,300 MW of installed wind capacity, approximately 6% wind penetration on an energy basis, for a 2008 study year (GE Energy 2005a). The study focused on assessing net load variability, determining operational and reliability effects over a range of time scales, evaluating the effect of wind forecast accuracy on the value of wind generation, and quantifying the effective capacity of wind generation.

The 3,300 MW of wind capacity modeled were sited primarily in upstate New York, with a smaller amount of offshore wind capacity. As such this study covered a relative small geographic area compared to several of the other studies. Non-wind generating facilities and transmission infrastructure were derived from NYISO's 2008 system model and were not optimized for wind. Concurrent wind penetration in neighboring regions was not modeled, potentially affecting the analysis of the interchange with these systems. The NYISO operates a day-ahead unit commitment market based on forecasted load. Economic dispatch commands are issued at 5-minute intervals to balance generation with load, so much of the sub-hourly balancing activity is managed through this economic re-dispatch process. Regulation adjustments, made by the AGC system at 6-second intervals, are used to balance variability at the sub 5-minute time scale.

As with several other studies in this review, the study used AWS TruePower meteorological models to generate wind data. These models simulated hourly wind speed data with 8-km grid resolution using historical weather records for 2001 through 2003. Later studies used AWS data with higher spatial and temporal resolution. The researchers applied the hourly wind speeds to the power curve for a generic 1.5 MW turbine and then smoothed the resulting power output with a moving-average filter. The filter slightly reduces the variability in power outputs and was intended to reflect the smoother power output of a multi-turbine wind plant relative to a single wind turbine (GE Energy 2005b). AWS also provided day-ahead and hour-ahead wind forecasts using a Markov chain to generate data with forecast error. In addition, GE created 108 3-hour blocks of wind data with 1-minute output data and six 10-minute blocks of 1-second wind output data. These higher resolution datasets were created by extracting 1-minute/1-second deviations from the hourly trend in plant output at a 105 MW wind project in northwestern Iowa. Scaling these deviations to match the size of the modeled study sites and applying these extracted deviations to the hourly AWS output produced 1-minute/1-second plant output datasets (GE Energy 2005b). Load data from 2001 through 2003 were scaled upward to match projected 2008 load levels.

The authors used a variety of analytical methods in the study. First, they computed standard deviations of net load variability at hourly, 5-minute, and 6-second intervals. As with many of the other studies, GE applied Gaussian statistics to characterize this variability and to assess reserve requirements. Specifically, regulation was set equal to three standard deviations of 6-second net load variability. Second, GE used a suite of simulation programs to evaluate the effect of wind integration on system operating costs, transmission congestion and system reliability on an hourly time scale. GE's Multi-Area Production Simulation (MAPS) program was employed to evaluate the change in system operating costs and its Multi-Area Reliability Simulation (MARS) program was used to assess system reliability effects. Finally, several stability analyses were performed using a QSS model based on GE's Positive Sequence Load Flow (PSLF) and dynamic simulation using GE's Positive Sequence Dynamic Simulation (PSDS) software.

The study concluded that existing NYISO procedures and generators would be sufficient to accommodate the increased variability caused by the 3,300 MW of new wind capacity at all timescales, including the incremental uncertainties cause by errors in wind forecasts. According to the study, maintaining existing levels of control performance would require an increase of 36 MW of regulating capacity, which would constitute an increase in regulating capacity of 0.1% of peak load. As a result of new wind, the standard deviation of net load step changes increased by approximately 6% at the hourly level and 3% at the five-minute level, relative to load alone. These changes are well within the existing capabilities of the existing dispatch capability of the system. Contingency and spinning reserve requirements were not affected by the introduction of wind power. The study also found that power factor correction at the wind generation sites, enabling the plants to operate in the +/- 0.95 power factor range, had significant reliability benefits. Though the study did not focus on economic effects, hourly production cost simulations suggested that new wind generation will result in fuel cost savings in the range of \$40 - \$50 per MWh of wind production, and a decrease in zonal spot prices by as much as 10%. The exact value of these savings depends in part on the ability to incorporate wind into the day-ahead market, with not more than 10% day-ahead forecast error. Given the observed anti-correlation between wind and load, the study estimated the ELCC of inland wind generation to be approximately 10% of their nameplate capacity.

Overall, this study separated the analysis among different time scales in a reasonable manner, and provided specific conclusions about the different types of reserves needed for each time scale. As with other studies that created wind data with fine temporal resolution by hybridizing outputs from NWP models with empirical data from existing wind plants, questions remain about the representativeness of the empirical data, in the case the output of single wind plant in Iowa, and how accurately scaling and applying the variability from these data to the NWP outputs reproduces actual wind output behavior. As is the case in many of these studies, the use of Gaussian methods are problematic for modeling low probability, high effect events, and could result in an underestimation of regulation requirements, particularly given the small size of the 6 second dataset.

3.2. Minnesota 2006

In 2006, the Minnesota Public Utilities Commission contracted with EnerNex to conduct a wind integration study looking at 15%, 20%, and 25% wind penetration on an energy basis, in Minnesota and the eastern Dakotas for a 2020 study year (EnerNex 2006). The study estimated the costs associated with integrating wind power into the existing generating mix as well as the ability of wind to contribute to supply adequacy in Minnesota.

New wind sites for the 15% and 20% penetration scenarios were distributed throughout the study area, while the additional wind necessary to reach 25% penetration was concentrated in a relatively small area with high wind potential. No additional wind capacity was modeled in the larger Midwest Independent System Operator (MISO)[1] footprint, although the entire MISO market was included in the study model runs. As with the majority of wind integration studies, the transmission and non-wind generating infrastructure modeled in the study were those that existed in the ISO's existing model rather than a system that was optimized for wind. In addition,

[1] MISO changed its name to the Midcontinent Independent Systems Operator, Inc. on April 26, 2013.

the entire study area was modeled as a single balancing authority, because MISO was in the process of consolidating a number of balancing authorities. The MISO market structure includes a day-ahead market and a real-time market that clears in five-minute intervals. Variability over time scales shorter than 5 minutes is managed by AGC regulation.

The wind data used in this study were produced by WindLogics using the MM5 mesoscale NWP model with a 5 minute sampling interval (WindLogics 2006). The model conducted three separate year-long simulations initialized with National Center for Environmental Prediction (NCEP) data from 2003, 2004 and 2005. The model was run using "telescoping" spatial resolution to maintain computational efficiency with a base 12 km resolution and a finer 4 km resolution at potential wind installation sites. Wind speeds were translated to power, using a "power plant" (as opposed to single turbine) model, based on empirical data from a 30 MW installation. Wind forecast data were generated using the NCEP NAM and Rapid Update Cycle models used by the National Weather Service. Load data were gathered from Minnesota utility archives for 2003-2005 and scaled to reflect expected load growth for the year 2020.

The study used basic statistical analysis of net load data to estimate reserve requirements. It estimated regulation requirements based on a hybrid dataset, which combined the mesoscale model data with higher resolution data, the details of which are not specified, from NREL. Analysis of the hybrid data showed the output fluctuations of wind to be less the 2% of wind nameplate capacity over an unspecified "regulation time frame." The authors used Ventyx PROMOD, a production cost simulation model that optimizes plant outputs based on hourly load, transmission, available generating units and required reserve margins, to assess the operational effects of wind integration. Reliability analysis in this study was conducted using GE MARS and a program called Marelli by New Energy Associates to ensure that system adequacy remains above a loss of load probability (LOLP) target of 2.4 hours per year. Wind power was represented in MARS as a load modifier. The ELCC of wind was estimated by comparing runs with and without this load modifier.

One of the main conclusions in this report was that increasing spatial diversity dramatically reduced the number of periods without significant wind generation, and thus reduced requirements for reserve generation capacity, given the assumptions in the study. Nonetheless, the study found that wind integration required additional balance and regulating reserves. Overall balancing reserves increased by approximately 2% of peak load in the 25% wind case, including an increase in regulation equal to 0.1% of peak load. The annual cost imposed by wind variability and uncertainty depended on the level of wind penetration and on the specific wind profile for the study year. The study found that, relative to dispatchable generation, wind imposed additional costs ranging from $2.11 per MWh (15% wind, 2003 baseline weather data) to $4.41 per MWh (25% wind penetration, 2005 baseline weather data). The authors found that combining balancing authorities significantly decreased certain ancillary services requirements, including balancing reserves (both regulation and load following) by approximately 50%. The study suggested that wind development would have modest effects on changes in net load along regulation (5-10 minute) time scales, and larger effects on hourly step-changes. The study also suggested that ELCC varies substantially (between 5% and 20% of nameplate capacity) from year to year.

This study had many positive attributes. It obtained 5-minute wind data from a respected weather simulation model, included a relatively accurate transmission system model (through PROMOD) in its simulations and the unit commitment method was appropriate for hourly analysis. However, there are a number of shortcomings to the sub-hourly analysis, which depended heavily on Gaussian statistics to calculate balancing reserve requirements. The reliability models were hourly models, whereas the study modeled 5-minute data, leaving a short-term analysis gap. The assumption that wind fluctuations on the regulating time scale were less than 2% of nameplate capacity and uncorrelated to load fluctuations is poorly supported in the report. Finally, as the authors note, the results obtained in this study depend heavily on Minnesota's participation in the larger MISO market, for which increased wind was not modeled; therefore the effective wind penetration levels could be considered to be lower than the stated 15%, 20% and 25% penetration levels.

3.3. Texas (ERCOT) 2008

In 2008, GE produced a wind integration analysis for the Electric Reliability Council of Texas (ERCOT) (GE Energy 2008). The study examined five scenarios with between 0 and 15,000 MW of wind capacity, representing 0 to 17% wind penetration on an energy basis. The study assessed the level of ancillary services required, as well as the cost of procuring those services, for each wind scenario.

The 5 wind scenarios in the study consisted of a 0 MW, a 5,000 MW, two 10,000 MW and a 15,000 MW scenario. The two 10,000 MW cases differed in the spatial distribution of selected wind sites. The study assumed that the non-wind generation portfolio remained constant (i.e., no generators are added to or retired from the model). Since Texas policy is to develop the transmission system to support new renewable generating capacity (GE Energy 2008), existing transmission constraints were not considered in this analysis. Additionally, ERCOT is not synchronously interconnected with other systems, so wind penetration outside the study area was not a consideration. At the time the study was performed, the ERCOT ancillary service market consisted of regulation, responsive reserve, non-spinning reserve and replacement services. Both ERCOT regulation and responsive reserves provide services that fall into the balancing reserve category describe in the introduction. As with many of the studies, the ERCOT study illustrated the lack of consistency in reserve nomenclature and categorization; in the study ERCOT's "responsive reserves" also act as contingency reserves. The study assumed 5-minute economic dispatch at the nodal level, a procedure ERCOT adopted in 2009.

Based on 2005 and 2006 meteorological data, AWS TruePower developed two years of hourly wind data for this study using a mesoscale meteorological model with 10 km spatial resolution. These data were converted into hourly power output using performance curves for typical wind turbines after adjusting for wake interference. Minute-by-minute variability in power output was extracted from one-minute resolution, historical data from wind plants in Texas and applied to the simulated hourly data set to create a hybrid two-year, minute-by-minute wind production data set. Because they appeared much more frequently then would be seen if changes in wind output followed a normal distribution, changes in the 1-minute historical power data greater than 5% of nameplate capacity were assumed to reflect curtailment events or other non-wind phenomenon and were excluded from this process. AWS also provided next-day and four-hour ahead wind forecast for the study period. Analysis of load was based on actual minute-by-minute load data for 2005 and 2006.

The study used statistical analysis to characterize net load, the correlation between wind and load, and regulation deployments. Gaussian statistics were used to characterize variability, but regulation requirements were specified based on the larger of the 98.8th percentile of regulating events in the same month in the preceding year or of the preceding month, after removing fast ramps from the data as specified above. Regulating events were defined as the difference between net load and the economic dispatch for each 5-minute increment. Hourly production cost simulation was conducted with GE MAPS. Outputs from the MAPS simulations were used to determine the generating capacity available to provide regulation in each hour. The study did not include any transmission modeling or identify transmission constraints in the system.

The authors concluded that load and wind generation forecast errors were essentially independent and that severe errors in both forecasts were unlikely to occur in the same hour. Moreover, while net load forecast accuracy decreased as wind penetration increases, the largest wind forecast errors tended to underestimate wind generation. This increased operating costs by increasing reserve requirements, but did not decrease system security. Because of the increased variability in net load, regulation and reserve requirements also increased with increased wind penetration. At the one-minute time frame, net load variability was found to increase linearly with wind penetration. The average increase in regulation deployment with 15,000 MW of wind was 18 MW but this increased to 54 MW of up-regulation and 48 MW of down-regulation at the 98.8th percentile, which represent an increase in regulation of approximately 0.08% of peak load, which is quite small. Sufficient capacity was available to provide up-regulation in all hours but changes in commitment and dispatch procedure may be needed to meet all down-regulation needs. Overall, the study concluded that 15,000 MW of wind could be added to ERCOT without dramatic changes to operating procedures. It is worth noting, that as of 2013, ERCOT has over 10,400 MW of installed wind capacity (ERCOT 2013). The authors noted that this conclusion assumed that the current mix of thermal generation will remain constant and that if wind penetration caused plant retirements, the ancillary services market could be negatively affected.

This study was one of only two, along with (Charles River Associates 2010), which set regulation requirements based on a threshold, in this case the larger of 98.8th percentile of the regulation deployment rather than establishing the regulation criteria based on the standard deviation of net load. Given the non-Gaussian nature of wind output this approach is likely to produce more accurate results, relative to using the standard deviation approach. The creation of the hybrid wind dataset, however, systematically eliminated the most extreme wind ramping events from the historical plant data. While the authors correctly stated that many of these events are due to curtailment or other non-wind speed factors, the data in Section 2 show that this outlier removal process may exclude operationally important wind variability from the final dataset. Conversely, since the geographic diversity of the selected wind sites is somewhat limited, variability may be lower than was modeled in the study.

3.4. United States 20% Wind (NREL) 2008

Sponsored by U.S. DOE, NREL's "20% Wind Energy by 2030" (U.S. DOE 2008) was a very broad report on the feasibility of 20% wind penetration of at the national level. Much of the study was a high-level discussion of wind power technology, manufacturing, and environmental effects. The quantitative portions of the study focused on identifying the wind resources and transmission capacity additions needed to supply 20% of electric energy from wind and the costs and benefits associated with this scenario, rather than detailed analysis of the operational effects of wind power. Because of its broad goals, it is not an "integration" study in the same sense as other studies in this review. However, given that this report is widely cited in the literature, and to illustrate the evolution in wind modeling approaches, it is included in this review.

As stated, the study considered a single scenario with 20% penetration on an energy basis, which required the construction of 293 GW of wind capacity. The study used a large optimization model to choose an optimal subset of potential sites, resulting in 50 GW of new offshore wind, primarily along the eastern seaboard, and 243 GW of new land-based wind capacity. The 20% scenario was compared to a base case that assumed no expansion of wind or other renewables beyond the installed capacity in 2006.

The wind data for this study came from state-by-state, seasonal and diurnal capacity factor estimates from AWS True Power and National Commission on Energy Policy/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis data. These capacity factors were applied to state wind speed maps from a variety of sources to estimate available wind power at different wind speed classes.

The study used an engineering-economic optimization approach to reach its conclusions. The study included a broad analysis of the costs associated with building new transmission to meet increased demand for energy. Transmission system modeling was conducted with NREL's Wind Deployment System (WinDS), which models U.S. capacity expansion using a large linear optimization model. WinDS assumed that transmission flows could be fully directed, based on a transportation-style model of transmission connections between U.S. states. WinDS did not model existing flows in the power network, but rather assumed that 10% of the existing interstate transmission capacity could be used to move new wind power.

The study concluded that the 20% wind scenario would require the construction of an extensive 765 kV transmission backbone across the country. However, it was not transparent how the modeling results lead to this conclusion. The study proposed only two lines linking the western mid-Atlantic states to the East coast and no transmission was added to link to the southeastern states. Given the transmission bottlenecks in the Eastern U.S., this imbalanced transmission footprint was somewhat surprising. It is possible that this could be a result of the approximate transmission system model used for this study. In addition, the study found that the additional cost of including 20% wind penetration would only be 2% over the base-case cost, though they conceded that this assumed rather optimistic cost and performance assumptions for both wind and conventional units.

This study was notable for being the first to catalog, in a systematic way, the available wind power at various wind speed class levels at a national level. Relative to more recent integration studies, however, this study had a number of weaknesses. The wind data, derived from a variety or source using different techniques, lacked the consistency and spatial and temporal resolution of the data used in other studies. Additionally, using a transportation model of the power grid, as included in WindDS, made it difficult to determine the extent to which the transmission construction results are accurate.

3.5. California (CEC) 2010

In 2010, the California Energy Commission (CEC) released a report produced by KEMA, Inc. (now DNV KEMA) that examined scenarios in which renewables energy resources (wind and solar) contributed 20% of total energy for 2012 and 33% of total energy in 2020 (KEMA 2010). The study's primary focus was to determine the optimal use of grid-connected storage to provide ancillary services and meet NERC standards when renewable energy resources provide a significant portion of the energy used within the California ISO.

In order to consider the effect of seasonality, the 20% and 33% penetration scenarios were modeled for one day in each of February, April July and October in both 2012 and 2020. The model treated each of California, the Southwest, the Northwest, and the mountain region (Colorado and Wyoming) as tightly connected groups of generators. The model assumed no additional renewable generation outside of California. Planned generating unit retirements and planned unit repowering were also included in order to provide a relatively accurate picture of the scenario years.

The California ISO provided historical demand, photovoltaic and concentrating solar generation, wind generation, conventional generation, as well as frequency and interchange data at 4-second resolution for the four base days in the study: Wednesday July 9, 2008; Monday, October 20, 2008; Monday, February 9, 2009; and Sunday, April 12, 2009. The 4-second wind data came from two hubs within California and were scaled up to match the studied penetration scenarios. Approximately one third of the future wind capacity was assumed to be in the BPA control area in the neighboring Northwest market and 50% of this wind power was assumed to be levelized (with no variability) prior to import into the California ISO. Wind forecast data were synthesized based on historical forecast errors for the base days. For the purposed of model calibration, the California ISO also provided 4-second data on a large number of parameters, including system frequency, Area Control Error (ACE), interchange schedules, and total system generation for all areas modeled in the analysis. Forecast errors were assumed to be similar to those for existing wind power plants, and unchanging over time.

The central modeling tool used in this study was a dynamic model developed by KEMA, known as KERMIT, a calibrated dynamic simulation, which was designed to provide second-by-second frequency and inter-area interchange data for 24-hour periods (see section 2.3.6). Within each area, generators were modeled using dynamic models that accounted for generator ramp rates, rotational speeds, frequency control systems and the control actions of balancing authorities to regulate flows in and out of each area (regulation). Using KERMIT, the study estimated the need for regulation services and the role of storage in supporting these regulation requirements. This was the only study in this review that estimated regulating reserves using dynamic modeling.

The study found that sustained but opposite ramping of load and wind in the mornings and evenings had the largest effects on system performance. Overall, the authors concluded that California would need to add balancing reserves equal to approximately 0.7% of peak load for the 20% case and 2.1% of peak load in the 33% case. Notably, the study concluded that to reach 20% or 33% renewable penetration California would need to invest in substantial amounts of high ramp-rate power resources. The report argued that storage could provide balancing services with lower greenhouse gas emissions than would result from the use of thermal plants for balancing. Because of faster ramp rates and the ability to both generate and consume power, the study found that a 30-to-50 MW storage device could be as effective, in terms of regulating frequency to within limits, as a 100 MW combustion turbine used for regulation. The study did not conduct an economic or benefit-cost analysis for these options, however.

As the first integration study to used detailed dynamic modeling of regulating reserves, the dynamic modeling approach used in this study has substantial methodological value. The generalizability of the study's conclusions about balancing reserves was fairly limited, however, due to the very limited quantity of wind data used.

3.6. Nebraska 2010

The 2010 Nebraska Statewide Wind Integration Study examined varying penetration levels of wind in the area covered by the Nebraska Power Association (NPA) for the year 2018. NPA conducted the study on behalf of NREL, with help from the EnerNex Corporation and Ventyx, in order to quantify the effect of wind integration costs and determine the merit of alternative transmission and penetration scenarios, particularly with respect to the necessary amount of balancing reserves. The study examined 4 scenarios, with wind penetration levels ranging from 10% of total energy sales to 40% of total energy sales, and was designed to quantify both reserves and wind integration costs in the NPA and greater SPP region, of which the NPA is a part.

The study included a 10% wind scenario, two 20% scenarios, and one 40% scenario. To obtain the desired penetration levels, the study added additional sites to existing Nebraska wind plants based on both the wind resources available and geographic diversity. The first two scenarios (10% and 20%) included only existing and currently planned transmission, although a few transmission constraints were removed without specifying what infrastructure improvements were used to remove these constraints. In the other two scenarios (20% and 40%) an extra high voltage (765 kV) expansion overlay was added. The structure of the overlay was derived from a previously developed proposal for the SPP territory. For each of the four scenarios, penetration levels in the rest of the SPP area were assumed to match the Nebraska levels (i.e., 10%, 20%, or 40%), in order to keep pricing within the region comparatively consistent. Wind penetration outside SPP was set to approximately 6% for all four scenarios, which the authors noted would increase the amount of wind energy exported from SPP.

The data used for the study were taken from NREL's 10-minute resolution mesoscale data estimated for 2004-2006 for wind plants east of the Rocky Mountains, the same data used for the EWITS (EnerNex 2011) study. Regulating reserve requirements were estimated from a hybrid higher resolution wind and load dataset. The study did not provide details of the methods used to develop this dataset. The study used hourly load forecast data for Nebraska from 2004-2006, as well as actual hourly load data for all of SPP for the same time period.

The study used the Ventyx PROMOD IV regional production cost simulation model, which included the transmission network, for cost and dispatch analysis. The four scenarios were each run 3 times, once for each year of data. Day-ahead forecast data were used to produce unit commitment schedules. Additionally, with regard to the cost analysis, the study attempted to model day-ahead, real-time and ancillary services markets (which were not present in the SPP at the time of the study), to represent future market conditions. Within the study, three balancing areas of NPA were fully represented, while the remaining Nebraska utilities were included in the model in aggregate.

The study found that the 10% scenario required additional balancing reserves of about 1% of peak load and the 20% scenarios required additional balancing reserves of just below 2% of peak load. The 40% scenario required additional reserves of close to 4% of peak load. In the 40%

penetration scenario, the inclusion of realistic forecast errors resulted in an 18% increase in combined cycle plant usage, relative to a perfect information case. The study determined that no significant wind curtailment was necessary for any of the scenarios, as all scheduled wind generation was accommodated by re-dispatching other generation sources and exporting excess wind. However, the authors noted that additional transmission would be necessary regardless of curtailment due to a number of constraint violations within the transmission model, but that these constraints were largely eliminated by the transmission overlay. Based on the study's modeling efforts, wind integration costs, including production costs due to wind forecast error and balancing reserves, ranged from $1.32 to $1.75 per MWh (in 2009 dollars) for the 4 scenarios. The authors noted that this estimate could be low if wind penetration outside of SPP exceed than the modeled 6% penetration level.

3.7. New York (NYISO) 2010

Building on the earlier New York wind integration study performed by GE (GE Energy 2005a), NYISO conducted its own study looking at the effect of 3,500 to 8,000 MW of in-state wind capacity, approximately 5% to 12% penetration on an energy basis, on operational costs, market operations and transmission requirements. When the study was conducted, the NYISO Interconnection included 1,275 MW of wind capacity.

The study conducted analysis for three study years, 2011, 2013 and 2018 with progressively higher wind penetration levels. All existing wind sites were included in the analysis and new sites were selected from projects in the NYISO interconnection queue. Wind generation in neighboring regions was not modeled, which may have influenced the accuracy of power import/export results in this study. NYISO uses, and the study simulated, 5-minute dispatch and AGC regulation to provide sub-hourly balancing.

NYISO and AWS True Power developed wind plant data for 1-minute, 10-minute and hourly intervals based on the wind profiles generated for EWITS (EnerNex 2011). Due to the fact that NYISO updates its dispatch schedules every 5 minutes, and that short-term wind forecast data were not included in their dataset, there was a need to simulate 5-minute ahead forecast. This short-term simulation was added to the NWP-derived simulated wind by using the assumption that the wind production in the next 5-minutes would be equal to the current wind production. Combining this with load data produced both a net load time series, as well as a 5-minute ahead net load forecast. The changes in net load, which were used to determine regulation, were calculated by subtracting the changes in wind over 10-minute increments from changes in load over five-minute increments. NYISO developed load profiles internally based on 2005 and 2006 historical load data.

As in most of the studies, the authors used Gaussian statistics to characterize wind variability. The standard deviation of 5-minute net load step changes was multiplied by three to produce monthly regulation requirements. Production cost simulation was conducted using ABB's GridView, which modeled both security constrained unit commitment and security constrained economic dispatch based on transmission network data. To analyze network constraints, transmission path limits were modeled using the PSS/MUST simulation program. PSS/MUST calculated the transmission path capacities, which accounted for uncertainties in interactions between sources and sinks of power, and variability in the dispatch pattern. Once the grid constraints were identified, the group developed several transmission investment plants and performed a benefit-cost analysis for each plan.

The NYISO study concluded that net load variability increases linearly, on all time scales, with wind penetration. It estimated that for each 1,000 MW of wind power added from between 4,250 MW to 8,000 MW, the regulation requirement would increase by 9% due to higher magnitude ramping events. This is a relatively modest increase in regulation requirements, equal to 0.3% of peak load in the 12% penetration case. The study also suggested that the existing NYISO dispatch processes could handle the higher magnitude ramping events that wind generation would bring. To achieve this, some current fossil fuel generation would need to be committed for use in regulation. This study concluded that the 8 GW of wind power would offset 1.6 to 2 GW of fossil-fuel generation. The authors estimated that 9% of potential wind generation would need to be curtailed due to transmission limitations. To reduce curtailment, the study suggested upgrades to the existing high voltage system, rather than the construction of new EHV lines, as other studies have suggested.

The strength of the study was in its analysis of transmission constraints, the upgrades needed to accommodate increased wind penetration and how wind affects current fossil fuel generation. It primary weakness came, as with many of the studies, from it use of standard deviations to estimate regulation requirements.

3.8. Southwest Power Pool (SPP) 2010

In 2010, Charles River Associates (CRA) conducted a fairly detailed study of wind integration in the SPP region (Charles River Associates 2010). This study looked at 10%, 20%, and 40% regional wind deployment, by energy, although the analysis was less detailed at the 40% level. The study conducted power flow analysis in order to identify the transmission upgrades required to minimize wind curtailment. The study also approximated the operational and market effects of wind integration via PCS, which analyzed congestion patterns, unit commitment and dispatch, and the effect of forecast errors.

Wind plants for each scenario were selected from the SPP generation interconnection queue. Because plants in the queue clustered in regions of high wind resource potential, the scenarios included less geographic diversity than some other studies. The baseline scenario included all of the commercial wind generators operating as of February 2009, about 4% wind penetration on an energy basis. For each of the 10%, 20%, and 40% scenarios, comparable wind penetration was assumed to occur in the neighboring regions with high wind potential, which improved the credibility of inter-regional modeling. The SPP region was modeled as a single balancing authority, rather than the 13 balancing authorities that operated within the region at the time the study was conducted, reflecting operation changes anticipated by the end of 2013. This allowed the study to simulate a co-optimized energy and ancillary service market. The simulated market included day-ahead unit commitment scheduling and real-time dispatch signals sent to generators at 5-minute intervals. In addition to the existing transmission infrastructure, several transmission upgrades were considered. These upgrades were selected purely on the basis of improved transmission system operations; no economic analysis was conducted surrounding these upgrades.

As with several of the studies, this study drew on 10-minute simulated wind power data from AWS TruePower. Data from wind plants were scaled to reflect plant-size differences between the sites selected from current generation interconnection queue, and those in the original data set. SPP provided historical hourly load profiles for the years 2004-2006, corresponding to the base years used to generate the wind profiles. Hourly load data for neighboring regions were drawn from FERC filings for 2002.

As with other studies, this study estimated reserve requirements based on the statistical analysis of wind and net load step-change data. However, the study reported more detailed statistics then did most other studies, including 5th and 95th percentile step changes and maximum hourly increase/decrease in net load as well as the more commonly reported mean and standard deviation.

To assess the effects of wind integration on the SPP transmission system, the authors conducted AC contingency analyses for the peak load hour in the summer and winter, the minimum net load in the spring and the peak wind, peak load hour in the fall for the base case and 10% and 20% penetration scenarios. When the contingency analysis found violations of SPP criteria that could not be avoided by shifting dispatch among generators, additional transmission was added to the system. The resulting power flow cases were used to analyze voltage and transient stability as well as available transfer capability. Production cost simulation was performed using GE MAPS, which was used to identify potentially costly transmission constraints, the effect of wind on ancillary service requirements, and the effects of wind forecasting error.

The study's analysis of wind and net load data revealed several interesting points. Because the SPP service area is comparatively flat, wind power production from difference plants had a higher correlation than was reported for other regions. Possibly related to this, hourly changes in wind output exhibited a heavier-tailed distribution relative to that reported in other studies. Net load variability was also shown to vary non-linearly with wind capacity at both the hourly and 10-minute time frame. Rather than using standard deviations to estimate regulating reserve requirements, the study proposed a new heuristic method for calculating the quantity of regulation required to meet NERC control performance standards, based on the assumption wind and non-wind contributions to regulation are minimally correlated. The proposed heuristic for estimating the amount of up-regulation needed, R_{up}, is as follows:

$$R_{up} = \left((0.01L_{peak} + L_{10})^2 + a(\Delta W_{95})^2\right)^{1/2} - L_{10} \qquad (17.6)$$

where L_{peak} was the peak load, L_{10} was a constant used in NERC reliability criteria (CPS2), a was a constant to adjust the relative contributions of wind to regulation requirements, and ΔW_{95} is the 95 percentile step change (increase) in wind. Using this metric, the study estimated that additional regulation equal to approximately 0.05%, 0.2%, and 0.6% of peak load would be required for the 3 scenarios, respectively. While this approach seems preferable to using standard deviations, additional research is needed to determine if this approach would meet NERC requirements for ACE, and if ignoring larger step changes (beyond the 5 and 95 percentiles) would have adverse effects on system reliability. CRA found that there was a need for additional transmission upgrades to transport wind power from the western region to load centers in the eastern portion of SPP. The study noted that selecting sites based on geographic diversity could reduce the need for new transmission. Finally, although wind facilities do not fail as a single unit, the study recommended that the loss of connection to large wind farms be considered when scheduling contingency reserves.

This study stood out as one of the most detailed and thorough in this review. It was one of only a few that included detailed AC contingency analysis, and used percentiles rather than standard deviations to set regulation requirements. While the 5% - 95% 10-minute forecast error thresholds match NERC's CPS2 standard, these threshold still excluded more extreme events that may be operationally important. In addition, the estimation of regulation requirements based on 10-minute, rather than 1-minute, wind data indicates that these results provide an estimate of what is needed to satisfy CPS2, but may understate the regulating reserves necessary to meet CPS1.

3.9. Western United States (WWSIS) 2010

The Western Wind and Solar Integration Study (WWSIS) (GE Energy 2010) was prepared by GE for NREL. The study was designed to assess the operational effects of up to 35% (30% wind, 5% solar) renewable energy penetration for the 2017 study year. Key research objectives included quantifying the potential benefits of geographically dispersed wind sites, balancing area cooperation and improved forecasting/integration of forecasting into the unit commitment process and developing reserve requirement guidelines that adequately account for wind variability.

Geographically, WWSIS focused on the WestConnect service area, which consists of northern California, Nevada, Arizona, New Mexico, Colorado and parts of Wyoming. The study examined 12 scenarios with different wind penetrations and siting criteria. These scenarios were divided into 4 cases, one with 10% wind penetration throughout the Western Interconnection, one with 20% wind penetration in the WestConnect but 10% in the rest of the Western Interconnection, one with 20% wind throughout the Western Interconnection, and a case with 30% wind in WestConnect but 20% wind in the rest of the Western Interconnection. For each of these penetration levels, the study examined three different wind-siting heuristics. The first, the "In Area" scenario, required that each state in the WestConnect achieve the targeted wind penetration level using the best wind resources within that state. This scenario did not include any additional transmission. The second, the "Mega Project" scenario, achieved the wind penetration targets using the best wind resources in the WestConnect without any consideration of state lines. In this scenario, the majority of wind generation was sited in Wyoming and new transmission was added to transport power from this area. Lastly, the "Local Priority" scenario used the best wind sites within the WestConnect, but included a 10% capital cost advantage to resources within each state, resulting in a scenario that was a combination of the In Area and Mega Project scenarios. Wind in the Western Interconnection but outside of WestConnect was always modeled using the "In Area" criteria. Transmission and non-wind generation infrastructure were modeled based on 2017 projection and not optimized for wind integration. The authors noted that increased flexible generation and transmission would likely be available in a 35% renewable penetration case, thus making their results conservative. On the market side, WECC was modeled with 5 balancing authorities rather than the 37 that are currently operating in WECC. In addition, all generators were assumed to be available for least-cost economic dispatch and not encumbered any by power purchase agreements. Generation and interstate exchange within WECC were scheduled on an hourly basis and economic dispatch was modeled at 5-minute intervals.

The 3TEIR Group produced the base wind speed data for WWSIS using the Weather Research and Forecasting (WRF) NWP, based on measurements from 2004-2006. The WRF model provided 10-minute wind speed data with a 2-km spatial resolution, along with day-ahead hourly wind forecasts. To avoid unrealistically accurate forecasts, forecast wind profiles were created using weather data from the Global Forecast System rather than WRF. Unfortunately, the aggregate annual energy from the forecast wind profiles exceeded that of the WRF wind profiles, resulting in forecast errors that were biased upward. To mitigate this problem to some extent, all forecasts were reduced by 10%. Due to the size of the area being modeled, the WRF model was run in 3-day blocks and the data subsequently merged. Though some smoothing was performed at the seams of the 3-day blocks, these days still exhibited more variability than days that did not have seams (GE Energy 2010). For this reason, these days were excluded from the analyses of hourly and ten-minute variability (GE Energy 2010). Because mesoscale meteorological models, like WRF, tend to understate the wind speed variability at short timescales, the modeled wind speed data were converted into power data using a statistical model (SCORE-lite) intended to replicate empirically observed turbine ramping characteristics (Potter et al. 2008). Once the 10-minute power data were generated, analysts developed hybrid 1-minute data based on empirical data from an unspecified number of existing wind plants. Ventyx provided hourly load data for the western region, which were interpolated using a cubic spline to create 1-minute and 10-minute load data. It is important to note that this interpolation smooths out intra-hour variability, which could affect the conclusions drawn from these data.

The study used three main analytical approaches. First, statistical analysis of step changes was used to characterize the frequency and magnitude of wind and net load ramping events over a variety of time scales and determine regulation and balancing reserves requirements. Second, the GE MAPS PCS model and GE MARS reliability model were used to simulate production and reliability on an hourly basis. Finally a MATLAB-based quasi-steady-state (QSS) model with one-minute time steps was used to validate their regulating reserve estimates for selected periods with large changes in wind output.

Along with EWITS (EnerNex 2011), WWSIS (GE Energy 2010) is one of the most comprehensive integration studies. The study concluded that the 35% renewable case is feasible, but that increased net load variability would require additional balancing resources. The study suggests that balancing reserves should equal three times the standard deviation of 10-minute net load or, more heuristically, 3% of load plus 5% of short-term forecast wind. Of these reserves, one standard deviation of the 10-minute net load variability should be available for regulation. In practice, these requirements equated to additional regulation of less than 0.5% of peak load and additional balancing reserves equal to approximately 1% of peak load for the 30 % case. Because existing thermal units would be dispatched less frequently, rather than de-committed to accommodate renewables, the study suggested that up-reserves could be provided from existing generation. In case of a severe over-forecast, spinning reserves may be required to provide regulation resulting in shortfalls in the contingency reserves which could be managed through a variety of means including increasing spinning reserves, storage or demand side management.

The study also suggested several operational changes in order to facilitate wind integration. In particular it found that greater cooperation would be needed between balancing areas, that sub-hourly scheduling should be incorporated into system operation, and that existing transmission infrastructure must be utilized at a higher rate. Sub-hourly scheduling could reduce ramping by load-following generators by approximately 50%. The study also suggested incorporating day-ahead wind forecasts into unit commitment procedures, increasing the flexibility of dispatchable generation and requiring wind plants to provide down reserves. In the 35% renewable case, the results suggested a 40% decrease in system operating costs due to reduced fuel consumption and emissions, neglecting the increased operational cost due to increased net load variability. Finally the study found that wind resources in the study area had a capacity value in the range of 10% - 15% of nameplate capacity using a capacity valuation method that is a few percent more conservative than ELCC.

The WWSIS study (as with EWITS (EnerNex 2011)) was commendable because the 10-minute wind datasets upon which they were based are publically available. The study was also quite clear and thorough in documenting the assumptions behind the analyses. Though issues with the data persist, such as the seam effect discussed above, considerable effort, such as the application of SCORE-lite in WWSIS, went into replicating observed wind outputs over large geographic areas. Unfortunately, the higher resolution 1-minute data are not publically available and the methods used to validate the hybrid data were less well documented. WWSIS included analyses across a wide range of timescales, for the most part using appropriate modeling tools. While the study used standard deviations to estimate reserve requirements, the use of QSS simulation provides some validation of their approach.

3.10. Eastern United States (EWITS) 2011

The Eastern Wind Integration and Transmission Study (EWITS) covered the U.S. Eastern Interconnection (EnerNex 2011) and was in many ways a companion to the Western U.S. study above (GE Energy 2010). Led by EnerNex, the study modeled the Eastern Interconnect in 2024 as though it were managed by seven large balancing authorities with a market structure that used day-ahead bidding. The analysis focused on developing the transmission capacity necessary to support the modeled wind penetration scenarios, assessing the operational effects of wind generation and determining the capacity value that-wind generation could provide.

The study examined four wind penetration scenarios for the 2024 study year. The first three scenarios all considered 20% wind energy penetration with differing wind plant siting criteria. The first scenario focused on onshore generation at high capacity factor sites. This resulted in substantial wind development in the Great Plains. The second scenario shifted more generation eastward and had limited off-shore wind development. The third scenario focused on siting wind plants near load centers. The third scenario had the lowest level of wind development in the Great Plains and the highest off-shore wind development. Finally, the fourth scenario considered 30% penetration with over 300 GW of on- and offshore development.

This study, as with (EnerNex et al. 2010) and (Charles River Associates 2010), used wind data developed by AWS TruePower using the propriety Mesoscale Atmospheric Simulation System (MASS) model (Brower 2009) based on historical weather data from 2004 through 2006. The MASS model data had a 10 minute temporal and 2 km spatial resolution. The authors noted that the model results tend to underestimate wind speed at most sites and that at several sites night time winds speeds were overestimated while daytime speeds were underestimated (Brower 2009). For each site, the raw output from the NWP model was filtered to adjust for model bias, the proportion of the modeled plants that fell within each grid cell, wake effects and other adjustments. Next, the adjusted wind speeds were applied to power curves for IEC class one, two and three turbines. Each of these power curves was a composite of two to three commercial turbines. Finally the results were filtered to reduce variability, reflecting effect of spatial diversity in turbines within large wind plants (Brower 2009). Wind power forecasts were produced for a day ahead, 6-hour ahead, and 4-hour ahead timeframes (EnerNex 2011). In addition, 1-minute interval power output data was synthesized for selected periods based on historical plant data from 17 locations in ERCOT. To create this hybridized dataset, minute-to-minute variability was extracted from the ERCOT data by calculating 10-minute trends using a bicubic fitting process and applying the residuals to the simulated power outputs (Brower 2009). In addition, the study used 2004-2006 load data from the PowerBase database and 2006 power flow case data from FERC (EnerNex 2011).

Transmission requirements for each scenario were modeled using Ventyx PROMOD IV, a deterministic PCS. From the PCS model, hourly transmission flows were calculated, using a use DC power flow model. While the DC model neglected voltage control and reactive power in the network, it was a substantial improvement over the transportation model used in (U.S. DOE 2008) and the report explicitly identified the limitations in the DC model. From the resulting transmission flow data the study suggested that significant transmission investment would be required to support the wind-power deployment in the proposed scenarios. To estimate the costs for this transmission investment, the study chose several potential transmission overlays, including high voltage direct current lines and ultra-high voltage AC lines. As with most of the studies reviewed, EWITS uses the standard deviation of step-change data to estimate regulation requirements. Specifically, they estimate regulation requirements for hour h (R_h) as follows:

$$R(h) = 3\sqrt{\left(\frac{0.01L(h)}{3}\right)^2 + \sigma_{ST}(h)^2} \tag{17.6}$$

where $L(h)$ is the load in hour h and $\sigma_{ST}(h)$ is the expected standard deviation of the wind step changes during hour h. This is internally consistent only if wind and load are uncorrelated, and only if the standard deviation fully characterizes the variability, as is the case with a Gaussian distribution, neither of which is accurate.

The study concluded that 20-30% wind penetrations was feasible, given a substantial expansion of the existing transmission infrastructure and aggregation of many small balancing areas into a small number of large ones. The study estimated overall integration costs for the 20% scenarios at between \$3.10 and \$5.13 per MWh of wind production depending on where wind plants were sited. The integration costs were lowest in Scenario 3 where wind capacity was spread fairly evenly across the study area and highest in Scenario 1 where wind capacity was more geographically concentrated in the Great Planes. Integration costs in the 30% penetration scenario equaled \$4.54 per MWh. The study found wind curtailment of 2% - 10%, given substantial transmission expansion. The authors also presented a range of capacity credit values for wind which vary substantially depending on the wind siting and transmission scenarios modeled. Assuming current transmission infrastructure the study found ELCC values between 16% and 30% of nameplate capacity. With expanded transmission, these values increased to 24% - 33% of nameplate capacity. In all cases, the scenario with wind sited close to load centers produced the highest ELCC estimates. It is worth noting that these values were calculated across multiple capacity markets, a technique which resulted in comparatively high ELCC values and was criticized by the WWSIS team (GE Energy 2010).

In many ways this study was among the most technically sound of those reviewed here. It analyzed a broad set of issues related to wind integration quite well. The authors made a commendable effort to explicitly consider many of the issues that were not included in other studies, most notably transmission constraints. However, as in other studies, the use of standard deviations to estimate reserve requirements without substantial validation was problematic.

3.11. United States 80% Renewables (NREL) 2012

NREL's Renewable Energy Futures report studied the technical barriers to increasing renewable energy penetration in the United States to 80% by 2050 (NREL 2012). As with (U.S. DOE 2008), this study was not intended as a complete integration study but rather focused on the ability of renewable resources to match a high proportion, up to 80%, of total load.

The study modeled several different penetration levels, but focused on reaching an 80% renewable target that included wind and other renewable resources. Different 80% scenarios were developed based on the potential evolution of renewable energy technology, levels of transmission investment, types of storage and demand-side balancing resources and different supply portfolios. In these scenarios, wind power was projected to provide from 32%-43% of overall electricity demand. Sensitivity analysis was performed on both fossil fuel costs and demand growth assumptions. The majority of the scenarios expanded the transmission infrastructure and access to existing transmission capacity to support renewable energy deployment, and the models included the retirement of thermal generation, without allowing for the construction of new units. No assumptions were made about future policy measures, such as tax credits, that could potentially affect renewable deployment.

Wind speed data were assembled from several sources, including mesoscale data from AWS TruePower and anemometer data from Pacific Northwest National Laboratory and other regional entities. Capacity factors for potential wind farms were estimated based on the wind resource class and projected improvements in wind turbine designs – primarily from larger rotors and advanced tower designs. The simulated wind data had an hourly resolution.

This study used two different models for cost estimates: the Regional Energy Deployment System (ReEDS) and ABB GridView. ReEDS is a capacity and transmission expansion model developed by NREL that used linear programming to simultaneously compute optimal dispatch and transmission expansion plans. Like WinDS from (U.S. DOE 2008), ReEDS used a transportation model to model the effect of new transmission. The model also captured some policy issues such as emissions and siting constraints, and reserve requirements. For wind and solar power, the study estimated that balancing reserves were needed to cover two standard deviations of the expected forecast error. ReEDS did not differentiate between different ancillary services, and therefore the study noted that it may underestimate the need for short-term storage. GridView was used to supplement ReEDS because it had a more robust simulation of real-time grid operation. The generation and transmission capacity output from ReEDS was run through GridView to make sure the developed scenario was feasible. GridView also incorporated unit commitment and dispatch and had a DC transmission model.

The study concluded that achieving 80% renewable energy penetration was technically feasible and consistent with renewable resource availability. These conclusions were predicated on significant investments in renewable capacity and transmission infrastructure and increased flexibility in the electric system through a combination of storage, demand-side response and flexible dispatch and ramping of conventional generating units. Because of increased distances from generation sites to load centers, transmission and distribution losses were projected to range from 8.4%-9.5%, up from 6.4% without the additional of new renewables. In the 80% scenarios, 8.1% of wind, solar, and hydropower generation were curtailed. In the higher renewable penetration scenarios, thermal plants were assumed to change roles in the system; natural gas plants were used entirely as peaking plants, and coal plants had increased diurnal and seasonal ramping. However, no market systems were suggested to ensure these plants stayed profitable. Depending on the trajectory of renewable technologies, the study suggests that the retail price of electricity will increase between 21%-45% in the 80% renewable scenario.

This study was unique among the others in this chapter, because of the extremely high penetration levels considered. Given the challenge, it does a reasonable job of describing what changes would likely necessary to reach such a high penetration level. However, the study's transportation model of the transmission network raise questions about the reliability of the transmission investment plans.

3.12. Additional integration studies

While the eleven studies reviewed above are representative of most large-scale integration studies, this list is by no means comprehensive. Here we briefly mention a few additional, notable recent studies.

Two studies looked at wind integration in the U.S. state of Idaho. In a 2007 study (EnerNex 2007), EnerNex looked at the effect of up to 1,200 MW of new wind capacity in the Idaho system, and estimated the operating cost of wind integration to be approximately $10/MWh. A follow-up study in 2013 (Idaho Power 2013) found similar results for the average integration costs, but suggested that the incremental cost of additional wind energy at the higher levels of wind penetration ranged from $15 to $50/MWh.

Using a similar method to the EWITs study (EnerNex 2011), NREL published a wind integration and transmission study for the Hawaiian island of Oahu (Corbus et al. 2010). This study was unique in that it looks at the feasibility of a very high renewables penetration scenario (40% of energy from renewables) in a location without the ability to share resources across regions. The study identified the need for storage, substantial operational changes (such as ramp-rate limits and wind curtailment) and inter-island DC transmission links to support the proposed level of wind integration.

3.13. Related academic studies

In addition to the industry studies reviewed above, wind integration has also received considerable attention in the peer-reviewed academic literature. While a complete review of all related literature is beyond the scope of this chapter, it is useful to note a few particularly relevant research articles.

Several articles have used simplified power system models to study the broader effect of large-scale wind on power system economics and operations. DeCarolis and Keith (2006) used a greenfield model (no existing transmission capacity) to evaluate optimal low-carbon generation scenarios, and found that the variability of wind increased combined fuel and capital costs by about 10%. They also found that there is no threshold beyond which integration costs sharply increase. Denny and O'Malley (Denny and O'Malley 2007) used a detailed power system model, including PCS, to model total system benefits, in terms of fuel savings and emissions benefits, of wind integration. They found that there was a threshold (about 25% penetration by energy) above which the marginal benefits of wind capacity begin to decrease. On the other hand, a more recent study (Budischak et al. 2013) used a capacity expansion model of the PJM territory, without transmission constraints, to look at the optimal combinations of generation and storage required to achieve 30, 90, and 99.9% renewable scenarios. They concluded that it was feasible to achieve very high penetration levels, and, interestingly, that it was more cost effective to over-build and over-generate and curtail renewable generation than it was to build large amounts of storage.

A number of peer-reviewed research articles suggest and evaluate various methods for wind integration studies. Holttinen et al. (2008) suggest the use of standard deviations for establishing the reserve requirements for systems with high levels of wind power, a method that was used in many of the studies reviewed. More recently, Papavasiliou et al. (Papavasiliou et al. 2011) studied a stochastic optimization approach to estimating reserve requirements, and found that this approach substantially outperforms heuristic methods. A number of recent articles suggest, and apply, methods for quantifying costs associated with wind power variability. Mauch et al. (Mauch et al. 2013a) estimated reserves requirements based on day-ahead load and wind forecast uncertainty. They found that the forecast uncertainty is greatest on days when the wind is forecast to be blowing strongly (see also Mauch et al. 2013b), thus there are some days when significant reserves are required, and other days when much smaller reserves are needed. Because of the additional uncertainty associated with estimating the reserves that are needed to cover 95% of the day-ahead forecast errors, Mauch et al. (2013a) find reserve requirements substantially higher than those reported in many of the studies reviewed here. They suggest that a dynamic method should be used to schedule reserves, based on the day-ahead forecast values, noting that ERCOT's requirement that operational reserves to cover 95% of the day-ahead forecast errors may not be the most cost-effective method to handle day-ahead uncertainty. Fertig et al. (2012) show that interconnecting wind plants between regions provides a reduction in variability very dependent on the time scale considered; there is only modest benefit in smoothing the large variability at time scales of ~12 hours; the smoothing from interconnection is largely in the ~1 hour variability. Lueken et al. (2012) used regulation prices and data from wind, solar PV and solar thermal plants to estimate the cost of variability from each technology. They conclude that, given their modeling approach, which schedules up and down regulation to match the variability of wind/solar power, variability can add $15-40/ton CO_2 to the cost of abating emissions using these technologies. Katzenstein and Apt (2012) use a similar approach and conclude that wind variability adds $3-$10 / MWh in variability costs and that, as a result, the marginal benefits from wind plants diminish quickly after the addition of only a few additional plants.

A paper by Soder and Holttinen (2008) highlighted different modeling approaches and assumptions that could be used in wind integration studies and made several recommendations about which of these approaches were most desirable. This article suggested, for example, that wind data used in integration studies should reflect the smoothing effect of aggregating large numbers of individual turbines and that dispatch models should include the ramp constraints for thermal generators. Many of the recommendations in (Soder and Holttinen 2008), have been widely incorporated into recent integration studies. The application of other recommendations, such as the full-scale dynamic analysis of the power system, remains relatively rare.

Finally, a paper on best practices for wind integration studies by Holttinen et al. (2013) provided recommendations for wind integration studies, based on the authors' experience with such studies (including several of those reviewed here). Holttinen et al. outlined five steps for integration studies – data collection, system configuration and reserve estimation, capacity estimation, system flexibility, and transmission simulation.

Table 1 Summary of data and methods for reviewed studies

Study	Wind Speed/Power Data Sources	Sample Interval (minutes)	Statistical Methods for Characterizing Net Load Variability and Reserve Requirements	Power System Models
NYSERDA 2005	AWS 8-km met. model Historical plant data from IA	60 1/60	Gaussian methods for reserve calculations	GE MAPS GE MARS GE PSLF and PSDS
MN 2006	MM5 4-km met. model	5	Gaussian methods for reserve requirements	PROMOD GE MARS
ERCOT 2008	AWS 10-km met. model Historical plant data from TX	60 1	Regulation requirements set to the 98.8th percentile of regulation events.	GE MAPS
NREL 2008	AWS, state mapping programs	60	N/A	WinDS
CEC 2010	96 hours of plant data from CA	1/60	Small sample – not characterized	KERMIT
NE 2010	Same dataset as EWITS 2011		Gaussian methods for reserve requirements	PROMOD IV
NYISO 2010	Same dataset as EWITS 2011		Gaussian methods for reserve requirements	ABB GridView PSS/MUST
SPP 2010	Same dataset as EWITS 2011		Reserve requirements based on the 5th and 95th percentile deviations between wind forecast and output.	GE MAPS
WWSIS 2010	3TEIR Group 2-km met. model and probabilistic power output model Historical wind plant data	10 1	Gaussian methods for reserve requirements	GE MAPS GE MARS QSS
EWITS 2011	AWS 2-km met. model Historical plant data from TX	10 1	Net load variability characterized by standard deviations.	PROMOD IV GE MARS
NREL 2012	AWS, state mapping programs	60		ABB GridView ReEDS

4. Comparison of reserve estimation results

While all studies found that increased wind generation increases that variability in net load, several pointed out that existing power system technology and practices were designed to manage load variability and that managing the additional variability from wind was not fundamentally different from managing load variability (GE Energy 2008). In all of the studies, high levels of wind penetration were found to be technically feasible but frequently to require some modifications in system characteristics (e.g., generating mix, transmission capacity, and balancing authority extent) or operating practices (plant commitment scheduling frequency, wind participation in down regulation, etc.). In addition, geographic diversity in wind resources and improved wind forecast accuracy were found to offer substantial benefits. Wind integration was consistently found to require an increase in the reserves required to maintain operational reliability as well as to have an associated economic cost.

Given the substantial focus of almost all of the reviewed studies on estimating operating reserves, this section compares the quantitative reserves estimates from the studies, as well as some key contributors to those findings.

4.1. Reserve Requirements

As noted in Section 1 and in (EnerNex 2011; Holttinen et al. 2011; NERC 2011), the terminology used to define different reserve types has evolved over time and varies from country to country and region to region. NERC defines two reserve types, which are commonly estimated in wind integration studies: regulation reserves that must be responsive to AGC and contingency reserves that are available to cover the unexpected loss of a generating unit (NERC 2011). In addition to regulating and contingency reserves, the concept of load following reserves was also used frequently in these studies. Many of the studies refer to load following resources (sometimes termed reserves), which are not defined by NERC guidelines, and which adjust for changes in net load of periods of several minutes to hours in response to sub-hourly economic dispatch commands (EnerNex 2011). Several studies suggested the formalization of a load following or “variability” reserve category (for example, Charles River Associates 2010; GE Energy 2010). For this review, we use the term balancing reserves to refer to all balancing actives inclusive of load following and regulation.

Under NERC standards, regulating reserves are responsible for maintaining system balance in the period between economic re-dispatch 95% of the time. These standards do not define a specific amount of regulating reserves that must be procured but this requirement is often heuristically implemented as 1% of peak load. Those studies that estimated regulation (Charles River Associates 2010; EnerNex 2006; GE Energy 2005a, 2008, 2010; NYISO 2010) did so based on statistical characterization of wind power, net load, or wind forecast errors. Figure 17.6 shows the annual average of the hourly increase in regulating capacity estimated by these studies. These estimates were broadly consistent across studies and relatively modest. Even at 40% wind penetration the increased regulating reserves were on the order of 0.8% of peak load (Charles River Associates 2010), less than twice the baseline regulation level. The NYSERDA study (GE Energy 2005a), which examined 6% wind penetration, estimated the need for additional regulation as three times the standard deviation of 6-second net load variability. In (EnerNex 2006), regulating reserves were estimated based on the assumption that wind output fluctuation would be less than 2% of wind nameplate capacity. These findings are consistent with the observation made in chapters 2 and 8 that the variability of wind and solar power at short periods is several orders of magnitude less than the low-frequency variability.

Current procedure in ERCOT is to procure regulation based on the 98.8th percentile of historical regulation deployments for same hour of the day in the prior month and the same month in the prior year (GE Energy 2008). This same method was found to be adequate for the wind penetration cases studied, although it was suggested that incorporating wind forecasts into the procurement process could improve the accuracy of regulation procurement (GE Energy 2008). The SPP study approximated the amount of regulation based on the 5th and 95th percentile step changes in 10-minute wind power output using the equation described in Section 3.9 (Charles River Associates 2010). WWSIS estimated regulation at one standard deviation of 10-minute net load variability based on the observation that 10-minute variability is approximately twice 5-minute variability and thus one standard deviation of 10-minute variability was equal to two standard deviations of 5-minute variability and therefore assumed to cover 95% 5-minute variability (GE Energy 2010). QSS modeling in WWSIS generally supported this approach. The NYISO study set a regulation requirement equal to 3 standard deviations of 5-minute net load variability (NYISO 2010). EWITS (EnerNex 2011) described a method for calculating regulation reserves similar to that used in (EnerNex 2006) and described in Section 3.11 but did not provide an numerical estimate of regulation requirements.

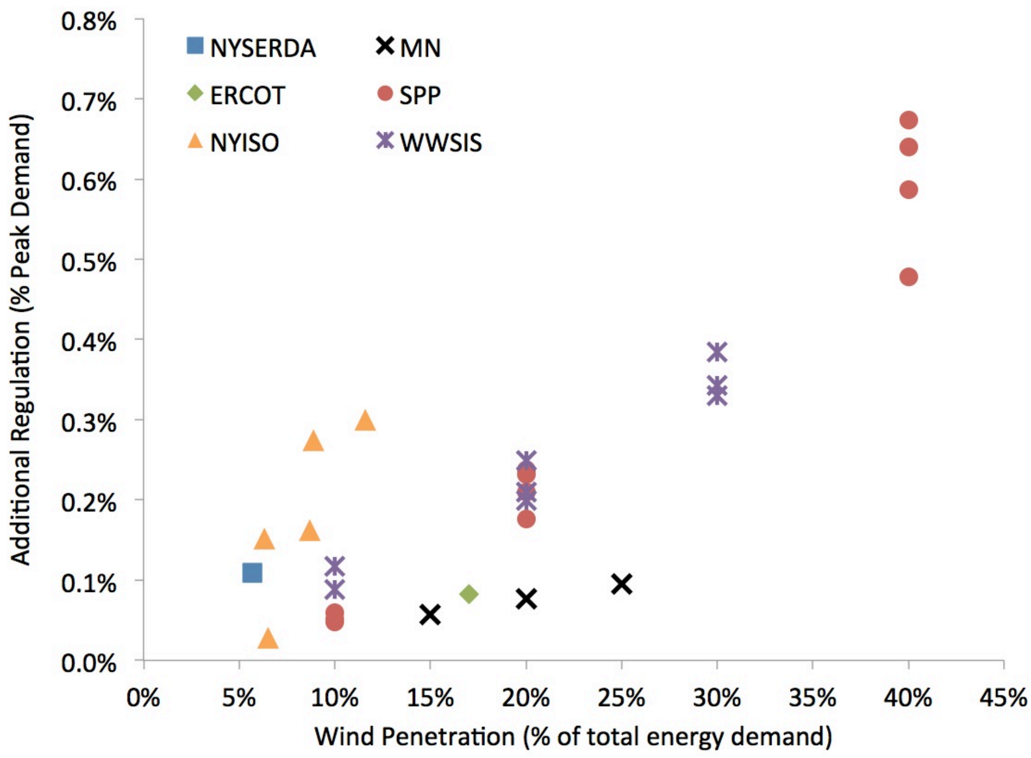

Figure 17.6. Additional regulating reserves estimated to be required with increasing wind penetration. Note that both WWSIS and SPP provide multiple estimates for each level of wind penetration. In the case of WWSIS these represent different geographic distributions of wind generation while for SPP these represent estimates for each of the four seasons.

With the exception of (KEMA 2010), which used a scenario-based dynamic modeling approach, the studies reviewed here estimated the additional balancing reserves required to manage wind variability and uncertainty statistically (EnerNex 2006, 2011; EnerNex et al. 2010; GE Energy 2005a, 2010). Note that (KEMA 2010) referred to its estimate as an estimate of increased regulation but defines this as “a proxy for the net amount of capacity capable of fast ramping to follow system changes via regulation and balancing energy” and thus it more closely aligned with our definition of balancing reserves. The average increase in balancing reserves estimated by each study is show in Figure 17.6. As with regulation, the estimates are relatively linear and relatively consistent across the studies. The estimated total balancing reserves required were, of course, higher than the reserves required for regulation alone. The EWITS study (EnerNex 2011) produced the highest estimated reserves. The Minnesota study (EnerNex 2006), estimated the additional load following and operating reserves components of balancing reserves at two times the standard deviation of 5-minute net load variability and at two times the standard deviation of the next-hour forecast error respectively. Exploring forecast error, both this study and (EnerNex 2011) concluded that wind output variability, and therefore forecast error, was greatest in mid-range of the aggregate production curve. Thus, in keeping with the recommendation in (Holttinen et al. 2013), these studies produced reserve requirements that varied with meteorological conditions. WWSIS estimated total balancing reserves at 3 times the standard deviation of 10-minute net load variability.

The WWSIS study also suggested two heuristics for grid operators to use to procure these reserves (GE Energy 2010). The first was that reserves should equal 3% of load plus 5% of *forecasted* wind power. The second of these was a regionally specific variation of this rule with different load and wind components to maximize the fit with the 3 standard deviation rule (GE Energy 2010). The EWITS study estimated total balancing reserves as the sum of its regulation estimate and one standard deviation of next- hour wind forecast error, as determined by a regionally and weather specific function (EnerNex 2011). The Nebraska study (EnerNex et al. 2010) used the same methodology as (EnerNex 2011). Both (Charles River Associates 2010; GE Energy 2008) suggested that load following would increase with wind penetration but did not estimate the required reserves explicitly.

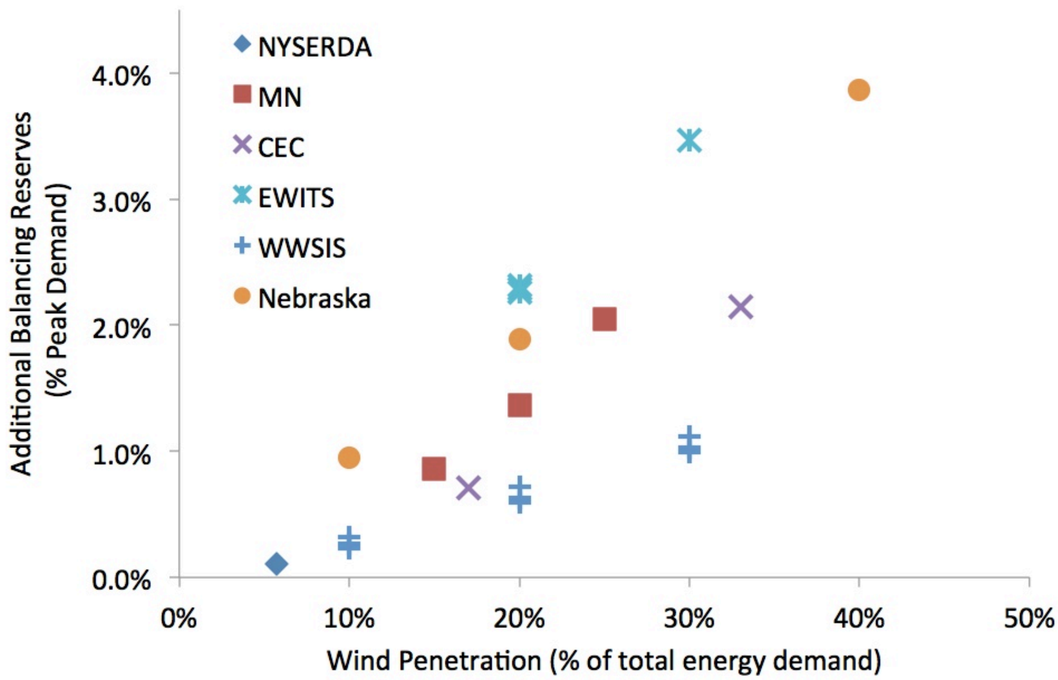

Figure 17.7. Total additional reserves estimated to be required with increasing wind penetration. Note that both WWSIS and EWITS provide multiple estimates for each wind penetration level. These estimates represent different geographic distributions of wind generation.

Figures 17.6 and 17.7 both show a surprising level of consistency in the reserves estimates among the various studies. This may reflect the fact that the heuristic methods used for reserves estimation were remarkably similar among the studies, and that the data used for these studies come from a small number of mesoscale modeling groups. The CEC study alone (KEMA 2010) used a substantially different methodology, but came to similar conclusions regarding the absolute quantity of reserves, though with additional analysis regarding the need for fast-ramping storage.

Figure 17.8 compares the balancing reserves required for study level results with the balancing reserves required at the state level in the WWSIS assessment (GE Energy 2010). These results are for the Mega-Project scenario, in which large wind sites were concentrated at the sites with the greatest wind potential, resulting in dramatically higher levels of wind penetration in New Mexico and Wyoming than in the other West Connect states. For the 10% 20% and 30% penetration scenarios, wind generation in Wyoming, for example, reached approximately 45%, 125% and 195% of the total load in the state. These results pointed out the necessity of aggregating wind over large balancing areas.

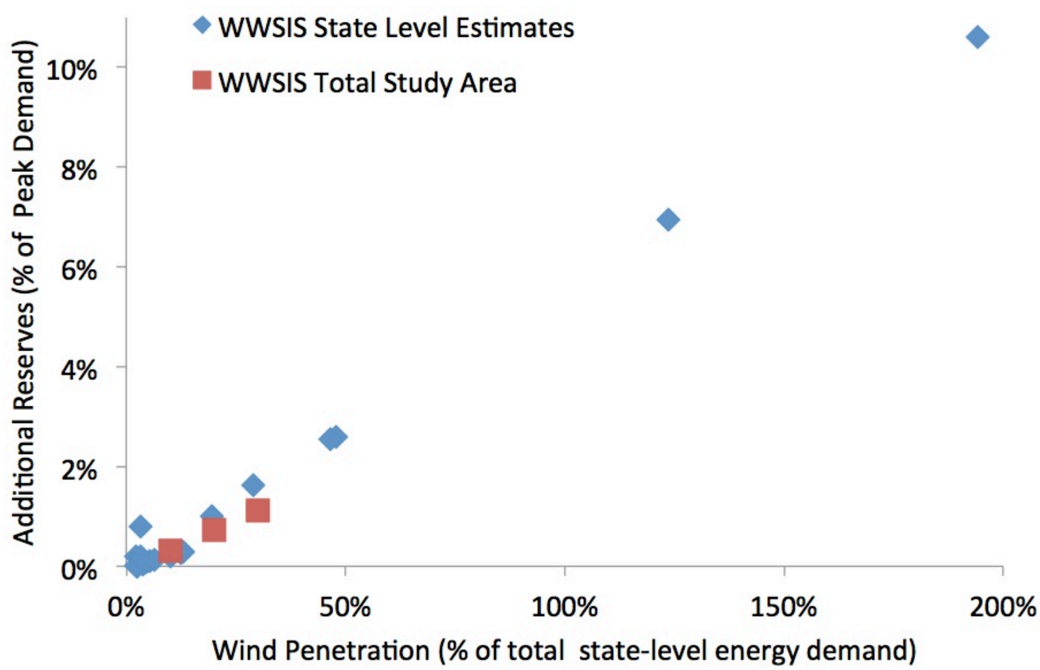

Figure 17.8. Additional balancing reserves estimated to be required with increasing wind penetration, from the WWSIS study (GE Energy 2010).

For contingency reserves, NERC requires available reserves equal to the most severe single contingency (NERC 2012). In WECC, this is implemented as the larger of the most severe contingency or the sum of 5% of hydro generation and 7% of thermal generation, at least half of which must be spinning reserves (GE Energy 2010). WWSIS reported that this requirement was generally put into practice as spinning contingency reserves equal to the larger of 3% of load or 50% of the worst contingency (GE Energy 2010). Generally, wind plants are not large enough to constitute the worst contingency in a system and also do not fail as a single unit so do not affect the contingency reserves requirements (EnerNex 2006, 2011; GE Energy 2005a; NYISO 2010). Several studies did suggest that the wind could affect contingency requirements and the highest penetration levels (Charles River Associates 2010; EnerNex 2011; GE Energy 2010).

4.2. Effects of Geographic Diversity

Geographically dispersed wind sites were also commonly cited as a factor that reduces wind variability (EnerNex 2006, 2011; EWEA 2009; GE Energy 2010). The studies did relatively little, however, to determine the benefits and costs of diversity. Differing wind siting scenarios in EWITS were intended to capture the benefits of geographic diversity and the authors noted that the integration costs tend to be lower when wind is spread more evenly across the study area but the extent to which this attributable to geographic diversity was not quantified. The WWSIS study (GE Energy 2010), found that for 30% wind penetration, the standard deviation of 1-hour net load variability in Wyoming was 87% higher than for load alone while for the WestConnect service area this increase was only 4% of the variability of load alone and attributed this to the effects of "temporal averaging, geographic diversity and wide area aggregation" but did not separate out the benefits provide by geographic diversity from those of aggregation. Moreover, WWSIS also concluded that there were not significant differences among the sitting scenario and the location of wind resources was not critical so long as there was adequate transmission infrastructure. One study notes that the effect of geographic diversity was likely to be lower in areas with relative flat, uniform terrain (Charles River Associates 2010). There is also a growing academic literature on the effects of wind diversity and aggregation discussed in chapters 3 and 12.

4.3. Wind forecast accuracy

Improved wind forecasting techniques also mitigate the difficulty of incorporating wind into the power system (see chapter 9). Several studies provided estimates of the benefits of perfect wind forecast relative to state of the art wind forecast and found significant operational improvements with improved forecasting (EnerNex 2011; GE Energy 2005a, 2010). EWITS determined that perfect, day-ahead wind forecast would reduce the cost of wind generation by between $2.26 and $2.84/MWh. WWSIS concluded that perfect wind forecast would decrease WECC operating cost by $1 to 2/MWh of wind energy relative to current state-of-the-art forecasts and prevent the need for any wind curtailment (GE Energy 2010). The NYSERDA study found perfect wind forecasts to be worth approximately $1.50 per MWh of wind generation (GE Energy 2005a). Under-forecasting wind does not pose significant challenges to system stability as it can be managed by curtailing wind if necessary but it does reduce the economic competitiveness of wind production (GE Energy 2008).

4.4. Suggested System Changes and Operating Practices

The effect of wind integration depends heavily on the system in which it is being integrated. These studies made numerous recommendations that could reduce the cost of wind integration. First, several of the studies concluded that larger balancing authority areas were better suited to managing wind variability then smaller balancing authorities (Charles River Associates 2010; EnerNex 2006, 2011; GE Energy 2008, 2010). Large balancing areas reduced variability in net load and provided a large pool of generating units from which to manage deviations from forecasted net load. Balancing area consolidation is discussed in chapter 5.

Second, wind benefits from systems with greater flexibility in the generating portfolio as more startups and shorter cycles are required to accommodate net load variability caused by wind (Charles River Associates 2010; KEMA 2010).

Third, robust transmission is also important as this allows for the aggregation of wind and regulating units over large geographic areas (Charles River Associates 2010; EnerNex 2011; EnerNex et al. 2010; EWEA 2009; GE Energy 2010; NYISO 2010). Without significant transmission enhancements, wind curtailment could be significant (EnerNex 2011).

Finally a number of market mechanisms have the potential to reduce the cost of wind integration including increasing the frequency of scheduling in intra-day and sub-hourly markets (Charles River Associates 2010; EnerNex 2011; GE Energy 2010), incorporating wind forecasts into the day ahead markets (GE Energy 2005a, 2008) and having wind participate in regulatory markets by providing regulation down through wind curtailment (Charles River Associates 2010; GE Energy 2008, 2010).

Several studies noted that wind generation reduced the amount of thermal generation that was used, freeing up addition generating units to respond to net load variability. This process reduced the profitability of these thermal units, however, and could lead to plant retirements that would reduce the plants available for regulation and load following as noted in (EnerNex 2011; GE Energy 2008; NREL 2012). This issue requires further study.

5. Discussion and Conclusions

We have reviewed eleven large, North American, wind integration studies. This review highlights a number of areas where wind integration studies have evolved to provide valuable insight, as well as a few areas where improvements in methods and additional research are needed to facilitate greater insight from future studies. We now summarize our observations and conclusions from this review.

5.1. Wind data sources

The quality of the wind data used for wind integration studies has improved substantially over time. Almost all of the wind integration studies used data from mesoscale numerical weather prediction models. Early studies used models with a 10-km resolution, whereas the most recent models used 2-km spatial and 10-minute temporal resolution. As shown in Section 2, mesoscale models can produce wind speed data that underestimates variability at small time scales. However, the more recent of the two datasets reviewed (the updated EWITS (EnerNex 2011) data) showed less evidence of this reduction than the data from the WWSIS model, although the methods used in the updated EWITS data are not documented. The decision to release the data for these two studies publically is commendable, making it possible to perform a variety of validation analyses, which should motivate further improvements in the quality of these data.

Accurately translating wind speed data to statistically representative wind power output data continues to be a challenge. One of the studies (GE Energy 2010) used a statistical technique (SCORE/SCORE-lite (Potter et al. 2008)) to add additional variability to 10-minute resolution power output data to compensate for the reduced variability in the mesoscale data, but there is some evidence that this process may produce data with too much, rather than too little, variability (Milligan et al. 2012). Several of the studies combined high-resolution data from power plants with 10-minute simulated data in order to look at faster time scale phenomena, such as regulating reserves. However, it is not possible to independently verify that the data have the correct statistical properties, since most of the methods, and all of the data, for this hybridization process are not public.

Finally, there is a need for more research to develop methods that reliably combine high-resolution measured plant data with mesoscale model data, to produce hybrid data with statistical properties similar to those of actual wind farms. Some progress has been made in this area. For example (Rose and Apt 2012) introduce a method for synthesizing high-resolution data from low-resolution data, based on the spectral properties of wind power. A significant barrier to this research is the lack of publically available wind power production data, with which to validate candidate methodologies. While it is feasible to obtain proprietary data from some generators, it is difficult to publish reproducible methods using proprietary data. Making some historical, high-resolution power plant production datasets pubic would be tremendously valuable to the electricity industry.

5.2. Statistical modeling and balancing reserves

Almost all of the studies in this review used net load step change statistics to estimate the need for additional balancing (regulation and load-following) reserves. Most of the studies implicitly or explicitly assumed that load and wind are uncorrelated, and that the data fit Gaussian statistical models, neither of which is accurate. Methods, such as the one proposed in (Charles River Associates 2010), which use the magnitude of low-probability ramping events, rather than standard deviations, are likely to produce balancing resource estimates that more accurately predict what will be needed to maintain system reliability. An even more useful improvement would be to build on the methods in (KEMA 2010), which used a dynamic power system model to simulate the effect of different amounts and types of balancing resources.

High-penetration wind scenarios, as they move from concept to deployment, are very likely to motivate substantial changes in the ways that ancillary resources are scheduled, purchased and dispatched. Operational changes, such as the large-scale use of pumped hydro in high-renewable penetration countries such as Portugal, Germany and Ireland, illustrate the types of changes that are likely to be needed. Many of the studies in this review explicitly assumed that the structure of the energy and ancillary services markets will be largely unchanged, with the exception of more frequent dispatch intervals and balancing area aggregation. In future studies, it may be valuable to think more broadly about, and model more explicitly, the ways in which different types of balancing services can be purchased from different types of power plants. For example, storage and demand response could provide highly responsive balancing services, but will be deployed only if electricity markets reward power plants for their responsiveness. Modeling studies of fast-ramping resources, such as in (KEMA 2010), pushed the state of the art, making it increasingly feasible to quantify the benefits of responsive resources.

There are a growing number of research papers that estimate balancing reserve requirements from historical data. For example, Mauch et al. (2013a) estimated total balancing reserve requirements in Texas and the U.S. Midwest, and estimated that 0.07 – 0.30 MW of day-ahead reserves are needed per MW of wind. These reserve requirements are based on day-ahead load and wind forecast uncertainty. Forecast uncertainty is greatest on days when the wind is forecast to be blowing strongly (Mauch et al. 2013b), thus there are some days when significant reserves are required, and other days when much smaller reserves are needed. Because of the additional uncertainty associated with estimating the reserves that are needed to cover 95% of the day-ahead forecast errors, the reserves estimates in (Mauch et al. 2013a) are substantially higher than those reported in many of the studies reviewed here and in Figures 17.7. Mauch et al. (2013a) suggest that a dynamic method should be used to schedule reserves, based on the day-ahead forecast values. Additional research is needed into methods that can dynamically predict the reserve requirements for high wind scenarios. For example, one could imagine scheduling reserves at a level of half the uncertainty in the day-ahead forecast, and rescheduling after an intra-day unit commitment, when uncertainties are lower.

Another area for which improvements in methods are needed is in the modeling of wind forecast errors. Some early work (e.g., (Doherty and O'Malley 2005)) assumed that wind and load are uncorrelated Gaussian random variables, which, as shown in Section 2, is not supported by the data. More recent research in this area (e.g. (Hodge et al. 2012; Mauch et al. 2013b)) points out the heavy-tailed nature of the distributions. Appropriate use of these results should allow for increasing statistical accuracy, and thus more insightful results, in future integration studies. This topic is also discussed in chapter 9.

5.3. Production cost simulation (PCS)

The technology for power system PCS has improved substantially across the studies in this review. While some early studies either did not include PCS (e.g.,(GE Energy 2008)), or did not include accurate transmission system models (e.g., WindDS in (U.S. DOE 2008)) the most recent studies used detailed PCS models that modeled unit commitment, generator ramp rate constraints and transmission limits. Given that these costs can be important contributors to wind integration costs (Mount et al. 2012), including these details is important. Since most PCS is performed on hourly data, the fine time-scale data challenges described in Sections. 5.1 and 5.2 are unlikely to have a significant effect on PCS results.

Going forward there is a need to improve the ways in which uncertainty and wind forecasts are handled in PCS. The vast majority of the studies used deterministic PCS models, whereas uncertainty, particularly in wind and solar forecast data, become increasingly important to unit commitment decisions as renewable penetration increases. Also, a number of the studies assumed that the entire fleet of existing power plants would continue to be available for unit commitment, even under 20-40% wind scenarios. Clearly, at least some economically uncompetitive power plants would be retired in high renewables cases. This retirement process should be simulated in order to understand which plants, or types of plants, need to be incentivized to remain operational in order to manage the costs of transition to high renewables penetration scenarios.

5.4. Power system reliability modeling

Power system reliability modeling is important to wind integration studies, particularly given the potential for long periods of low wind and the need to accurately compensate wind plants for their contribution to system adequacy. Regarding the computation of capacity credits for wind, most of the studies used some variant of the ELCC method from (Keane et al. 2011), but with only 2 or 3 years of data. As suggested in (Hasche et al. 2011), accurate estimates of ELCC require 5 or more years of data because substantial inter-annual variations in wind resources are possible. Going forward, capacity credit calculations in wind integration studies should be based on at least five years of wind data.

A majority of the studies reviewed used GE MARS for reliability modeling. While this tool is useful for generation adequacy assessment, reliability is a function of both generation and transmission. The transmission network models used in GE MARS do not capture the physics of actual power flows, which can be very important to reliability. The methodology for composite generation and transmission reliability modeling is relatively mature in the research literature, with specialized methods available specifically for wind integration studies (e.g., (Billinton et al. 2009)). We suggest that future wind integration studies incorporate composite system adequacy assessment methods with at least DC transmission system models, in order to provide more useful insight into the reliability effects of large-scale wind integration. This will be particularly important in studies that estimate the effect of power-plant retirement and transmission system overlays, since both of these can have important reliability effects.

5.5. Analysis of transmission system investments

Several of the studies suggested the need for substantial transmission expansion in order to facilitate high penetration renewables scenarios. While some transmission expansion is certainly warranted, large-scale expansion of the bulk transmission network is costly, and will face substantial siting barriers. Thus there is, in our opinion, a need for creative thinking about how to most effectively use existing transmission resources, with perhaps a minimum amount of network expansion, to facilitate high-renewables scenarios. As an example of the type of analysis that is needed, Hoppock and Patino (2010) compared the levelized cost of energy from distant, high-capacity-factor wind sites to energy from near, lower-capacity-factor sites. They found that transmission investment costs could make the lower-quality sites less expensive. The existing technology available for studying optimal transmission expansion is a significant barrier to further progress in this area. Only in the most recent study (NREL 2012) did analysts attempt to optimize their transmission expansion plans, and in this case a transportation model of the grid was used, rather than a power flow model. Research on optimization methods for transmission switching (Barrows and Blumsack 2012; Fisher et al. 2008) and transmission expansion (Alguacil et al. 2003) suggest approaches to this problem, but substantial research is needed before these algorithms can be applied to large-scale problems.

As methods for optimal system expansion planning improve, future large-scale studies should examine creative combinations of off-shore wind, strategically located on-shore wind, solar (which is often more-easily located near load centers and is increasingly cost-competitive), storage, controllable AC or DC transmission lines, and demand response resources. There may be synergies among these technologies that enable higher-penetration scenarios, while minimizing curtailment, ancillary service costs and reliability effects.

5.6. Looking forward

The future state of the electricity industry always differs from the scenarios analyzed in large-scale integration studies. Given this fact, studies should focus more on quantifying the relative effect of particular changes in operating policy, or technologies, rather than seeking to precisely quantify the economic or reliability effect of a particular penetration scenario. For example, a conclusion that using fast-ramping storage will reduce ancillary service costs by 10% is likely to be more useful than one that says that the ancillary service costs will be $1.52/MWh for scenario X. This is particularly the case, given the fact that new technology and new policies are likely to cause substantial changes in the way that power systems operate in the 10-20 year time horizons that are typical in integration studies.

6. References

Akhmatov, V., and P. B. Eriksen. 2007. A large wind power system in almost island operation: A Danish case study. *IEEE Transactions on Power Systems,* 22 (3), 937-943.

Alguacil, N., A. L. Motto, and A. J. Conejo. 2003. Transmission expansion planning: A mixed-integer LP approach. *IEEE Transactions on Power Systems,* 18 (3), 1070-1077.

Andersson, G., P. Donalek, R. Farmer, N. Hatziargyriou, I. Kamwa, P. Kundur, N. Martins, J. Paserba, P. Pourbeik, and J. Sanchez-Gasca. 2005. Causes of the 2003 major grid blackouts in

North America and Europe, and recommended means to improve system dynamic performance. *IEEE Transactions on Power Systems,* 20 (4), 1922-1928.

Apt, J., 2007. The spectrum of power from wind turbines. *Journal of Power Sources,* 169 (2), 369-374.

Barrows, C., and S. Blumsack. 2012. Transmission switching in the RTS-96 test system. *IEEE Transactions on Power Systems,* 27 (2), 1134-1135.

Billinton, R., and A. Jonnavithula. 1997. Composite system adequacy assessment using sequential monte carlo simulation with variance reduction techniques. *IEE Proceedings-Generation Transmission and Distribution,* 144 (1), 1-6.

Billinton, R., and W. Li. 1994. *Reliability assessment of electrical power systems using monte carlo methods.* New York: Plenum Press.

Billinton, R., G. Yi, and R. Karki. 2009. Composite system adequacy assessment incorporating large-scale wind energy conversion systems considering wind speed correlation. *IEEE Transactions on Power Systems,* 24 (3), 1375-1382.

BPA. Wind generation & total load in the BPA balancing authority. Available from: http://transmission.bpa.gov/business/operations/wind/ [Accessed: 7/7, 2013].

Brower, M., 2009. Development of eastern regional wind resource and wind plant output datasets. *NRELlSR-550-46764, National Renewable Energy Laboratory*.

Budischak, C., D. Sewell, H. Thomson, L. Mach, D. E. Veron, and W. Kempton. 2013. Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time. *Journal of Power Sources,* 225 (0), 60-74.

Canizares, C. A., and F. L. Alvarado. 1993. Point of collapse and continuation methods for large ac/dc systems. *IEEE Transactions on Power Systems,* 8 (1), 1-8.

Charles River Associates. 2010. *SPP witf wind integration study.* (CRA Project No. D14422). Little Rock, AR.

Corbus, D., M. Schuerger, L. Roose, J. Strickler, T. Surles, D. Manz, D. Burlingame, and D. Woodford. 2010. *Oahu wind integration and transmission study.* NREL. (NREL/TP-5500-48632).

DeCarolis, J. F., and D. W. Keith. 2006. The economics of large-scale wind power in a carbon constrained world. *Energy Policy,* 34 (4), 395-410.

Denny, E., and M. O'Malley. 2007. Quantifying the total net benefits of grid integrated wind. *IEEE Transac- tions on Power Systems,* 22 (2), 605–615.

Dillan, J., 2013. Grid constraints mean less power output from wind projects. *Vermont Public Radio,* 1/30/2013.

Doherty, R., and M. O'Malley. 2005. A new approach to quantify reserve demand in systems with significant installed wind capacity. *IEEE Transactions on Power Systems,* 20 (2), 587-595.

EnerNex. 2006. *Final report - 2006 minnesota wind integration study: Volume one.*

EnerNex. 2007. *Operational impacts of integrating wind generation into idaho power's existing resource portfolio* Boise: Idaho Power.

EnerNex. 2011. *Eastern wind integration and transmission study.* National Renewable Energy Laboratory report, NREL/SR-5500-47078, www.nrel.gov/docs/fy11osti/47078.pdf.

EnerNex, Ventyx, and Nebraska Power Association. 2010. *Nebraska statewide wind integration study.* National Renewable Energy Laboratory. (NREL/ SR-550-47519).

ERCOT. Winter wind propels ercot to a new wind record of 9,481 mw. Available from: http://www.ercot.com/news/press_releases/show/26398 [Accessed: 10/11].

FERC. 2012. *Order no. 764: Integration of variable energy resources.* Federal Energy Regulatory Commission.

Fertig, E., J. Apt, P. Jaramillo, and W. Katzenstein, 2012. The effect of long-distance interconnection on wind power variability. *Environmental Research Letters*, 7 (3), 034017.

Fisher, E. B., R. P. O'Neill, and M. C. Ferris. 2008. Optimal transmission switching. *IEEE Transactions on Power Systems,* 23 (3), 1346-1355.

Gautam, D., L. Goel, R. Ayyanar, V. Vittal, and T. Harbour. 2011. Control strategy to mitigate the impact of reduced inertia due to doubly fed induction generators on large power systems. *IEEE Transactions on Power Systems,* 26 (1), 214-224.

GE Energy. 2005a. *The effects of integrating wind power on transmission system planning, reliability and operations, report on phase 2: System performance evaluation.*: New York State Energy Research and Development Authority.

GE Energy. 2005b. *NYSERDA phase 2: Appendices.* New York State Energy Research and Development Authority.

GE Energy. 2008. *Analysis of wind generation impact on ercot ancillary services requirements.*

GE Energy. 2010. *Western wind and solar integration study.* National Renewable Energy Laboratory. (NREL/SR-550-47434).

Ghajar, R., and R. Billinton. 1988. A monte-carlo simulation-model for the adequacy evaluation of generating systems. *Reliability Engineering & System Safety,* 20 (3), 173-186.

Gu, Y., L. Xie, B. Rollow, and B. Hesselbaek. 2011. Congestion-induced wind curtailment: Sensitivity analysis and case studies. *In: North American Power Symposium (NAPS),* Boston, MA: IEEE.

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

Hodge, B.-M., E. Ela, and M. Milligan. 2012. Characterizing and modeling wind power forecast errors from operational systems for use in wind integration planning studies. *Wind Engineering,* 36 (5), 509-524.

Hodge, B., and M. Milligan. 2011, 24-29 July 2011. *Wind power forecasting error distributions over multiple timescales.* Paper presented at the Power and Energy Society General Meeting, 2011 IEEE.

Holttinen, H., D. Flynn, H. Abildgaard, S. Lennart, A. Keane, J. Dillon, and M. O'Malley. 2013. Steps for a complete wind integration study. *In: 46th Hawaii International Conference on System Sciences,* Hawaii: IEE Computer Society.

Holttinen, H., P. Meibom, A. Orths, B. Lange, M. O'Malley, J. O. Tande, A. Estanqueiro, E. Gomez, L. Söder, G. Strbac, J. C. Smith, and F. van Hulle. 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., M. Milligan, B. Kirby, T. Acker, V. Neimane, and T. Molinski. 2008. Using standard deviation as a measure of increased operational reserve requirement for wind power. *Wind Engineering,* 32 (4), 355-378.

Hoppock, D. C., and D. Patiño-Echeverri. 2010. Cost of wind energy: Comparing distant wind resources to local resources in the midwestern united states. *Environmental Science & Technology,* 44 (22), 8758-8765.

Idaho Power. 2013. *Wind integration study report.* Boise.

Katzenstein, W., E. Fertig, and J. Apt. 2010. The variability of interconnected wind plants. *Energy Policy,* 38 (8), 4400-4410.

Katzenstein, W. and J. Apt, 2012. The Cost of Wind Power Variability. *Energy Policy*, 51: 233-243.

Keane, A., M. Milligan, C. J. Dent, B. Hasche, C. D'Annunzio, K. Dragoon, H. Holttinen, N. Samaan, L. Soder, and M. O'Malley. 2011. Capacity value of wind power. *IEEE Transactions on Power Systems,* 26 (2), 564-572.

KEMA. 2010. *Research evaluation of wind generation, solar generation, and storage impact on the california grid.* Public Interest Energy Research Program, California Energy Commission. (CEC-500-2010-010).

Kundur, P., 1994. *Power system stability and control.* McGraw-Hill.

Lew, D., 2009. *Western data set irregularity.* National Renewable Energy Laboratory.

Lueken, C., G. Cohen, and J. Apt, 2012. The Costs of Solar and Wind Power Variability for Reducing CO2 Emissions. *Environmental Science & Technology*, 46 (17), 9761-9767.

Mackin, P., R. Daschmans, B. Williams, B. Haney, R. Hunt, J. Ellis, and J. Eto. 2013. *Dynamic simulation study of the frequency response of the western interconnection with increased wind generation.* Paper presented at the System Sciences (HICSS), 2013 46th Hawaii International Conference on.

Madaeni, S. H., and R. Sioshansi. 2013. The impacts of stochastic programming and demand response on wind integration. *Energy Systems,* 4 (2), 109-124.

Mauch, B., J. Apt, P.M.S. Carvalho and P. Jaramillo. 2013a. What Day-Ahead Reserves are Needed in Electric Grids with High Levels of Wind Power? Environmental Research Letters 8: 034013.

Mauch, B., J. Apt, P. S. Carvalho, and M. Small. 2013b. An Effective Method for Modeling Wind Power Forecast Uncertainty. In Press at Energy Systems. Published online June 2, 2013 DOI 10.1007/s12667-013-0083-3.

Milligan, M., E. Ela, D. Lew, D. Corbus, W. Yih-huei, and B. Hodge. 2012. Assessment of simulated wind data requirements for wind integration studies. *Sustainable Energy, IEEE Transactions on,* 3 (4), 620-626.

Mount, T., A. Lamadrid, S. Maneevitjit, B. Thomas, and R. Zimmerman. 2010. *The hidden system costs of wind generation in a deregulated electricity market.* Paper presented at the System Sciences (HICSS), 2010 43rd Hawaii International Conference on.

Mount, T. D., S. Maneevitjit, A. J. Lamadrid, R. D. Zimmerman, and R. J. Thomas. 2012. The hidden system costs of wind generation in a deregulated electricity market. *The Energy Journal,* 33 (1), 161-186.

Mullane, A., G. Lightbody, and R. Yacamini. 2005. Wind-turbine fault ride-through enhancement. *IEEE Transactions on Power Systems,* 20 (4), 1929-1937.

NERC. Planning resource adequacy analysis, assessment and documentation. Available from: http://www.nerc.com/files/BAL-502-RFC-02.pdf [Accessed: 10/15].

NERC. 2011. *Balancing and frequency control: A technical document prepared by the nerc resources subcommittee.* North American Electric Reliability Corporation.

NERC. 2012. Standard bal-002-1a — disturbance control performance North Amarican Electric Realibability Corporation.

NREL. 2012. *Renewable electricity futues study.* (NREL/TP-6A20-52409). Golden, CO.

NYISO. 2010. *Growing wind final report of the nyiso wind generation study.*

Papavasiliou, A., S. S. Oren, and R. P. O'Neill. 2011. Reserve requirements for wind power integration: A scenario-based stochastic programming framework. *IEEE Transactions on Power Systems,* 26 (4), 2197-2206.

Pennock, K., 2012. *"Updated eastern interconnect wind power output and forecasts for ergis" technical report # nrel/sr-5500-56616.* National Renewable Energy Laboratory. (NREL/SR-5500-56616).

Pope, S. B., 2000. *Turbulent flows.* Cambridge: Cambridge University Press.

Potter, C. W., D. Lew, J. McCaa, S. Cheng, S. Eichelberger, and E. Grimit. 2008. Creating the dataset for the western wind and solar integration study (usa). *Wind Engineering,* 32 (4), 325-338.

Rose, S., and J. Apt. 2012. Generating wind time series as a hybrid of measured and simulated data. *Wind Energy,* 15 (5), 699-715.

Sauer, P. W., and M. Pai. 1997. *Power system dynamics and stability.* Prentice Hall.

Seman, S., J. Niiranen, and A. Arkkio. 2006. Ride-through analysis of doubly fed induction wind-power generator under unsymmetrical network disturbance. *IEEE Transactions on Power Systems,* 21 (4), 1782-1789.

Skamarock, W. C., 2004. Evaluating mesoscale nwp models using kinetic energy spectra. *Monthly Weather Review,* 132 (12), 3019-3032.

Soder, L., and H. Holttinen. 2008. On methodology for modelling wind power impact on power systems. *International Journal of Global Energy Issues,* 29 (1), 181-198.

Stauffer, D. R., and N. L. Seaman. 1994. Multiscale four-dimensional data assimilation. *Journal of Applied Meteorology,* 33 (3), 416-434.

Stott, B., J. Jardim, and O. Alsac. 2009. Dc power flow revisited. *IEEE Transactions on Power Systems,* 24 (3), 1290 – 1300.

Takriti, S., J. R. Birge, and E. Long. 1996. A stochastic model for the unit commitment problem. *IEEE Transactions on Power Systems,* 11 (3), 1497-1508.

U.S. DOE. 2008. *20% wind energy by 2030: Increasing wind energy's contribution to u.S. Electricity supply.* (DOE/GO-102008-2567).

Vaiman, M., K. Bell, Y. Chen, B. Chowdhury, I. Dobson, P. Hines, M. Papic, S. Miller, and P. Zhang. 2012. Risk assessment of cascading outages: Methodologies and challenges. *IEEE Transactions on Power Systems,* 27 (2), 631-641.

Vittal, E., M. O'Malley, and A. Keane. 2010. A steady-state voltage stability analysis of power systems with high penetrations of wind. *IEEE Transactions on Power Systems,* 25 (1), 433-442.

Wang, C., and J. D. McCalley. 2013. Impact of wind power on control performance standards. *International Journal of Electrical Power & Energy Systems,* 47, 225-234.

Weber, C., P. Meibom, R. Barth, and H. Brand. 2009. Wilmar: A stochastic programming tool to analyze the large-scale integration of wind energy. *In: Optimization in the energy industry*: Springer, 437-458.

WindLogics. 2006. *Final report - mn wind integration study: Volume ii.*

Wu, L., M. Shahidehpour, and T. Li. 2007. Stochastic security-constrained unit commitment. *IEEE Transactions on Power Systems,* 22 (2), 800-811.

Xie, L., P. M. S. Carvalho, L. A. F. M. Ferreira, J. Liu, B. H. Krogh, N. Popli, and M. D. Ilic. 2011. Wind integration in power systems: Operational challenges and possible solutions. *Proceedings of the IEEE,* (in press), 214-232.