Wind Energy

WIND ENERGY
Wind Energ. 2014; **17**:1411–1424
Published online 13 June 2013 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/we.1640

RESEARCH ARTICLE

Variability and uncertainty of wind power in the California electric power system

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ABSTRACT

The California generation fleet manages the existing variability and uncertainty in the demand for electric power (load). When wind power is added, the dispatchable generators manage the variability and uncertainty of the net load (load minus wind power). The variability and uncertainty of the load and the net load are compared when 8790 MW of wind power are added to the California power system, a level expected when California achieves its 33% renewable portfolio standard, using a data set of 26,296 h of synchronous historic load and modeled historic wind power output. Variability was calculated as the rate of change in power generated by wind farms or consumed by the load from 1 h to the next (MW/h). Uncertainty was calculated as the 1 h ahead forecast error [MW] of the wind power or of the load. The data show that wind power adds no additional variability than is already present in the load variability. However, wind power adds additional uncertainty through increased forecast errors in the net load compared with the load. Forecast errors in the net load increase 18.7% for negative forecast errors (actual less than forecast) and 5.4% for positive forecast errors (actual greater than forecast). The increase in negative forecast errors occurs only during the afternoon hours when negative load forecasts and positive wind forecasts are strongly correlated. Managing the integration of wind power in the California power system should focus on reducing wind power forecast uncertainty for wind ramp ups during the afternoon hours.
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KEYWORDS
wind integration; ramp rates; forecast error; operating reserve; California Renewable Portfolio Standard

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Received 27 December 2011; Revised 28 February 2013; Accepted 21 April 2013

1. INTRODUCTION

California, several other states in the USA, and many countries worldwide, have renewable energy goals that include the building of large capacities of wind power generation. California legislation requires a 33% renewable portfolio standard (RPS) by 2020,[1] that is likely to encourage 6–9 GW of wind power to be installed into an approximately 50 GW peak load electric power system.[2,3] Impacts from integrating large quantities of wind energy into such a power system have been identified[3–5] since wind energy is a variable energy resource as defined by[6,7] the US Federal Energy Regulatory Commission and North American Electric Reliability Corp. that does not operate like conventional power plants. Both rapid increases in wind power as well as rapid decreases are of concern to power system operators. The output power of most conventional power plants can be controlled, and they are considered to have a constant fuel supply available. Hydropower is an exception in that its output is dispatchable depending on reservoir or river levels.

Electric power independent system operators (ISOs) maintain *operating reserve* to balance load and generation during real time system operation. Operating reserve provides frequency regulation and is used to manage load forecasting error as well as generation and transmission outages.[8] It consists of partly loaded or fast-start generation and interruptible loads with defined capacity and response requirements. The ISO uses this reserve to manage the variability and forecast uncertainty of load, generation, and transmission within specified operational reliability standards. The addition of wind power generation, a variable energy resource, can lead to a greater requirement for operating reserve because it increases generation variability, which is a function of the underlying renewable energy resource, and uncertainty, which is a function of the error in wind power forecasts. This increase in the operating reserve required when wind power is added to the system is called *variability reserve* in the work of Lew and Piwko,[9] since the requirement for it exists because of the variability and uncertainty in wind power output. Variability reserve, however, covers only the incremental increase in the system wide variability and uncertainty from the addition of wind power, not the entire variability and uncertainty in wind power output, much of which is already managed by existing operating reserve or eliminated through load and generation aggregation. In the works of Venkataraman and Helman and Lew and Piwko,[2,9] the cost of procuring or maintaining additional operating reserve is considered part of the integration cost of wind power, although several reserve products such as demand response and energy storage may reduce the requirement for variability reserve.

Different electric power systems define and procure operating reserve capacity and energy in different ways.[10] In California,[2] *regulating reserve* (frequency regulation) is used within a 5 min period through automatic generation control, and *load following reserve* is used over a 1 h time scale. Several studies[2,9,11–13] have identified that with higher penetrations of wind generation capacity the variability of wind power output on the 5 min and 1 h time scale is likely to require additional operating reserve capacity and energy. The variability or ramp rate of wind power output from one period to the next may exceed the capability of conventional generators to ramp their output up or down to balance load and generation. In particular, the California wind regime has a strong diurnal pattern that presents two challenging conditions. The first is a morning event, during which the load increases and wind power decreases, which requires conventional generators to increase their output faster than if wind power was not in the system. The second is an evening event, during which load decreases and wind power increases, which requires conventional generators to decrease their output faster than if wind power was not in the system. An example of this is illustrated with historic data in Figure 1.

To investigate how the ramp rates of wind farms will affect the California electric power system ramp rates, this paper uses a case study of the California system operating with 8790 MW of wind power using 26,296 h of synchronous historic load and simulated historic wind power data described in Section 2. The variability (Section 3) and forecast uncertainty (Section 4) of the load are compared with that of the net load (i.e., load less wind power) to identify the change in the 1 h ramp rate capability needed in the operating reserve if all wind farms are operated as 'must-take' generators. This study is distinct from the Western Wind and Solar Integration Study[9] and similar studies[2,11,12] in the following ways: (i) the study uses the Western Wind Dataset exclusively in California and with the California system where as the Western Wind and Solar Integration Study focused on the WestConnect states of Arizona, Colorado, New Mexico, Nevada, and Wyoming; (ii) California is distinct from the rest of the western states in that its grid is market-based and operated by an independent system operator; (iii) California has the highest RPS by 2020 of any state and the most existing and planned (in transmission queue) wind capacity of all the WECC states; (iv) the methodology uses only publically available data sets allowing verification and study replication; and (v) the study splices the data into an hourly view to examine the specific diurnal impacts of wind power on the electric power system.

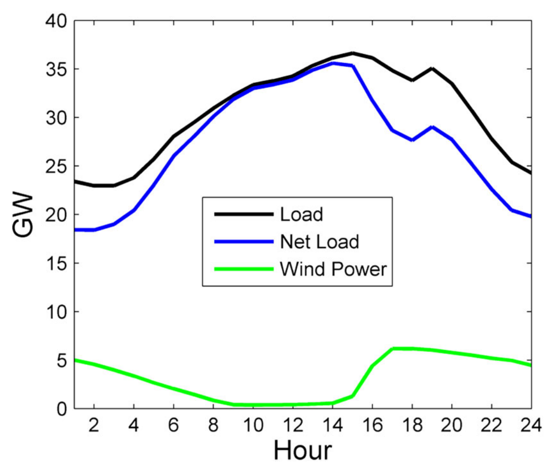

Figure 1. Historic load and simulated historic wind power for California for 1 day in 2004.

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2. DATA

2.1. California system load data

The 2004–2006 hourly average load and hour ahead load forecast data for the California system were downloaded from the California Independent System Operator's (CAISO) *Open Access Same-time Information System*.[14,15] This data set has 26,304 h. The load and forecast data are referenced to the ending hour so that the average system load from 1:00 to 2:00 is reported as the average system load for the hour ending 2. This convention was adopted for the wind power data in Section 2.2 and throughout the paper. The hourly average load data from 2004 to 2006 were integrated and show approximately 720 TWh of electricity demand in the CAISO balancing area or 240 TWh/year on average with a peak hourly load of 50,198 MW and a minimum hourly load of 17,943 MW.

2.2. Simulated historic wind power data

The Western Wind Dataset developed by 3Tier for NREL[16] contains the 10 min resolution power output of a simulated 30 MW wind farm operating from 2004 to 2006 located at 2881 onshore sites in California. Some of these sites include existing wind farms, whereas other sites are potential wind farm sites. The 10 min resolution wind power data were corrected from GMT to Pacific Standard Time and averaged to hourly resolution to match the hourly resolution of the California load data described in Section 2.1. The Western Wind Dataset has a seam issue because the atmospheric model was run for 3 days, and model runs were stitched together.[16] Occasionally, the blending algorithm between model runs artificially alters the variability of wind power when aggregating over many sites. This data artifact would be most present at 16:00 PST (00:00 GMT) and be reflected in wind ramps plotted at 15:00 and 16:00 PST (change in power from 15:00 to 16:00). The net effect of this bias is discussed in Section 4.

The California Energy Commission's Renewable Energy Transmission Initiative[17] has identified *competitive renewable energy zones* (CREZ) based on the renewable energy resource, transmission access, land use, and environmental and legal constraints along with stakeholder input. To identify which of the 2881 simulated 30 MW wind farms in the Western Wind Dataset best represented a realistic portfolio of wind farms in California, the Western Wind Dataset wind farm sites were overlaid on the map of California CREZs.

Selecting 30 MW wind farm sites from the Western Wind Dataset that were inside each CREZ boundary and then aggregating an integer number of these 30 MW wind farms so that the capacity matched closely to the wind farm capacity specified for the CREZ resulted in 58 potential and existing farms that ranged in size from 30 to 420 MW. The total capacity of the 58 farms was 8790 MW, which included the existing 3599 MW of wind farms in California. By combining the Western Wind Dataset and the Renewable Energy Transmission Initiative, the data set contained 3 years (26,296 h in Pacific Standard Time) of simulated historic hourly wind power data from a feasible portfolio of 8790 MW of wind power that is synchronous with the hourly load data of Section 2.1.

On the basis of modeled wind speeds, these wind farms would have generated 71,985 GWh of renewable electricity from 2004 to 2006, or approximately 10% of the CAISO area electricity demand. The 8790 MW of wind power in the data set is larger than the expected portfolio of in-state wind power in the California 20% RPS scenario with 6688 MW[2] and the 33% RPS reference scenario with 7573 MW,[3] but lower than the 9575 MW in the 33% RPS high wind power scenario.[3]

2.3. Net load data

Net load, which is the load the rest of the generation system supplies after wind power is subtracted,[18] is defined at each hour h in equation (1).

$$Net\ Load_h = Load_h - Wind\ Power_h \tag{1}$$

Net load data were calculated for each hour for the years 2004, 2005, and 2006 with the synchronous historic load data from Section 2.1 and the simulated historic wind power data in California from Section 2.2. This created a net load time series consisting of 26,296 h.

3. HOURLY VARIABILITY OF THE LOAD, WIND POWER, AND NET LOAD

3.1. Hourly variability of the load

The historic hourly load variability of the CAISO area during 2004–2006 is shown in Figure 2. The maximum ramp up variation was 5749 MW/h in 2004, and the maximum ramp down variation was −4890 MW/h in 2006. The extreme values

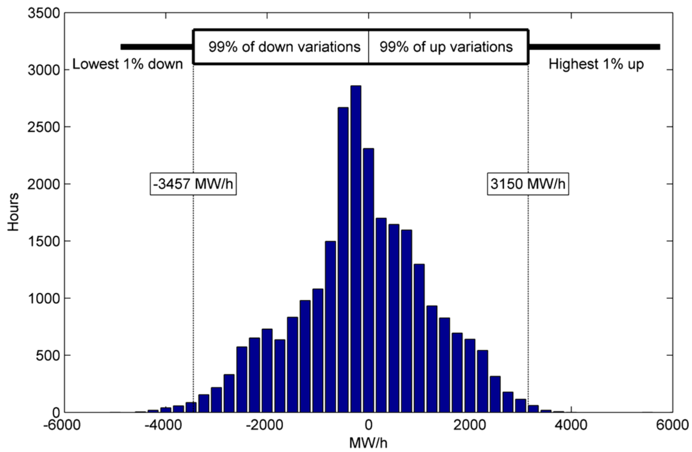

Figure 2. Histogram of the California system load hourly variability in 250 MW/h bins during 2004–2006. The box and whisker plot at the top shows 99% of the up and 99% of the down variations (box) and the highest 1% of up and the lowest 1% of down variations (whiskers).

were rare, and 99% of the up variations were less than 3150 MW/h and 99% of the down variations were less in magnitude than −3457 MW/h. The hourly load variability in 2004, 2005, and 2006 was within the range of hourly variability throughout the years 2001–2009 and contained the largest hourly variations with the largest ramp up event in 2004 and largest ramp down event in 2006. Figure 2 indicates the load generally ramps down at greater rates than it ramps up as indicated by the longer left tail of the histogram.

The hourly variability of the load is shown by hour of the day in Figure 3. There is a clear diurnal pattern of morning hour up variations, late afternoon variations in both directions, and evening down variations. The large variations in hours 16–21 generally represent the seasonal change of daylight and changes in the residential use of electricity as the daylight varies with the season.

3.2. Hourly variability of the wind power

The variability of the 8790 MW of simulated historic wind power is shown in Figure 4. The maximum up variation was 3656 MW/h in 2005, or 41.6% of the installed 8790 MW of wind power capacity. The maximum down variation was −2442 MW/h also in 2005, or 27.8% of the wind power capacity. Wind power hourly variations were greater in magnitude in the up direction with 99% of the up variations less than 1745 MW/h compared with 99% of the down variations less in magnitude than −1148 MW/h. The longer tail of up variations is consistent with wind speeds increasing rapidly as a front approaches and slowly decreasing as a front moves away.

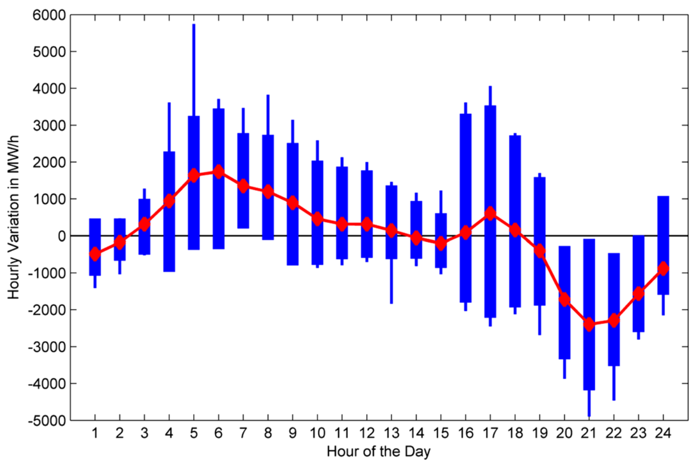

Figure 3. California system load hourly variability by hour of the day during 2004–2006. The box covers 99% of the up and 99% of the down hourly variations (MW/h). The whiskers are the highest 1% of up and lowest 1% of down hourly variations. The diamonds and accompanying line show the average variation for each hour across all 3 years of data.

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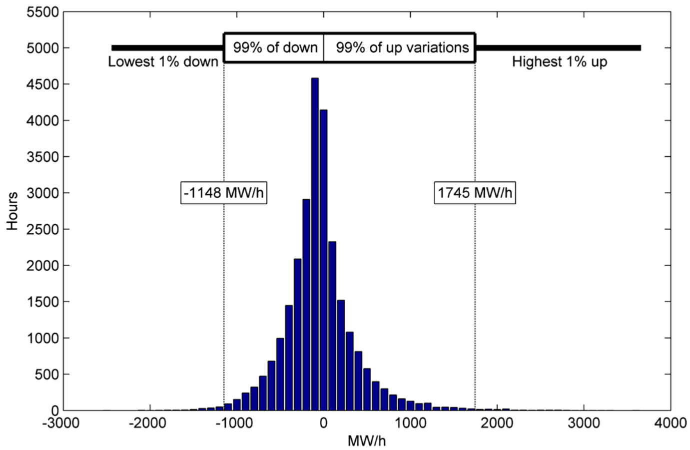

Figure 4. Histogram of the hourly variability of 8790 MW of wind power in 100 MW/h bins during 2004–2006.

The 3 year seasonal average hourly power output profile of wind power is shown in Figure 5(a). It shows that California's onshore winds generally peak in the evening and night with rapid ramp ups in the late afternoon especially for the spring and summer. The hourly change or variability of the wind power by hour of the day is shown in Figure 5 (b). The largest variations are during hours 15–18 when up variations may exceed 25% of the 8790 MW of wind power capacity. Only in hour 20 does the down variation exceed 25% of the wind power capacity. Late afternoon rapid wind power ramp ups are typical of the California diurnal wind regime driven by thermal gradients between the coast and the interior valleys and deserts of the state.

3.3. Hourly variability of the net load

The hourly variability of the net load is shown in the histogram in Figure 6. The maximum up variation was 5730 MW/h in 2004, and the maximum down variation was −4556 MW/h also in 2004.

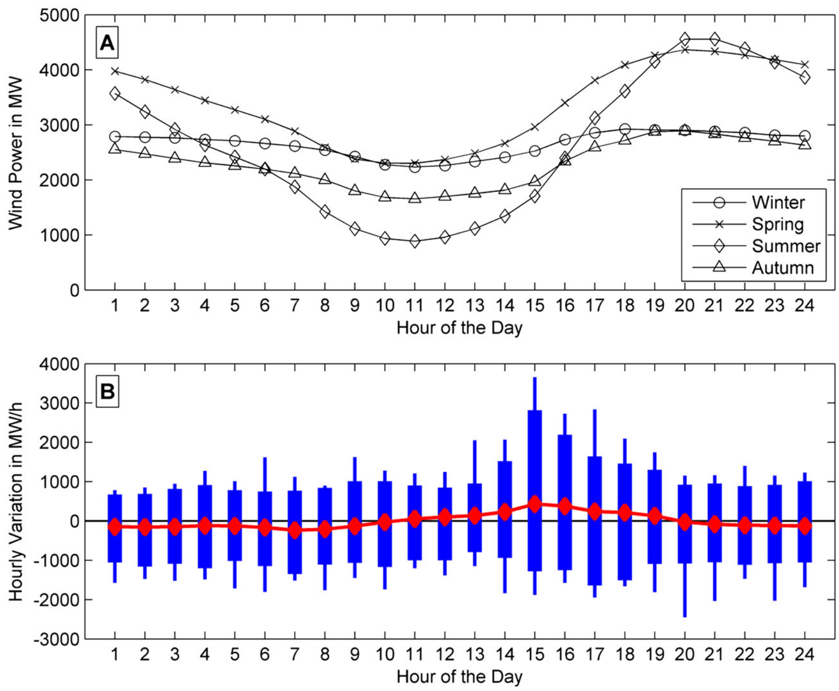

Figure 5. (a) Average diurnal output of 8790 MW of wind power in California by season during 2004–2006. (b) Hourly variability of 8790 MW of wind power by hour of the day during 2004–2006.

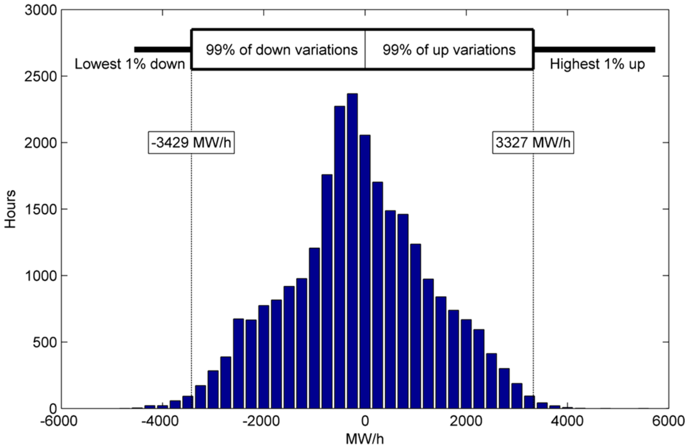

Figure 6. Histogram of the net load hourly variability in 250 MW/h bins during 2004–2006.

The hourly variability of the net load by hour of the day is shown in Figure 7. The largest variations are similar to the load only variations with morning ramp up events and evening ramp down events in addition to significant variability up and down in the afternoon hours.

3.4. Comparison of the hourly variability of the load, wind power, and net load

Figure 8 shows that the maximum and 99% level of hourly variability of the load and of the wind power do not add linearly to increase the maximum or the 99% level of hourly variability of the net load. The extreme and 99% level of ramp events are similar for the net load and the load. This indicates the CAISO balancing area should not expect a significant increase in the magnitude of ramp up or down events on the hourly time scale with the addition of 8790 MW of wind power. Sufficient capacity to meet these ramp events already exists since the power system has historically held sufficient operational flexibility in scheduling unit commitment, real time energy markets, and operating reserve to meet hourly variations of this magnitude without wind power and no additional operating reserve capacity needs to be built.

The hourly variability of the load and net load are compared in Figure 9. The histogram of load variations is overlaid on the histogram of net load variations. Although the maximum up and down variations do not increase for the net load, there is an increase in the frequency of large up and down variations for the net load compared with the load without wind power. This is confirmed by the increase of 177 MW/h in the 99% of up variations. This indicates that although the system already has the capacity to meet the net load ramp events because the extreme ramps are not larger for the net load than the load, it will use this capacity more frequently. More frequent use of operating reserve products may increase system costs.

Figure 10 compares the hourly load variations with the hourly net load variations by hour of the day. There is no significant change in the hourly variation direction or magnitude for the net load except for the noticeable increase in down variations between hours 14–18 and up variations for hours 20 and 21. This shows that the afternoon ramp up of wind power

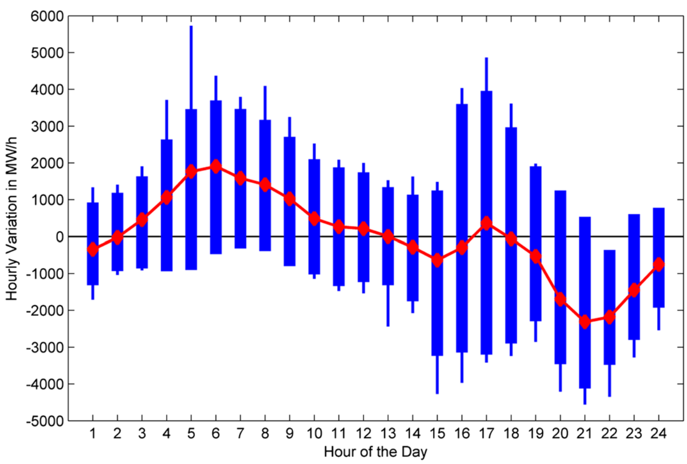

Figure 7. Net load hourly variability by hour of the day during 2004–2006.

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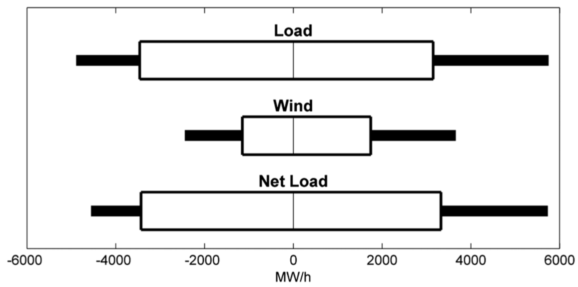

Figure 8. Comparison of the load, wind power, and net load hourly maximum and 99% variations during 2004–2006.

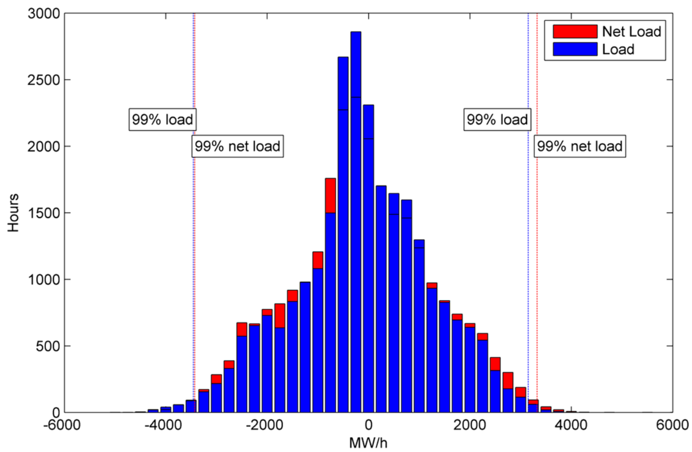

Figure 9. Comparison of the histograms of the load hourly variability with the net load hourly variability during 2004–2006. The load histogram is overlaid on the net load histogram.

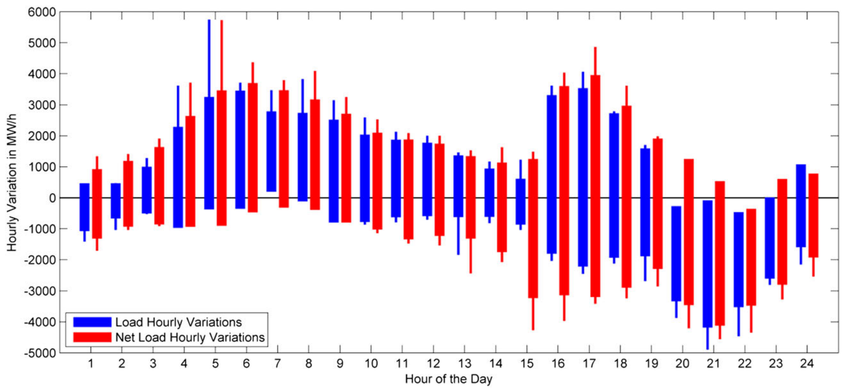

Figure 10. Comparison of the load hourly variability with the net load hourly variability by hour of the day during 2004–2006.

will increase the frequency and magnitude of ramp down events for the balance of the generation fleet serving the CAISO area. The CAISO should expect to hold greater operating reserve capacity online in the hours 14–21 than has been held historically. The remainder of the day the system will not see ramping events outside the normal historic diurnal patterns of the load without the 8790 MW of wind power.

The comparison between the load and net load shows that the power system has already met historic variations as large as those expected with 8790 MW of wind power added to the system and that no increase in the operating reserve capacity should be expected. However, the increased frequency of the larger hourly variations indicate that more energy is likely to be procured from flexible generation and operating reserve, especially during the late afternoon and evening hours as previously shown in Figure 10.

4. HOUR AHEAD FORECAST ERROR OF THE LOAD, WIND POWER, AND NET LOAD

4.1. Hour ahead forecast error of the load

The hour ahead load forecasts made by the CAISO during 2004–2006 were taken from the CAISO OASIS database with only 2.25% of the total 26,304 h missing. The hour ahead forecast error is defined in equation (2).

$$\text{Hour Ahead Load Forecast Error}_h = \text{Load}_h - \text{Load Forecast}_h \tag{2}$$

A positive hour ahead load forecast error occurs when the load is greater than its forecast, and a negative hour ahead load forecast error occurs when the load is less than its forecast. The 3 years of hour ahead load forecast errors are shown in the histogram in Figure 11. There is a higher frequency of negative forecast errors than positive forecast errors. The largest negative forecast error was −3770 MW, and the largest positive forecast error was 3232 MW.

Figure 12 shows the hour ahead load forecast errors by hour of the day. There was no significant diurnal pattern in the hour ahead load forecast errors for the 99% level other than hours 2–5 having low errors. There was some diurnal pattern in the extreme 1% forecast error events. The hours from 11 to 18 had large negative forecast error events, and the hours from 6 to 8 and from 22 to 1 had large positive forecast error events. Hour 16 had both large positive and negative forecast errors. The large negative forecast error events in the afternoon that indicate generators scheduled and committed on the hour ahead forecast would likely be ramped down or taken offline.

4.2. Hour ahead forecast error of the wind power

The persistence wind forecast model assumes the wind power forecast in hour h is equal to the wind power output in the previous hour $h-1$ as in equation (3).

$$\text{Wind Forecast}_h = \text{Wind Power}_{h-1} \tag{3}$$

The persistence model serves as the benchmark upon which other forecast methods and models seek to improve. These include numerical weather models, statistical models, and hybrids.[19] Since most wind farms' power output is forecast with one of the more sophisticated methods, the persistence model provides an upper conservative estimate of the forecast error of wind power for system wide studies.[18] The hour ahead forecast error of wind power with the persistence model is defined in equation (4).

$$\text{Hour Ahead Wind Forecast Error}_h = \text{Wind Power}_h - \text{Wind Forecast}_h \tag{4}$$

When equation (3) is substituted into equation (4), the hour ahead forecast error is the same as the hourly variability of wind power shown previously as a histogram in Figure 4 and by hour of the day in Figure 5(b). Those figures show that the hour ahead forecast error can be larger for wind power ramp up events with 99% of the hour ahead positive forecast errors using persistence forecasting (up variations) at 1745 MW (MW/h) compared with 99% of the hour ahead negative forecast errors (down variations) at −1148 MW (MW/h). The frequency of large hour ahead forecast errors for wind power occur between hours 14 and 20. This is a time of day when the load also has some of its largest forecast errors.

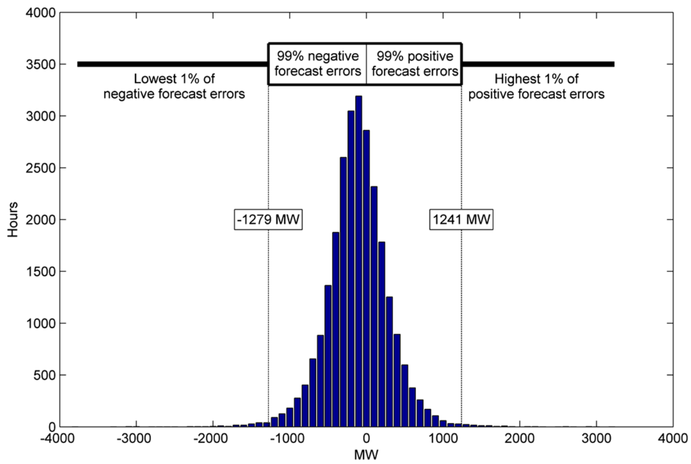

Figure 11. Histogram of the hour ahead load forecast errors in 100 MW bins during 2004–2006.

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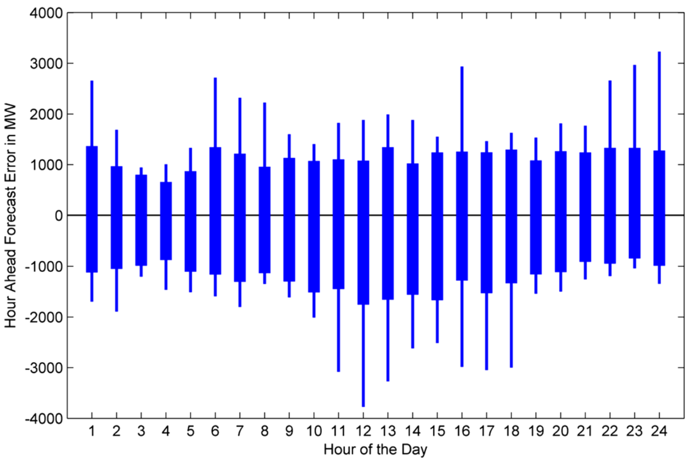

Figure 12. Hour ahead load forecast errors by hour of the day during 2004–2006.

4.3. Hour ahead forecast error of the net load

The hour ahead forecast for the net load includes the load and wind power hour ahead forecasts as in equation (5).

$$\begin{aligned} \textit{Hour Ahead Net Load Forecast}_h &= \textit{Load Forecast}_h - \textit{Wind Forecast}_h \\ &= (\textit{Load}_h - \textit{Load Forecast}_h) - (\textit{Wind Power}_h - \textit{Wind Forecast}_h) \end{aligned} \tag{5}$$

The correlation between the load and wind power forecast errors can increase or decrease for each hour the net load forecast error compared with the load only forecast error. Figure 13 shows the hour ahead net load forecast errors as a histogram. The largest negative forecast error was −4476 MW, and the largest positive forecast error was 3407 MW. Like the load forecast errors, there is a greater frequency of negative forecast errors than positive forecast errors.

The hour ahead net load forecast errors by hour of the day are shown in Figure 14. The afternoon and evening hours contain the largest errors with some large positive forecast error events at hours 23 and 24 and large negative forecast error events at hours 16–18. Considering only the 99% level of forecast errors, the only significant diurnal pattern is the high frequency of afternoon negative forecast errors.

4.4. Comparison of the hour ahead forecast error of the load, wind power, and net load

Figure 15 shows the maximum and 99% level of hour ahead forecast errors for load, wind power, and net load. Negative load forecast errors and positive wind power forecast errors combine to create large negative forecast errors in the net load that are larger than negative forecast errors for the load without wind power. The maximum negative forecast error event

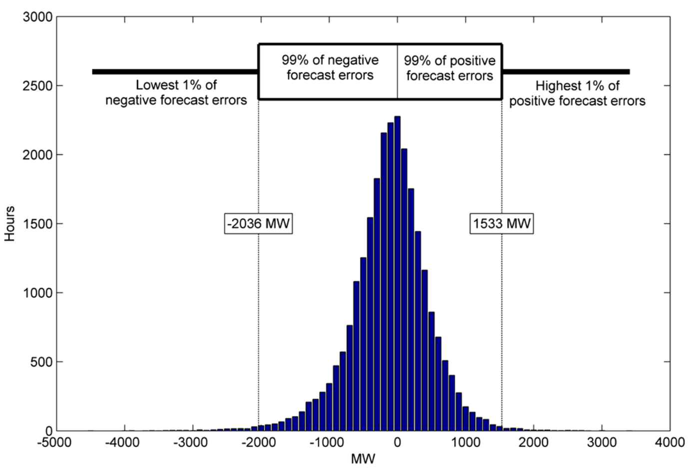

Figure 13. Histogram of the hour ahead net load forecast errors in 100 MW bins during 2004–2006.

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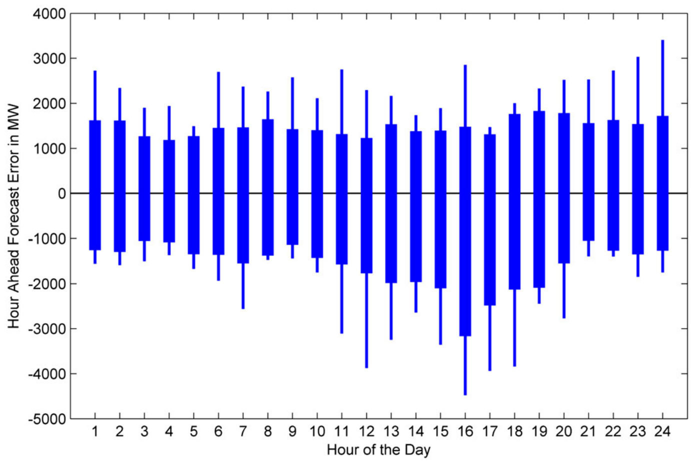

Figure 14. Hour ahead net load forecast errors by hour of the day during 2004–2006.

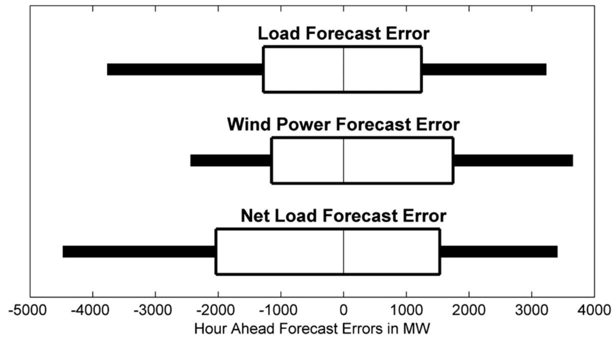

Figure 15. Hour ahead net load forecast errors by hour of the day during 2004–2006.

was −3770 MW for the load and −4476 MW for the net load, a forecast error increase of 706 MW (18.7%), which shows wind power introduced greater uncertainty. The 99% level of negative forecast error events was −1279 MW for the load and −2036 MW for the net load, a forecast error increase of 757 MW (59.2%), which shows wind power also introduced more uncertainty. The maximum positive forecast error event was 3232 MW for the load and 3407 MW for the net load, a forecast error increase of 175 MW (5.4%). The 99% level of positive forecast error events was 1241 MW for the load and 1533 MW for the net load, an increase of 292 MW (23.5%).

The histogram in Figure 16 shows an increased frequency of positive and negative forecast events for the net load compared with the load. The distribution of forecast errors has widened for the net load. Figure 2 shows the net load experiences greater and more frequent forecast errors than the load for most hours of the day.

The central observation of Figures 16 and 17 is that wind power introduces more and greater uncertainty in the net load compared with the load as indicated by the increased frequency and magnitude of the hour ahead forecast errors. Figure 2 shows that the additional uncertainty from wind power in the hour ahead forecast error has a diurnal pattern created by the correlation between the California diurnal wind regime and the diurnal load profile. The net load has greater positive forecast errors than the load mostly in the morning and night hours, and greater negative forecast errors in the afternoon and evening hours near the system peak. In particular, the negative forecast events in hours 15–20 are significantly greater for the net load than for the load. This occurs because the load negative forecast events in the afternoon hours are correlated with the wind power positive forecast events in the afternoon hours as shown previously in Figures 12 (load forecast errors) and 5(b) (wind power forecast errors with persistence model).

However, the diurnal pattern of the net load forecast errors mitigates the challenge the greater uncertainty from wind power may pose to the system. The increase in positive forecast events in the morning and night imply that conventional generators will need to ramp up or come online faster because wind power has ramped down more rapidly than forecast. Since this occurs in the morning and night when many generators are operating at low set points and many other generators are available because the load is low, sufficient capacity should be available to ramp up to meet the greater than forecasted

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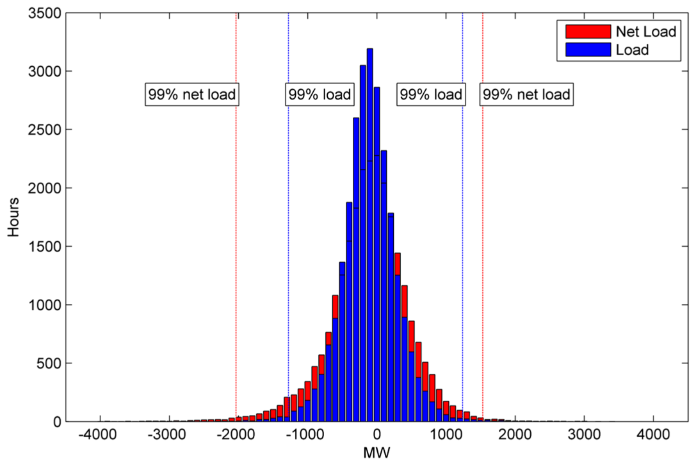

Figure 16. Comparison of the histograms of the hour ahead load and net load forecast errors in 100 MW bins during 2004–2006. The load histogram is overlaid on the net load histogram.

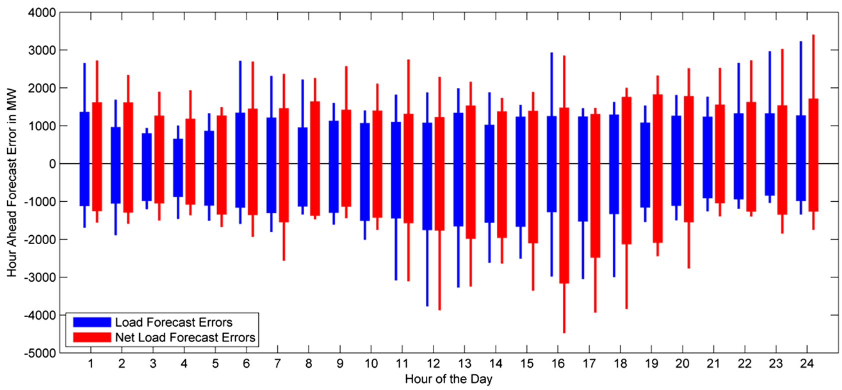

Figure 17. Hour ahead load and net load forecast errors by hour of the day during 2004–2006.

load. For example, the net load has larger positive forecast errors more often than the load for hours 1–5, but in hour 6 the load without wind power has a larger maximum positive forecast error than the net load. This indicates no additional ramp up capacity is required in the system to manage the increase in positive forecast events because of wind power, but the existing capacity will be used more frequently.

Similarly, wind power is likely to ramp up rapidly during the afternoon and evening hours and contribute to large negative forecast errors in the net load. This increase in negative forecast events occurs when most of the generation stack is online and the power system is often operating the highest marginal cost generator to meet the daily system peak. To manage large negative forecast errors, conventional generators will be required to ramp down or go offline faster and more frequently in the afternoon. The likely system response is to ramp down or take offline the most expensive and most flexible peaking generators. An increase in wind power output that was not forecasted will likely displace expensive generators such as combustion turbines and flexible generators such as hydropower. Since these ramp down events for conventional generators occur when the system has the most flexibility to ramp down and the highest marginal costs, the wind power ramp up events (net load negative forecasts) are not likely to challenge system operation significantly.

5. DISCUSSION

The additional variability and uncertainty in the net load, which was quantified in Sections 3 and 4 from the addition of 8790 MW of wind power, may also be mitigated or managed by several existing and new operating strategies and technologies. First, the CAISO operates a 5 min real time energy market, and this intra-hour balancing mechanism facilitates more efficient dispatch of generators and system resources in response to deviations from the hour ahead forecasted load and wind since their forecasts improve at decreasing forecast horizons. The 5 min market also mitigates large step changes in generator dispatch each hour as generators committed in the hour ahead market adjust their output between hourly schedules. Second, modern pitch controlled wind turbines can spill wind energy to limit ramp ups using set points in the SCADA system, and this strategy has been suggested by Lew and Piwko.[9] This would mitigate much of the increase in ramp down events for the net load, which was quantified for the California system as the largest impact of wind power at this penetration level. This form of curtailment could also be introduced with a bidding process for wind farms as in other market systems. Third, complementary renewable energy resources such as solar or wave power can balance each other's changes in power output.[20–23] For California, wind and solar complement each other's daily ramps with solar ramping down and wind ramping up in the afternoon and evening hours. Although this often mitigates the aggregate ramp, the winter evening system peak at around 18:00 is out of phase with the solar ramp down around 16:00, whereas wind does not exhibit a strong late afternoon ramp up in the winter to balance the solar ramp down (Figure 5(a)). Fourth, the addition of offshore wind power, which is a larger day time resource[24] not synchronized with the thermal wind regime of the Tehachapi area where most of California's onshore wind is located, would add additional geographic diversity to the portfolio of California wind farms and further reduce ramp rates. Fifth, emerging demand response[25,26] and storage technologies[27–29] can assist with managing the daily and hourly variability and uncertainty issues of wind power since both technologies are well suited to shift or store and supply energy on the 1–12 h time scale. Sixth, modern wind power forecasting methods have lower mean absolute errors than the persistence method. The use of advanced forecasting methods will reduce the frequency of large uncertainty in the net load, although large forecast errors are still present for the timing of ramp events and of wind cut out speed events, which are the most impactful events of wind power on power systems. Finally, the Western Wind Dataset has a seam issue discussed in Section 2.2 that may introduce artificial variability in the wind power around 16:00 PST. The net effect of this bias is that wind variability may be overestimated although the observed behavior of wind in California matches the overall pattern of wind ramp ups and corresponding net load ramp downs as seen in this data and confirmed in other studies.[2] This indicates that the results presented in Sections 3 and 4 are conservative estimates of the need for additional operating reserve in the California system due to 8790 MW of wind power.

6. CONCLUSION

Section 3 showed that wind power variability will not increase the maximum hourly variability that already occurs in the California system caused by changes in load. The diurnal pattern of wind power variability may increase the hourly variability of the net load for some hours of the day, especially during the afternoon hours 14–18, but the increased variability in those hours is still below the maximum variability already caused by load during other hours. This means the California power system should not need to build any additional operating reserve capacity. However, the California ISO may be required to hold more flexible generation resources and operating reserve capacity online in the afternoon hours to manage the additional variability from wind power experienced during those hours.

Section 4 showed that wind power uncertainty will increase the maximum hour ahead forecast errors for the California power system once it builds out the expected 8790 MW of wind power by 2020. The frequency of hour ahead forecast errors in the net load will also increase especially in the afternoon and evening hours from wind power ramp up events and in the morning and night hours for wind power ramp down events. This means that the California power system must have online sufficient operating reserve to manage the increase in uncertainty that wind power adds to the system on the 1 h time scale. The challenge of meeting wind power ramp up and ramp down events may be mitigated by the diurnal pattern of such events, which generally occur when the power system is most capable of managing them.

The data in this case study showed that wind power's uncertainty with forecast errors presents a more challenging grid integration issue than wind power's variability with 1 h ramp rates when 8790 MW of wind power are added to a 50 GW peak electric power system. The variability of the load and net load were similar, but the forecast errors of the net load showed increases in both magnitude and frequency compared with the forecast errors of the load. Many studies[2,9,11–13,30–36] have attributed the cost of integrating wind power at moderate penetration levels primarily to errors in wind power forecasting. Improved forecasting methods have been shown to reduce the cost of integration,[9,13,34] and this case study confirms that uncertainty in the forecast of wind power output will be the central challenge when adding 8790 MW of wind power to the 50 GW California power system.

ACKNOWLEDGEMENTS

This work was supported by the Charles H. Leavell Graduate Student Fellowship and the U.S. EPA under Agreement R833371.

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Wind Energ. 2014; **17**:1411–1424 © 2013 John Wiley & Sons, Ltd.
DOI: 10.1002/we