The Value of Improved Short-Term Wind Power Forecasting

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Technical Report
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Executive Summary

This report summarizes an assessment of improved short-term wind power forecasting in the California Independent System Operator (CAISO) market and provides a quantification of its potential value. Performed for the Lockheed Martin Corporation, the study was accomplished in a technology-agnostic fashion to estimate savings from regulation and flex reserves, as well as production savings, to provide insight into their product within the context of current and future CAISO markets. A simulation approach was required with a design of experiment to capture feasible operating points, and state-of-the-art modeling and Western Interconnection (western United States) data were used to estimate realistic value streams. Two major scenarios were considered: (1) a low wind scenario (SC4) with 8% wind penetration and (2) a high wind scenario (SC3) with 25% wind penetration. The design of experiments consisted of short-term (sub-hourly) wind power forecasting improvements of 0%, 10%, 25%, and 50% above the current state of the art. Results show that cost savings from flex reserves are estimated to range from \$1.27 to \$17.1 million. Cost savings from regulation reserves are estimated to range from \$0.917 to \$12.7 million. Production cost savings are estimated to range from \$2.87 to \$116 million. Total cost savings from improved short-term wind power forecasting are estimated to range from \$5.05 to \$146 million. The study results led to three main points for consideration: (1) Economics are changed by commitments, and reliability is changed by the dispatch, so short-term forecasting inherently fails to address the lion's share of improvement opportunities; (2) The results from the study are a strong function of gas prices, which are currently low but have an uncertain future; and (3) From the low penetration scenario, results show that cost savings are likely "in the noise." What follows from the study's outcomes is the recommendation that within the current CAISO market an investment in short-term wind power forecasting technologies would be risky; however, within the next decade or two, wind penetration levels will be significant enough to warrant investment in short-term wind power forecasting technologies. In the near term, these technologies might be better suited for reliability issues and later evolve into more dispatch-centric devices as wind penetration levels increase.

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Introduction

A modeling and simulation study was conducted to quantify the potential value of Lockheed Martin's product in a technologic-agnostic fashion. The study relied on data-driven analyses of short-term wind power forecasting in the California Independent System Operator (CAISO) market. It is important to note that CAISO in this study includes some additional small California balancing authority areas, which were considered as part of the larger CAISO system because of their frequent and strong interactions. Within a design-of-experiments approach, short-term (less than one-hour) improvements were considered in wind power forecasting to evaluate the grid-wide impact of such improvements and to estimate savings in terms of both costs and emissions. Unit commitment and economic dispatch models were simulated using the PLEXOS tool as part of a scenario-based approach. Both current and future scenarios of the CAISO market were considered as shown in Table 1 and further detailed below. The design of experiments and analysis were conducted within the context of two primary scenarios: the current and best-estimate future CAISO market with corresponding wind penetration levels. To ensure that system-wide impacts were captured and realistic dispatch patterns were observed in response to variable and uncertain wind power production, the complete Western Interconnection was modeled and simulated with a focus on the CAISO market.

Table 1. Scenarios for the Study

Scenario	Current Forecasts	Perfect Forecasts	Uniform Forecast Improvements (40-Minute Interval)
TEPPC[a] Case – Low Wind (8% Wind, SC4)	WWSIS-2	40-minute interval	10%, 25%, 50%
Future Case – High Wind (25% Wind, SC3)	WWSIS-2	40-minute interval	10%, 25%, 50%

[a] Transmission Expansion Planning Policy Committee of the Western Electricity Coordinating Council (WECC)

This study was based on the Western Wind and Solar Integration Study Phase 2 (WWSIS-2) [1]. However, significant extensions were applied to this Western Interconnection model to capture current CAISO market realities and a best-estimate future CAISO market according to evolving policy. The forecasting improvements shown in the table were assumed to occur only in the CAISO market, and it was not possible to decouple this analysis from the rest of the western United States, so the remaining markets utilized the numerical weather prediction forecasts from WWSIS-2. Within the CAISO market, assumptions on market design and wind forecasting implementation were extracted from policy documents [2-5]. As implemented in the PLEXOS tool, the following sections give a brief overview of the CAISO market design, assumptions required to solve the unit commitment and economic dispatch problem, and the importance of the CAISO market relative to the Western Interconnection as a whole.

CAISO Market Design

Toward the goals established for Task 1b by Lockheed Martin and the project team, the assessment of short-term wind power forecasting improvements within the CAISO market required four time intervals for modeling the unit commitment and economic dispatch process. The following time intervals were used in the PLEXOS simulations:

- Day-ahead
- 4-hour-ahead
  - Representative of rolling reliability unit commitment
- 15-minute market
  - Where forecasting improvements were made
  - Forecasts were of 40-minute persistence to represent the CAISO market
- 5-minute "real-time" dispatch
  - No forecasts; actual values were used
  - Deviations were handled by regulation reserve

A previous portion of this study (Task 1a) focused on forecasting improvements in the first two time intervals and quantified their value in terms of the reduced reserves that must be held over these longer, sequential time frames. As discussed in this report, Task 1b required the first two time intervals, but the forecasting improvements were made only in the 15-minute market. In addition to the unit commitment and economic dispatch within the PLEXOS tool, this required a completely new analysis of reserves, as detailed in a later section. The cost and emissions savings from improved forecasts were separately evaluated in terms of regulation and flexibility reserves, as well as production savings. Benefits from forecasting improvements are attributed to the CAISO market generically, and this work does not seek to provide guidelines and recommendations on how those benefits can be extracted.

The two scenarios shown in Table 1, and the design of experiments contained within them, provided an adequate study of the value of improved short-term wind power forecasting through the examination of feasible ranges of forecast improvements via the technology according to Lockheed Martin staff. Nevertheless, the forecasting improvements could be realized in a technology-agnostic fashion because of their numerical nature. The improvements were aligned with the timescale of interest for the technology and examined as such, in a uniform convention at all points in time, without the consideration of ramp forecasting magnitude or timing improvements. That is, all analyses herein were a function of the validity of the improvements examined in a numerical setting, and no physical modeling of the forecasting process was considered, only the impact of such numerical realizations of such forecasts.

Generating the numerical, uniform forecasting improvement was accomplished by examining the forecast error and decreasing this error by different percentages according to the design of experiments. This required scripting programming routines to query the WWSIS-2 database, locate the specific bus of interest in the CAISO region, and perform the forecasting improvement calculations. The "actuals" are the realizations of sampled events at 5-minute intervals, and the forecasts are also the realizations of sampled events at 5-minute intervals but inherently erroneous because of imperfect knowledge of the physical processes. The original forecasts came from numerical weather prediction routines as detailed in the WWSIS-2 final report, and the forecasts utilized in this study were improved according to Table 1.

Unit Commitment and Economic Dispatch

PLEXOS is an electricity market modeling and power system simulation tool. The modeling utilized in this study made use of its deterministic linear programming methods to minimize an objective function. In this case, the objective function was the expected cost of electricity dispatch while numerous constraints were observed—for example, the operational, part-load performance of generating plants and their availability, fuel costs, renewable power availability, transmission constraints, etc.

This study made use of the CAISO market established in the previous section for a full year's time. During this year-long period, the PLEXOS model accounted for every period of energy trading and maintained chronological order throughout the optimization horizon. Optimization decisions were based on each generator's start-ups and shutdowns while observing the parameters governing individual plants' operating characteristics, such as minimum generation and ramping up/down times. Tracking all of these technical details requires the mathematical sophistication of mixed-integer programming to solve not only binary decisions—i.e., whether the generator is on or off—but the fractional operating points to ensure that supply meets demand. Such an approach allows for a realistic model of the actual, physical operation of generators in a power market.

Because this study uses the WWSIS-2 as a basis, numerous assumptions were required to adequately model the Western Interconnection. For brevity, the reader is referred to the WWSIS-2 final report [1] for all assumptions, in which all methodologies and analyses were overseen by a technical review committee for credibility and realism. Only global, fundamental assumptions that were carried over into this study are stated below:

- An average gas price of $4.60/MMBtu was used.
- Significant balancing authority area cooperation was inherent to the analysis.
- Least-cost economic dispatch and transmission usage with bilateral transactions were not explicitly modeled.

Because the primary concern of this study was the improvement in short-term wind power forecasting in CAISO, variability could be expected not only in the wind as a power source during seasonal, daily, and hourly time frames, but of particular interest were sub-hourly variations and how reductions in these errors could lead to costs and emissions savings. Only through modeling the Western Interconnection and PLEXOS simulations or similar mixed-integer programming could this be quantified. This was the approach undertaken in this study.

CAISO Within the Western Interconnection

The CAISO market was chosen as a test bed for quantifying the value of short-term wind power forecasts for numerous reasons: (1) It has a high-quality resource for wind power; (2) It has the distinction of being the most developed market in the Western Interconnection; (3) California has one of the highest renewable energy portfolio standards in the United States; (4) California is expected to add significant amounts of new wind power capacity by 2020; and (5) Vast amounts of data are available for studying the CAISO system.

From the WWSIS-2 study, a data set of simulated wind power for a large number of plants is available with time-synchronized load data. The data are for the accurate value assessment of wind power forecasting in power system operations, and, further, creating one for new regions is a costly and time-consuming process [8].

The CAISO control area consists of three primary utility companies: Pacific Gas & Electric, San Diego Gas & Electric, and Southern California Edison. Because it is likely that wind power generated outside the CAISO control area is used within the CAISO control area, load and wind power from surrounding utility areas were also included in this study. Table 2 shows the utilities and their mean loads based on the WWSIS-2.

Table 2. Utilities and Mean Loads (MW)

Utility	Utility Name	Mean Load (MW)
CFE	Comisión Federal de Electricidad	1,965
IID	Imperial Irrigation District	523
LDWP	Los Angeles Department of Water and Power	3,358
PG&E_BAY	Pacific Gas & Electric (Bay Area)	5,258
PG&E_VLY	Pacific Gas & Electric (Central Valley)	7,529
SCE	Southern California Edison	13,082
SDGE	San Diego Gas & Electric	2,643
SMUD	Sacramento Municipal Utility District	2,117
Total		36,474

Details on the Western Interconnection are provided in Table 3 and Table 4 for the low wind (WECC TEPPC) and high wind (Future) scenarios. These tables illustrate the diversity of wind power generation and its spatial distribution. Of course, the temporal variability in the wind resource will determine its instantaneous (renewable) penetration level and the extent to which the forecasting improvements influence the dispatch of generation.

Table 3. Low Wind (TEPPC) Scenario

	Rooftop PV		Utility-Scale PV		CSP		Wind		Total	
State	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**
Arizona			1,171	22%	472	43%	3,681	30%	5,324	30%
California			3,545	25%	3,221	44%	7,299	30%	14,065	32%
Colorado			1,342	20%	169	37%	3,256	29%	4,767	27%
Idaho							523	27%	523	27%
Montana							838	34%	838	34%
Nevada			304	22%	334	42%	150	25%	788	31%
New Mexico			140	27%	156	39%	494	28%	790	30%
Oregon							4,903	26%	4,903	26%
South Dakota										
Texas										
Utah			571	20%			323	31%	894	24%
Washington							4,652	27%	4,652	27%
Wyoming							1,784	42%	1,784	42%
Total			**7,074**	**23%**	**4,352**	**43%**	**27,900**	**29%**	**39,326**	**30%**

Table 4. High Wind (Future) Scenario

	Rooftop PV		Utility-Scale PV		CSP		Wind		Total	
State	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**	**Capacity (MW)**	**CF**
Arizona	1,975	19%	2,330	25%	3,303	43%	4,941	30%	12,548	31%
California	4,875	18%	5,372	25%	2,469	45%	11,109	30%	23,824	28%
Colorado	1,059	18%	1,128	22%	169	37%	6,226	35%	8,581	31%
Idaho	3	15%	2	16%			1,333	29%	1,338	29%
Montana	22	15%	34	17%			6,658	36%	6,714	36%
Nevada	398	19%	344	22%	439	42%	3,270	31%	4,452	30%
New Mexico	172	20%	209	27%	156	39%	4,784	38%	5,321	37%
Oregon	91	14%	101	22%			5,473	26%	5,665	26%
South Dakota	4	17%	6	19%			2,640	36%	2,650	36%
Texas	76	20%	122	27%					198	24%
Utah	361	17%	489	21%			1,343	32%	2,193	27%
Washington	371	13%	492	20%			5,882	27%	6,745	26%
Wyoming	9	18%	18	21%			10,184	43%	10,211	43%
Total	**9,417**	**18%**	**10,647**	**24%**	**6,536**	**43%**	**63,840**	**34%**	**90,439**	**32%**

Reserve Requirements

Although Task 1a focused on the anticipated cost savings from improved short-term wind power forecasting, it did so for the 1-hour and 4-hour-ahead markets in CAISO. Representatives from Lockheed Martin determined that their product was more applicable to the sub-hourly time frame and thus a new reserve requirement analysis had to be conducted. Even in the sub-hourly CAISO market, the reduction in the amount of reserves that must be carried to accommodate the uncertainty of wind power output was anticipated to be one of the largest cost savings. An advanced reserve calculation algorithm was thus applied to estimate the reserve reductions that various wind power forecasting improvements would allow; this methodology was originally developed during the WWSIS-2 project. Improved forecasting (on average) reduces the amount of reserves that must be held, and the various types of flexibility reserves are defined by:

- Spin reserve = 70% confidence interval
- Non-spin reserve = 95% confidence interval

and illustrated in Figure 1.

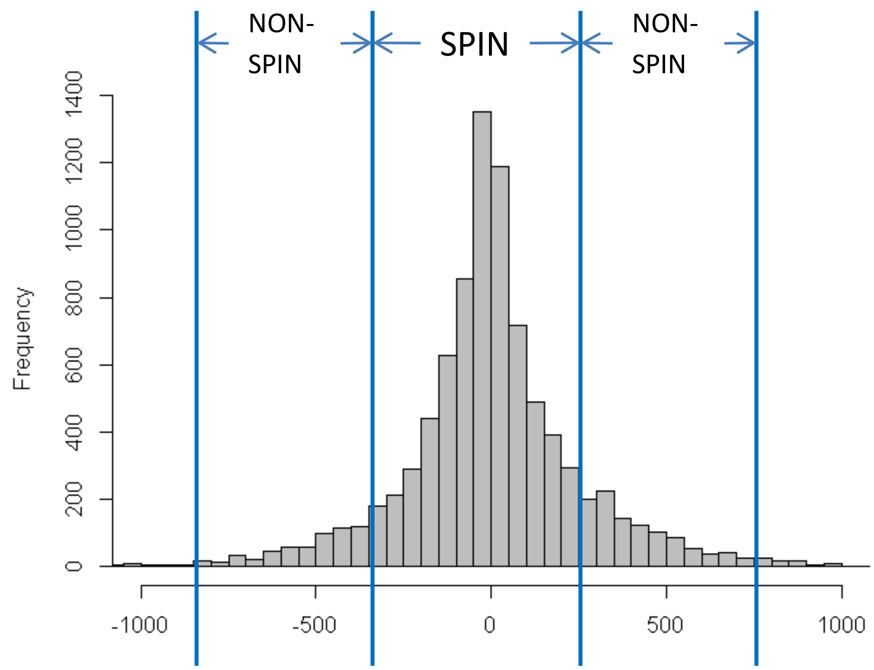

Figure 1. Spin and non-spin reserve defined by confidence intervals

Base case reserves are calculated using a persistence method. Both the spin and non-spin reserves are a function of the distribution of forecast errors. During a given forecast interval Δt, one error observation is power measured at t + Δt minus power measured at t, as shown in Figure 2, adapted from [6].

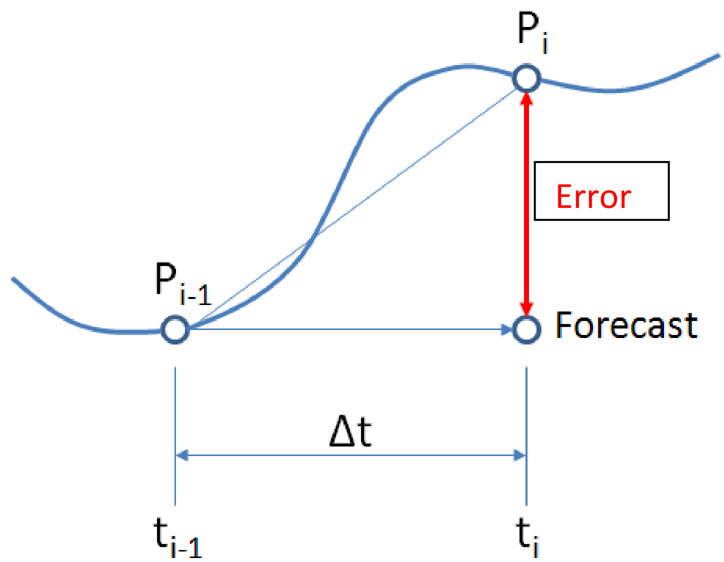

Figure 2. Calculation of one error observation using the persistence method

Using the persistence approach, the forecast at ti is Pi-1 and error is (Pi – Pi-1). The two types of reserves can be calculated for different time intervals, or requirements such as percent of time needed to meet the unanticipated change in power. Figure 3 illustrates how an improved forecast can potentially reduce the error, which in turn would reduce the amount of reserves required. In this case, the forecast at ti replaces Pi-1 in the error equation. For an overall reduction in reserves to be realized, the forecast must be consistently closer to Pi than to Pi-1 for most time periods.

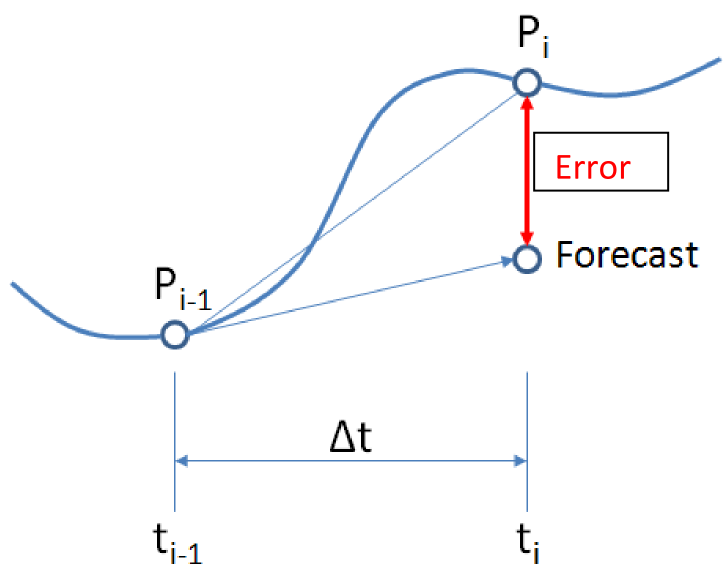

Figure 3. Reduction in the error observation with an improved forecast

An overall evaluation of each forecast in the design of experiments was obtained by calculating errors using the persistence method for the complete year under investigation and then using the forecast method for the same year. Figure 4 illustrates the persistence distribution for the low wind scenario (SC4) compared to the distribution using the sub-hourly forecast with 50% uniform improvement. Figure 5 does the same for the high wind scenario (SC3). The distribution did not appear to follow normality in either of these cases. Appendices provided include all distribution of errors for each region of interest and all design-of-experiment variables considered.

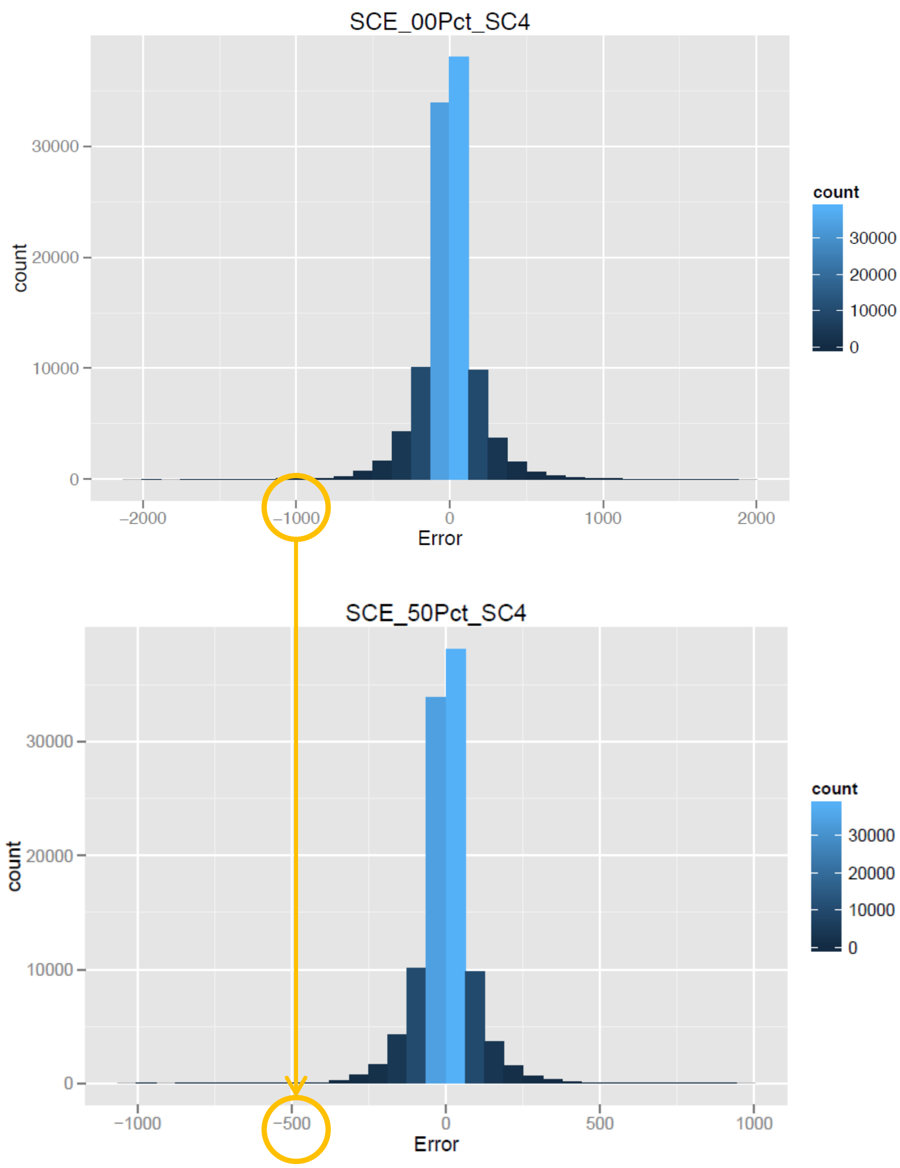

Figure 4. Error distributions using the persistence method and a forecast with 50% uniform improvement on low wind scenario (SC4) data

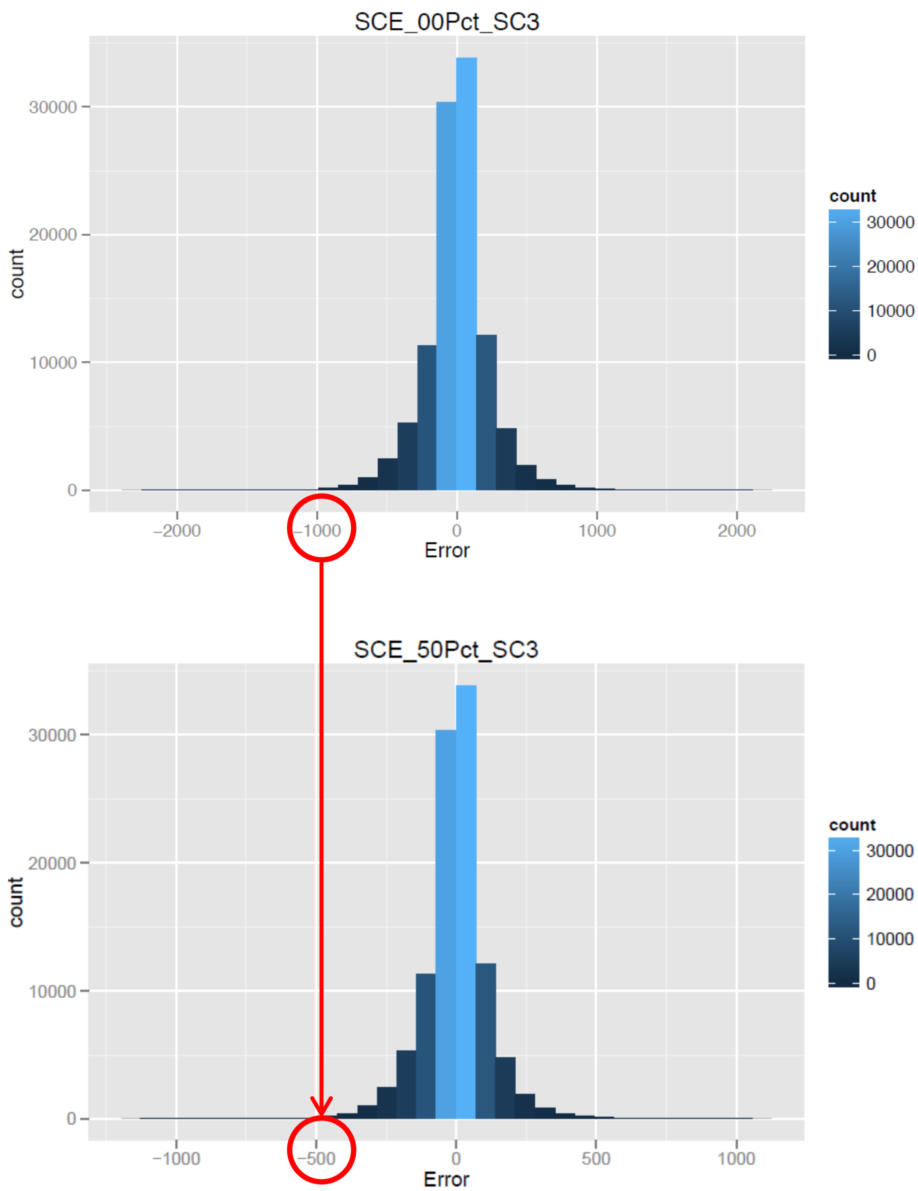

Figure 5. Error distributions using the persistence method and a forecast with 50% uniform improvement on high wind scenario (SC3) data

In both cases, there appeared to be a narrower distribution when the sub-hourly forecasts with 50% uniform improvement were used to determine errors. A differentiation needed be made between the positive and negative errors, i.e., an "over-forecast" or "under-forecast" for the type of reserve being evaluated. This was accomplished by using a confidence interval for the specific type of reserve and extracting the lower percentile of the distribution (under-forecast) and an upper percentile of the distribution (over-forecast). Over-forecast minus under-forecast gives the confidence interval range. A percent improvement could then be estimated by comparing the confidence interval range determined using the forecast to the confidence interval range determined using the persistence method.

Also of interest in evaluating the reserves is that on average the error varied with turbine power, as shown in Figure 6 and Figure 7 with the 70th percentile range (under-forecast = 15th percentile, over-forecast = 85th percentile) and 99th percentile range (under-forecast = 0.5th percentile, over-forecast = 99.5th percentile) for ramps calculated using the persistence method on low wind (SC4) and high wind (SC3) data, respectively.

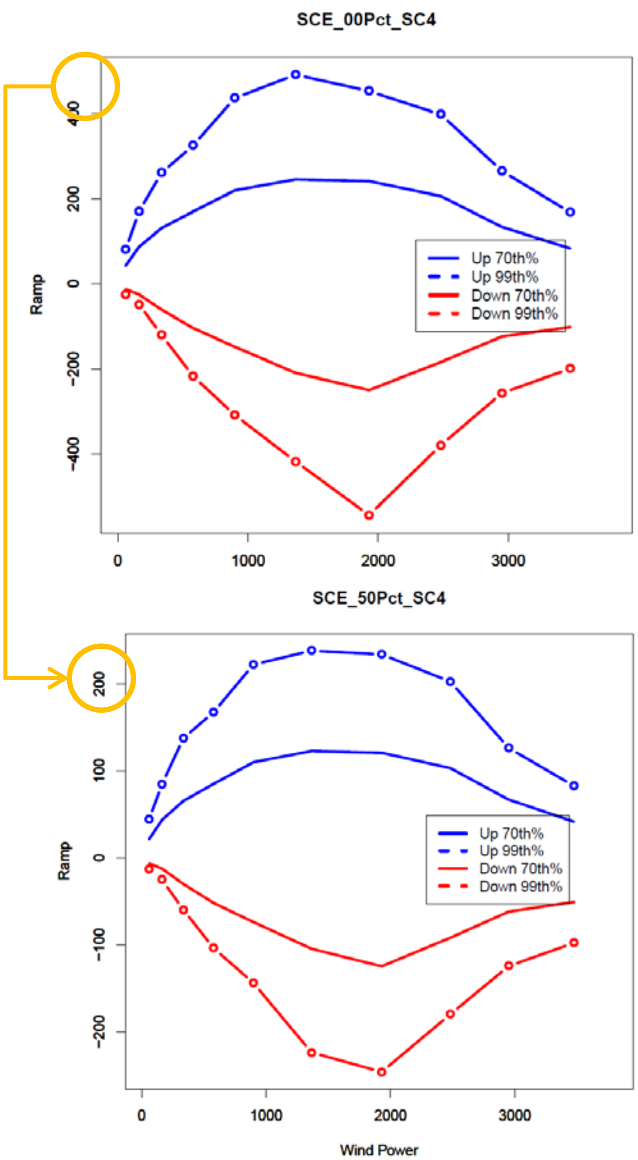

Figure 6. Error distributions as a function of wind power in the low wind scenario (SC4)

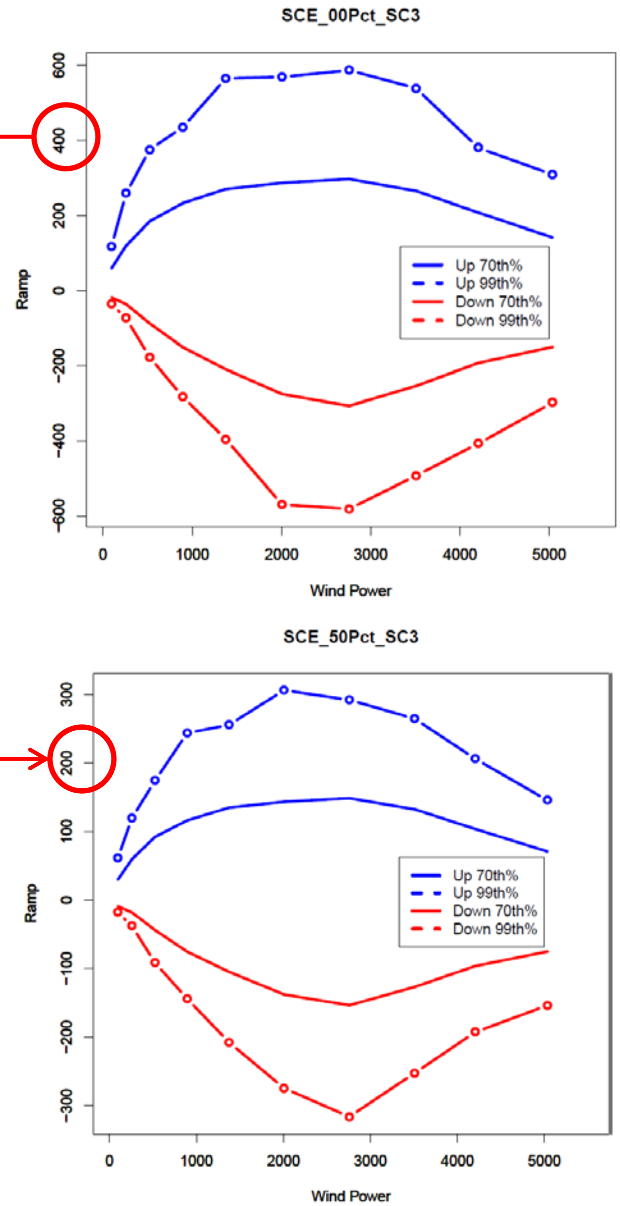

Figure 7. Error distributions as a function of wind power in the high wind scenario (SC3)

As observed in the figures, the distribution in error values was narrower at low power conditions, wider at midrange power conditions, and narrower again at high power conditions. In general, this pattern was observed for almost all wind turbine sites. The figures also demonstrate the sizeable difference in a moderate range (70th percentile) versus the range needed to achieve high certainty (99th percentile).

Comparing the errors among persistence and forecast allows one to understand how the accuracy of the forecasts changes as a function of wind power, as shown in Figure 8 and Figure 9 for the low wind and high wind scenarios, respectively. Again, as shown in the figures, the distribution in ramp values was narrower at low power conditions, wider at midrange power conditions, and narrower again at high power conditions. Appendices provided include all error (ramp) versus wind power plots for each region of interest and all design-of-experiment variables considered.

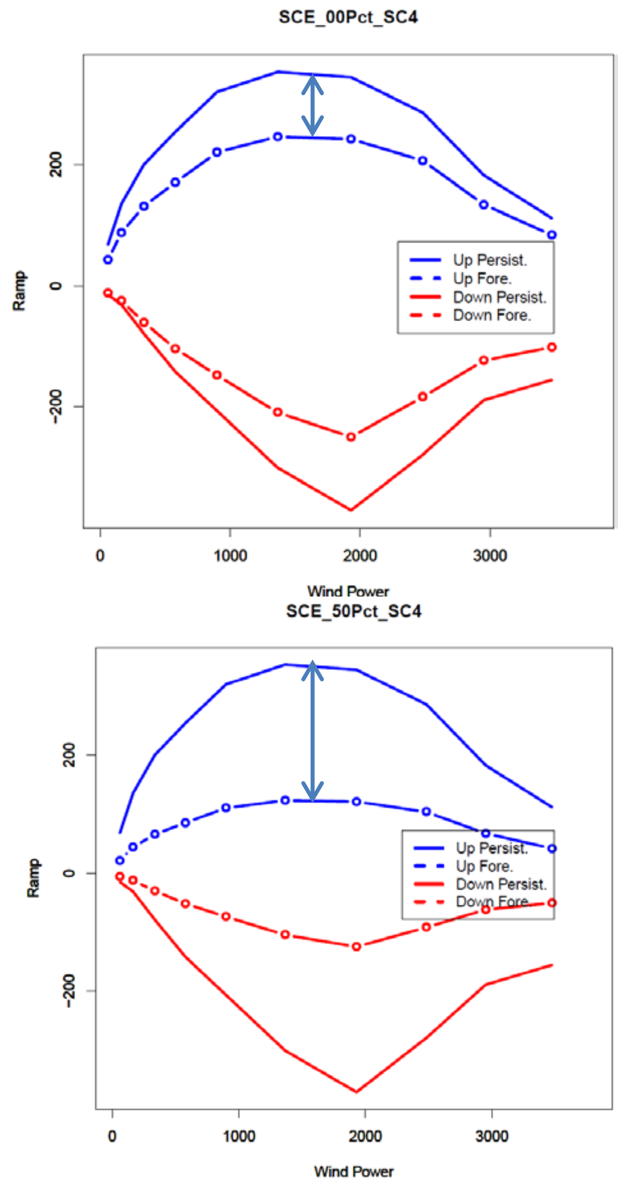

Figure 8. Comparing error distributions for persistence and forecasts as a function of wind power in the low wind scenario (SC4)

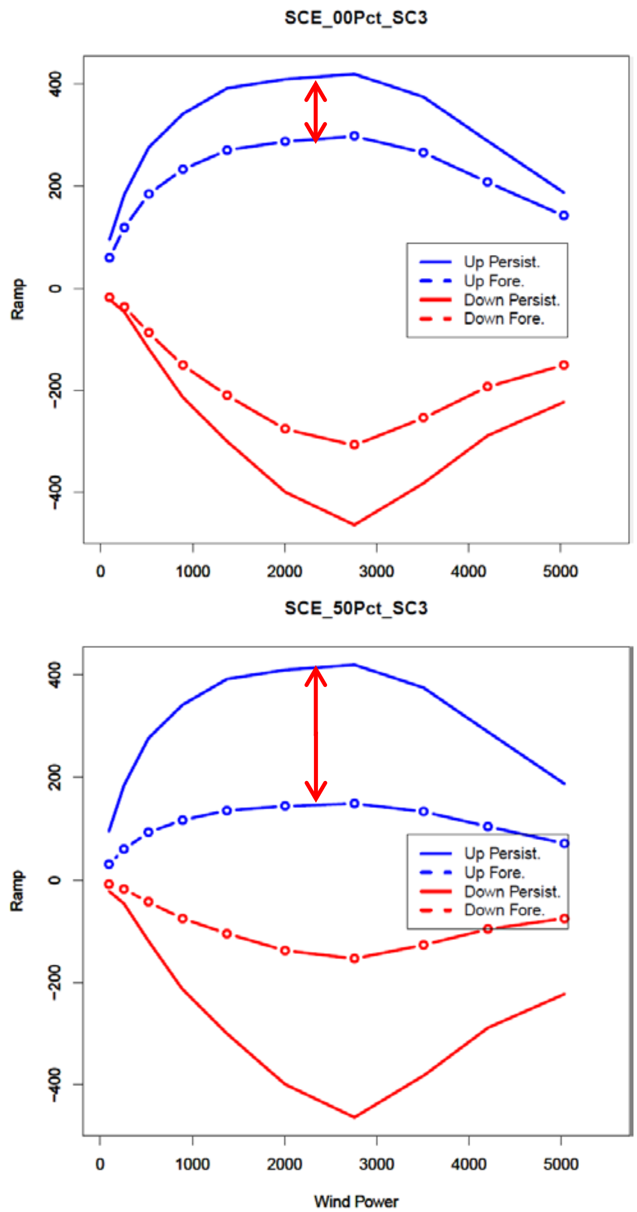

Figure 9. Comparing error distributions for persistence and forecasts as a function of wind power in the high wind scenario (SC3)

Flexible Reserve Cost Savings

To evaluate flexible reserve, the 70% confidence interval was utilized: an under-forecasting error was determined by evaluating the 15th percentile of the error values, and an over-forecasting error was determined by evaluating the 85th percentile of the error values. The sub-hourly time interval was used to determine flexible reserve. A visual comparison of the persistence method and forecasts is shown in Figure 8 and Figure 9, and Table 5 shows a numerical comparison.

Table 5. Numerical Comparison of Persistence Method and Forecasts

		Persistence			Forecast			
Wind Scenario	**Improvement Description**	**Up-Ramp**	**Down-Ramp**	**Mean CI diff.**	**Up-Ramp**	**Down-Ramp**	**MeanCI diff.**	**Percent Improve-ment**
Low	10% uniform improvement	225	-177	402	203	-159	362	10%
High	10% uniform improvement	296	-246	542	268	-220	488	10%
Low	25% uniform improvement	225	-177	402	169	-133	302	25%
High	25% uniform improvement	296	-246	542	223	-183	406	25%
Low	50% uniform improvement	225	-177	402	113	-88	201	50%
High	50% uniform improvement	296	-246	542	149	-122	271	50%

The holding of flexibility reserve is determined by economics, and the 70% and 95% confidence intervals were based upon economic realities of power system operations. The Eastern Wind Integration and Transmission Study [7] reserve methodology has been accepted in the wind integration community as a reasonable approach to determining reserve levels necessary under high wind power penetration scenarios. A similar methodology was adopted in the WWSIS-2 and used in this study. Carrying spin reserve is expensive, because this requires keeping generating units online throughout the 8,760 hours of a year, even if they are rarely used. As such, the methodology used utilizes spin reserve to cover only the 70% confidence interval of variability at this timescale. These are the levels of reserve that will be utilized more often, and thus are cost-effective to be held at all times. Non-spin reserve is held for more rare events, up to the 95% confidence interval. This type of reserve is slower to act (taking up to 10 minutes) but is much more cost-effective. This combination of reserve types helps to cover the vast majority of the additional variability seen from increased wind power penetration while doing so in a cost-effective manner. The 70% and 95% figures approximately represent the confidence intervals that would be covered by one and two standard deviations of variability, if the distributions were to follow a normal distribution.

Using the methodology described above and the equations detailed below, the cost savings from flex reserve were calculated for the design of experiments. As shown in Table 6, the costs savings trend with forecasting improvements, and the technology could be helpful for cost savings on the order of millions of dollars in terms of flexible reserve.

$$C_{flex} = H_{year} \times (c_{spin} \times R_{flex} + c_{non\text{-}spin} \times R_{95\%})$$

where

C_{flex} = total annual cost of flexible reserve

H_{year} = hours in one year

c_{spin} = cost in \$/MWh of spin reserve

R_{flex} = MW range for flexible reserve determined at the 70% confidence interval

$c_{non\text{-}spin}$ = cost in \$/MWh of non-spin reserve

$R_{95\%}$ = MW range outside of the 70% confidence interval

but within the 95% confidence interval.

Table 6. Cost Savings from Flex Reserve

Wind Scenario	Improvement Description	Persistence Method Cost Per Year	Forecast Method Cost Per Year	Annual Savings
Low	10% uniform improvement	$11,900,000	$10,600,000	$1,270,000
High	10% uniform improvement	$34,600,000	$30,900,000	$3,690,000
Low	25% uniform improvement	$11,900,000	$8,900,000	$2,940,000
High	25% uniform improvement	$34,600,000	$26,000,000	$8,530,000
Low	50% uniform improvement	$11,900,000	$5,950,000	$5,900,000
High	50% uniform improvement	$34,600,000	$17,400,000	$17,100,000

Regulation Reserve Cost Savings

For regulation reserve, the forecast error for a 10-minute moving window was calculated and a 95% confidence interval was selected—more stringent than the flexible reserve. This leads to increased certainty that a large deviation in energy demand can be accommodated. The 95%

confidence interval was chosen with consideration given to the North American Electric Reliability Corporation (NERC) area control performance standards (CPS). The CPS2 standard states that the 10-minute average area control error has to remain within a proscribed range 90% of the time. Because regulation reserve acts at this timescale, being able to cover 95% of the required regulation service provides assurance that the utility will fulfill their CPS2 obligations.

Using the methodology described above and the equations detailed below, the cost savings from regulation reserve were calculated for the design of experiments. As shown in Table 7, the costs savings were slightly less than those for flexible reserve and trend with forecasting improvements.

$$C_{reg} = H_{year} \times (c_{up} \times R_{up} + c_{down} \times R_{down})$$

where

C_{reg} = total annual cost of regulation reserves

H_{year} = hours in one year

c_{up} = cost in \$/MWh of up-ramp reserves

R_{up} = MW range for regulation up-ramp reserves

c_{down} = cost in \$/MWh of down-ramp reserves

R_{down} = MW range for regulation down-ramp reserves.

Table 7. Cost Savings from Regulation Reserve

Wind Scenario	Improvement Description	Persistence Method Cost Per Year	Forecast Method Cost Per Year	Annual Savings
Low	10% uniform improvement	$8,660,000	$7,750,000	$917,000
High	10% uniform improvement	$25,400,000	$22,900,000	$2,460,000
Low	25% uniform improvement	$8,660,000	$6,490,000	$2,170,000
High	25% uniform improvement	$25,400,000	$19,100,000	$6,310,000
Low	50% uniform improvement	$8,660,000	$4,330,000	$4,330,000
High	50% uniform improvement	$25,400,000	$12,700,000	$12,700,000

Results, Impacts, and Features of Interest

The set of results from the PLEXOS production simulations included a tremendous amount of detail on all aspects of the power system model, including generator commitment and dispatch, production costs, emissions, and transmission path flows for each 5-minute time step. Not included were fixed capital costs and power purchase agreements, which are not within the scope of this work. The power flow modeled in PLEXOS is an optimal direct current power flow that respects transmission constraints while using power transfer distribution factors. The following sections detail high-level outcomes that dictate the cost and emissions savings observed from the improved wind power forecasting.

Generation by Type

The generation by type will vary on a monthly basis based on the load, the availability of renewable resources, and the fossil fuel–based generation that must make up the difference. Of course, the dispatch stack is a function of price sensitivities, and slight trade-offs will occur between all of these factors throughout a year. Figure 10 and Figure 11 show the generation by type for all generators used in the Western Interconnection study for the months of January and July. These months were chosen to illustrate the extremes in differences throughout a year: on average, the month of January corresponds to maximum wind availability and minimum solar available, and the month of June is the opposite. As shown in the figures, most changes in production proportions were on the order of a few percentage points; however, even these slight differences constitute enormous value potentials because of the proportions of the Western Interconnection. Following sections further examine why and analyze details.

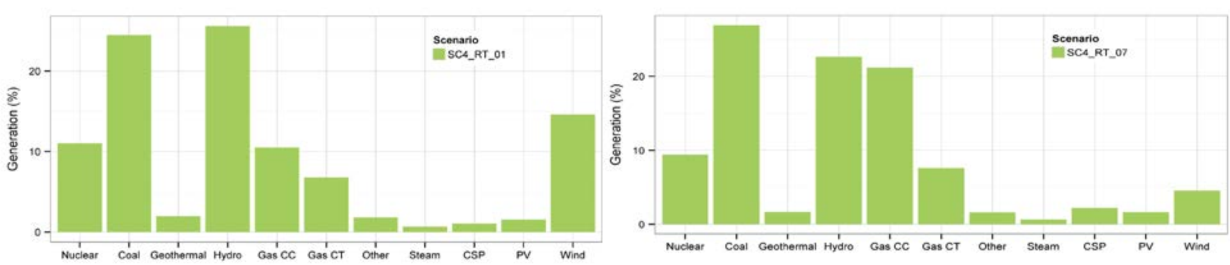

Figure 10. Generation by type observed in January and July for the low wind scenario (SC4)

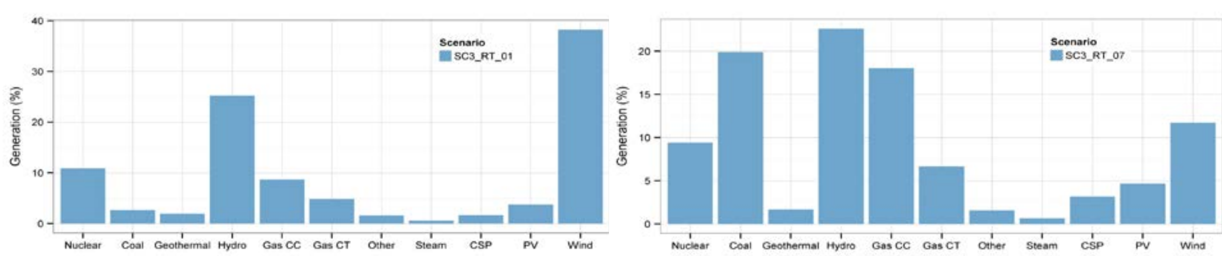

Figure 11. Generation by type observed in January and July for the high wind scenario (SC3).

Generation by Type—Impact from CAISO Improvements

Improved wind power forecasting in the CAISO led to an increased penetration of wind power because the cost of utilizing this additional amount of energy is practically zero and generators on the margin will be significantly more expensive. Any reduction in forecasting error is a reduction in uncertainty, and more certainty leads to increased reliance on renewable power. Figure 12 shows the average reduction in fossil fuel–based generation as a function of improved wind power forecasting for both low (SC4) and high (SC3) wind power scenarios.

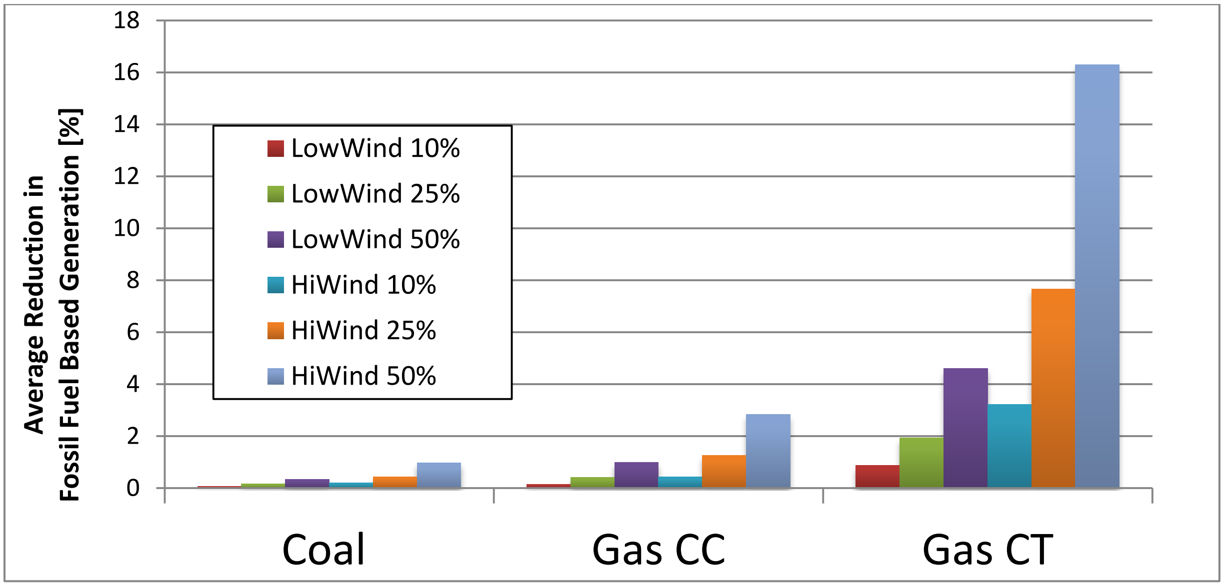

Figure 12. Impact in generation by type because of wind power forecasting improvements: average reduction in fossil fuel–based generation [%]

A few points should be noted when observing the figure and considering the relative changes in generation by type for the various levels of improved wind power forecasting within each of the scenarios:

- An average gas price of $4.60/MMBtu was used in accordance with best estimates detailed in the WWSIS-2 methodology.
- Increasing levels of wind and solar mostly displaced gas generation, while enhanced forecasting also reduced coal ramping.
- Day-ahead unit commitment was not impacted by short-term forecasting improvements, so savings were mostly from combustion turbine dispatch reductions.

These observations about the impact of short-term forecasting can be observed in the figure, and most changes were seen in fast-acting gas generators while minor generation displacement was felt elsewhere. The results are indicative of intuition, but their relative cost and emissions impact are assessed further with more focused analysis in later sections.

Renewable Penetration

With more accurate short-term wind power forecasting, the relative penetration of wind generation can be enhanced. In addition, for high levels of wind penetration, there will be reductions in the amount of curtailment required. Figure 13 and Figure 14 illustrate the daily generation of renewable power for the months of January and July. Again, these months were chosen to represent extremes in differences through a year (on average) and are indicative of the results obtained for the production cost simulation for improved wind power forecasting in both the low and high wind power scenarios.

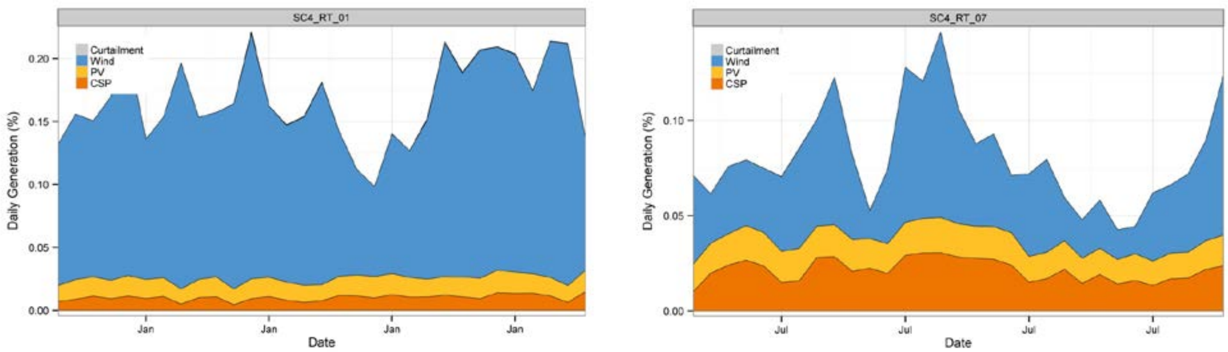

Figure 13. Renewable penetration observed in January and July for the low wind scenario (SC4)

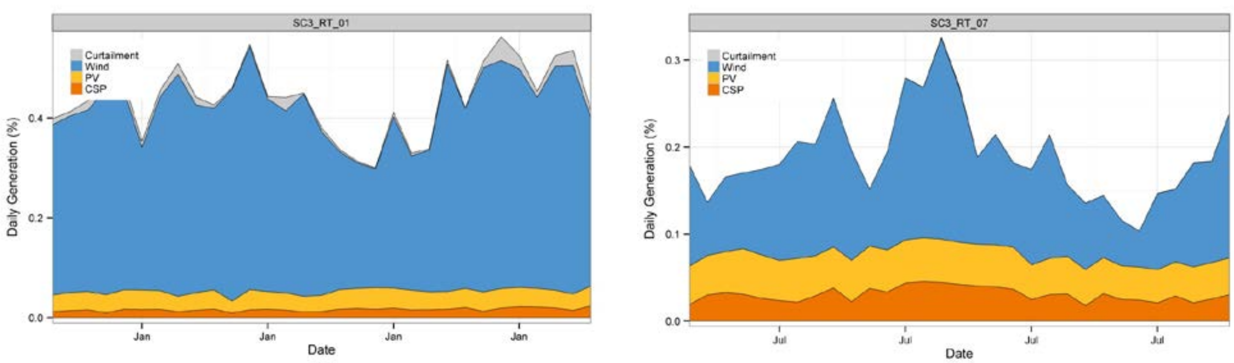

Figure 14. Renewable penetration observed in January and July for the high wind scenario (SC3)

As shown in the figures, only slight curtailment occurred during the windy month of January for the high wind power scenario. On average, the wind penetration was slightly enhanced, but this was mostly in the noise for the low wind power scenario. In all cases, solar power was not curtailed. This was because of the relatively low penetration of solar in both scenarios.

The figures and analysis showcase only slight increases in the penetration of renewables because the short-term wind power forecasts are sub-hourly and most fossil fuel based generation is already committed and the enhanced accuracy of the forecasts only slightly reduces the amount of fossil fuel based generation. As the forecasting accuracy improves on longer time horizons, one would expect the level of renewable penetration would increase more significantly because fossil fuel based generation would not be committed in the first place.

Renewable Penetration—Impact from CAISO Improvements

With respect to the CAISO market, the impacts of enhanced wind power forecasting led to average increases in the percentage of energy served by renewable generation on the order of 1% or less. Figure 15 shows an approximately exponential decay of increased renewable generation as short-term wind power forecasting moved away (right to left) from the maximum improvement considered and approached the current state of the art.

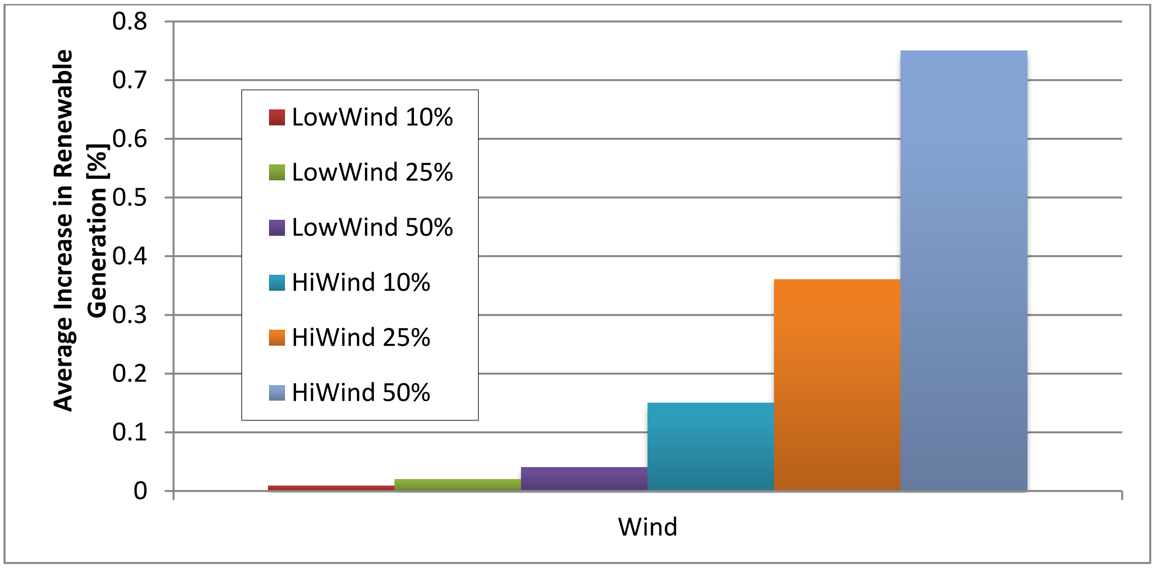

Figure 15. Impact on renewable penetration due to wind power forecasting improvements: average increase in renewable generation [%]

Curtailment

Curtailment was minimal for both the low and high wind penetration scenarios. However, it was observed when the other generators reached their minimum generation levels. Figure 16 and Figure 17 show the percentage of curtailment for the representative (extreme) months of January and July. As shown in both scenarios, the curtailment was mostly in the noise. Nevertheless, these curtailments are "lost-cost savings" that could be had with wind power forecasting improvements beyond the extent considered in this study.

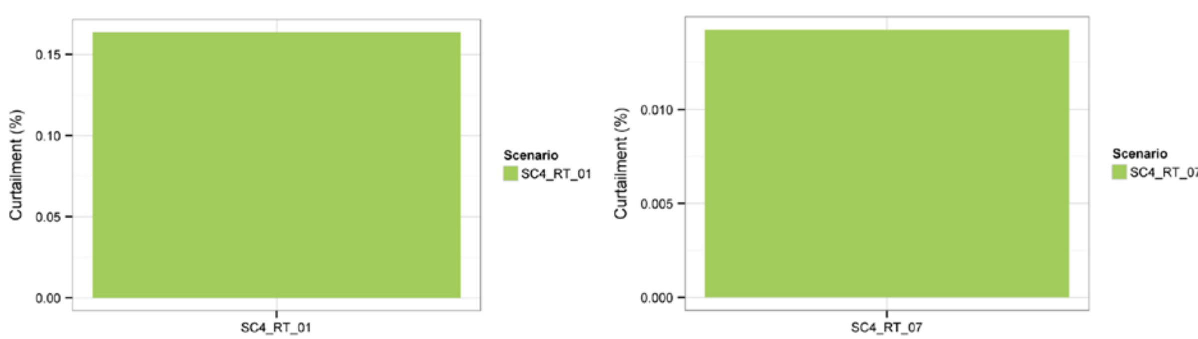

Figure 16. Curtailment observed in January and July for the low wind scenario (SC4)

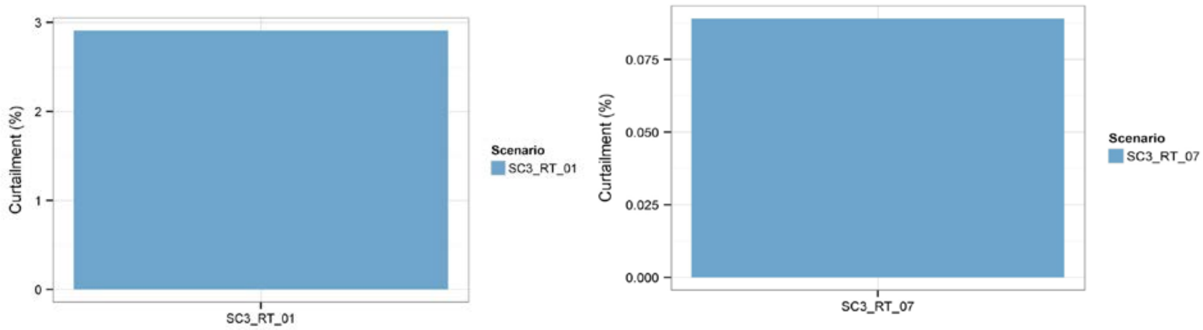

Figure 17. Curtailment observed in January and July for the high wind scenario (SC3)

Capacity Started by Type

The capacity started by type indicates the trade-offs between the improvements in wind power forecasting and the increased gas usage that comes with less-accurate forecasting. Figure 18 and Figure 19 show the capacity started by type for the months of January and July. The frequency of the gas generator starts was enormous compared to the coal units, but that does not mean that the gas-unit fluctuations do not affect the commitment of the coal unit, however slight that dependence might be.

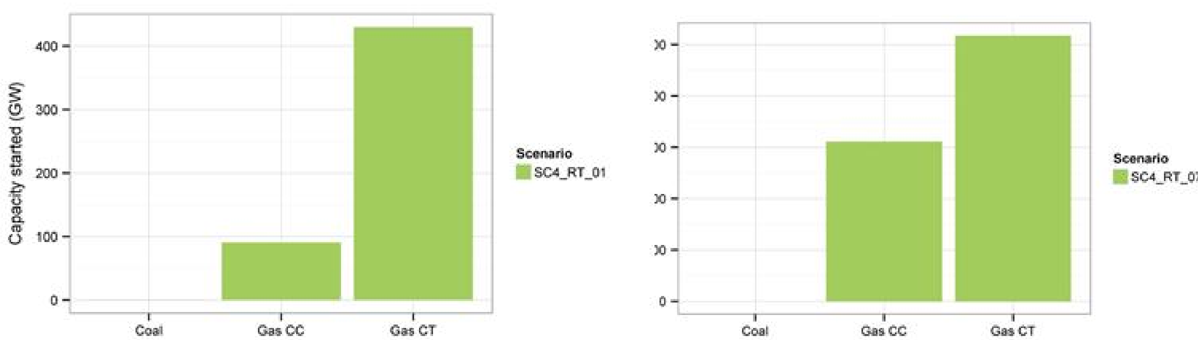

Figure 18. Capacity started by type observed in January and July for the low wind scenario (SC4)

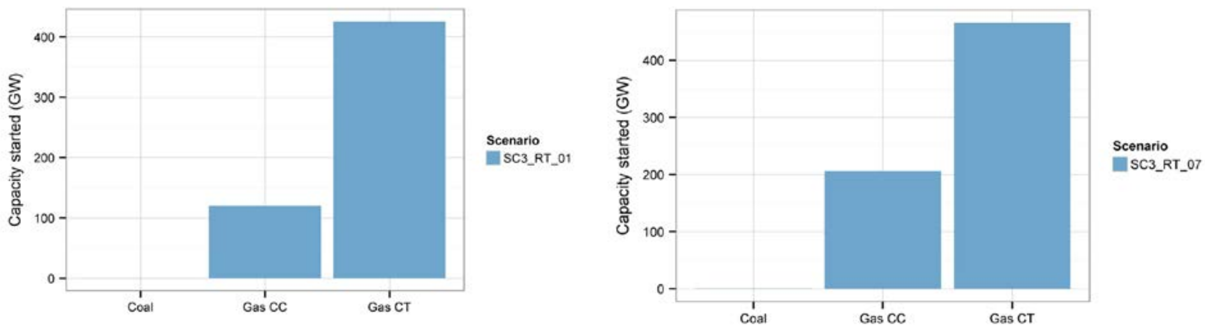

Figure 19. Capacity started by type observed in January and July for the high wind scenario (SC3)

Generation per Start—Impact from CAISO Improvements

The average reduction in generation per start as a result of improved forecasting for both the low and high wind power scenarios is shown in Figure 20. As expected, the trade-offs between forecasting accuracy and combustion turbine modulation are evident. For the most aggressive assumption about forecasting improvement (i.e., 50% in the high wind scenario), an 8% reduction in generation per start for the combustion turbines was observed. For the other units (e.g., gas combined cycle and coal), the reductions were likely in the noise of the simulations.

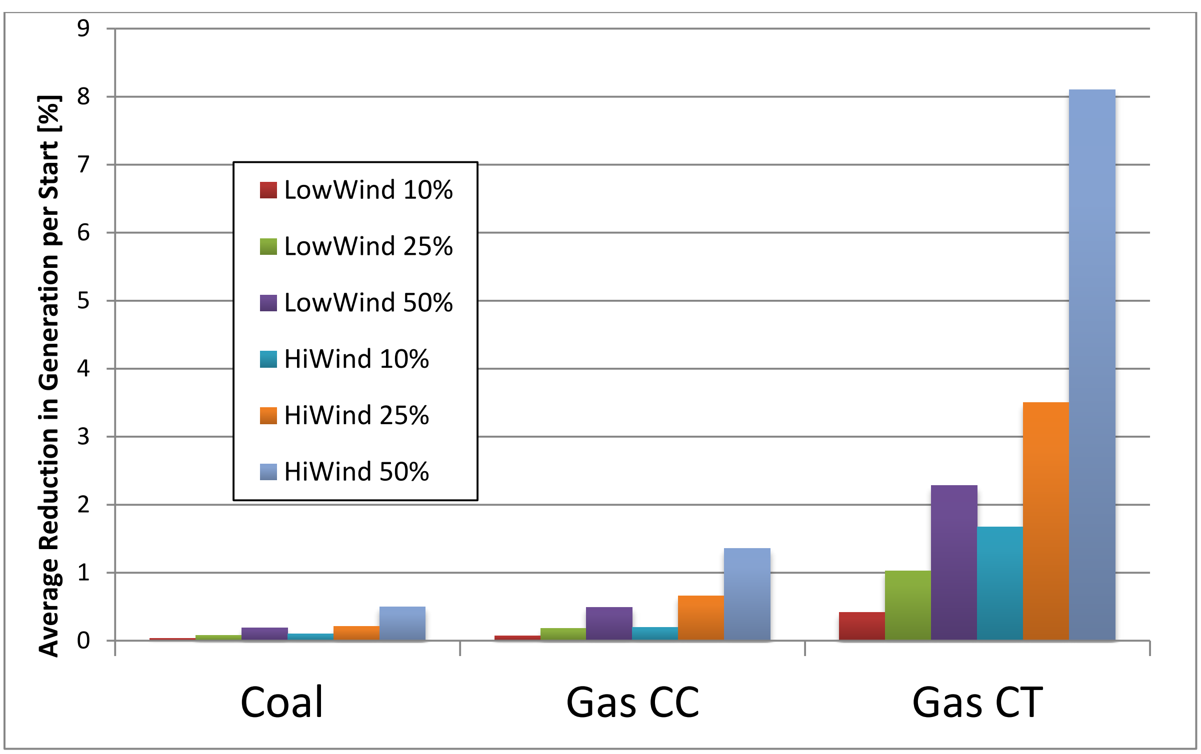

Figure 20. Impact on generation per start as a result of wind power forecasting improvements: average reduction in generation per start [%]

A couple of points can be gleaned from the analysis when coupled with other results:

- Uniform forecasting improvements slightly reduce the time and the capacity that combustion turbine and combined-cycle units must run to meet load.
- Savings were observed in the reduced ramping and cycling of coal units, which had a slight effect on CO_2, NO_X, and SO_2 emissions.

The emissions saved in the CAISO are discussed in the following section.

Generation Emissions—Impact from CAISO Improvements

The impact of generation emissions as a result of wind power forecasting improvements is shown in Figure 21. The average reduction was on the order of a couple percentage points or less for CO_2, NO_X, and SO_2 emissions. Although not explicitly addressed in this study, these savings could be very important to future markets in which the monitoring of emissions is crucial to operations (e.g., carbon markets).

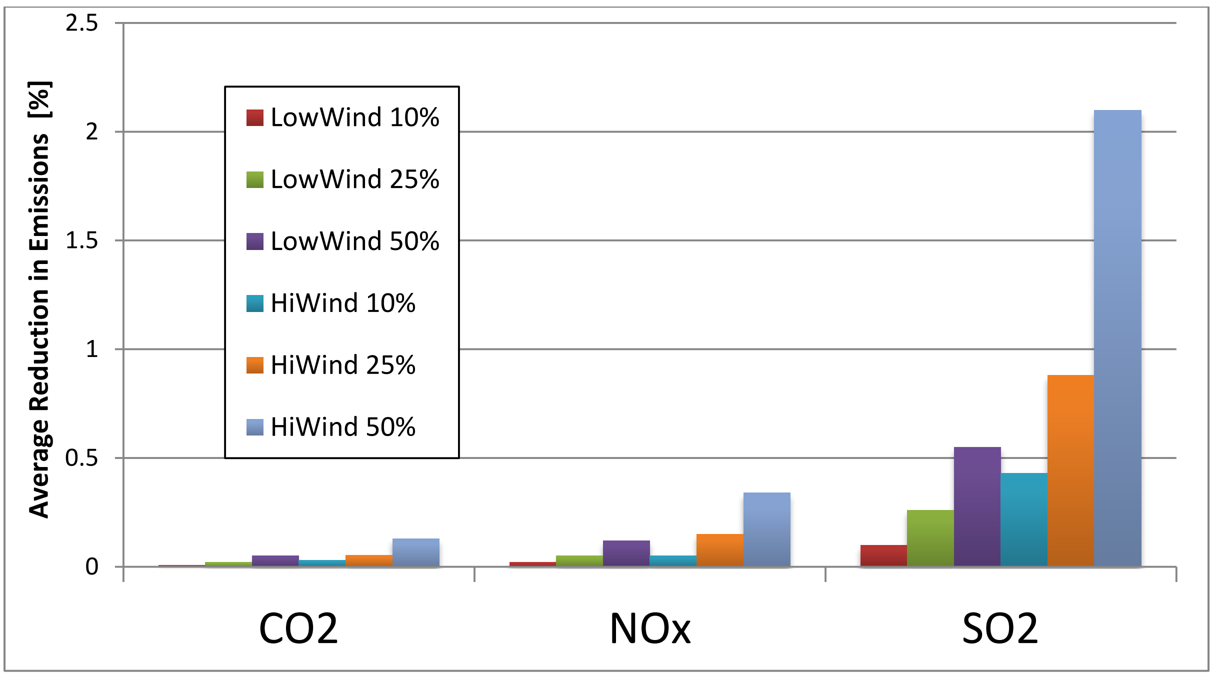

Figure 21. Impact on generation emissions because of of wind power forecasting improvements: average reduction in emissions [%]

Cost Implications

All of the analyses shown thus far have cost implications. The goal of this study was to quantify the value of improved short-term forecasting such that Lockheed Martin can assess the potential market value of their technology. The following sections detail the production cost savings, cycling costs, and implications of these savings in the CAISO market.

Production Costs

Figure 22 shows the lower and upper bound on estimated production costs, in terms of billions of U.S. dollars, for the low and high wind scenarios. The results are classified according to various costs: fuel; start-up fuel; and start-up, ramping, and noncyclical variable operations and maintenance (VOM). The dominant production cost savings come from fuel requirements.

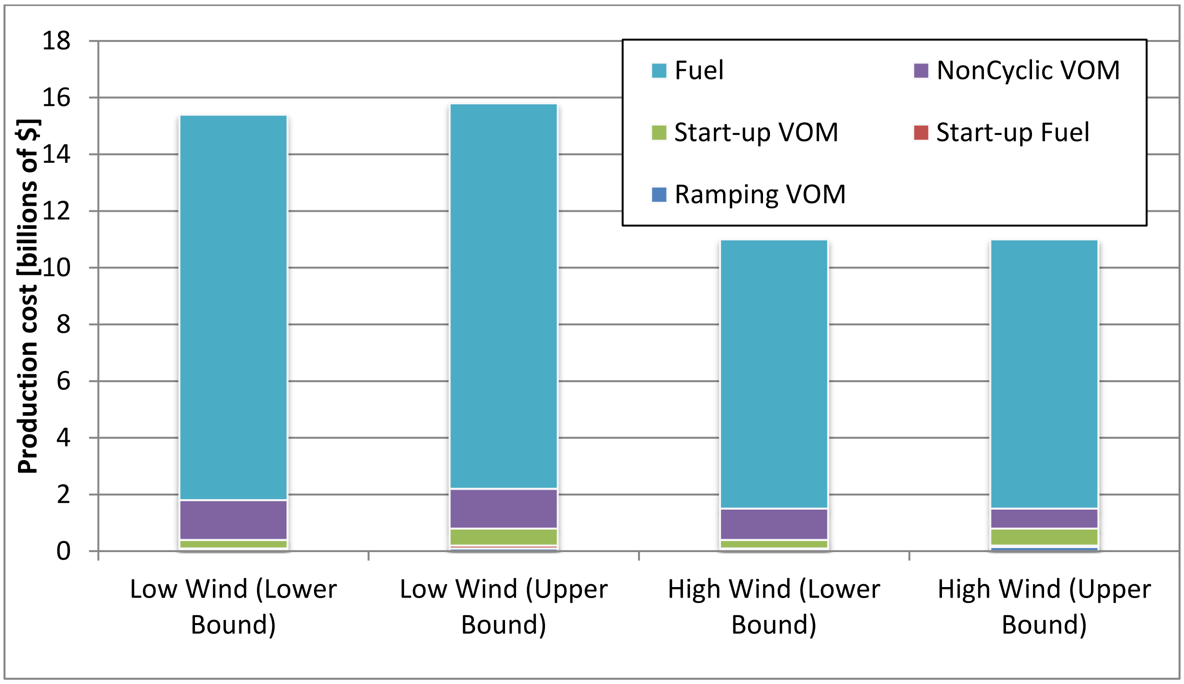

Figure 22. Lower- and upper-bound production costs [billions of dollars] for the low wind [SC4] and high wind [SC3] scenarios

Cycling Costs

Inaccurate wind power forecasts can lead to cycling in thermal units because of the increased variability and uncertainty. As one might imagine, this leads to excessive wear and tear on the units, and operators try to avoid such cycling. Figure 23 presents the lower and upper bound on cycling costs in billions of U.S. dollars for the low and high wind scenarios. Start-up VOM dominates the cycling cost, followed by start-up fuel and ramping VOM.

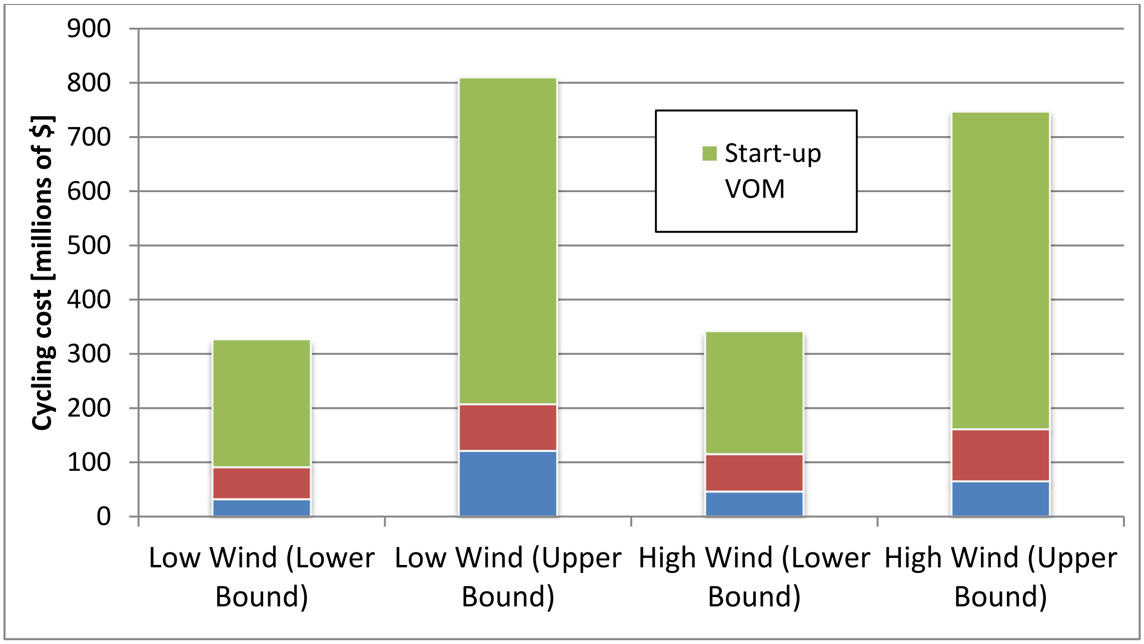

Figure 23. Lower- and upper-bound cycling costs [billions of dollars] for the low wind [SC4] and high wind [SC3] scenarios

CAISO Savings

The implication of production costs and cycling within the CAISO market are expressed in Figure 24. Savings of state-of-the-art wind power forecasting range from approximately nil to almost 5%. This can be a sizeable amount of money as quantified in the following sections.

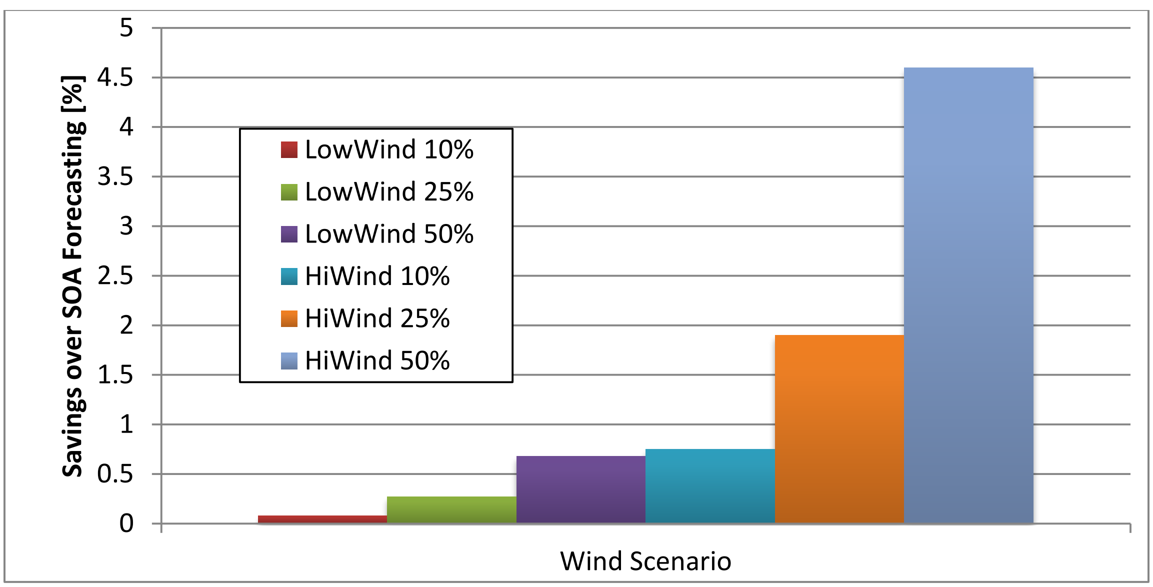

Figure 24. CAISO savings over state-of-the-art forecasting method using improvement assumptions

CAISO Production Cost Savings

The annual cost savings from production because of improved wind power forecasting are shown in Table 8. They range from slightly less than $2 million to more than $100 million. Although these savings are within CAISO for a one-year period, savings of the same order of magnitude could likely be obtained in other markets. However, it is important to note that the exact amount of savings in other markets would vary strongly with other factors, such as the transmission congestion, the generation portfolio, and the specific market procedures in place.

Table 8. Cost Savings from Production Savings as a Result of Improved Wind Power Forecasting

Wind Scenario	Improvement Description	SOA Forecasting	Improved Forecasting	Annual Savings
Low	10% uniform improvement	3,590,000,000	$3,590,000,000	$2,870,000
High	10% uniform improvement	2,540,000,000	$2,520,000,000	$18,980,000
Low	25% uniform improvement	3,590,000,000	$3,580,000,000	$9,690,000
High	25% uniform improvement	2,540,000,000	$2,490,000,000	$48,100,000
Low	50% uniform improvement	3,590,000,000	$3,560,000,000	$24,400,000
High	50% uniform improvement	2,540,000,000	$2,420,000,000	$116,000,000

CAISO Total Cost Savings

The total cost savings from improved short-term wind power forecasting in the CAISO market can be expressed with the simple summation below:

$$\textit{Total Cost Savings} = \textit{Flex Reserve} + \textit{Regulation Reserve} + \textit{Production}$$

Combining Table 6 and Table 7 with Table 8 leads to Table 9, the total cost savings from flex reserve, regulation reserve, and production cost savings from improved wind power forecasting.

Table 9. Total Cost Savings from Flex and Regulation Reserves, as well as Production Savings, From Improved Wind Power Forecasting

Wind Scenario	Improvement Description	Annual Savings
Low	10% uniform improvement	$5,050,000
High	10% uniform improvement	$25,100,000
Low	25% uniform improvement	$14,800,000
High	25% uniform improvement	$62,900,000
Low	50% uniform improvement	$34,700,000
High	50% uniform improvement	$146,000,000

Summary and Recommendations

This study assessed the value of improved short-term wind power forecasting in the California Independent System Operator (CAISO) market and provided an estimation of its potential system-wide value. Performed for the Lockheed Martin Corporation, the study was accomplished in a technology-agnostic fashion to estimate savings from regulation and flex reserves, as well as production savings, to provide insight into the potential of their product within the context of current and future CAISO markets. A simulation approach was required with a design of experiments to capture feasible operating points, and state-of-the-art modeling and Western Interconnection data (for the western United States) was used to produce realistic value estimates. Although this study did not make a business case for investing in short-term wind power forecasting technologies, it does aid such a decision-making process with the quantification of its potential value. Further, to summarize the study and provide some recommendations:

- Short-term, sub-hourly forecast improvements have relatively small impacts on system-wide costs:
    - Improvements in persistence may be “too little, too late” because of only slight deviations from commitment schedules.
    - Although the WWSIS-2 model is well-vetted, savings at low penetrations of wind power are likely “in the noise” because of assumptions—e.g., no bilateral (purchase power) agreements.
    - Forecasting improvements replace chiefly gas in quick-start units, therefore savings are a function of gas prices; gas prices are currently low but have an uncertain future.
- Results follow the adage “Economics are changed by commitments; reliability is changed by the dispatch.”
- Additional implications:
    - The first study showed the dominance of ramp prediction on reserve prices, which the technology could be quite helpful for predicting and is currently used by system operators for “situational awareness.”
    - The savings from the technology are a strong function of gas prices, which have an uncertain future as a result of energy policy.
    - FESTIV simulations could quantify the reliability benefits. This NREL-created model goes down to the four-second timescale to quantify the benefits of changing operational policies on control performance standard (CPS) scores.

These results show that although there may not be an economic case for extensive capital investments in improving ultra-short-term wind power forecasting at the moment, the need for this service will increase significantly with increased wind power penetration rates. The results shown follow the assumption that the last chance to improve the forecast will occur 40 minutes before real time in the market. With increased penetration of renewable generation, we expect to see corresponding changes in power system operations. This could also include shorter “gate-closing” times, which would allow even shorter-term forecasts to play a role. Moving closer to the operating time would presumably allow even greater increases in forecasting accuracy over the persistence model, and thus perhaps greater cost savings.

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Appendices

Appendix A: Distribution of Forecasting Errors in CFE

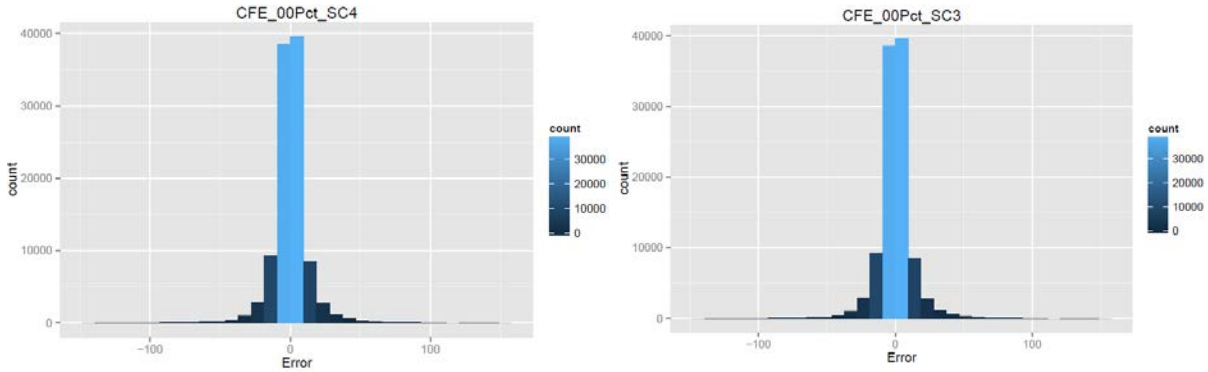

Figure A-1. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in CFE

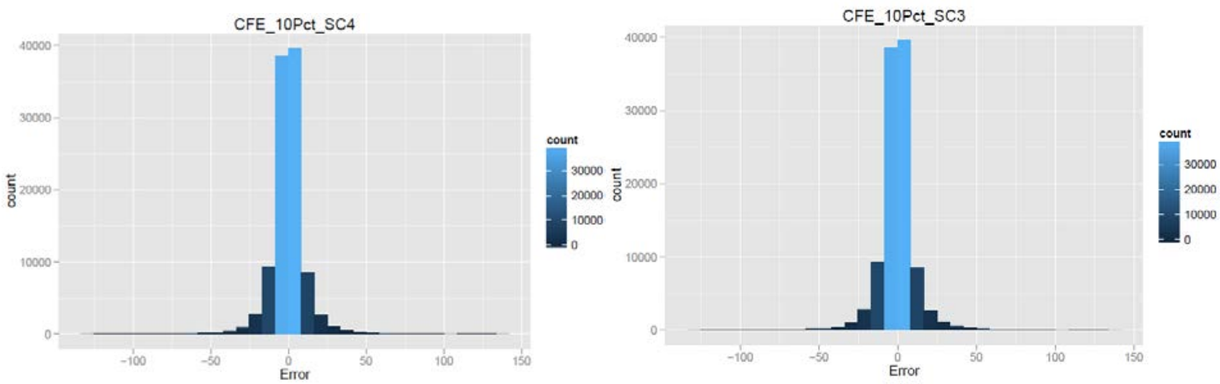

Figure A-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in CFE

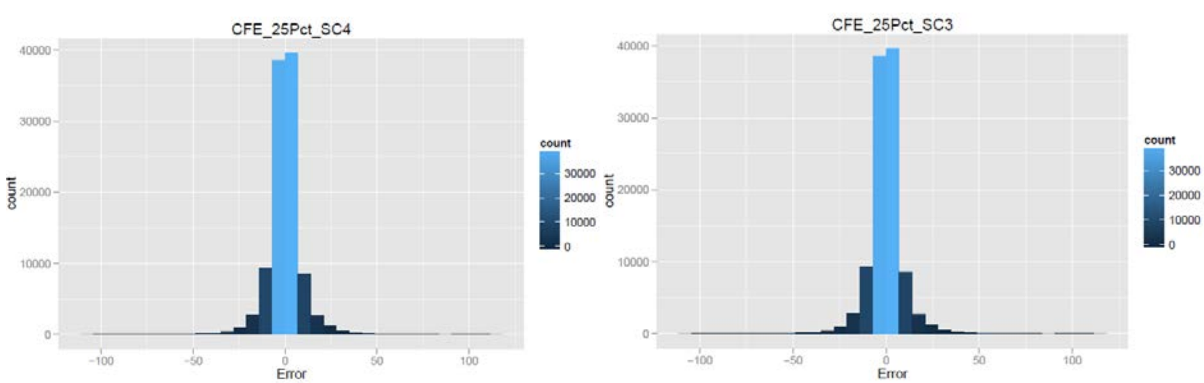

Figure A-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the art forecasting in CFE

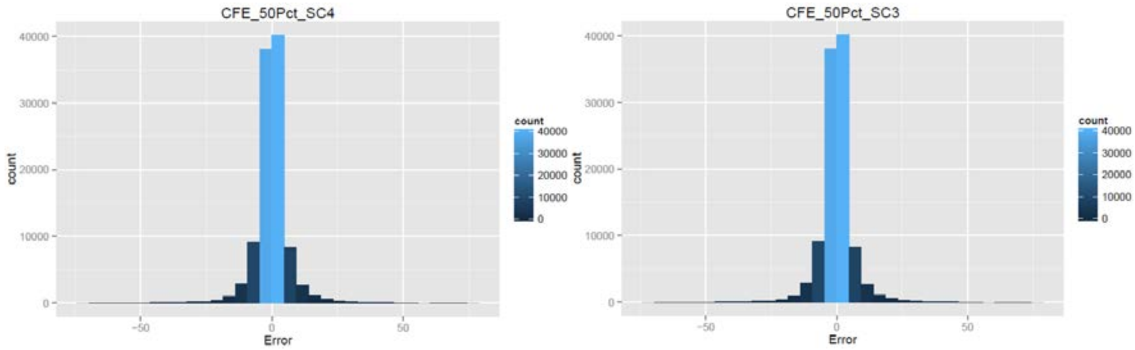

Figure A-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state of the art forecasting in CFE

Appendix B: Plots of Errors Versus Wind Power for Reserve Analysis in CFE

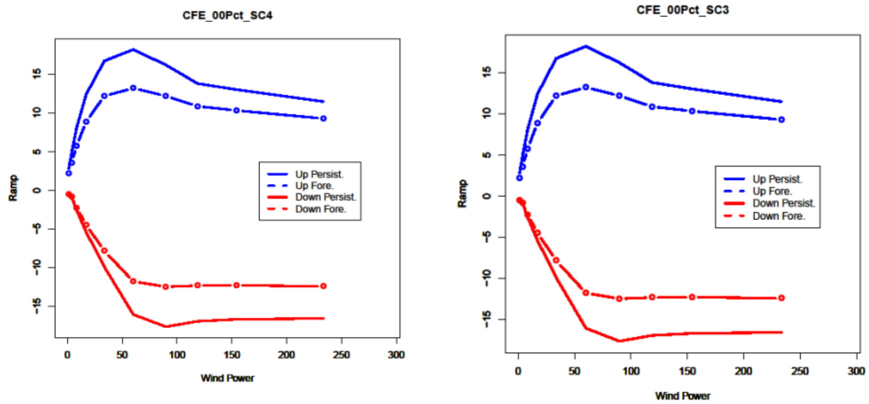

Figure B-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in CFE

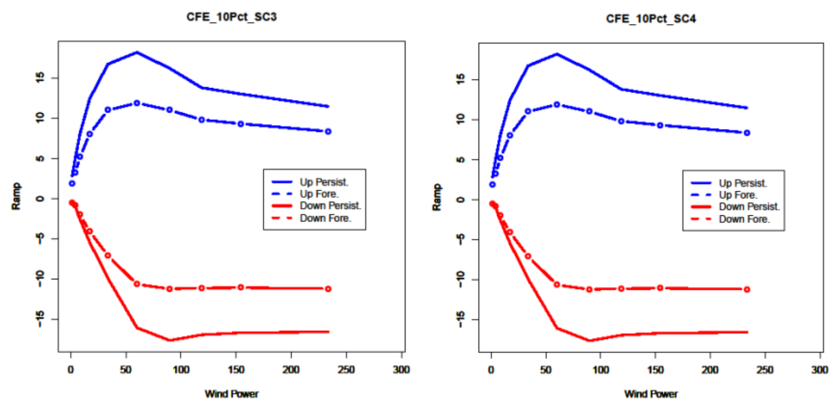

Figure B-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in CFE

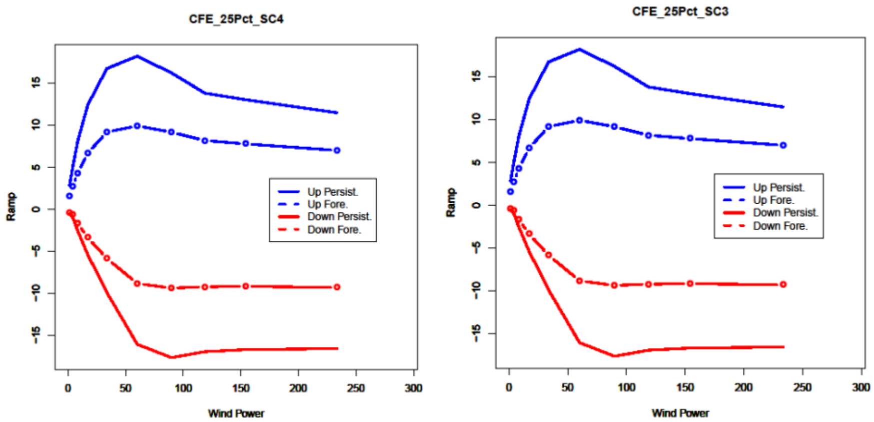

Figure B-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in CFE

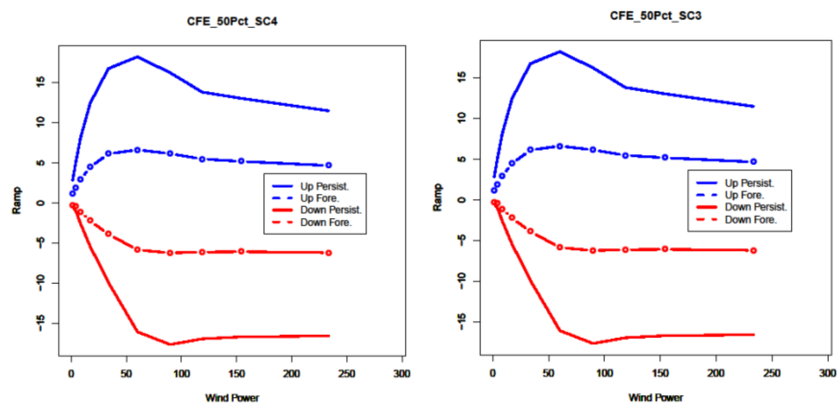

Figure B-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in CFE

Appendix C: Distribution of Forecasting Errors in IID

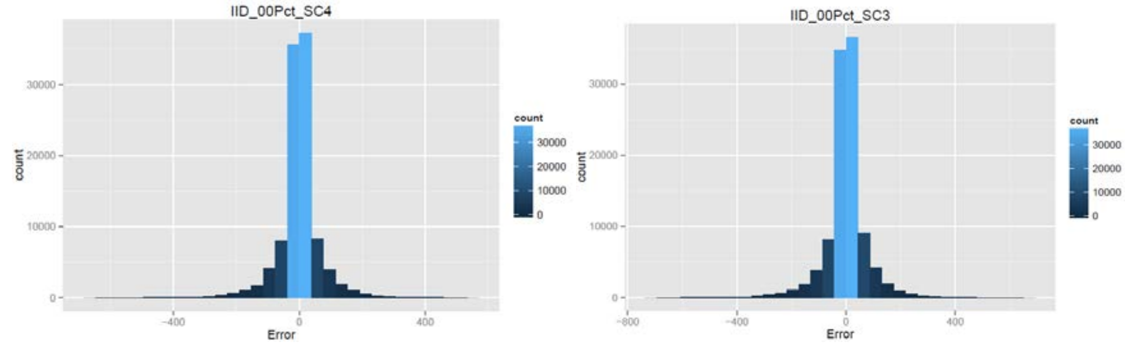

Figure C-1. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in IID

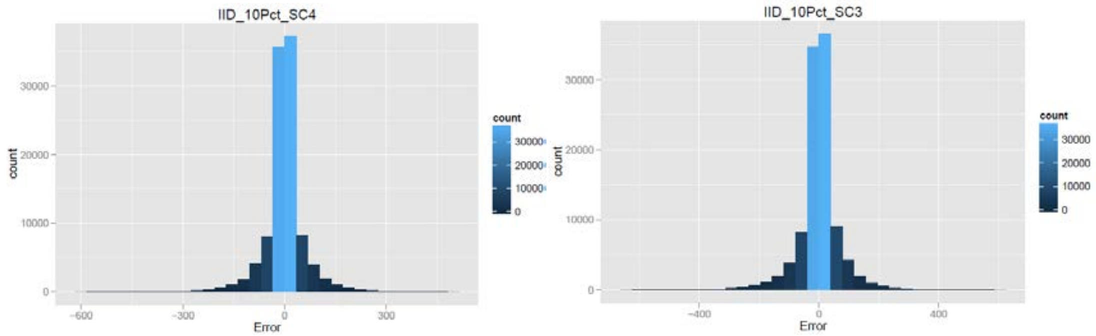

Figure C-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in IID

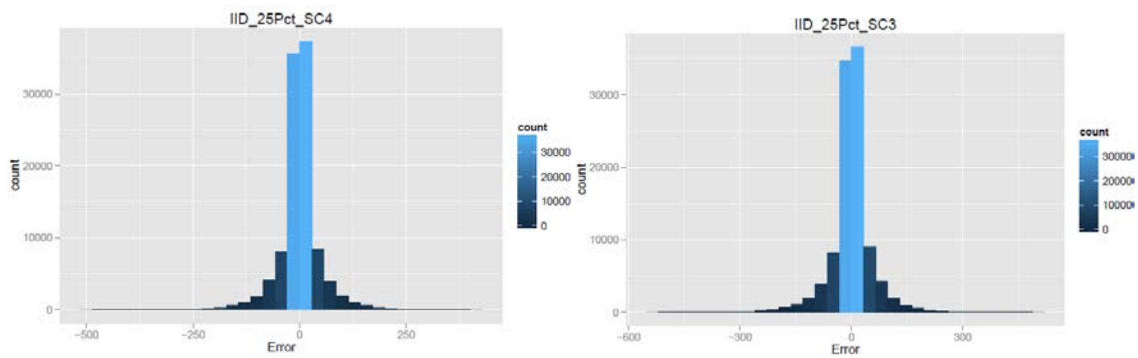

Figure C-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in IID

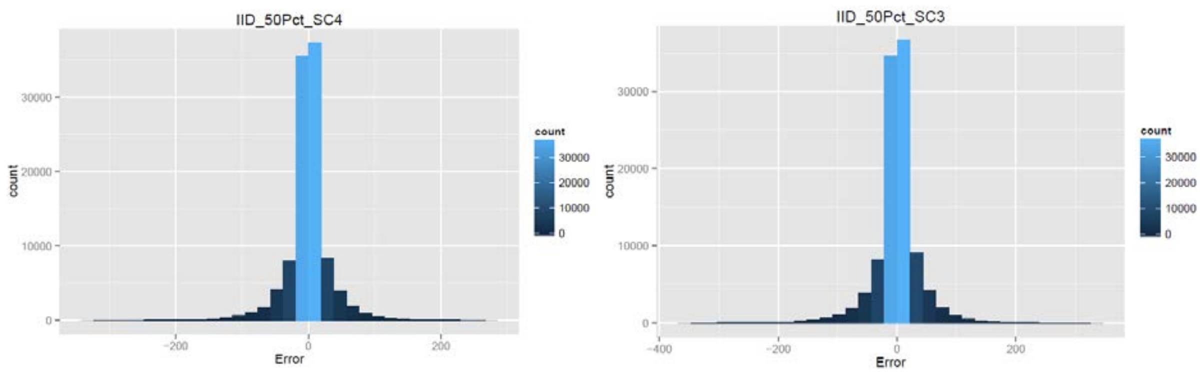

Figure C-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in IID

Appendix D: Plots of Errors Versus Wind Power for Reserve Analysis in IID

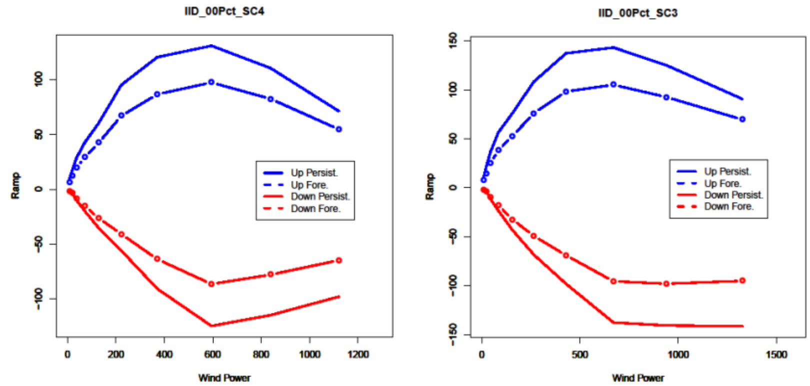

Figure D-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in IID

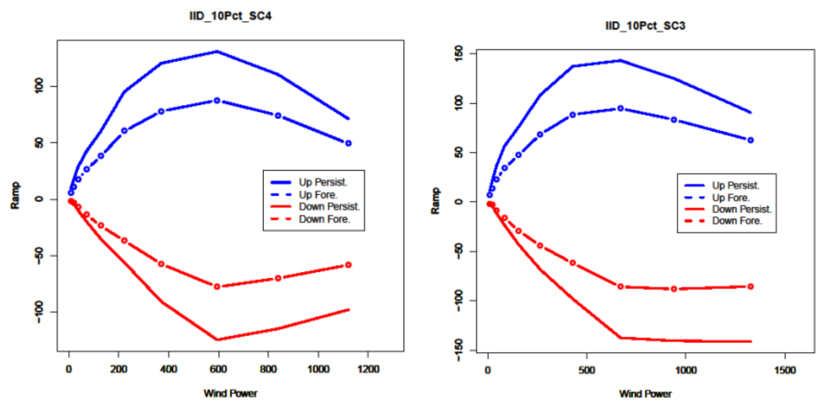

Figure D-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in IID

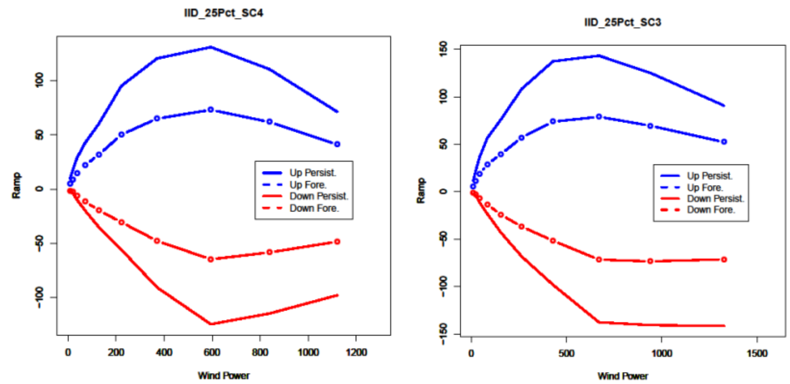

Figure D-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in IID

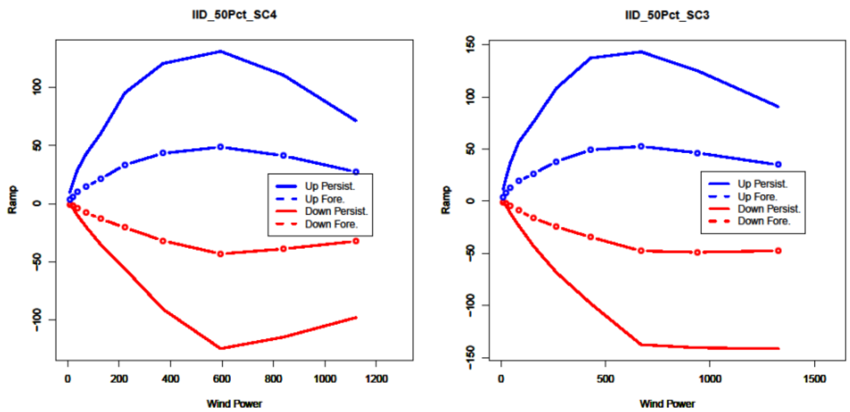

Figure D-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in IID

Appendix E: Distribution of Forecasting Errors in PGEVLY

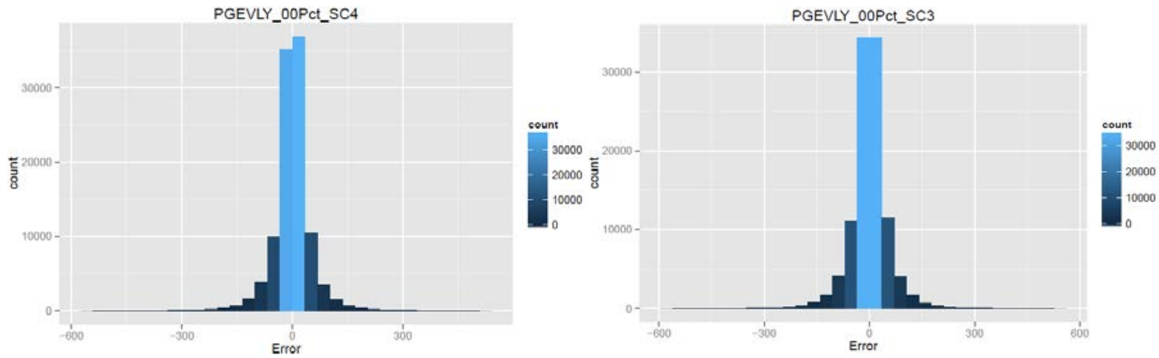

Figure E-1. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in PGEVLY

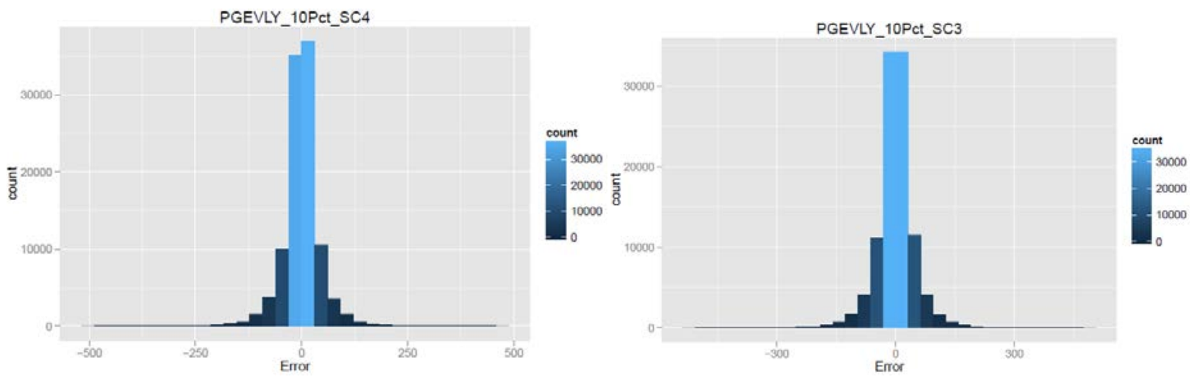

Figure E-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in PGEVLY

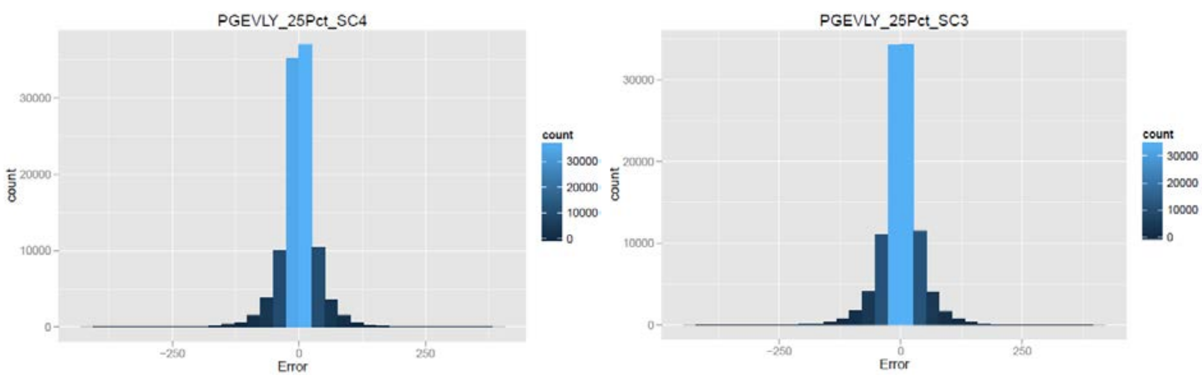

Figure E-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in PGEVLY

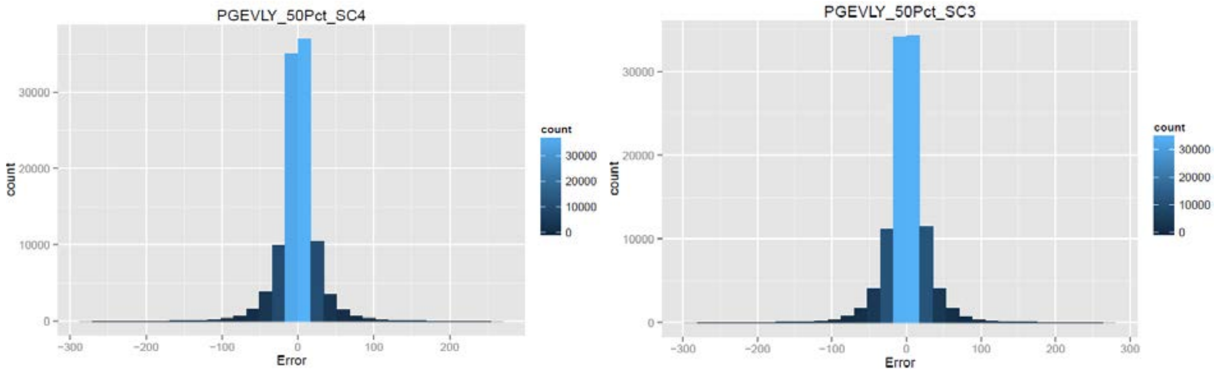

Figure E-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in PGEVLY

Appendix F: Plots of Errors Versus Wind Power for Reserve Analysis in PGEVLY

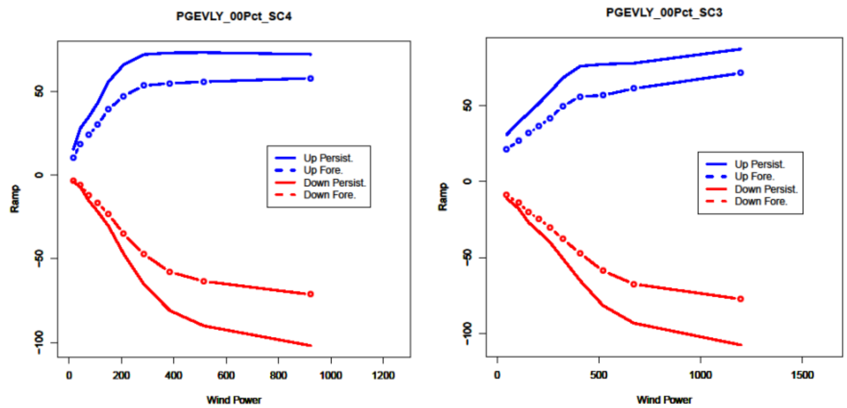

Figure F-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in PGEVLY

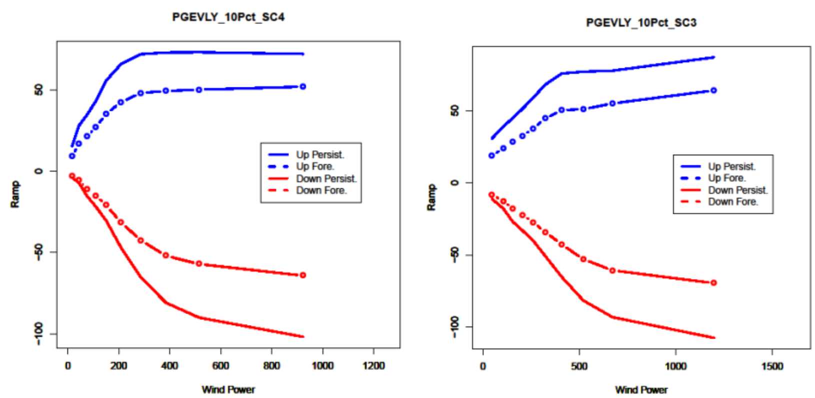

Figure F-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in PGEVLY

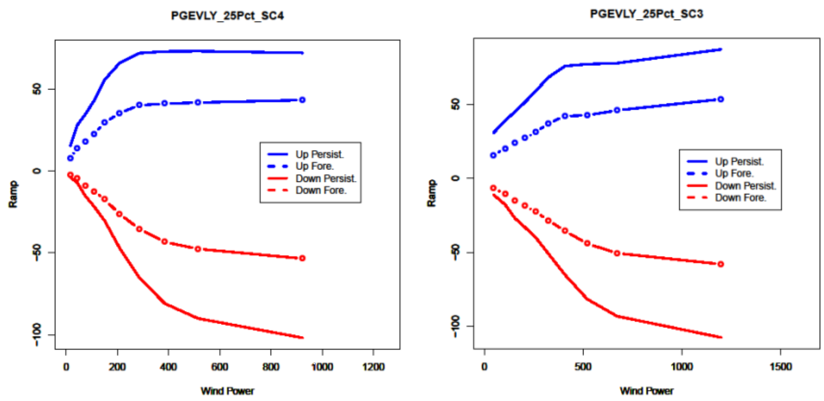

Figure F-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in PGEVLY

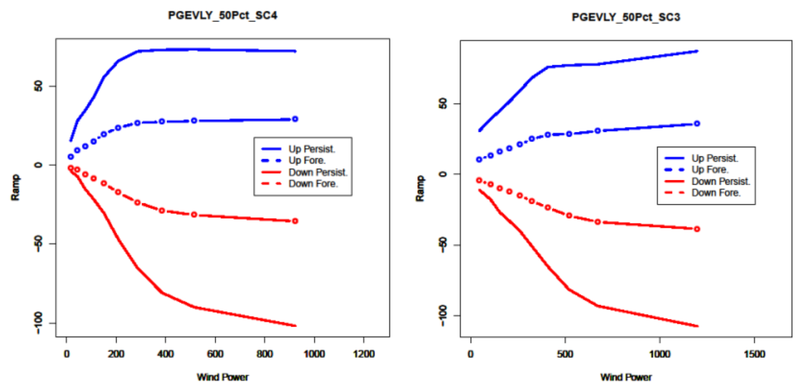

Figure F-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in PGEVLY

Appendix G: Distribution of Forecasting Errors in SCE

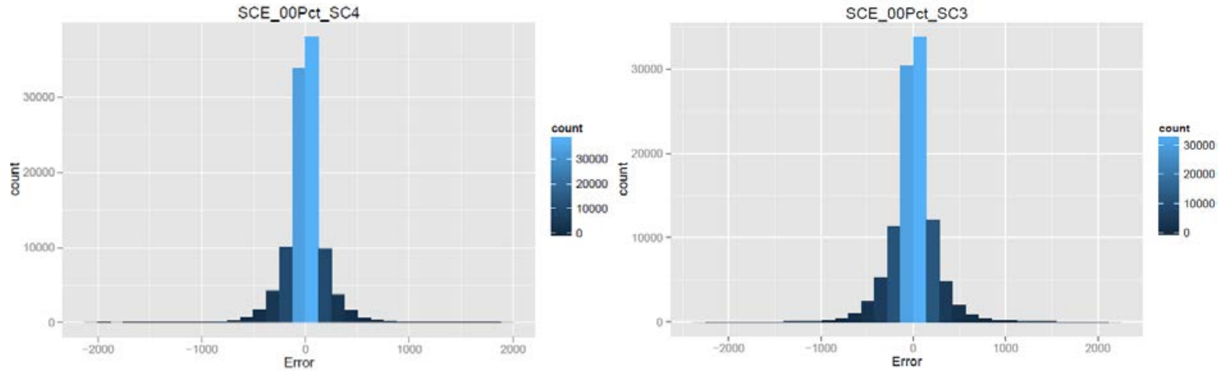

Figure G-1. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in SCE

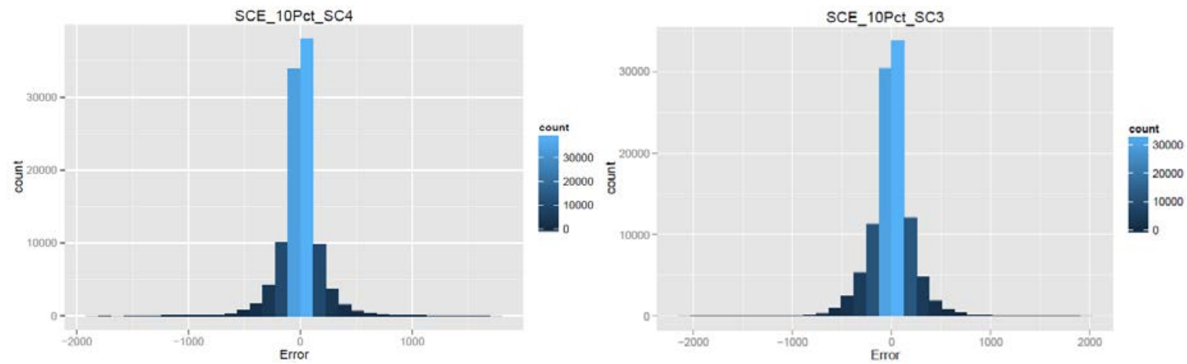

Figure G-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SCE

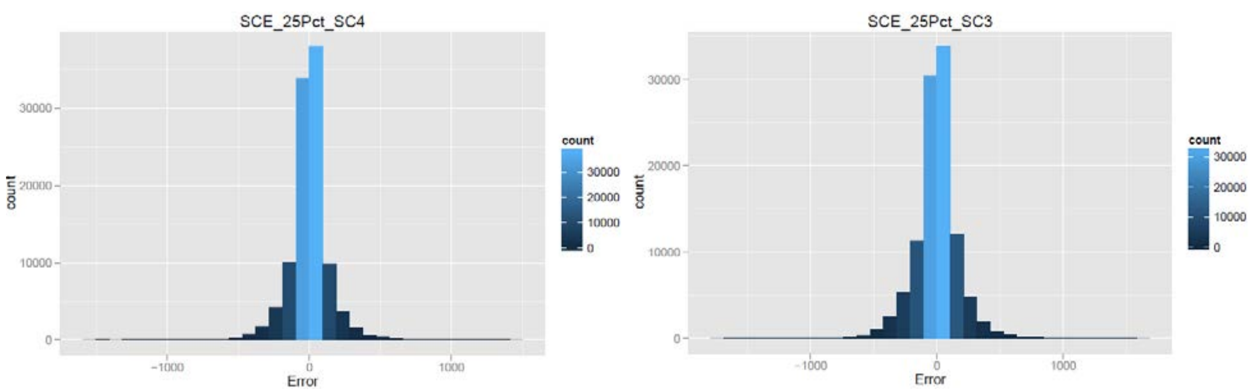

Figure G-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SCE

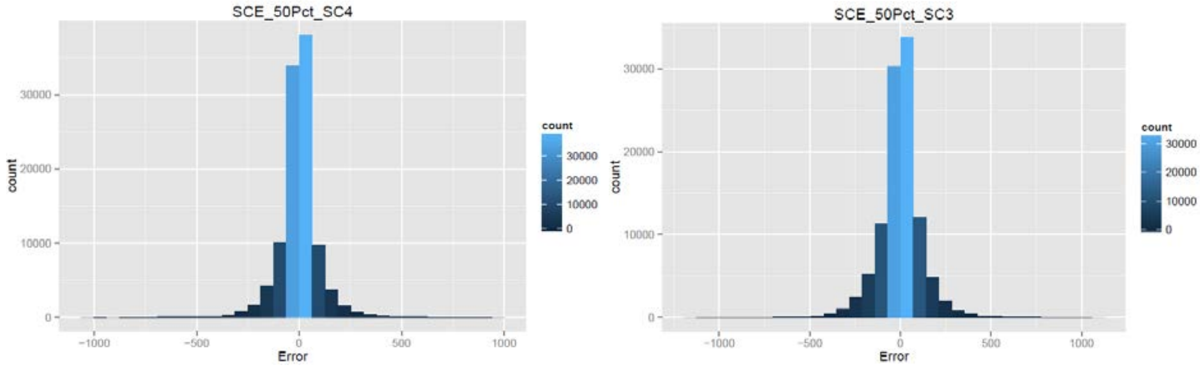

Figure G-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SCE

Appendix H: Plots of Errors Versus Wind Power for Reserves Analysis in SCE

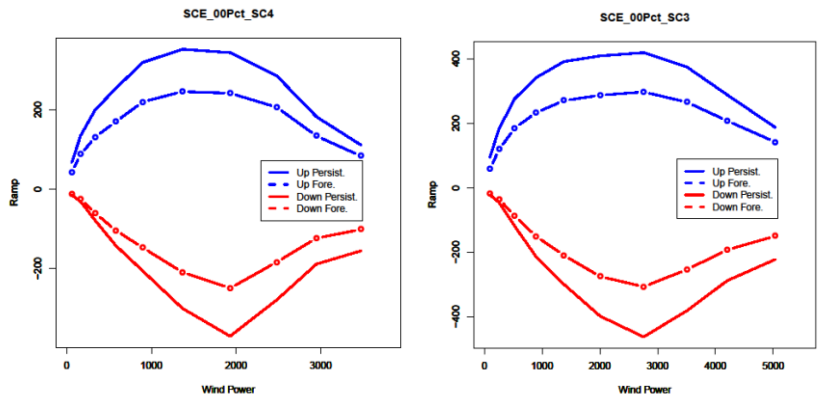

Figure H-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SCE

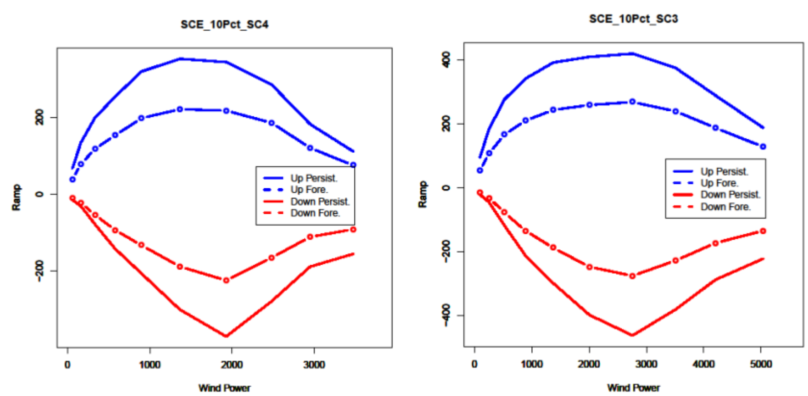

Figure H-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SCE

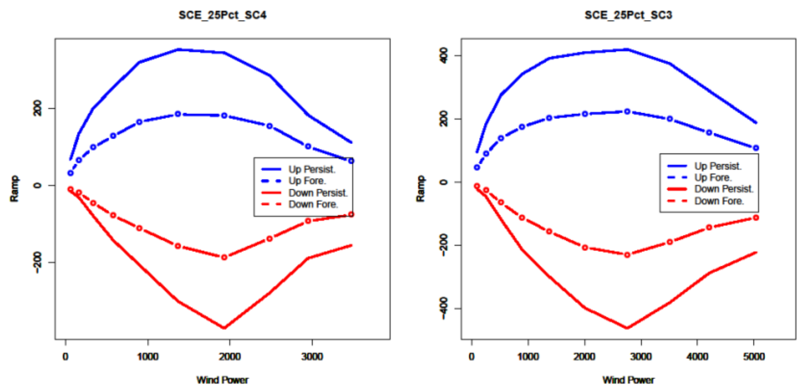

Figure H-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SCE

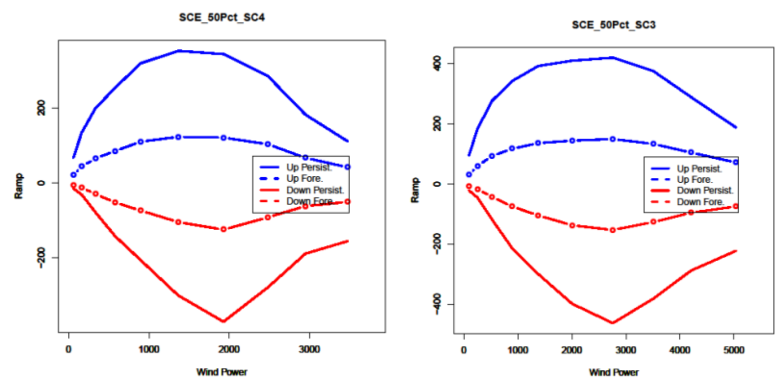

Figure H-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SCE

Appendix I: Distribution of Forecasting Errors in SDGE

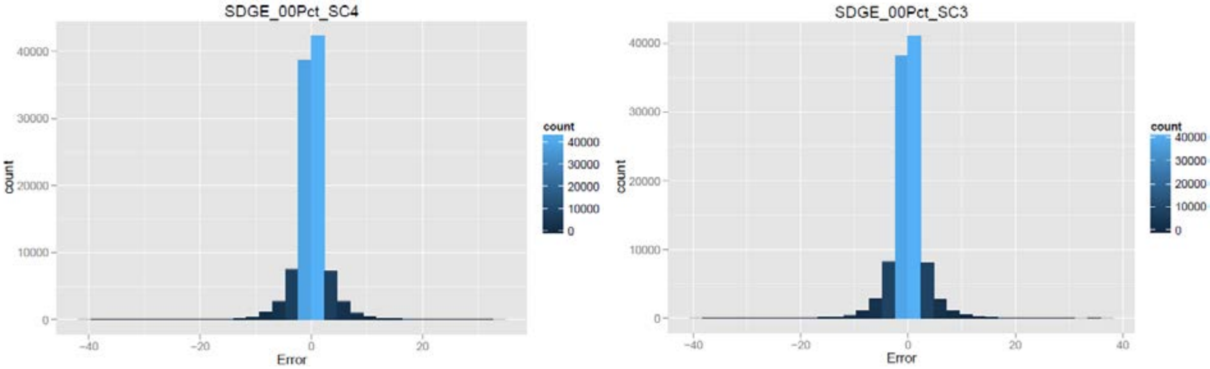

Figure I-1. Distribution of errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in SDGE

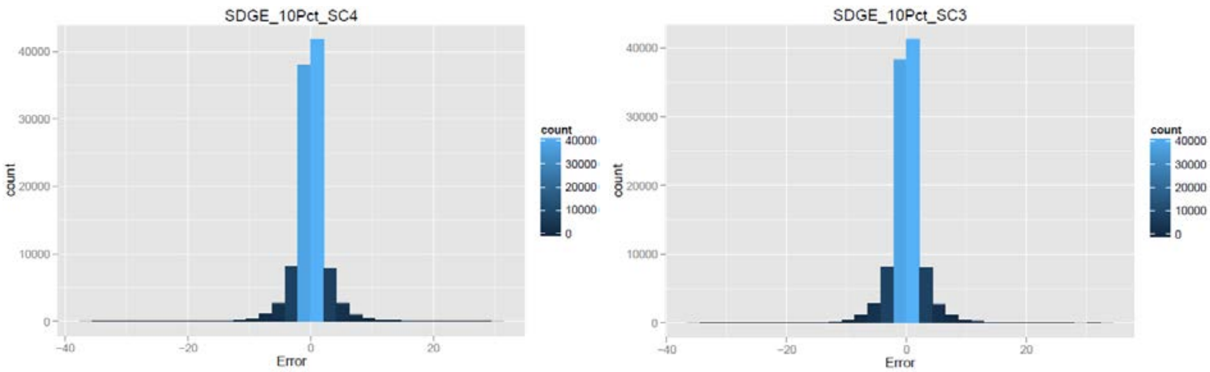

Figure I-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SDGE

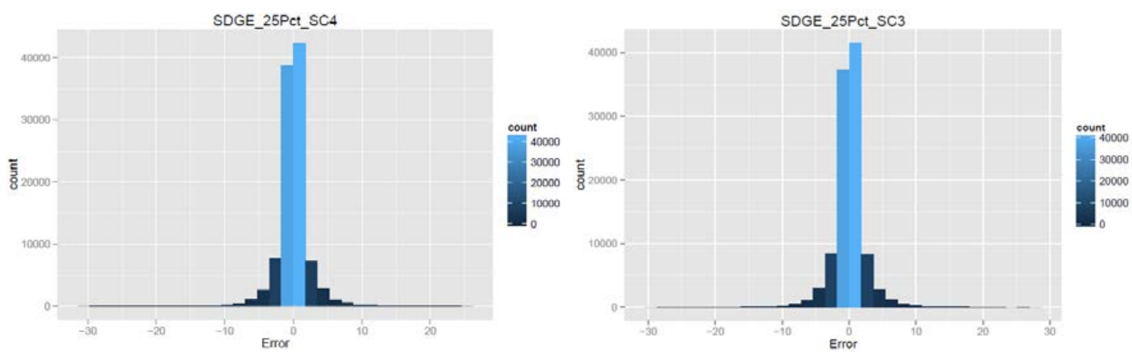

Figure I-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SDGE

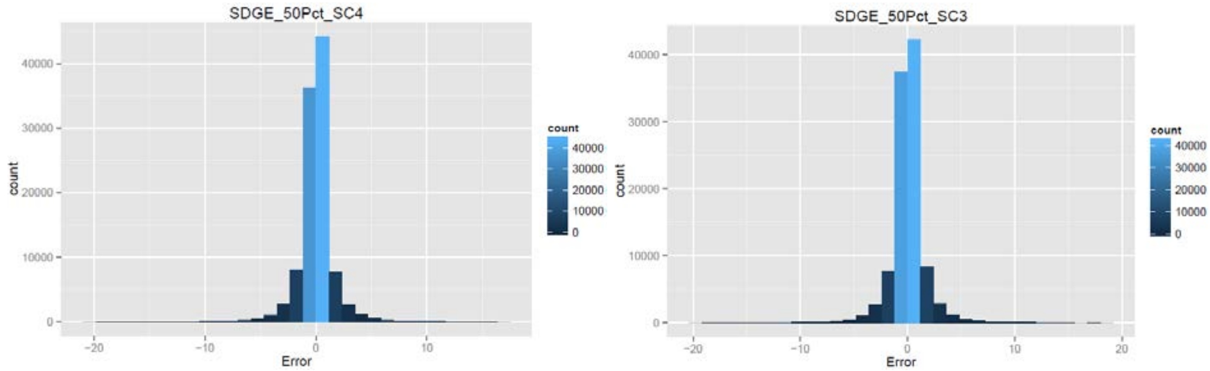

Figure I-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SDGE

Appendix J: Plots of Errors Versus Wind Power for Reserve Analysis in SDGE

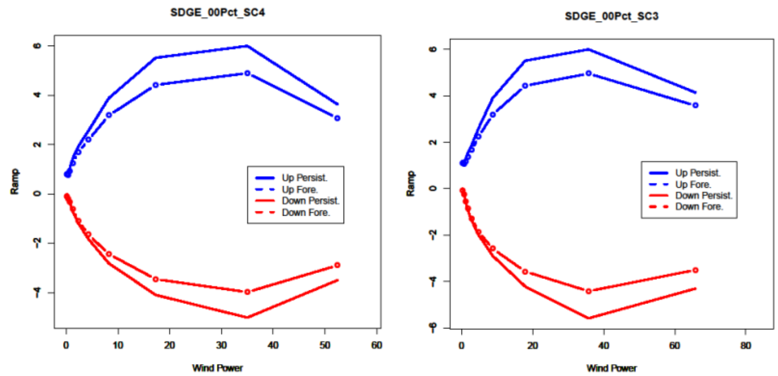

Figure J-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in SDGE

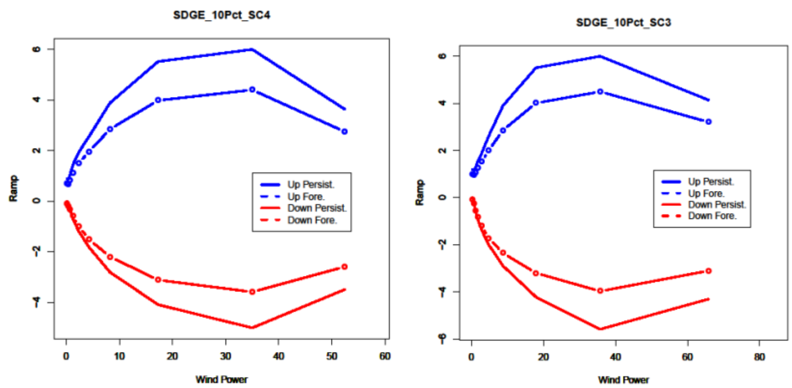

Figure J-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SDGE

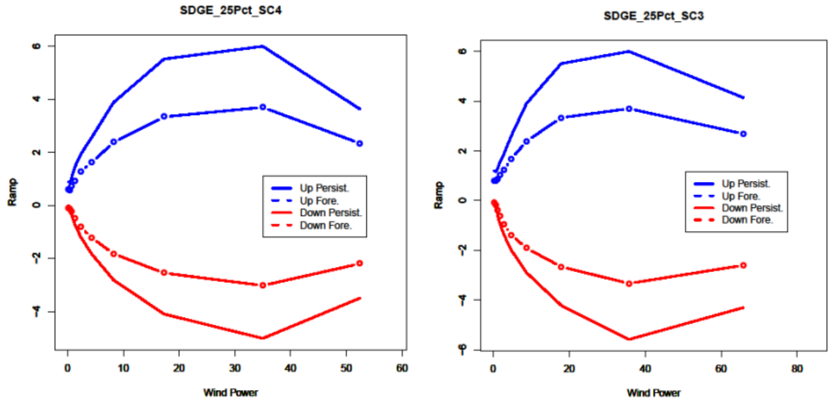

Figure J-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SDGE

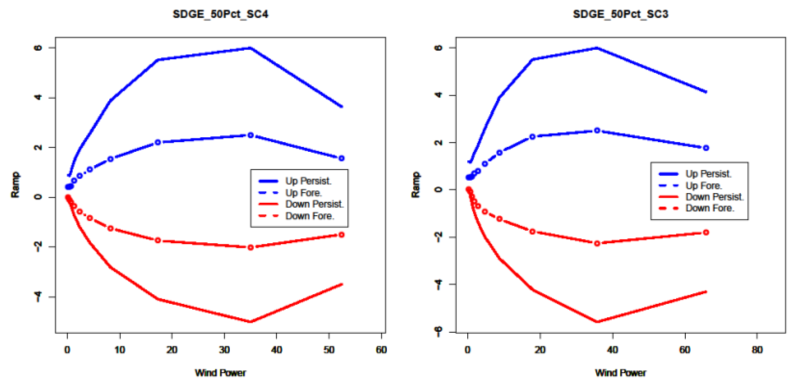

Figure J-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SDGE

Appendix K: Distribution of Forecasting Errors in SMUD

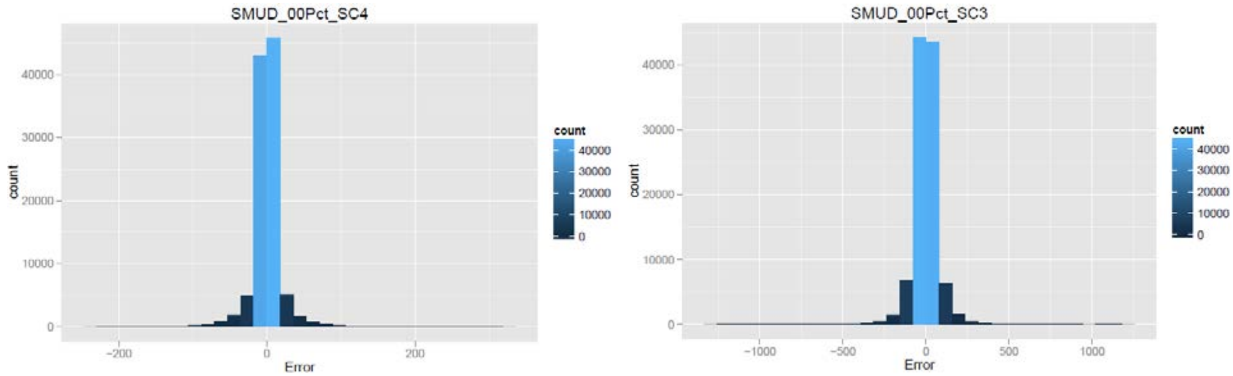

Figure K-1. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in SUMD

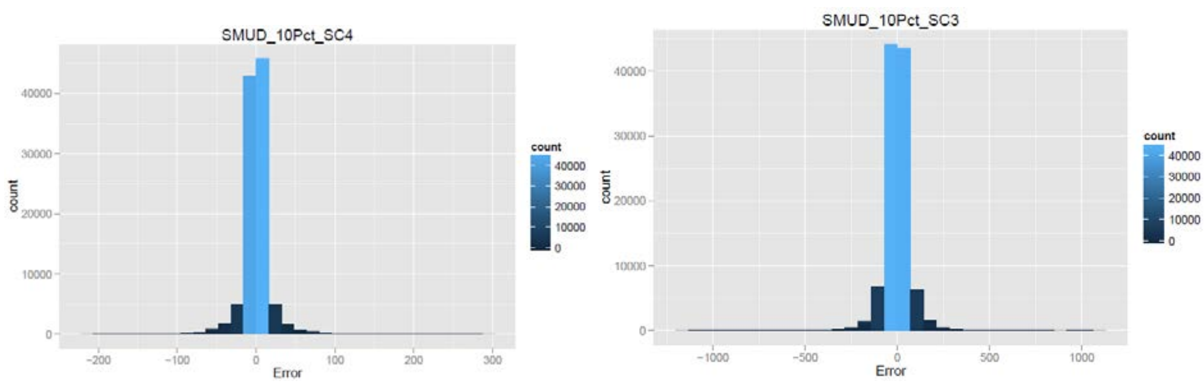

Figure K-2. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SMUD

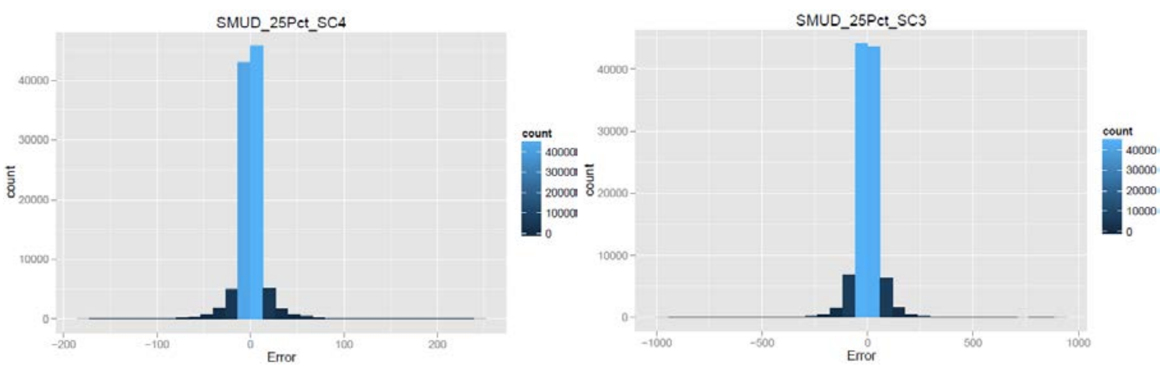

Figure K-3. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SMUD

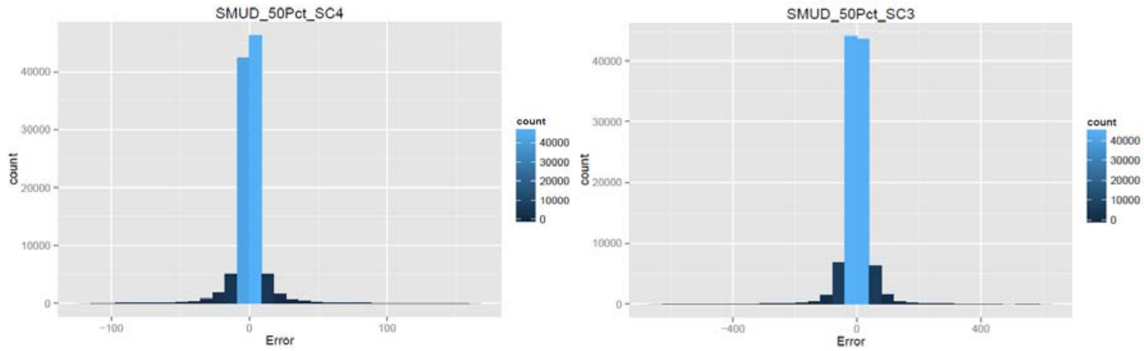

Figure K-4. Distribution of forecasting errors for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SMUD

Appendix L: Plots of Errors Versus Wind Power for Reserve Analysis in SMUD

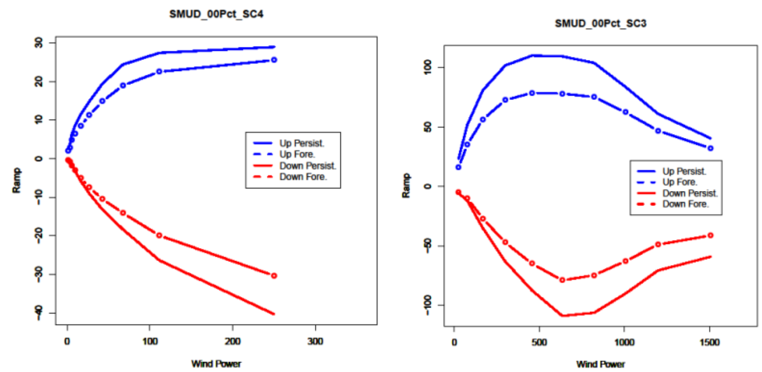

Figure L-1. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 0% improvement over state-of-the-art forecasting in SMUD

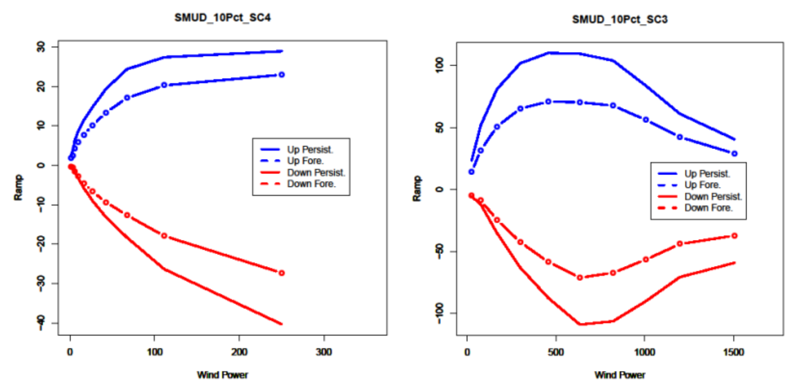

Figure L-2. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 10% improvement over state-of-the-art forecasting in SMUD

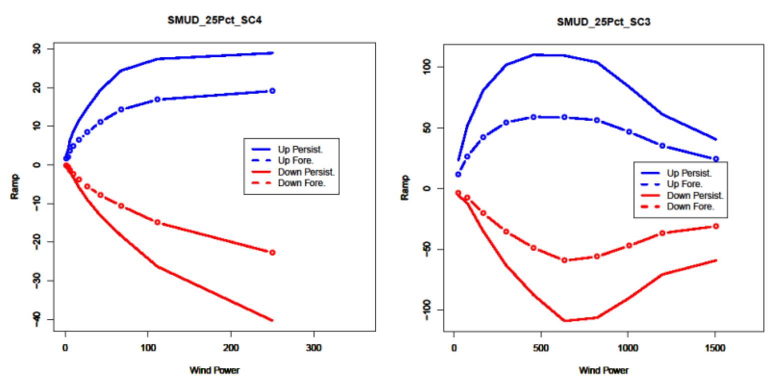

Figure L-3. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 25% improvement over state-of-the-art forecasting in SMUD

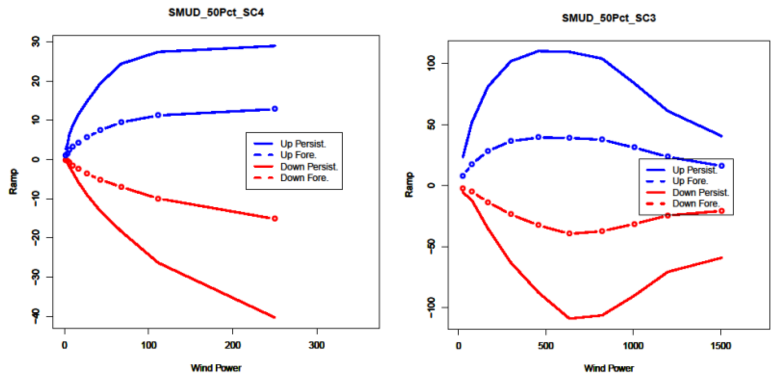

Figure L-4. Forecasting errors as a function of wind power for the low wind (SC4) and high wind (SC3) scenarios: 50% improvement over state-of-the-art forecasting in SMUD