2010 Wind Integration Study

- Draft -

August 12, 2010

1. Executive Summary

The purpose of the 2010 Wind Integration Study (the "Study") is twofold. First, the Study quantifies how wind generation affects the amount of operating reserve needed to maintain historical levels of reliability. Second, the Study tabulates the cost of integrating wind generation by measuring how system costs change with changes in operating reserve demand and by measuring how system costs are affected by daily system balancing practices.

Based upon historical and simulated wind generation data and historical load data, the Study shows that operating reserve demand for both regulation reserve service and load following reserve service increases with higher wind penetration levels. For purposes of this Study, regulation reserve service refers to operating reserves required by variability in both load and wind over ten-minute time intervals and load following reserve service refers to operating reserves required by both load and wind variability over hourly time intervals. Table 1 summarizes how operating reserve demand for both regulation and load following services increases as wind penetration levels grow from approximately 425 MW to approximately 1,833 MW. Table 2 depicts the change in operating reserve demand that is incremental to a load only calculation of the same types of reserve service.

Table 1. Annual average operating reserve demand by penetration scenario.

		Load Only	425 MW	1372 MW	1833 MW
West	Regulation Up	97	105	137	137
	Regulation Down	72	84	120	120
	Load Following Up	101	114	139	141
	Load Following Down	106	113	132	133
East	Regulation Up	138	140	201	231
	Regulation Down	107	110	185	222
	Load Following Up	139	144	207	245
	Load Following Down	144	147	198	237

Table 2. Annual average operating reserve demand incremental to the load only scenario.

		Load Only	425 MW	1372 MW	1833 MW
West	Regulation Up	0	7	39	39
	Regulation Down	0	12	48	48
	Load Following Up	0	13	38	39
	Load Following Down	0	7	26	27
East	Regulation Up	0	3	63	93
	Regulation Down	0	3	78	116
	Load Following Up	0	4	68	106
	Load Following Down	0	3	54	93

The costs of integrating wind as calculated in this Study include costs associated with increased operating reserve demand as outlined above and the costs from daily system balancing practices. Both types of costs were calculated using the Planning and Risk model (PaR), which is a production cost simulation model configured with a detailed representation of PacifiCorp's system. For each wind penetration scenario, a series of PaR simulations were completed to isolate each wind integration cost component by using a "with and without" approach. For instance, PaR was first used to calculate system costs without any incremental operating reserve demand and then again with the added incremental reserve demand. The change in system costs between the two PaR simulations drives the integration cost calculation. Table 3 summarizes the wind integration costs established in this Study alongside those costs calculated as part of the 2008 Integrated Resource Plan.

Table 3. Wind integration costs per MWh of wind generated as compared to those in the 2008 IRP.

Study	2008 IRP	2010 Wind Integration Study	2010 Wind Integration Study
Wind Capacity Penetration	2,734 MW	1,372 MW	1,833 MW
Tenor of Cost	20-Year Levelized	3-Year Levelized	3-Year Levelized
Interhour / System Balancing ($/MWh)	$2.45	$0.82	$0.86
Reserve ($/MWh)	$7.51	$8.03	$8.85
Total Wind Integration ($/MWh)	$9.96	**$8.85**	**$9.70**

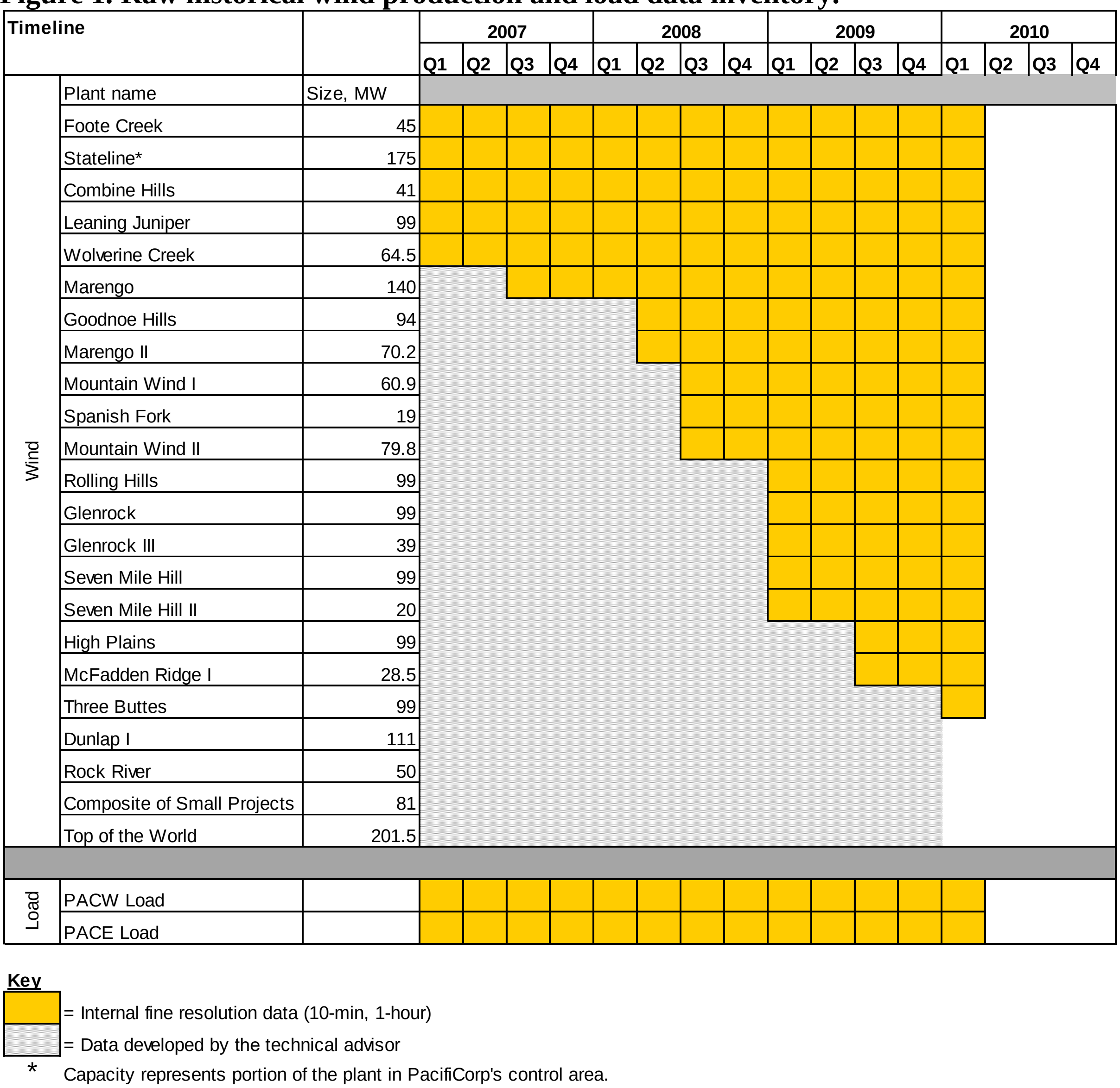
As shown above, the Study finds that operating reserve demand and the associated costs increase with wind capacity penetration. System balancing costs, driven by day-ahead forecast errors for wind and load, trend similarly as wind penetration increases from 1,372 MW to 1,833 MW; however, as expected, system balancing integration costs are much lower than integration costs for operating reserves.

2. Data Collection

2.1 Overview

The calculation of Operating Reserve demand was based on load and production data over the 2007 to 2009 period (the "Initial Term"). Figure 1 shows that over this period, ten-minute interval data was not available for all wind resources included in the Study. Nonetheless, PacifiCorp chose to use this data because it represented the best base of observed data available within the company, it includes significant concurrent load and wind generation data, and it includes year-on-year variability in weather and other variables affecting load and wind generation levels.

Figure 1. Raw historical wind production and load data inventory.



The data inventory summarized in Figure 1 contains as much real, observed, concurrent data as possible, owing to the volatile and unpredictable nature of wind generation output as well as the many fine variations available in real load data that can be difficult to capture with simulated data. Nonetheless, the data set selected for the Study contains gaps, and as a result, PacifiCorp utilized the services of the Brattle Group, the technical advisor that assisted with this study, to simulate missing wind data pertaining to the Initial Term. The simulation of wind data is discussed at length in its own section later in this report.

2.2 Historical Load and Load Forecast Data

The historical load data for the East and West Balancing Authority Areas was collected for the Initial Term from the PacifiCorp PI system[1]. These data were used for all the calculations involving historical load in the Study. The hourly day-ahead load forecasts were gathered from PacifiCorp's load forecast group, as were the day-ahead hourly load forecasts used to set up the generation system through the Initial Term period.

2.3 Historical Wind Generation and Wind Generation Forecast Data

2.3.1 Overview of the Wind Generation Data Used in the Analysis

Ten-minute interval metered wind generation data were available for a subset of the wind sites as summarized in Figure 1. The wind output data were collected by PacifiCorp at each physical project location using the PI software system. In addition to historical wind generation data, the Study required historical day-ahead wind forecasts, modeled day-ahead wind forecasts for simulated data, and the creation of an ideal wind profile. All of these data sets were needed to establish wind integration costs using PaR and are discussed in turn below.

2.3.2 Historical Wind Generation Data

As shown in Figure 2, a cluster of PacifiCorp owned and contracted wind generation plants is located in Pacific Power's service area (PacifiCorp's West Balancing Authority Area) and another is located in the Rocky Mountain Power service area (PacifiCorp's East Balancing Authority Area). It is worth noting that two wind sites, Wolverine Creek in Idaho, and Spanish Fork in Utah are part of the East Balancing Authority Area, but are geographically distant from both the western and the eastern clusters.

[1] The PI system collects load and generation data and is supplied to PacifiCorp by OSISoft http://www.osisoft.com/software-support/what-is-pi/what_is_PI_.aspx .

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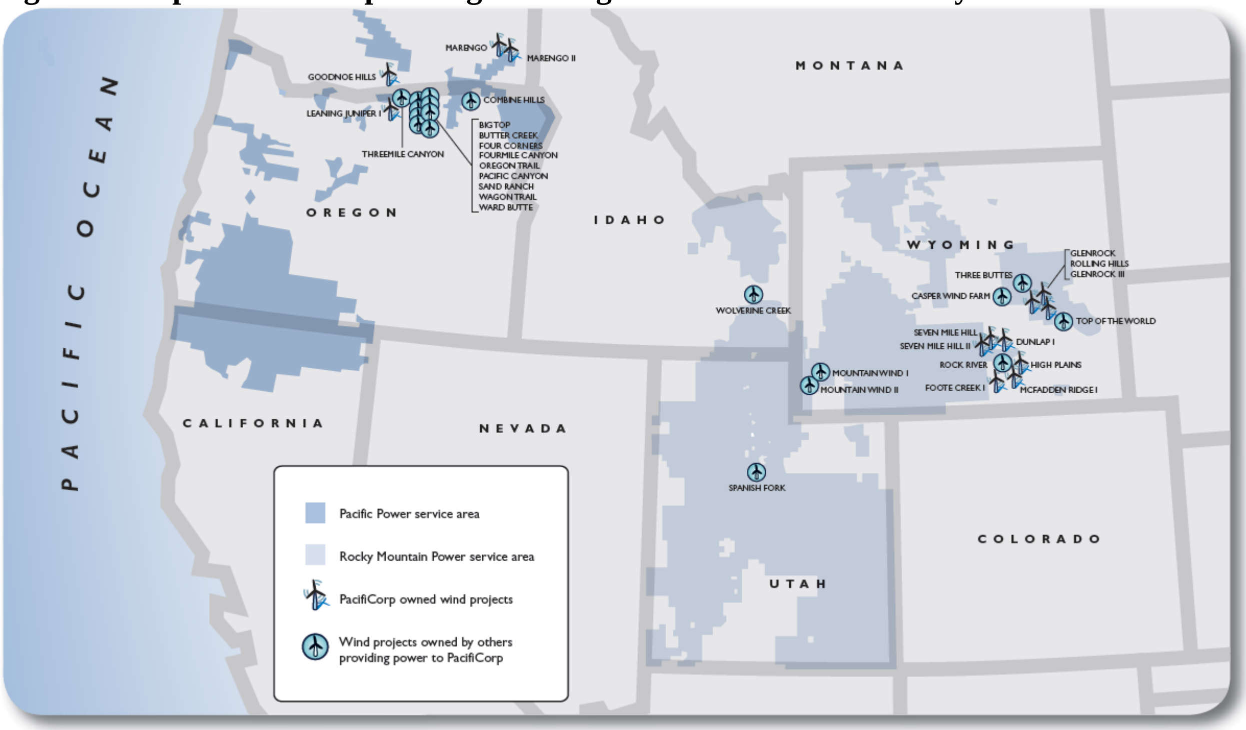
Figure 2. Map of PacifiCorp wind generating stations used in this study.



The available historical ten-minute wind generation data were examined to produce some initial statistical diagnostics for each site and between sites. For each site, Table 4 shows: (1) number of 10-minute interval data observations available, (2) standard deviation of observed capacity factors, (3) the minimum capacity factor, and (4) the maximum capacity factor. Small negative capacity factor values (that show up as the minimum) in the data are the result of power consumption associated with routine operation of the wind projects even during times when the project itself is not producing energy.

Table 4. Statistical properties of wind site capacity factor data.

Plant Name	Number of Observations	Standard Deviation	Min	Max
Goodnoe	83,520	32%	0%	100%
Leaning Juniper	157,824	35%	0%	100%
Combine Hills	157,824	38%	-3%	100%
Stateline	157,824	24%	-1%	100%
Marengo	79,776	33%	-11%	100%
Wolverine Creek	157,824	29%	-1%	100%
Spanish Fork	74,736	29%	-4%	87%
Mountain Wind	66,096	29%	0%	100%
Foote Creek	157,824	30%	-2%	100%
Seven Mile Hill	52,704	31%	0%	100%
McFadden Ridge	11,952	34%	-1%	100%
High Plains	15,840	21%	0%	67%
Glenrock	50,256	29%	0%	100%

Table 5 shows the correlation observed among aggregate hourly load and wind generation data in 2008. By and large, hourly changes in load and wind generation output, which drive operational planning, do not appear to be correlated.

Table 5. Hourly correlation of system wind and system load.

	Overall	Rolling 6 hour	Rolling 12 Hour
January	-2.5%	-2.9%	-3.4%
February	-2.8%	-0.6%	-1.7%
March	-0.4%	-1.4%	-2.2%
April	-6.4%	-3.5%	-5.9%
May	-10.4%	-3.0%	-6.4%
June	-12.0%	-9.2%	-11.9%
July	-12.4%	-12.3%	-14.2%
August	-9.1%	-8.4%	-9.8%
September	-6.5%	-0.6%	-4.0%
October	-3.5%	-4.8%	-6.7%
November	-7.5%	-3.6%	-4.4%
December	-2.0%	0.3%	-1.1%

2.3.3 Historical Day-ahead Wind Generation Forecasts

Day-ahead wind forecasts were collected from daily historical files maintained by PacifiCorp commercial operations. The files contained day-ahead hour-by-hour wind generation forecasts for the wind projects operating during the Initial Term. For those projects not operating during the Initial Term, day-ahead forecasts were created using the daily volumetric day-ahead forecast error from projects having complete data sets. As such, these data were used to bootstrap[2] the daily day-ahead forecast volumetric errors for the 1,372 MW and 1,833 MW scenarios, and the daily error (positive or negative) was applied to simulated wind generation data to create a modeled day-ahead forecast. The modeled day-ahead forecast maintained the same general hourly shape as the simulated wind generation data but was shifted vertically hour-by-hour on an equal percentage basis to keep the aggregate volumetric error constant.

2.3.4 Ideal Shape Wind Generation

In order to isolate wind integration costs from other system costs, a flat production profile is required for PaR modeling. This profile, deemed the ideal wind shape for purposes of the Study, treats all the energy produced by wind projects as monolithic blocks. Comporting with standard trading products among forward energy markets in the Western Interconnect, the energy produced in each 16-hour daily block between hour ending seven and hour ending 22 was treated as a single block. Similarly, energy produced in the 8-hour block between hour ending 23 and

[2] Bootstrapping is a common statistical method used to estimate data by extrapolating from existing data.

hour ending six was treated as a single block. For each block, the total energy delivered from wind generation is averaged, thereby flattening the generation pattern.

2.4 Wind Generation Data Simulation

The technical advisor assisted PacifiCorp in developing the Study methodology and in supplementing the historical wind generation data with simulated ten-minute interval wind generation data. This section summarizes the methodology used to simulate wind generation data and provides sample data and graphics to illustrate the details involved in each step of the process.

The overall approach to simulating wind generation data involved taking an historical data inventory; addressing data quality issues in the data inventory; identifying gaps requiring simulation; and finding the best suited relationship between pairs of sites; and using that relationship to approximate the wind output for periods with missing historical observations. However, it is worth noting that for sites with no historical data, the necessary numerical relationships were estimated between relevant locations by using simulated wind data made available by the National Renewable Energy Laboratory (NREL). Additional detail on simulation procedures is available in Appendix A.

2.4.1 Categorization of Historical Wind Data to Determine Simulation Scope

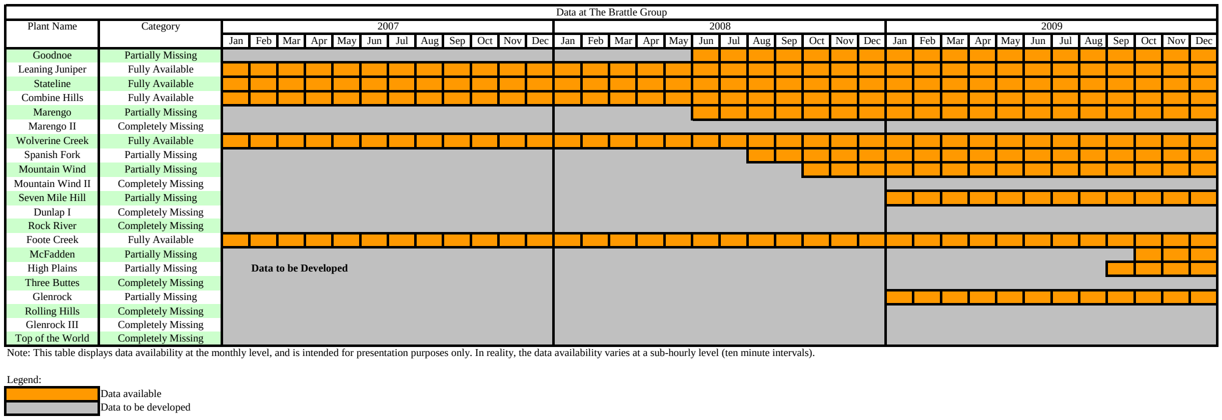
The historical wind data were classified into three groups to determine the periods requiring simulation for each site. The three categories are defined in turn below, and Figure 3 depicts how each site was categorized.

(1) *Fully Available*—this category refers to sites for which output data are available for the entirety of the Initial Term. Specifically, these wind plants include: Leaning Juniper, Combine Hills, Stateline, Wolverine Creek, and Foote Creek. These plants sum to 425 MW of capacity.

(2) *Partially Missing*—refers to sites for which output data are unavailable for a portion of the Initial Term. The wind plants that fall into this category are: Goodnoe Hills, Seven Mile Hill, Marengo, Spanish Fork, Mountain Wind, McFadden Ridge, High Plains, and Glenrock. One important feature of the partially missing data profiles is that the missing portions are always chronologically located at the beginning of the time period—once a partially missing data profile begins, it contains no further data "holes". These plants sum to 848 MW of capacity.

(3) *Completely Missing*—refers to wind projects, for which no output data are available for the 2007-2009 Initial Term. Those sites are: Dunlap, Rock River, Rolling Hills, Three Buttes, and Top of the World. These plants sum to 560 MW of capacity.

Figure 3. Categorization of wind generation data.



2.4.2 Simulation Process

The simulation process used in the Study evolved to become iterative in nature to ensure that simulated wind generation data used to establish operating reserve demand was reasonably aligned to the operating reserve demand calculated using observed wind generation data. As such, different methods of error sampling and simulation techniques (multiple linear, Tobit; for example) were evaluated in this manner. Tables 6 illustrates an example of how operating reserve demand calculated from observed and simulated data were used to evaluate different error sampling and re-addition methods used in this iterative process for the West Balancing Authority Area.

Table 6. Comparison of operating reserve demand calculated from actual wind generation plant data and simulated wind generation plant data estimated using a least squares regression and applying different scaling of errors added back into the raw prediction.

Actual Wind Generation Data			
	Load Following Up	Load Following Down	Regulation
	15.0	(19.1)	15.5
Test (Developed Wind Data)			
Error Scaling (%)	Load Following Up	Load Following Down	Regulation
10	9.9	(13.0)	11.1
50	10.6	(13.9)	12.3
75	11.7	(14.2)	14.3
100	12.4	(15.9)	17.1

Several simulation attempts ended with values above the feasible generation capacity range, or values beneath zero. Attempts to add the error term back into the prediction (a necessary simulation step) also faced significant hurdles in developing reasonable results. The highly variable ten-minute output led to error terms with ranges larger than the simulated values in many cases, which would also test the boundaries of either zero or maximum plant capacity delivered. Several processes were attempted to return a sampled error estimation back to the modeled estimate, per proper regression, including sampling of truncated error distributions, medians of the error distributions, and various bins of errors sampled and added back to the regression estimate. Various combinations of these methods were put through the operating reserve demand estimation calculations to assess whether the results were reasonable. Ultimately, the Tobit simulation method (described in more detail in section A.4.3) and a 3-step smoothed median of the sampled errors proved to offer reasonably stable results.

Ultimately, the iterative simulation process produced a simulation methodology comprised of several sequential steps:

(1) estimate the *Tobit* regressions;
(2) using the regression coefficients, generate estimates of the mean output of the *predicted*[3]
(3) calculate the regression residuals;
(4) randomly sample the residuals according to predefined simulated output ranges;
(5) apply a non-linear 3-step median smoother to the sampled residuals;
(6) add the smoothed residual series to the predicted mean output.

A more detailed description of each step appears in Appendix A, and the resulting regression coefficients appear in Appendix B.

[3] These are generally referred to in the literature as "y hat"

3. Methodology

3.1 Method Overview

This section of the Study presents the approach used to establish the enumeration of operating reserve demand and the method for calculating wind integration costs. Ten minute interval load and wind data is used to estimate the amount of operating reserve, both up and down, needed to manage fluctuations in load and fluctuations in wind within PacifiCorp's Balancing Authority Areas. The operating reserve discussed here is limited to spinning reserve and non-spinning reserve, which are needed for regulation, load following, and contingency reserve services. For purposes of this Study, regulation service refers to the operating reserve required to manage the variability of load and wind generation in ten minute periods, and load following service represents the operating reserve required to manage the variability as measured in hourly periods.[4] Contingency reserve, although mentioned, is supplied in accordance with the North American Reliability Corporation (NERC) standards and remains unchanged by the wind generation contemplated in this Study. Therefore, the operating reserve quantities discussed herein are only pertinent to supplying the demands of regulation and load following services, which are assessed in for load, and load net wind scenarios.

Once the amount of operating reserve is established for different levels of wind penetration, the cost of holding the reserve on PacifiCorp's system is calculated using PaR. In addition to using PaR for evaluating operating reserve cost, the PaR model is used to estimate wind integration cost associated with daily system balancing activities. These system balancing costs result from the unpredictable nature of wind generation on a day-ahead basis and can be characterized as system costs borne from committing generation resources against a forecast of load and wind generation and then dispatching generation resources under actual load and wind conditions.

3.2 Incremental Operating Reserve Demand

A dense data set of ten-minute interval wind generation and system load drives the calculation of the marginal reserve requirement in two components: (1) *regulation*, which is developed using the ten-minute interval data, and (2) *load following*, which is calculated using the same data but estimated using hourly variability. The approach for calculating incremental operating reserve necessary to supply adequate capacity for regulation and load following at levels required to maintain current control performance was based on merging current operational practice with a survey of papers on wind integration, as well as advisory from the technical advisor.[5] The Initial Term load data is used as the baseline case (zero wind generation) in each scenario. Coincident wind data (as observed, plus that simulated by the technical advisor) were added in increasing levels of wind capacity penetration to gauge the change in operating reserve demand. For purposes of the Study, the regulation calculation compares observed ten-minute interval load and

[4] PacifiCorp's definitions for regulation and load following are based on PacifiCorp's operational practice, and not intended to describe the operational practices or terminology used by other power suppliers or system operators.
[5] The external studies PacifiCorp has relied on can mostly be found on the Utility Wind Integration Group (UWIG) website at the following link: http://www.uwig.org/opimpactsdocs.html

wind generation production to a ten minute interval estimate, and load following compares observed hourly averages to an average hourly forecast.

3.2.1 Regulation Operating Reserve Service Demand

With no sub-hourly clearing or imbalance market, PacifiCorp must plan to meet sub-hourly load (and load net of wind) deviations with its own resources. This includes generating units on automatic generation control (AGC), demand side management (DSM), and the ramping of flexible generation units in real time operation, which requires that existing units be committed and then dispatched to provide operating reserve. Wind variability among ten-minute intervals can represent a quantity of generation required to ramp up or down to maintain system stability. Regulation service demand for wind generation variability was considered first. To parse the ten-minute interval wind variability from the ensuing load following analysis, a persistence forecast of the rolling prior 60 minutes was used to analyze the variation of each ten minute interval. The actual wind generation in each ten minute interval was subtracted from the rolling average of the prior six ten-minute intervals, and the standard deviation was computed for each monthly period. This approach follows the one used by the National Renewable Energy Laboratory (NREL) for its recent "Eastern Wind Integration and Transmission Study".[6]

$$\boldsymbol{Regulation}_{wind10min} = \boldsymbol{P}_{cps2}\,(\boldsymbol{Wind}_i)$$

Where:

$\mathbf{P_{CPS2}}$ = The percentile of a two-tailed distribution equaling the Balancing Authority Area's CPS2 performance[7]

$\boldsymbol{Wind_i}$ = the wind forecast error defined as ($\mathbf{Wind}_{Actual10min}$ **-**$\mathbf{Wind}_{10\text{-}min\text{-}forecast}$)

$\mathbf{Wind_{10\text{-}min\text{-}forecast}}$ = the rolling average of the wind generation in prior six ten-minute intervals, also referred to as a persistence forecast of the rolling prior 60 minutes

$\mathbf{Wind_{Actual10min}}$ = the observed wind generation for a given ten-minute interval

The load variability and uncertainty was analyzed comparing the ten-minute actual load values to a line of *intended schedule*, which was represented by a line interpolated between an actual top-of-the-hour load value and the next hour's load forecast target at the bottom of that (next) hour. A sample of how the intended schedule compares to actual load data is shown in Figure 4. The method approximately mimics real time operations process for each hour. At the top of the given hour, the actual load is known and a forecast for the next hour was made. For the purposes of this study, a line joining the two points was made to represent the ideal path for the ramp or decline expected within the given hour. The resulting actual ten-minute load values were compared to this straight line so as to produce a strip of error terms, as depicted in Figure 5 with data from February 2009.

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[6] NREL, *Eastern Wind Integration and Transmission Study*, prepared by EnerNex Corporation, (January 10, 2010), p. 143. The report is available for download from the following hyperlink:
http://www.nrel.gov/wind/systemsintegration/pdfs/2010/ewits_final_report.pdf

[7] The Control Performance 2 is a reliability standard is maintained by the North American Electric Reliability Council. A definition is available on page 3of the document at the following hyperlink:
http://www.nerc.com/files/Reliability_Standards_Complete_Set_2010Jan25.pdf

The errata were assembled monthly and their Regulation demand estimated similarly to the method used for the 10-minute values of the wind data:

$$\boldsymbol{Regulation}_{load10min} = \boldsymbol{P}_{cps2}\,(\boldsymbol{Load}_i)$$

Where:

$\boldsymbol{Load}_i$ = the load forecast error, calculated similarly to $\boldsymbol{Wind}_i$

Figure 4. Sample of intended schedule ten-minute load estimate and observed system load.

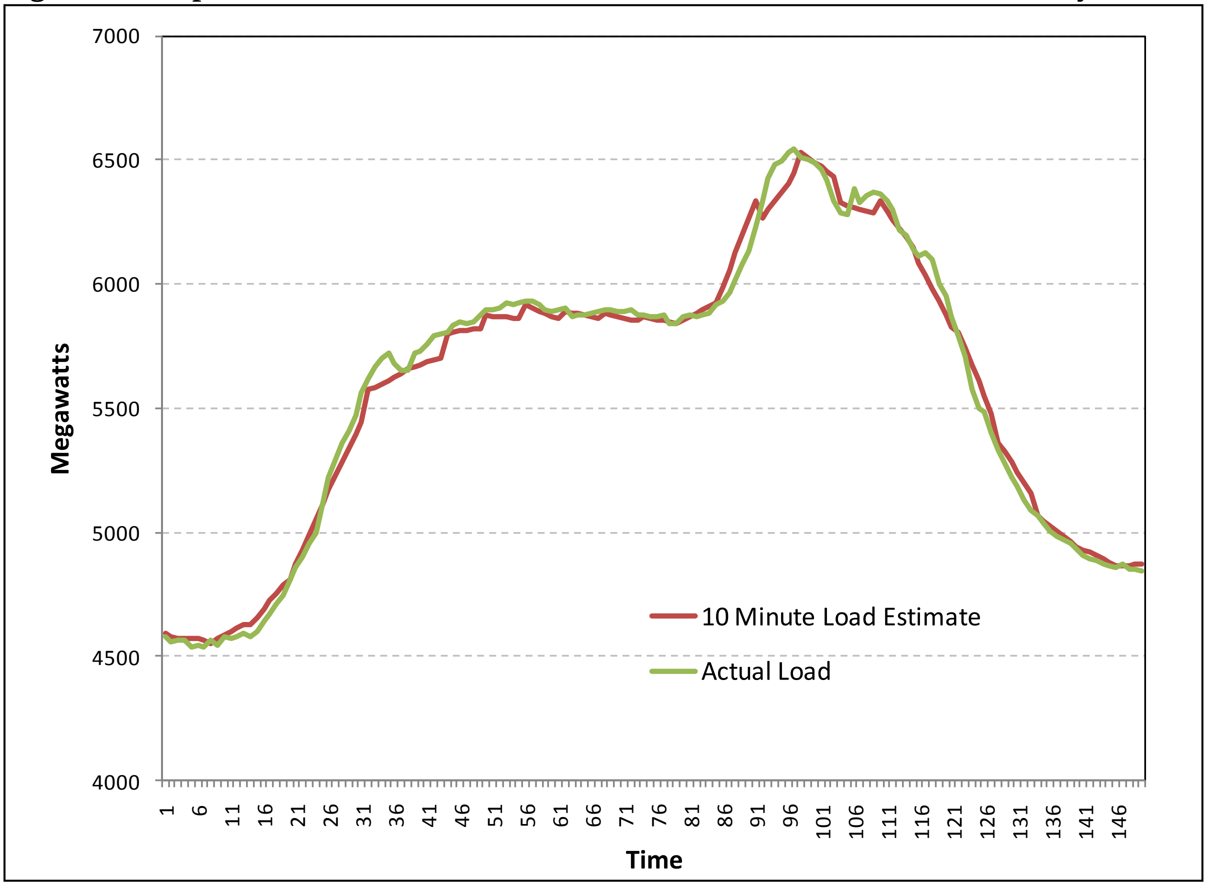
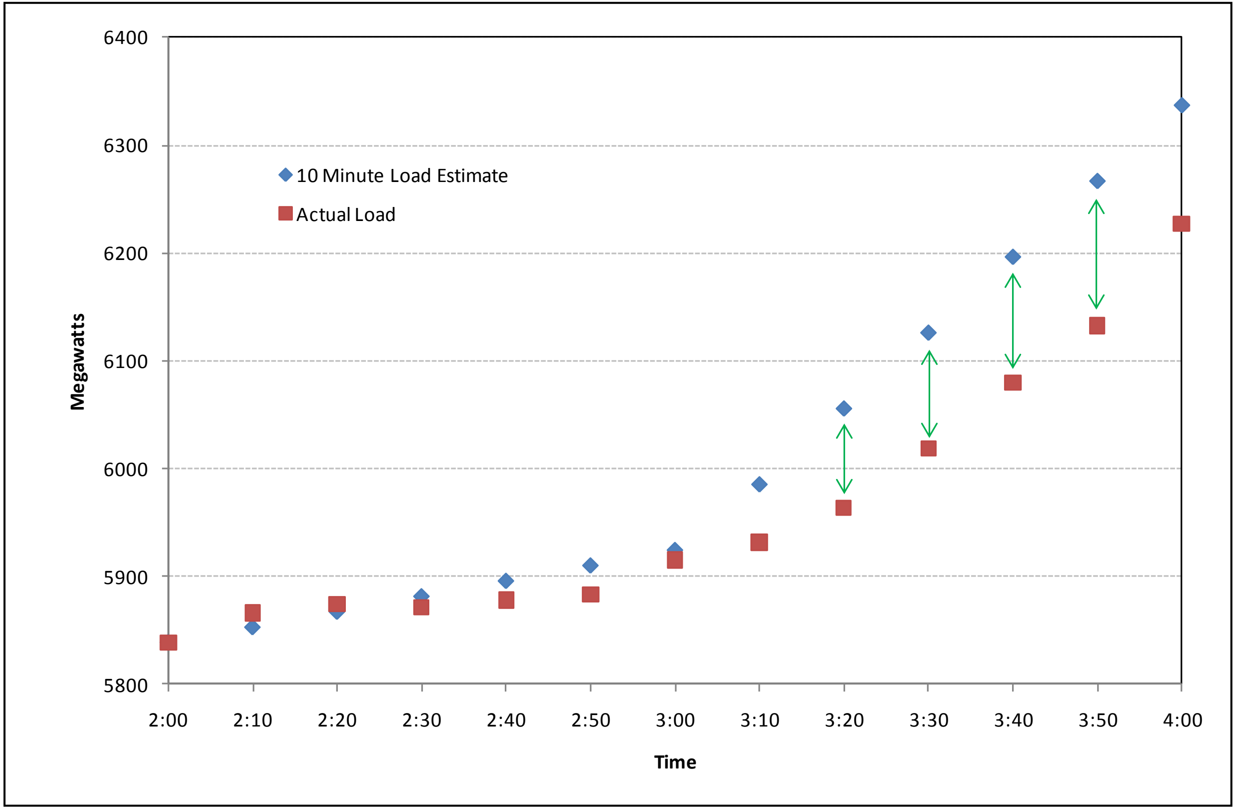


Figure 5. Variability between the line of intended schedule and observed load with errors highlighted by green arrows.



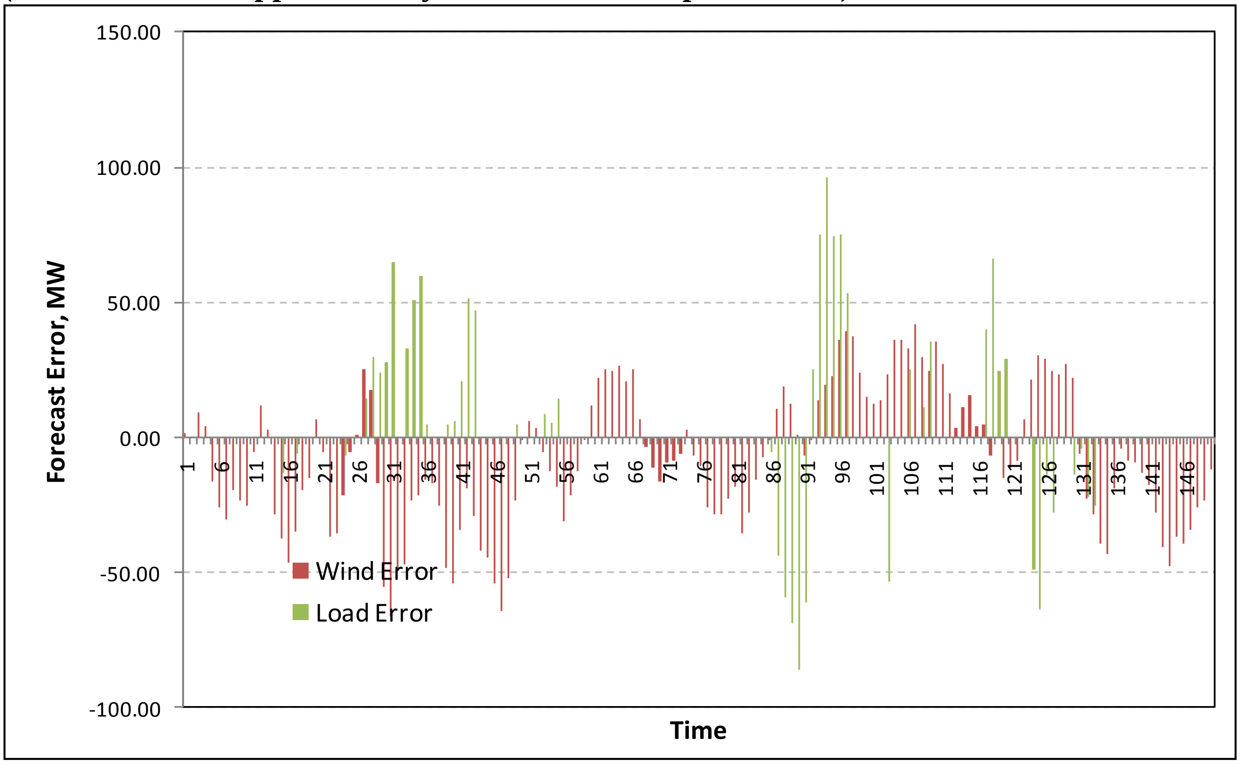
As the ten-minute load and wind errors each represent unpredictable change in the need for dispatchable generation, their variability was assessed separately and combined. The regulation demand of load net wind generation was estimated assuming short term variations in load are not correlated with changes in aggregate wind generation output through the use of a geometric average (shown for Regulation Up):

$$\boldsymbol{Regulation_{UP10min}} = \sqrt{Regulation_{LoadUP10min}{}^{2} + Regulation_{WindUP10min}{}^{2}}$$

As the need for regulation service can vary whether the wind is up or down, both Regulation Up and Regulation Down services were estimated at each end of the error distributions.

A sample of the errors logged for the same period, for load and wind, are shown in Figure 6. The independence of the forecast errors for wind and load was assumed. These errors, or differences between forecast and actual, comprised an estimate of the demand made on regulation service operating reserves during power system operations. These differences were calculated for every ten minutes of operation through the Initial Term period, and separated into monthly bins for further analysis.

Figure 6. Independent forecast errors in ten-minute interval load and wind generation (December 2008, approximately 890 MW of wind penetration).



Analyzing the results on a monthly basis as opposed to grouping all the calculations together annually allowed for the fact that some months' power service actually required less regulation (for example, July and August) than others, and so costs could be more accurately attributed with a weighted average of results as opposed to grouping the entire year's operations into a single analysis bin. This is due to operating reserve being employed to manage the tails of the distributions involved, and a single annual bin would apply the greatest tail occurrences to the entire year, as opposed to only the month in which it occurs. Figure 7 demonstrates the resulting distributions of regulation demand for wind generation, where regulation down demand is the negative side of the distribution. The vertical lines drawn on Figure 7 illustrate the operating reserve threshold defined in the Study and data labels are added to denote outlying data points. Similarly, Figure 8 illustrates the resulting distribution of regulation demand for load, where regulation up demand is the positive side of the distribution.

Figure 7. Wind Regulation errata plotted for the Mays of the Initial Term at the 1,372 MW wind capacity penetration level.

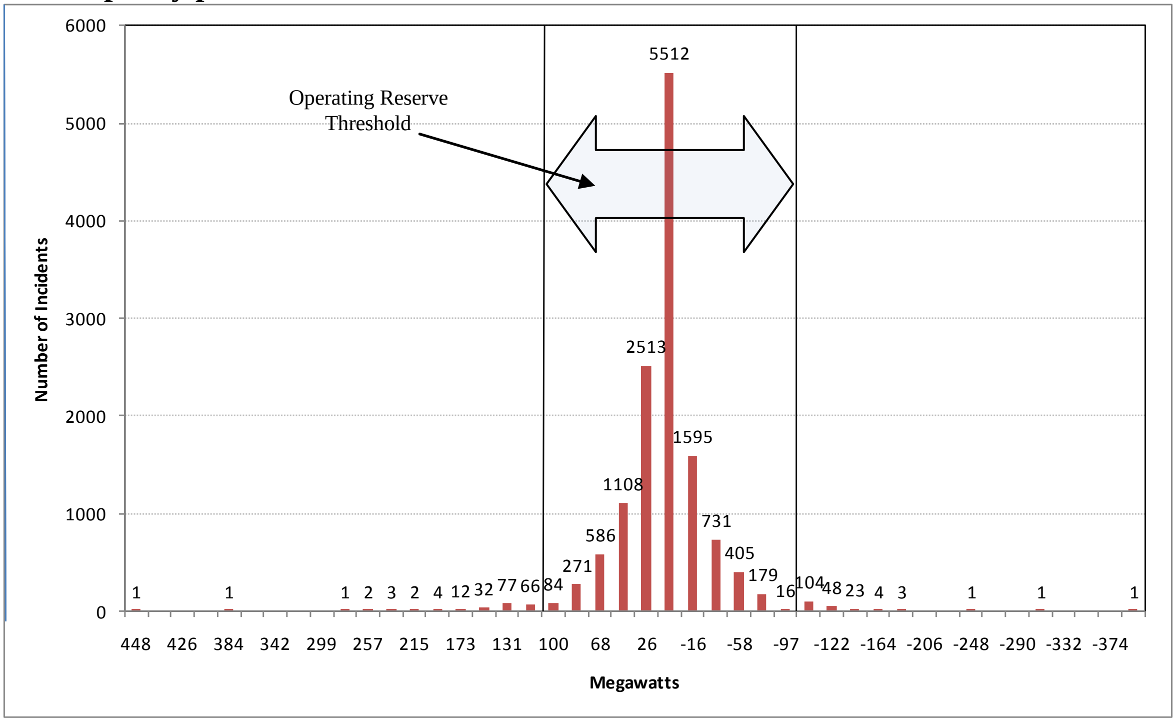
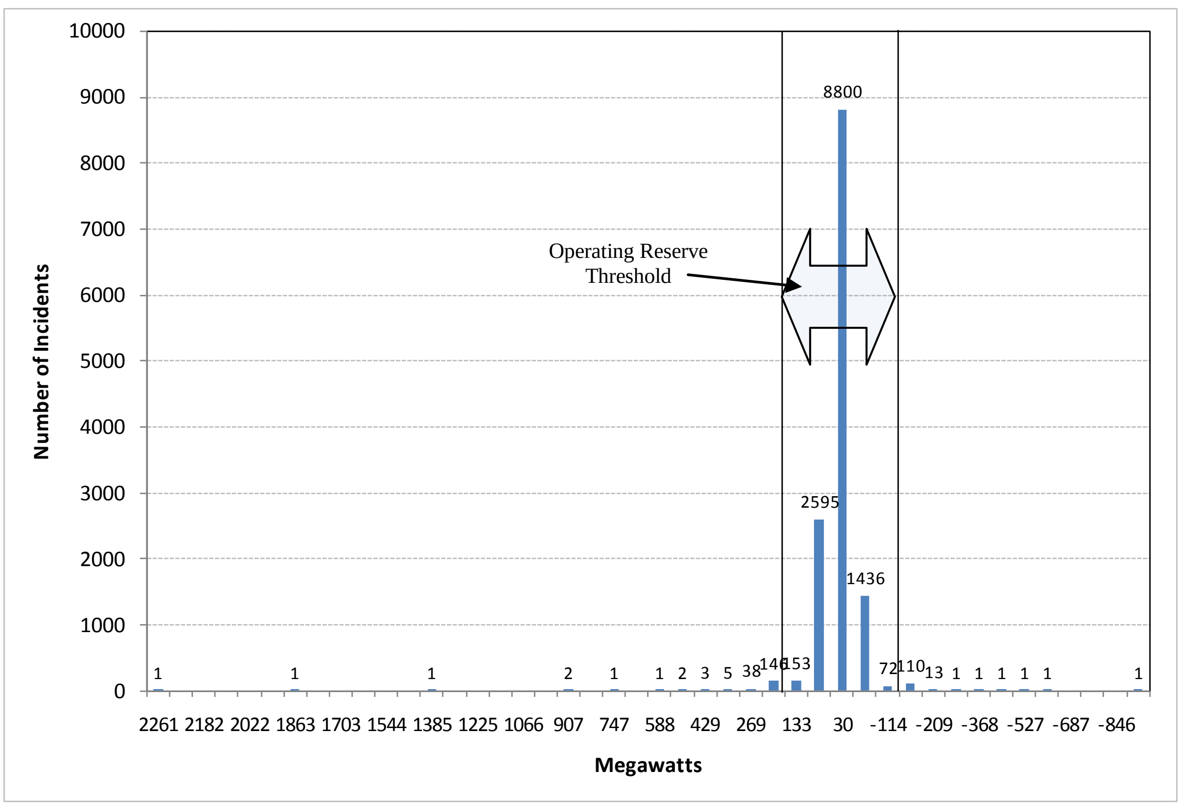


Figure 8. Load Regulation errata plotted for the Mays of the Initial Term.



3.2.2 Load Following Operating Reserve Demand

PacifiCorp maintains system balance by optimizing its operations to an hourly forecast with changes in generation and market activity. This planning interval represents hourly changes in generation which are assessed within roughly 20 minutes each hour to account for a bottom-of-the-hour (:30 after) scheduling deadline. Taking into account the conditions of the present and the expected load and wind generation, PacifiCorp must schedule generation to meet demands with an expectation of how much higher or lower system load (net of wind generation) may be.

PacifiCorp's real-time desk updates the next hour’s system load forecast forty minutes prior to each operating hour. This forecast is created by comparing the current hour load to the load of a similar-load-shaped day. The hour-to-hour change in load from the similar day and hours (the load delta) was applied to the “current” hour load and the sum is used as the forecast for the ensuing hour. For example, on a given Monday the PacifiCorp operator may be forecasting hour to hour changes in system load by referencing the hour to hour changes on the prior Monday, a similar-load-shaped day. If the hour to hour load change between the prior Monday's like hours was 5%, the operator will use a 5% change in load as the next hour forecast.

As for the corresponding short term operational wind forecast, the hourly wind forecast is done by persistence; applying the instantaneous sample of the wind generation output 20 minutes past the current hour to the next hour as a forecast and balancing the system to that point. The resulting operational modeling process therefore went as follows; at the top of the hour, wind generation output, dispatchable generation output, and load values were summarized, and trended using the methods above. The result was compared to the next hour’s schedule for gaps as soon as possible, with the generation and load values updated at roughly 20 minutes past the hour. In real time operations, this result would then be balanced through a combination of market transactions and scheduling adjustments to PacifiCorp resources to produce a balanced schedule for the ensuing hour; with all transactions having to be complete by 30 minutes past the hour. Meanwhile, for purposes of the calculation made in this Study, the hourly wind forecast consisted of the 20th minute output from the prior hour, and the load forecast was modeled per the approximation described above with a shaping factor calculated using the day from one week prior, and applying a prior Sunday to shape any NERC holiday schedules.

Using the Initial Term data for PacifiCorp’s Balancing Authority Areas, a comparison of the load and wind forecasts was implemented to measure the seasonal or annual trends in the variability between the hourly interval load and wind forecasts and the observed average hourly load and wind generation values. These differences were segmented into bins by load magnitude and wind generation magnitude using load and wind data, in order to facilitate making a weighted average of the reserves demand by load level and wind generation output level. An example of load and wind data segmented into bins appears in Figures 9 through 12. Figure 9 depicts forecast load in West Balancing Authority Area with a range of over and under predictions tied to Control Performance 2 (CPS2) performance level. Figure 10 shows the same data for the East Balancing Authority Area. In similar fashion, Figure 11 displays forecasted wind generation in the West Balancing Authority Area with a range of over and under predictions consistent with a 97% CPS2 performance level. Figure 12 shows the same wind generation forecast data for the East Balancing Authority Area.

Figure 9. Example of bin analysis for load following reserve service from load variability in the West Balancing Authority Area (May 2007-2009).

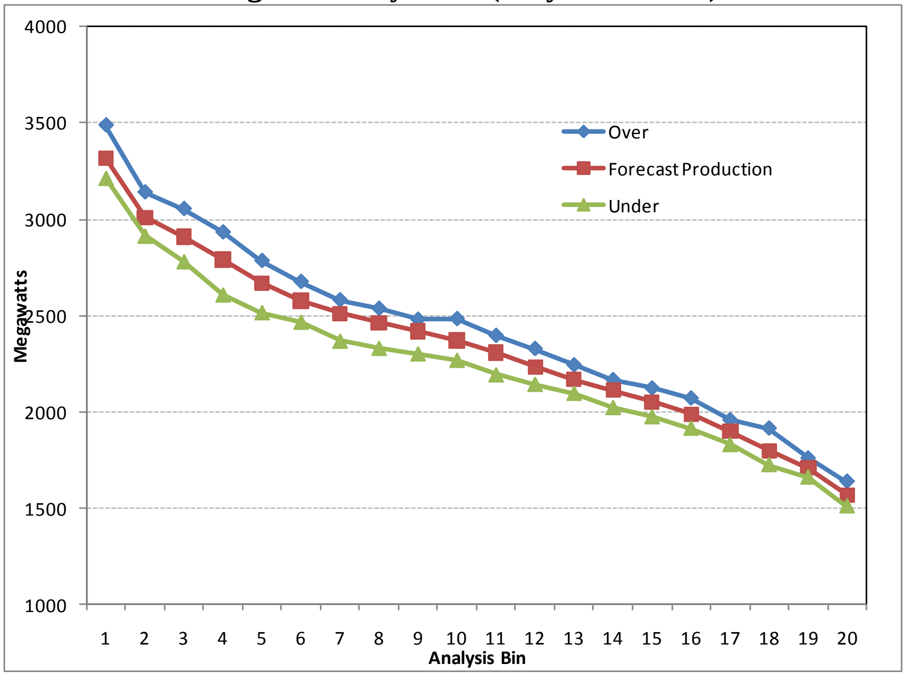


Figure 10. Example of bin analysis for load following reserve service from load variability in the East Balancing Authority Area (May 2007-2009).

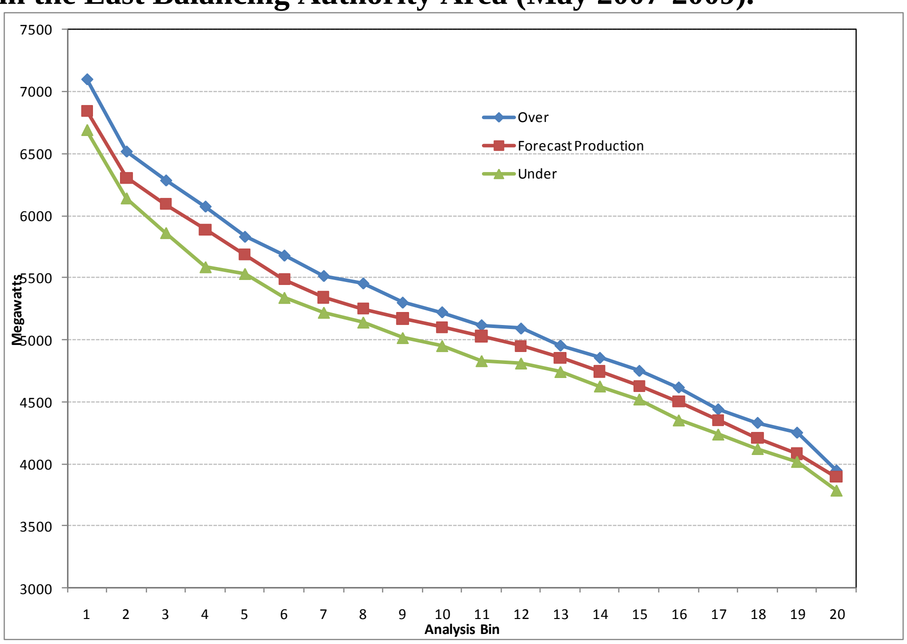


Figure 11. Example of bin analysis for load following reserve service from wind variability at the 1,372 MW penetration level for the West Balancing Authority Area (May 2007-2009).

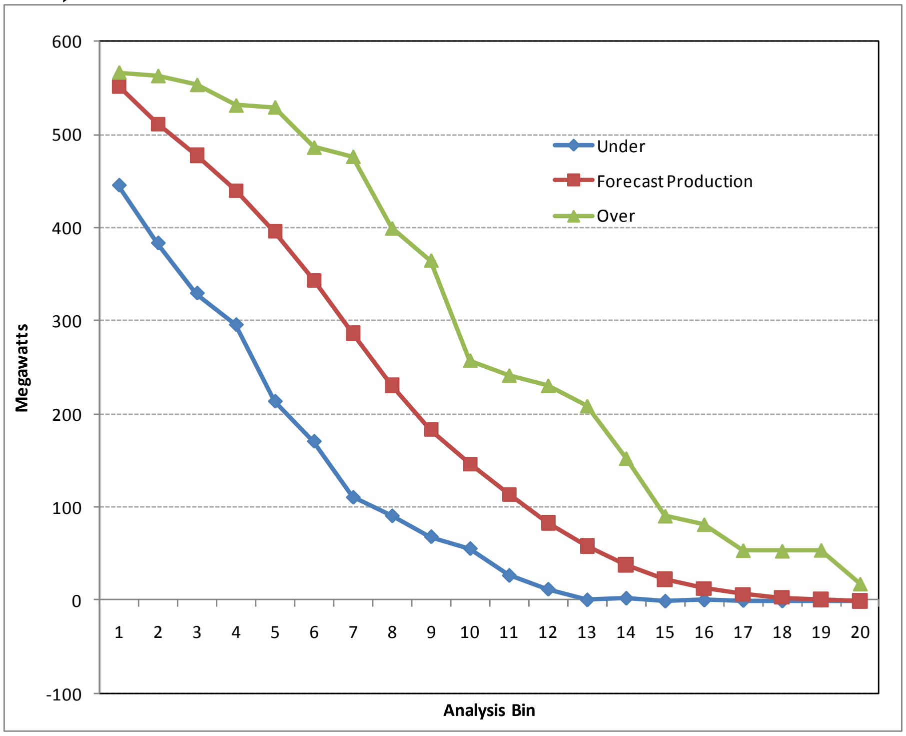
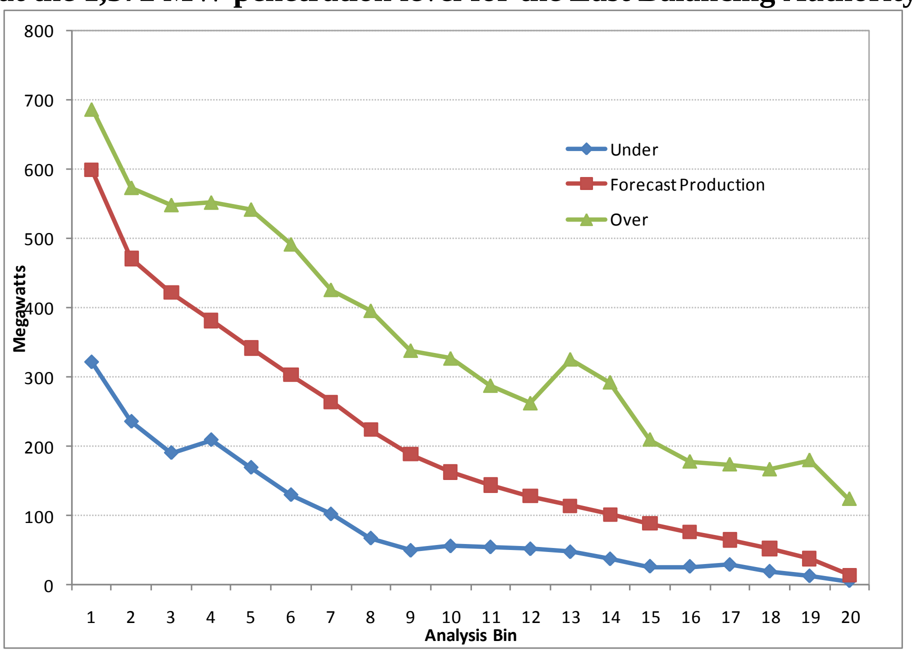


Figure 12. Example of bin analysis for load following reserve service from wind variability at the 1,372 MW penetration level for the East Balancing Authority Area (May 2007-2009).



Probabilities implied by the population of each bin, representing the expected amount of time spent in each load state, were represented by the historical data. The percentile equivalent to the historical CPS2 performance of PacifiCorp was sampled above and below the median of each of the bins. The average CPS2 performance for PacifiCorp's East and West Balancing Authority Areas over the period 2004 to 2009 was just below 97%. As the goal of this Study is to incorporate wind integration in PacifiCorp's current operations, the CPS2 performance of 97% was emphasized in these calculations. An assessment of the overall system power quality is a standalone topic that is beyond the scope of this Study, and thus, the Company assumed this level of reliability will be maintained. The difference between the CPS2 percentiles and the median of the bins represents the implied incremental load following service for operating reserve demand within that bin. As each respective bin also has an implied probability by the number of data points falling within it, the volumetric position over the study period was calculated as a simple weighted average.

To further explain the calculation method for load following reserve demand, the following example follows from the illustration in Figure 10. To assess the load following up reserve position for Bin 5, subtract the lower bound value (5,532 MW) from the system load forecast of 5,687 MW to arrive at an estimate of 154 MW for the occurrences within that bin. Integrating this process through all bins produced a composite load following up position for the East Balancing Authority Area in May, and the process was repeated for each month in the up and down directions. Wind generation was analyzed in exactly the same procedure, but with generation output representing the individual state variable. The wind and load reserve positions were combined using the root sum square calculation in each direction (up and down), assuming their variability in the short term is independent.

$$\boldsymbol{Reserves_{LoadFollowing}} = \sqrt{LoadReserves_{LoadFollowing}{}^{2} + WindReserves_{LoadFollowing}{}^{2}}$$

3.3 Determination of Wind Integration Cost

3.3.1 Overview

Owing to the variability and uncertainty of wind generation, each hour of power system operations features a need to set aside increased operating reserve (both spinning and non-spinning reserve), in addition to those set aside explicitly to cover load and contingency events which are inherent to the PacifiCorp system with or without wind. Additional costs are incurred with daily system balancing practice that is influenced by the unpredictable nature of wind generation on a day-ahead basis. To derive how wind generation affects operating reserve costs and system balancing costs, the Study utilizes the PaR model.

PacifiCorp's PaR model, developed and licensed by Ventyx Energy LLC, uses the PROSYM chronological unit commitment and dispatch production cost simulation engine and is configured with a detailed representation of the PacifiCorp system. For this study, four different PaR simulations were developed for a range of wind penetration scenarios as defined in Table 7. By carefully designing the four simulations, we were able to isolate wind integration costs associated with operating reserves and to separately calculate wind integration costs associated with system balancing practice. The former reflects integration cost that arises from short-term (within the hour and hour ahead) variability in wind generation and the latter reflects integration costs that arise from errors in forecasting load and wind generation on a day-ahead basis.

Table 7. Wind penetration scenarios used in PaR, as a percentage of total fleet capacity.

Representative Timing	Baseline	2007 End of Year	2009 End of Year	2010 End of Year
Installed Wind Capacity (Megawatts)	0	425	1,372	1,833
Wind Penetration Percentage	0%	3%	10%	12%

The four PaR simulations used for each penetration scenario in the Study are summarized in Table 8. The first two simulations are used to tabulate operating reserve wind integration costs, while the third and forth simulations support the calculation of system balancing wind integration costs. Table 8 identifies how key input variables change among the simulations. The simulations were run over the 2011 to 2013 forward term (three years), wherein 2007 wind generation and load data are used as inputs for 2011, 2008 wind generation and load data are used for 2012, and 2009 wind generation and load data are used for 2013. This calculation method combines the benefits of using actual system data available for the historic three-year Initial Term period with current forward price curves pertinent to setting the cost for wind integration service on a forward basis.[8] PacifiCorp resources used in the simulations are based upon the 2008 IRP Update resource portfolio.[9]

Table 8. Wind integration cost simulations in PaR.

PaR Model Simulation	Forward Term	Load (Initial Term)	Wind Profile (Initial Term)	Incremental Reserve	Day-ahead Forecast Error
1	2011 - 2013	Actual	Ideal Shape	None	None
2	2011 - 2013	Actual	Actual	Yes	None
Operating Reserve Integration Cost = System Cost from PaR simulation 2 less system costs from PaR simulation 1					
3	2011 - 2013	Day-ahead Forecast	Day-ahead Forecast	Yes	None
4	2011 - 2013	Actual	Actual	Yes	Yes (Commitment from PaR Simulation 3)
System Balancing Integration Cost = System Cost from PaR simulation 4 less system costs from PaR simulation 2					

[8] The Study uses the March 31, 2010 official forward price curve.

[9] The 2008 Integrated Resource Update report, filed with the state utility commissions on March 31, 2010. The report is available for download from PacifiCorp's IRP Web page using the following hyperlink:

http://www.pacificorp.com/content/dam/pacificorp/doc/Energy_Sources/Integrated_Resource_Plan/2008IRPUpdate/PacifiCorp-2008IRPUpdate_3-31-10.pdf

3.3.2 Calculating Operating Reserve Wind Integration Costs

To assess the effects of various levels of wind capacity added to the Balancing Authority Areas on operating reserve costs, each penetration scenario was simulated in PaR using both ideal (Simulation 1) and actual (Simulation 2) wind profiles. Both the ideal and actual PaR simulations excluded System Balancing costs. The ideal wind profile is a "flattened" representation of the actual profile, where wind generation is averaged across on- and off-peak blocks. Such a profile requires no additional operating reserve to support wind generation variability, and as such, Simulation 1 only included an operating reserve needed for load variability. In summary, Simulation 1 included actual historical loads, ideal wind profiles, and no incremental operating reserve to account for wind variability.

Simulation 2 used the actual wind generation profiles, which reflect the 2007 to 2009 observed and developed Initial Term wind data as inputs for the 2011 to 2013 forward period. These actual wind generation profiles reflect the same variability used to derive the incremental operating reserve requirements needed to integrate wind generation. Thus, the second PaR simulation includes the incremental operating reserve demand created by the variable nature of wind generation as well as the actual, variable wind generation profiles.

The system cost differences between these two simulations were divided by the total volume of wind generation in each penetration scenario to derive the wind integration costs associated with having to hold incremental operating reserve on a per unit of wind production basis.

3.3.3 Calculating System Balancing Wind Integration Costs

PacifiCorp conducted another series of PaR simulations to estimate daily system balancing wind integration costs consistent with the wind penetration scenarios studied. In this phase of the analysis, PacifiCorp generation assets were committed consistent with a day-ahead forecast of wind and load, but dispatched against actual wind and load. To simulate this operational behavior, two additional PaR simulations were necessary for each wind penetration scenario.

Simulation 3 was used to determine the unit commitment state of generation assets given the day-ahead forecast of wind generation and load. Simulation 4 used the unit commitment state from Simulation 3, but dispatches units based on actual wind generation and load. This actual wind and load data is pulled from the Initial Term , and thus, is identical to the actual wind generation and load inputs used to derive operating reserve wind integration costs as described above. In both of these PaR simulations, the amount of incremental reserve required for each penetration scenario was applied.

The change in system costs between Simulation 4 and the system costs from Simulation 2 already produced in the estimation of operating reserve integration costs isolates the wind integration cost due to system balancing. Dividing the change in system costs by the volume of wind generation in each penetration scenario produced a system balancing integration costs on a per-unit of wind production basis.

3.3.4 Allocation of Operating Reserve Demand in PaR

PaR Simulations 2 through 4 require operating reserve demand inputs that must be applied consistent with the ancillary services structure native to the model. The PaR model distinguishes reserve types by the priority order for unit commitment scheduling, and optimizes them to minimize cost in response to demand changes and the quantity of reserve required on an hour-to-hour basis. The highest-priority reserve types are regulation up and regulation down followed in order by spinning, non-spinning, and finally, 30-minute non-spinning.[10] Reserve requirements in the model need to be allocated into these PaR reserve categories and are expressed as a percentage of load.

The regulation up and regulation down reserves in PaR are a type of spinning reserve that must be met before traditional spinning and non-spinning reserve demands are satisfied. The incremental operating reserve demand needed to integrate wind generation was assigned in PaR as regulation up and regulation down. The traditional spinning and non-spinning reserve inputs are used for contingency reserve requirements, which remain unchanged among all PaR simulations in the Study. The 30-minute non-spinning reserve is not applicable to PacifiCorp's system, and thus it is not used in this Study.

Note that given the hourly granularity in PaR, there is no distinction between operating reserve categorized as regulation and load-following in terms of how the model optimizes their use. Thus both regulation reserve service demand and load following reserve service demand are combined as a geometric average and input in PaR as regulation up and regulation down. Further, owing to the hourly granularity of PaR and the fact that PaR optimizes dispatch for each distinct hour, regulation reserves are effectively released for economic dispatch from one hour to the next. The PaR model requires separate inputs for spinning operating reserve and non-spinning operating reserve. Table 7 summarizes how the services for operating reserves are applied in PaR.

Table 7. Allocation of operating reserve demand to regulation, spinning and non-spinning reserve categories in PaR.[11]

Reserve Service	PaR Regulation Up	PaR Regulation Down	PaR Spinning Reserves	PaR Non-Spin Reserves
$\text{RegulationUp}_{10Min}$	$\text{RegulationUp}_{10Min}$	0	0	0
$\text{RegulationDown}_{10Min}$	0	$\text{RegulationDown}_{10Min}$	0	0
Load Following Up	Load Following Up	0	0	0
Load Following Down	0	Load Following Down	0	0
Contingency	0	0	0.5*(5% of Hydro and Wind Generation output + 7% of Thermal generation output)	0.5*(5% of Hydro and Wind Generation output + 7% of Thermal generation output)
Total	Geometric Average of the above	Geometric Average of the above	Sum of the above	Sum of the above

[10] In PaR, spinning reserve is defined as unloaded generation which is synchronized, ready to serve additional demand and able to reach reserve amount within 10 minutes. Non-spinning Reserve is defined as unloaded generation which is non-synchronized and able to reach required generation amount within 10 minutes.

[11] Contingency Reserve is specified by the North American Energy Corporation in per http://www.nerc.com/files/BAL-STD-002-0.pdf .

3.3.5 Satisfying Reserve Service Demand in PaR

PacifiCorp's thermal and hydro units are able to meet the reserve demand entered in PaR as shown in Table 8. Regulation reserve is typically held by units operating in automatic generation control (AGC) mode.

Table 8. Reserve service capability of each generating unit in PaR.

Unit Name	Regulation Up	Regulation Down	Spin	Non-Spin
BEAR RIVER	No	No	No	Yes
CARBON 1	No	No	Yes	Yes
CARBON 2	No	No	Yes	Yes
CHEHALIS	Yes	Yes	Yes	Yes
CHOLLA 4	Yes	Yes	Yes	Yes
CLEARWATER 1 & 2	No	No	No	Yes
COLSTRIP 3 & 4	No	No	No	Yes
COPCO 1 & 2	No	No	Yes	Yes
CRAIG 1 & 2	No	No	No	Yes
CURRANT CREEK	Yes	Yes	Yes	Yes
DAVE JOHNSTON 1	No	No	Yes	Yes
DAVE JOHNSTON 2	No	No	Yes	Yes
DAVE JOHNSTON 3	No	No	Yes	Yes
DAVE JOHNSTON 4	Yes	Yes	Yes	Yes
FISH CREEK	No	No	No	Yes
GADSBY 1	No	No	Yes	Yes
GADSBY 2	No	No	Yes	Yes
GADSBY 3	Yes	Yes	Yes	Yes
GADSBY 4	Yes	Yes	Yes	Yes
GADSBY 5	Yes	Yes	Yes	Yes
GADSBY 6	Yes	Yes	Yes	Yes
HAYDEN 1 & 2	No	No	No	Yes
HERMISTON 1	Yes	Yes	Yes	Yes
HERMISTON 2	Yes	Yes	Yes	Yes
HUNTER 1	Yes	Yes	Yes	Yes
HUNTER 2	Yes	Yes	Yes	Yes
HUNTER 3	Yes	Yes	Yes	Yes
HUNTINGTON 1	Yes	Yes	Yes	Yes
HUNTINGTON 2	Yes	Yes	Yes	Yes
JC BOYLE	No	No	No	Yes
JIM BRIDGER 1	Yes	Yes	Yes	Yes
JIM BRIDGER 2	Yes	Yes	Yes	Yes
JIM BRIDGER 3	Yes	Yes	Yes	Yes
JIM BRIDGER 4	Yes	Yes	Yes	Yes
LAKE SIDE	Yes	Yes	Yes	Yes
LEMOLO	No	No	No	Yes
LITTLE MOUNTAIN	No	No	No	Yes
MERWIN	No	No	No	Yes
MID-COLUMBIA	Yes	Yes	Yes	Yes
NAUGHTON 1	No	No	Yes	Yes
NAUGHTON 2	Yes	Yes	Yes	Yes
NAUGHTON 3	Yes	Yes	Yes	Yes
SWIFT	Yes	Yes	Yes	Yes
TOKETEE-SLIDE	No	No	No	Yes
WYODAK	Yes	Yes	Yes	Yes
YALE	Yes	Yes	Yes	Yes

3.3.6 Modeling gas plant utilization in PaR

One of the objectives in calculating wind integration costs using PaR was to emulate observed real-time unit commitment and dispatch behavior of PacifiCorp's thermal plants during the simulation period. A specific focus was placed on east-side gas plants capable of providing regulation reserve service. The commitment status of these gas plants, consisting of Currant Creek, Lake Side, and Gadsby units 4 through 6, was initially set to "must run" in PaR to mirror recent utilization of these units. In the PaR framework, must run status means that the unit is committed, but not necessarily fully dispatched, at all times. PacifiCorp then compared the resulting simulated capacity factors for the simulation year 2013 against actual plant capacity factors for 2009 keeping in mind that 2009 wind generation and load data are used as inputs for the 2013 PaR simulation year. Differences in the capacity factors were reasonably small.

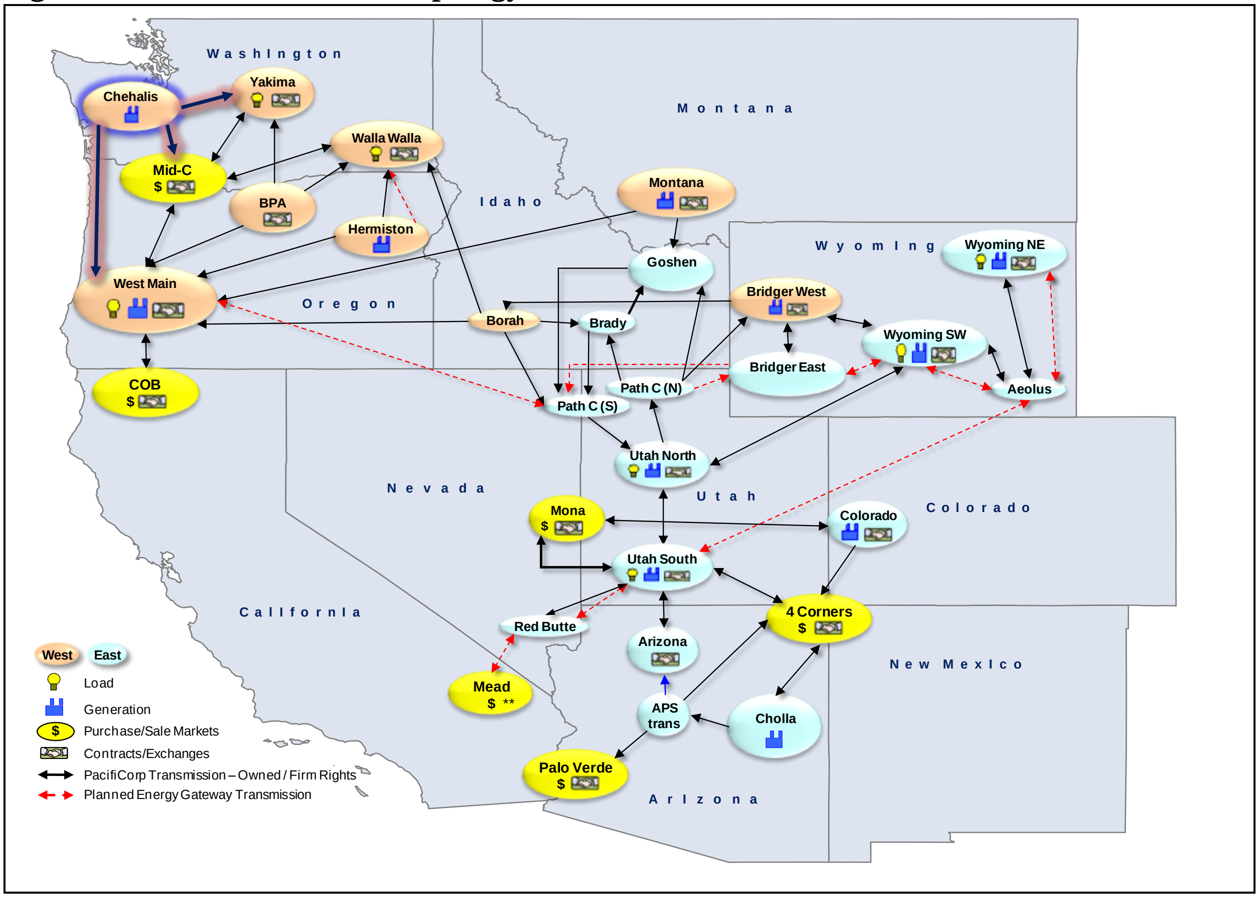
Given these findings, PacifiCorp concluded that PaR was reasonably aligned with actual operational characteristics of the east-side gas plants when setting Current Creek and Gadsby units 4 through 6 as must run. Consequently, this must run configuration was applied in PaR to circumvent the fact that PaR establishes unit commitment on price and not necessarily on operating reserve requirements. In this way, and consistent with recent operational practice, the Current Creek and Gadsby units 4 through 6 are available for meeting operating reserve obligations even when out-of-the-money from a pure market dispatch perspective.

The must run setting on Currant Creek and Gadsby units 4 through six was applied in PaR Simulations 2 through 4. In each of these simulations, incremental operating reserve demand needed to integrate wind is applied in the model, and must-run configuration ensures that the select set of east-side gas units will be available to meet the added reserve obligation even at times when they are out-of-the-money. In contrast, PaR Simulation 1 does not include any incremental operating reserve demand, and thus, the must-run setting was not used.

3.3.7 Transmission Topology in PaR

PacifiCorp used the PaR transmission topology consistent with the 2008 IRP Update as shown in Figure 13.

Figure 13. PaR transmission topology.



3.3.8 Carbon Dioxide Cost Assumptions in PaR

Given the 2011 to 2013 forward term used in the Study, there was no CO_2 cost applied to fossil-fired thermal generating resources. This assumption simplifies any comparison of the calculated wind integration cost among the three forward simulation years and avoids the possibility of disparity between plant dispatch costs and wholesale electricity market forward prices used over the term. This is in contrast to the 2008 IRP Update, in which PacifiCorp assumed that federal cap and trade carbon dioxide (CO_2) allowance prices go into effect in 2013, with prices starting at $8.58/ton in 2013 dollars and escalating at 1.8 percent per year thereafter.

4. Results

4.1 Operating Reserve Demand

Based upon historical and simulated wind generation data and historical load data, the Study shows that operating reserve demand for both regulation reserve service and load following reserve service increases with higher wind penetration levels. Table 9 summarizes how operating reserve demand for both regulation and load following services increases as wind penetration levels grow from approximately 425 MW to approximately 1,833 MW.

Table 9. Annual average operating reserve demand by penetration scenario.

		Load Only	425 MW	1372 MW	1833 MW
West	Regulation Up	97	105	137	137
	Regulation Down	72	84	120	120
	Load Following Up	101	114	139	141
	Load Following Down	106	113	132	133
East	Regulation Up	138	140	201	231
	Regulation Down	107	110	185	222
	Load Following Up	139	144	207	245
	Load Following Down	144	147	198	237

The increase in operating reserve necessary to support wind generation in grid operations is apparent in each of the penetration scenarios. For example, very little wind generation is added to the East Balancing Authority Area between the load-only and 425 MW scenarios, and understandably, there is little increase in the resultant incremental operating reserve demand. The same situation occurs between the 1,372 MW and 1,833 MW penetration scenarios on the West Balancing Authority Area, where again, there is little change to the calculated operating reserve demand. Additionally, as significant wind generation development impacts the East Balancing Authority Area between the 425 MW and 1,372 MW scenarios, and again between the 1,372 MW and 1,833 MW scenarios, there is clearly a proportionate growth of the operating reserve required to satisfy higher levels of wind penetration.

Tabular monthly results for each Balancing Authority Area and for each type of reserve service appear in Appendix C. For convenience, Figures 14 through 21 summarize monthly operating reserve demand results. In reviewing these figures, it is helpful to compare the growth of estimated reserve demand per MW of wind penetration recognizing that most of the wind capacity in the 425 MW penetration scenario is in the West Balancing Authority Area and that most of the incremental wind capacity in the 1,372 and 1,833 MW penetration scenarios is in the East Balancing Authority Area.

Figure 14. Load following up operating reserve service demand in the West Balancing Authority Area.

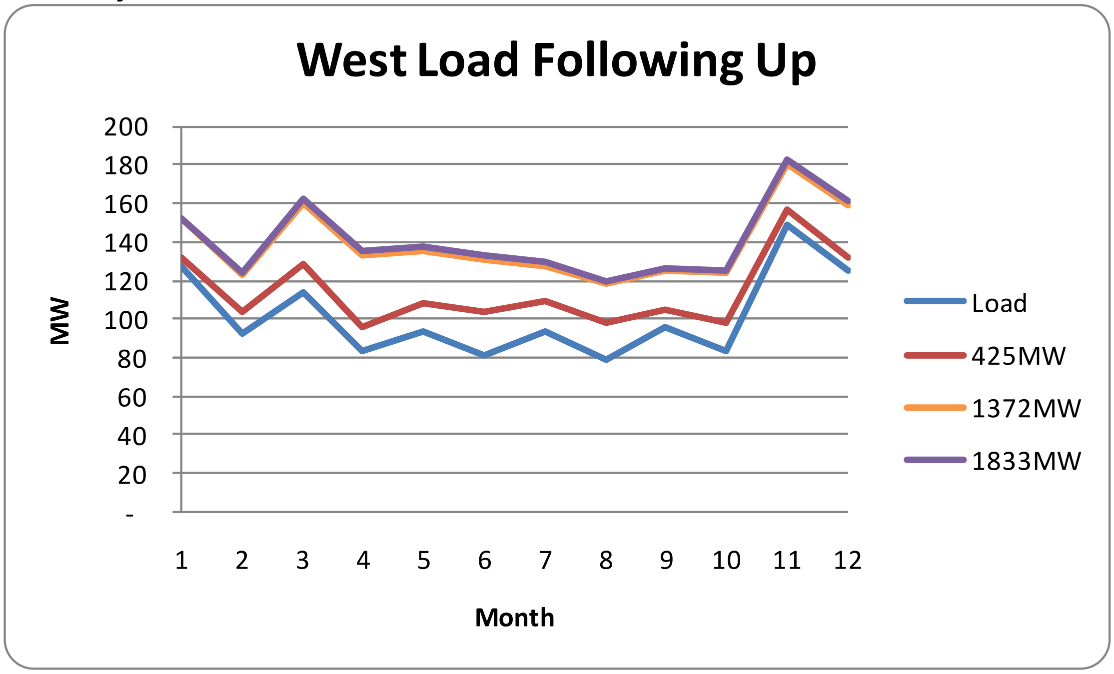


Figure 15. Load following down operating reserve service demand in the West Balancing Authority Area.

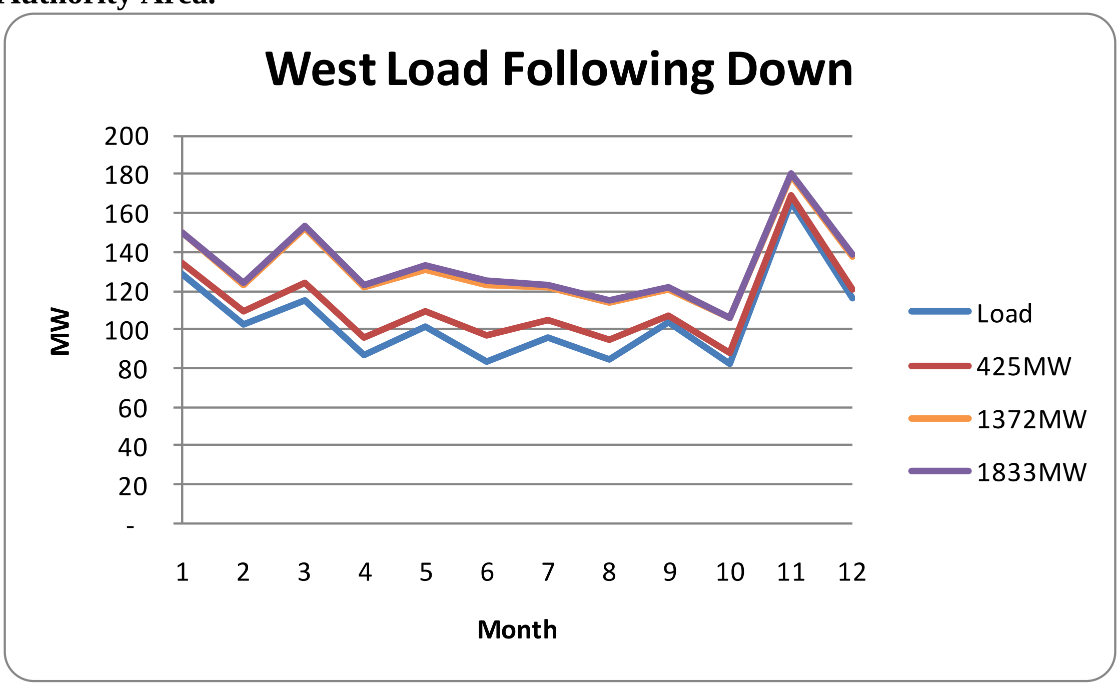


Figure 16. Regulation up operating reserve service demand in the West Balancing Authority Area.

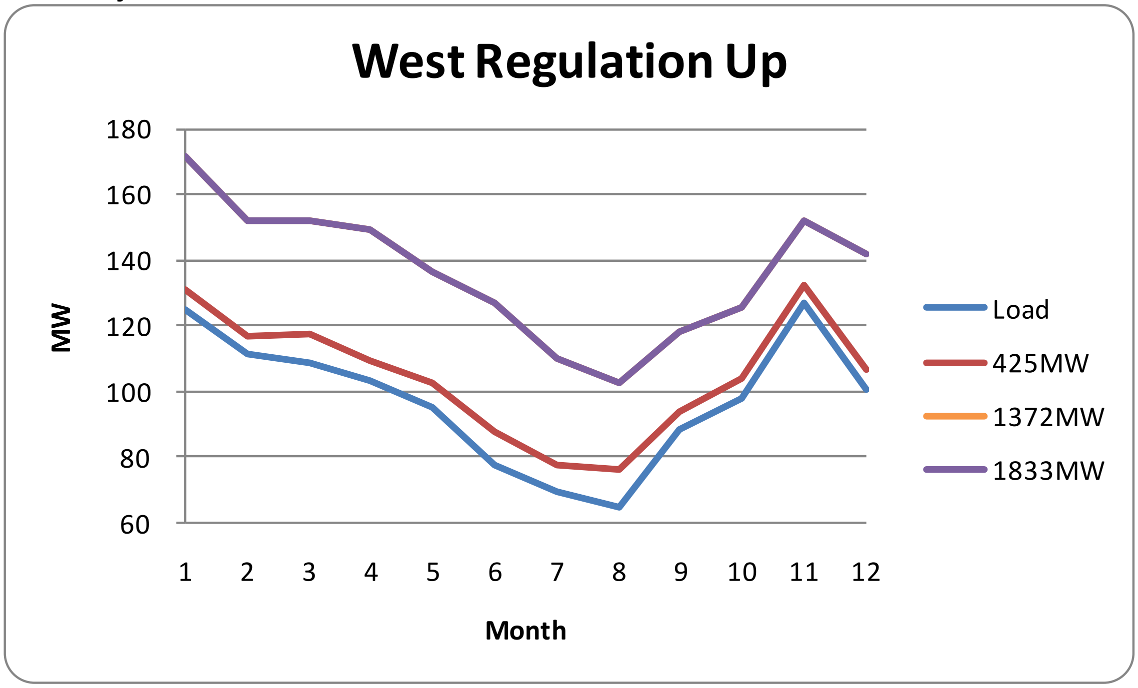


Figure 17. Regulation down operating reserve service demand in the West Balancing Authority Area.

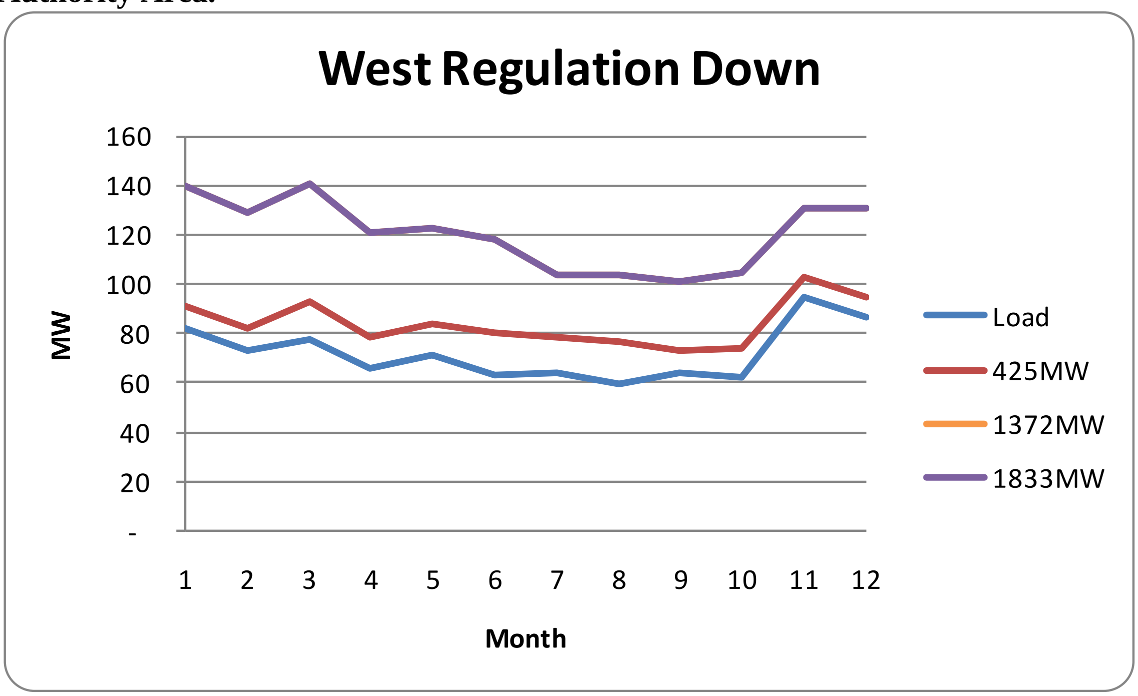


Figure 18. Load following up operating reserve service demand in the East Balancing Authority Area.

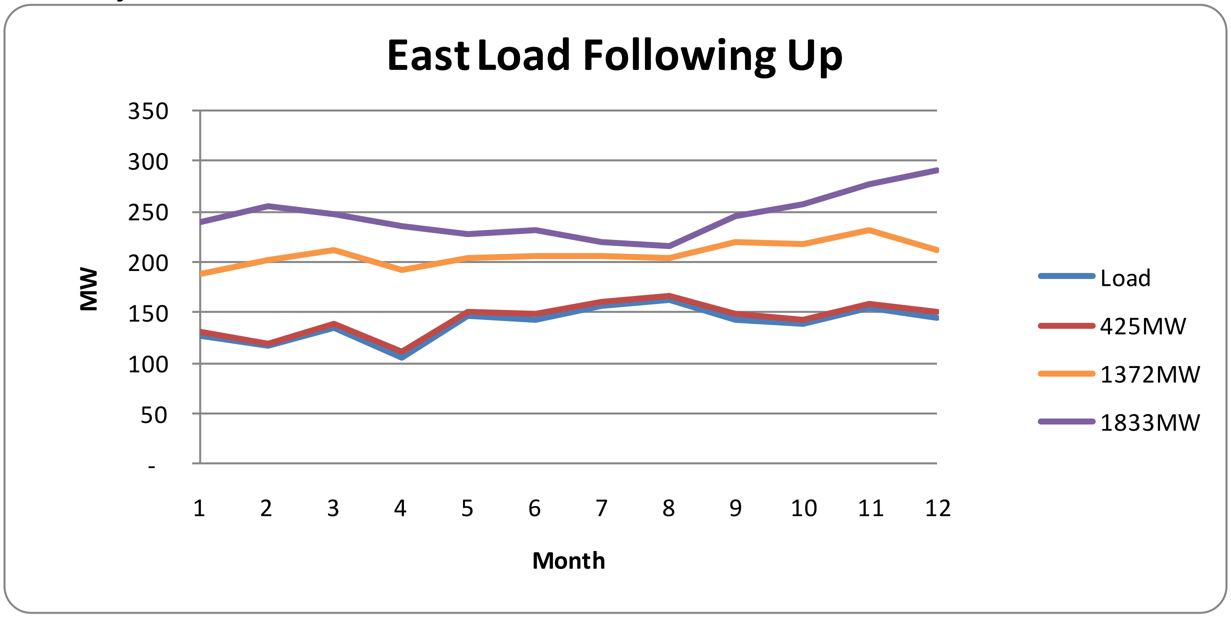


Figure 19. Load following down operating reserve service demand in the East Balancing Authority Area.

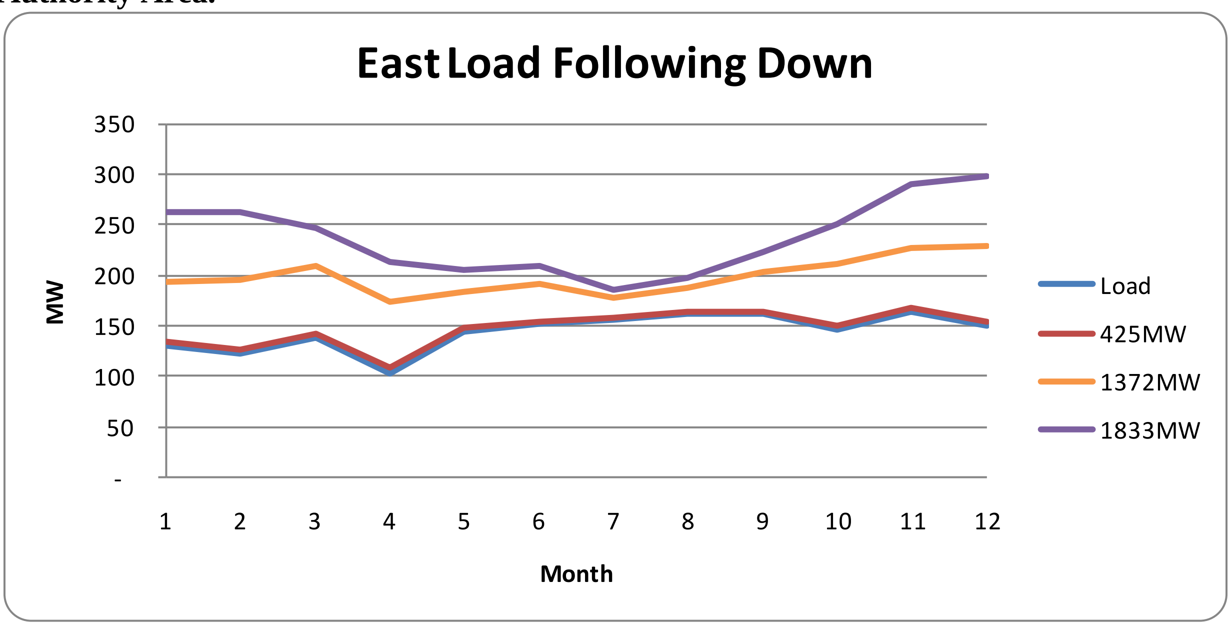


Figure 20. Regulation up operating reserve service demand in the East Balancing Authority Area.

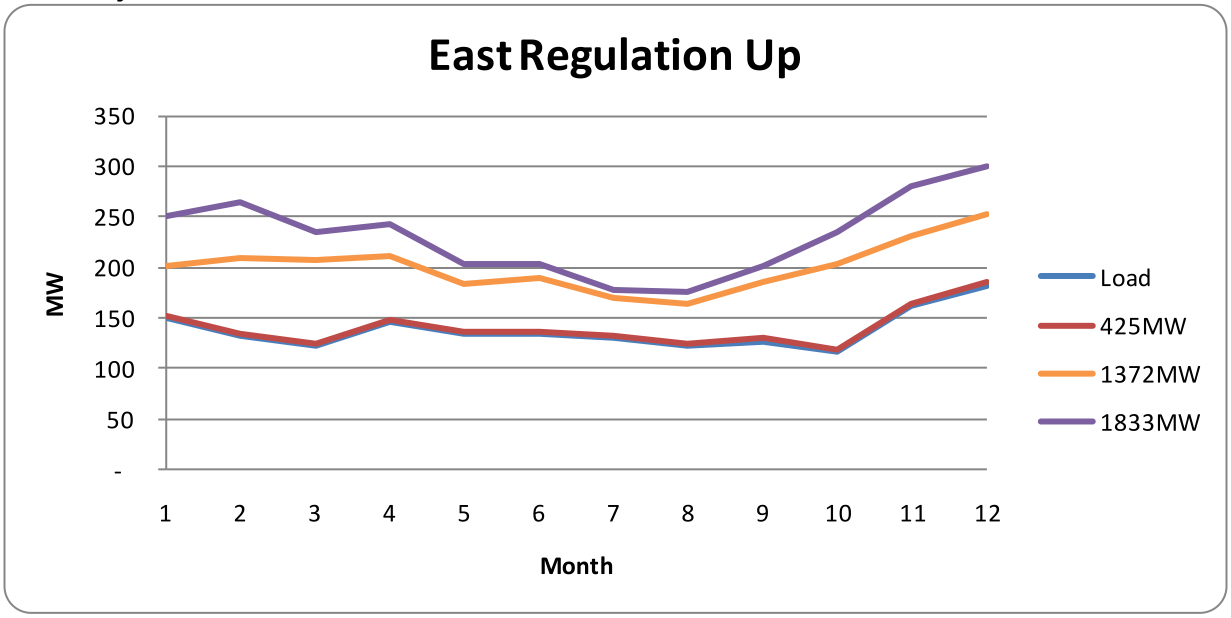
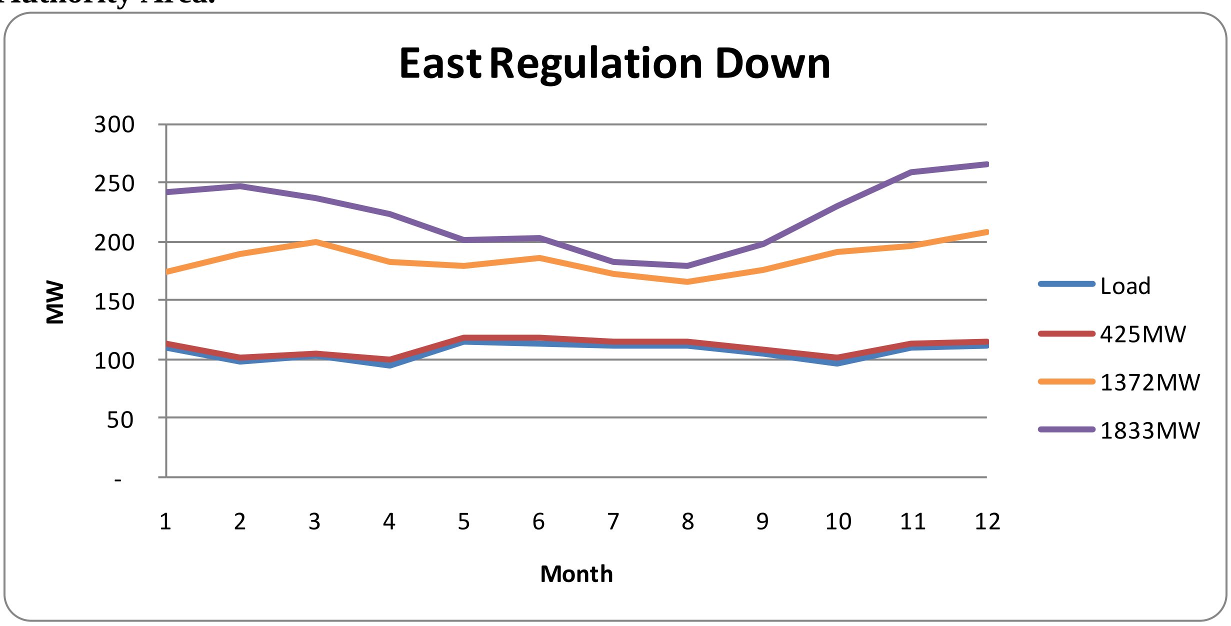


Figure 21. Regulation down operating reserve service demand in the East Balancing Authority Area.



Figures 14 through 21 identify both the seasonal nature of the operating reserve required to cover wind integration services and the tendency for the services' demand to be increased in months where more wind energy is generated. The monthly variation in operating reserve demand is built into the costing of the services in PaR, considering that the allocation of operating reserve for wind generation is less in the months where there is less need.

4.2 Wind Integration Costs

Tables 10 and 11 present the wind integration cost results for each wind penetration scenario. Costs are reported in both present value revenue requirement (PVRR) dollars and dollars per megawatt-hour of wind generation for each year in the study period. Levelized costs across the three year study term are also included.

Table 10. PaR simulation results for the load only scenario and the 425 MW wind penetration scenario.

		Load Only				425 MW			
Total variable costs		**2011**	**2012**	**2013**	**Levelized**	**2011**	**2012**	**2013**	**Levelized**
Base (No Wind, no must run)	thousands	$ 1,192,794.0	$ 1,311,178.0	$ 1,301,577.0		$ 1,192,794.0	$ 1,311,178.0	$ 1,301,577.0	
Simulation 1 (flat wind, no must run gas plants)		$ 1,192,794.0	$ 1,311,178.0	$ 1,301,577.0		$ 1,141,308.0	$ 1,251,695.0	$ 1,249,391.0	
Simulation 2 (must run gas plants)		N/A	N/A	N/A		$ 1,150,552.0	$ 1,261,783.0	$ 1,259,733.0	
Simulation 3 (must run gas plants)		$ 1,188,903.0	$ 1,300,920.0	$ 1,286,758.0		$ 1,145,876.0	$ 1,251,190.0	$ 1,241,733.0	
Simulation 4 (must run gas plants)		$ 1,201,530.0	$ 1,322,377.0	$ 1,313,055.0		$ 1,152,348.0	$ 1,264,907.0	$ 1,264,277.0	
Calculation of Integration Costs									
Operating Reserve (Sim 2 less Sim 1)	thousands	$ -	$ -	$ -	$ -	$ 9,244.0	$ 10,088.0	$ 10,342.0	$25,830.1
System Balancing (Sim 4 less Sim 2)		$ -	$ -	$ -	$ -	$ 1,796.0	$ 3,124.0	$ 4,544.0	$ 8,094.2
Total	thousands	$ -	$ -	$ -	$ -	$ 11,040.0	$ 13,212.0	$ 14,886.0	$33,924.3
Wind Generation (Actual)									
East Wind	GWh	-	-	-	$ -	534.2	602.6	519.8	$ 1,446.5
West Wind		-	-	-	$ -	754.0	793.8	665.3	$ 1,936.6
Total	GWh	-	-	-	$ -	1,288.2	1,396.4	1,185.1	$ 3,383.1
Operating Reserve	**$/MWh**	**$ -**	**$ -**	**$ -**	$ -	**$ 7.18**	**$ 7.22**	**$ 8.73**	$ 7.64
System Balancing		**$ -**	**$ -**	**$ -**	$ -	**$ 1.39**	**$ 2.24**	**$ 3.83**	$ 2.39
Total Wind Integration	**$/MWh**	**$ -**	**$ -**	**$ -**	$ -	**$ 8.57**	**$ 9.46**	**$ 12.56**	$ 10.03

Table 11. PaR simulation results for the 1,372 MW and 1,833 MW wind penetration scenarios.

		1372 MW				1833 MW			
Total variable costs		**2011**	**2012**	**2013**	**Levelized**	**2011**	**2012**	**2013**	**Levelized**
Base (No Wind, no must run)	thousands	$ 1,192,794.0	$ 1,311,178.0	$ 1,301,577.0		$ 1,192,794.0	$ 1,311,178.0	$ 1,301,577.0	
Simulation 1 (flat wind, no must run gas plants)		$ 1,046,895.0	$ 1,141,572.0	$ 1,148,139.0		$ 1,014,831.0	$ 1,103,397.0	$ 1,112,343.0	
Simulation 2 (must run gas plants)		$ 1,075,215.0	$ 1,172,782.0	$ 1,180,728.0		$ 1,053,713.0	$ 1,145,954.0	$ 1,156,774.0	
Simulation 3 (must run gas plants)		$ 1,080,733.0	$ 1,179,114.0	$ 1,176,686.0		$ 1,068,866.0	$ 1,163,768.0	$ 1,163,482.0	
Simulation 4 (must run gas plants)		$ 1,077,117.0	$ 1,175,126.0	$ 1,186,073.0		$ 1,057,087.0	$ 1,149,484.0	$ 1,162,164.0	
Calculation of Integration Costs									
Operating Reserve (Sim 2 less Sim 1)	thousands	$ 28,320.0	$ 31,210.0	$ 32,589.0	$80,134.7	$ 38,882.0	$ 42,557.0	$ 44,431.0	$109,512.1
System Balancing (Sim 4 less Sim 2)		$ 1,902.0	$ 2,344.0	$ 5,345.0	$ 8,165.0	$ 3,374.0	$ 3,530.0	$ 5,390.0	$ 10,609.1
Total	thousands	$ 30,222.0	$ 33,554.0	$ 37,934.0	$88,299.7	$ 42,256.0	$ 46,087.0	$ 49,821.0	$120,121.1
Wind Generation (Actual)									
East Wind	GWh	2,319.0	2,519.8	2,231.7	$ 6,175.3	3,229.5	3,483.4	3,106.0	$ 8,575.9
West Wind		1,462.3	1,556.4	1,332.1	$ 3,804.5	1,462.3	1,556.4	1,332.1	$ 3,804.5
Total	GWh	3,781.3	4,076.2	3,563.8	$ 9,979.9	4,691.8	5,039.8	4,438.1	$ 12,380.5
Operating Reserve	**$/MWh**	**$ 7.49**	**$ 7.66**	**$ 9.14**	$ 8.03	**$ 8.29**	**$ 8.44**	**$ 10.01**	$ 8.85
System Balancing		**$ 0.50**	**$ 0.58**	**$ 1.50**	$ 0.82	**$ 0.72**	**$ 0.70**	**$ 1.21**	$ 0.86
Total Wind Integration	**$/MWh**	**$ 7.99**	**$ 8.23**	**$ 10.64**	$ 8.85	**$ 9.01**	**$ 9.14**	**$ 11.23**	$ 9.70

The PaR model results demonstrate interesting trends in the component costs. Most notable is the reduction of system balancing costs for the 1,372 MW and 1,833 MW wind capacity penetration scenarios when compared to the 425 MW wind capacity penetration scenario. This is due to the domination of load forecast error in the 425 MW scenario system balancing integration cost line item, where total system costs are divided by wind energy production to derive system costs on a per unit of wind generation basis. The system balancing costs stabilize as wind generation increases in the higher penetration scenarios. Additionally, the operating reserve integration costs increase with additional wind capacity penetration. The rate of increase in costs is outpacing the increased wind energy produced, resulting in a higher price per megawatt-hour of wind energy produced. Finally, it is noteworthy that the addition of wind generation capacity lowers overall system costs.

Table 12 compares the results of the Study to integration costs developed for the 2008 IRP on a component by component basis. The primary differences in results are most apparent for inter-hour (2008 IRP)/system balancing (2010 Study) wind integration costs. This difference is explained by improvements in method. In the 2008 IRP, market transaction costs were used to estimate inter-hour integration costs, whereas the current Study calculates system balancing integration costs derived from the operation of PacifiCorp resources.

Table 12. Wind integration cost comparison to the 2008 IRP.

Study	2008 IRP	2010 Wind Integration Study	2010 Wind Integration Study
Wind Capacity Penetration	2734 MW	1372 MW	1833 MW
Tenor of Cost	20-Year Levelized	3-Year Levelized	3-Year Levelized
Expected to Day Ahead ($/MWh)	$0.28	-	-
Day Ahead to Hour Ahead ($/MWh)	$2.17	-	-
System Balancing ($/MWh)	-	$0.82	$0.86
Subtotal Interhour / System Balancing	$2.45	$0.82	$0.86
Intra Hour Reserves[1] ($/MWh)	$7.51		
2010 Study Operating Reserves ($/MWh)		$8.03	$8.85
Total Wind Integration	**$9.96**	**$8.85**	**$9.70**
Assumptions			
Forward Price Curve	Oct 2008, $8CO2	Mar 2010, No CO2	Mar 2010, No CO2

1 - IRP resources were available to meet Operating Reserve demand before the in-service year, which lowers wind integration cost

4.3 Application of Wind Integration Costs in the 2011 Integrated Resource Plan

The start of portfolio development for PacifiCorp's 2011 IRP is scheduled for September 2010. Portfolio development relies on the Company's capacity expansion optimization model, called *System Optimizer*. (Note that wind integration impacts are treated as an increased resource cost in the System Optimizer model.) The high-end wind capacity penetration scenario will not be completed until after portfolio development is well underway. Until costs are assessed for the high-end wind capacity penetration scenario, PacifiCorp will use the costs developed for the 1,833 MW penetrations scenario, totaling $9.70/MWh of wind generated power.

Appendix A
Simulation of Wind Generation Data

A.1 Detailed Discussion of Statistical Patterns of the Historical Wind Output Data

From the available ten-minute interval historical wind generation data over the 2007 to 2009 Initial Term, there are four key observations. First, wind output has a seasonal pattern. Taking one plant as an example, Figure 1A shows capacity factor data for Leaning Juniper in 2009. The red markers in the figure indicate the median of the distribution, and the wide bar delineates the 25^{th} to 75^{th} percentiles of the distribution. Figure 1A shows the median, as well as the range of observed capacity factors in each month in 2009 for Leaning Juniper varies significantly. Second, the monthly standard deviations for capacity factor output are very different across sites in most months. Figure 2A compares the output patterns across June, July, and August of 2009 for Leaning Juniper and Combine Hills and shows that non-normality is evident in the data. Again, the red markers indicate the median of the distribution, and the wide bar represents the 25^{th} to 75^{th} percentiles in the distribution. Third, the commonly-accepted notion that wind output follows a pronounced diurnal pattern is only partially supported by the various historical profiles in the dataset, as apparent in Figure 3A. In general, such recurring patterns are more easily found in average aggregate representations of the data on hourly level, rather than by examining higher resolution ten-minute data.

Figure 1A. Leaning Juniper 2009 monthly capacity factors.

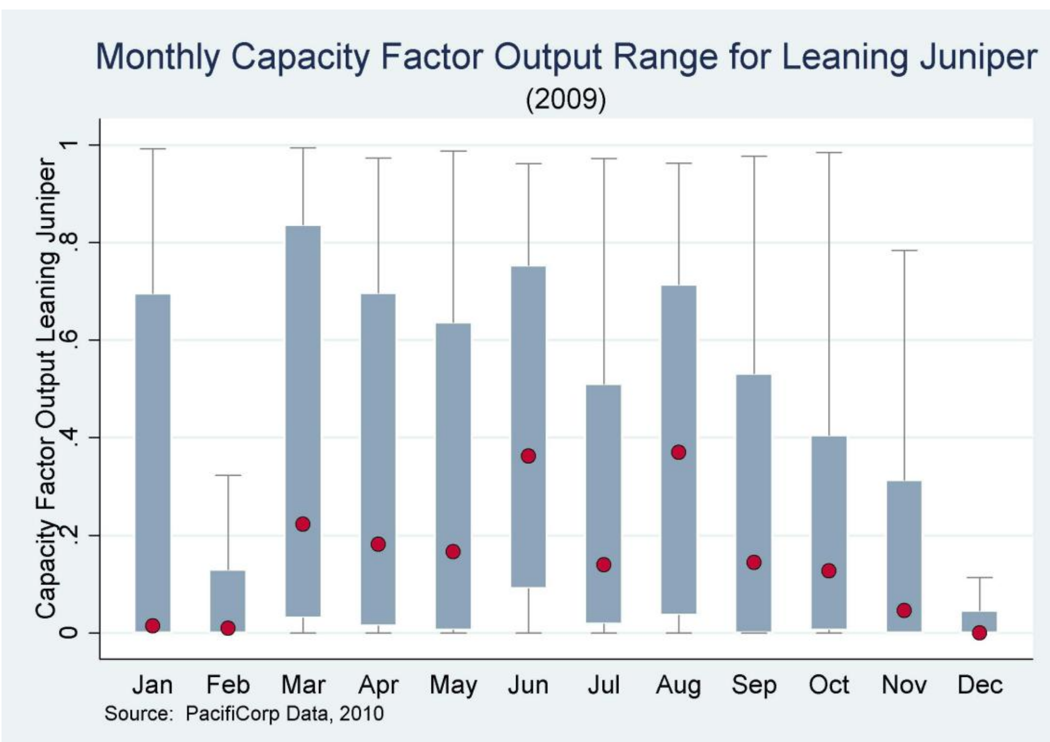


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Figure 2A. Comparison of Leaning Juniper and Combine Hills capacity factors.

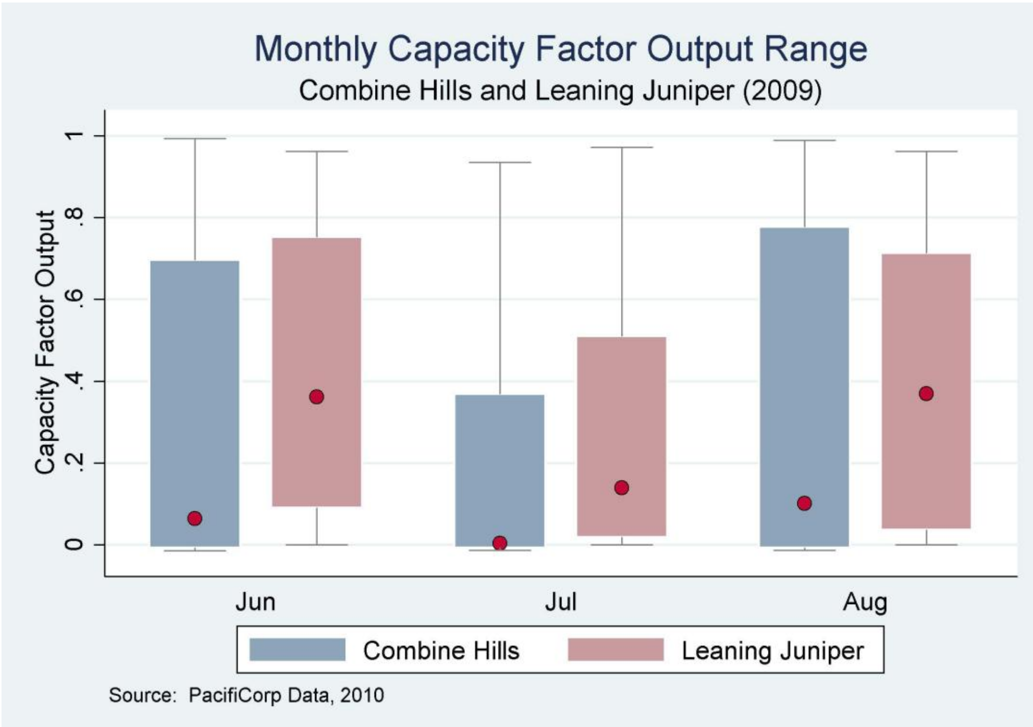
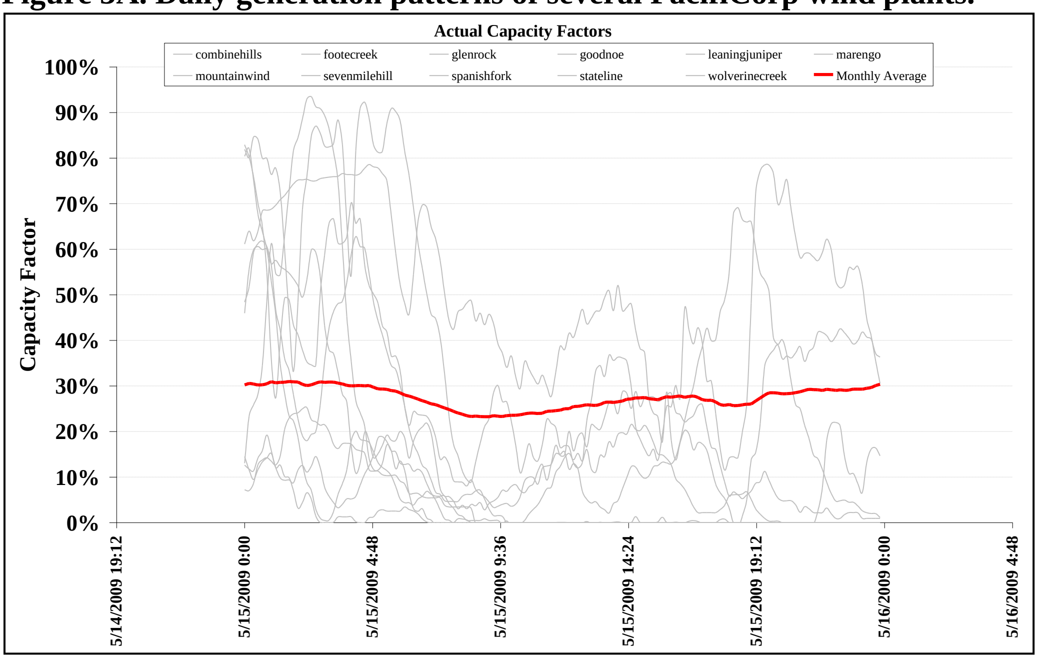


Figure 3A. Daily generation patterns of several PacifiCorp wind plants.



Finally, Figures 4A and 5A present the empirical distribution of the 2009 capacity factor output of Leaning Juniper and Combine Hills, respectively. Both plants' hourly capacity factor data represent two key patterns to the study. One, that there are a very substantial number of zero generation hours for each station. Two, the output varies greatly through the potential capacity range of each generating station, implying the wind generation will have the characteristic to vary from one time period to the next. This is different behavior than would be implied by a strong bimodal diurnal pattern, which would imply very regular on/off behavior with and without wind.

Figure 4A. Distribution of observed 2009 hourly capacity factors at Leaning Juniper.

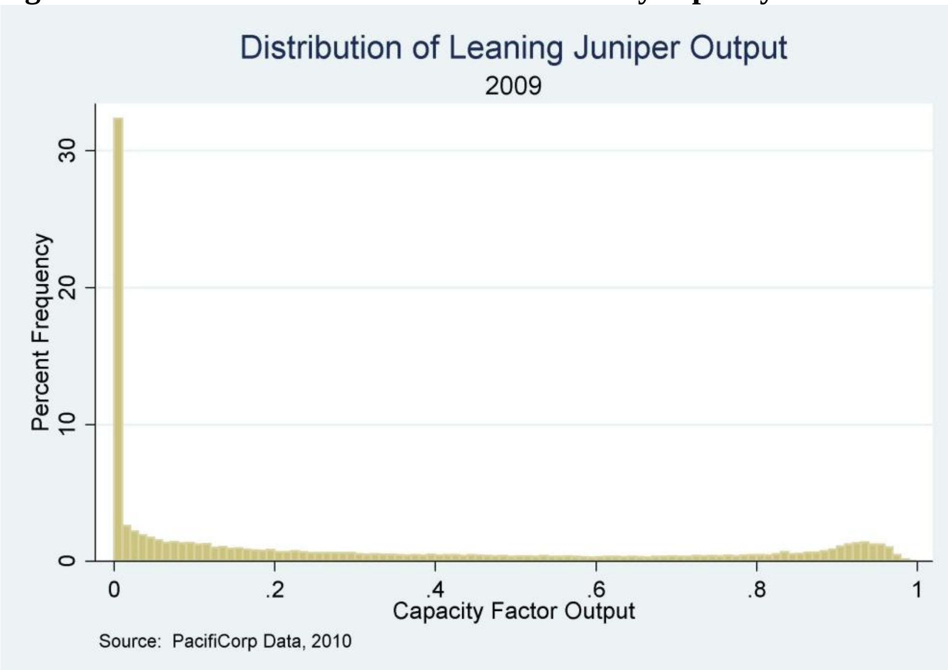


Figure 5A. Distribution of observed 2009 hourly capacity factors at Combine Hills.

A.2 Time Pattern of the Historical Wind Data

The time-series properties of the wind generation data are also important to the Study. Initial data analysis revealed that the wind generation profiles in the dataset were consistently characterized by a slowly decaying auto correlation process, while their partial autocorrelations are significant up to 6 period lags. In other words, the wind data in a ten-minute period is heavily consistent with the previous 10-minute interval and, therefore, over time, the wind pattern could be described as influenced by its behavior in the previous time periods. Partial correlation measures the autocorrelation at a specific lagged time frame, while controlling for the effect of preceding lags. Partial autocorrelation is useful in determining the number of lagged terms to include as explanatory variables in a regression model. Figures 6A through 9A show the full and partial auto correlation factors for the Leaning Juniper and Combine Hills wind plants. Figures 6A and 7A show that the predictive power fades regularly over time lag. Figures 8A and 9A show that the oscillating nature of wind generation is more apparent in the negative predictive power of the 2nd and 4th lags.

Figure 6A. Autocorrelation coefficients for successive ten minute lags in capacity factor for Leaning Juniper.

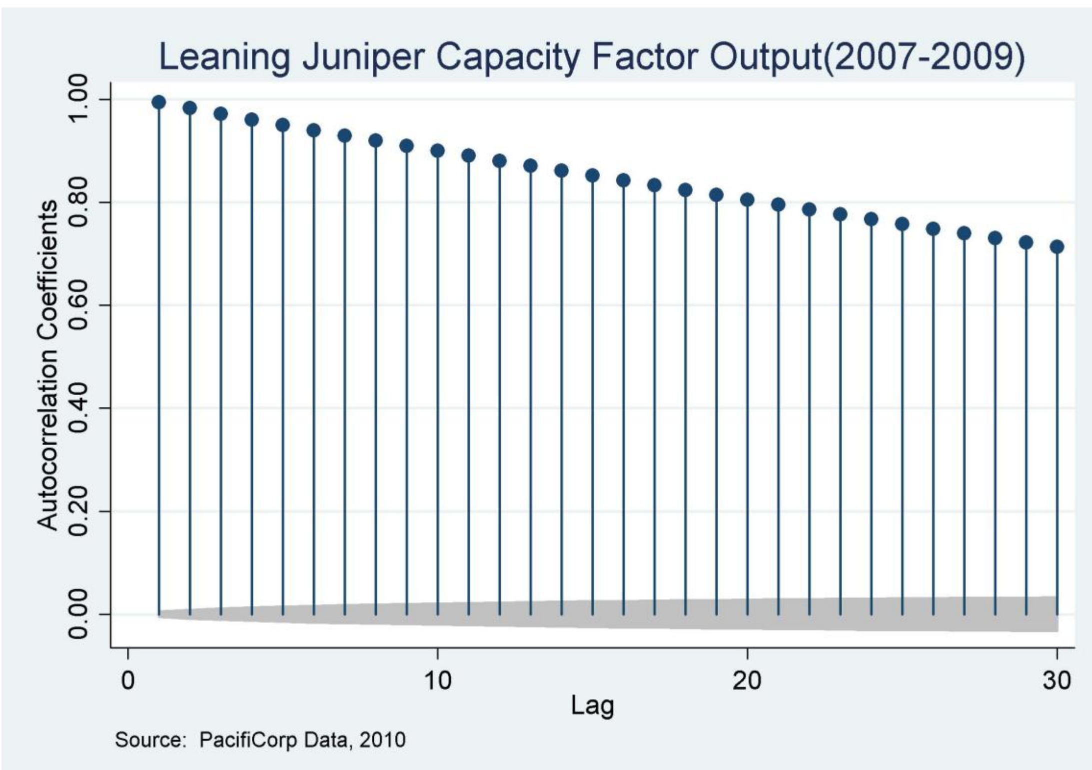


Figure 7A. Autocorrelation coefficients for successive ten minute lags in capacity factor for Combine Hills.

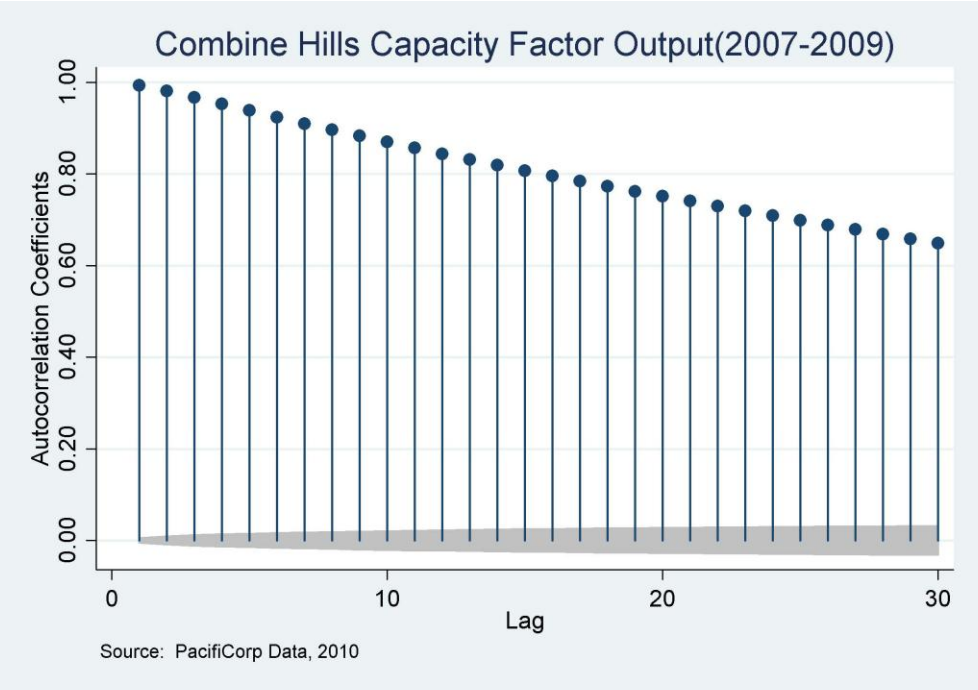


Figure 8A. Partial autocorrelation coefficients for lags in capacity factor for Leaning Juniper.

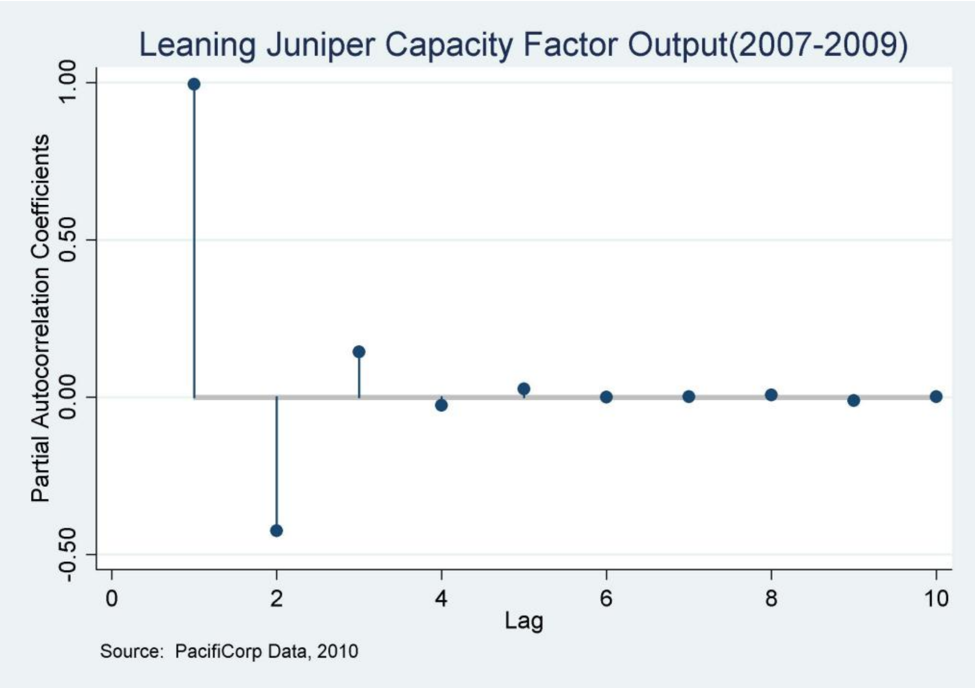
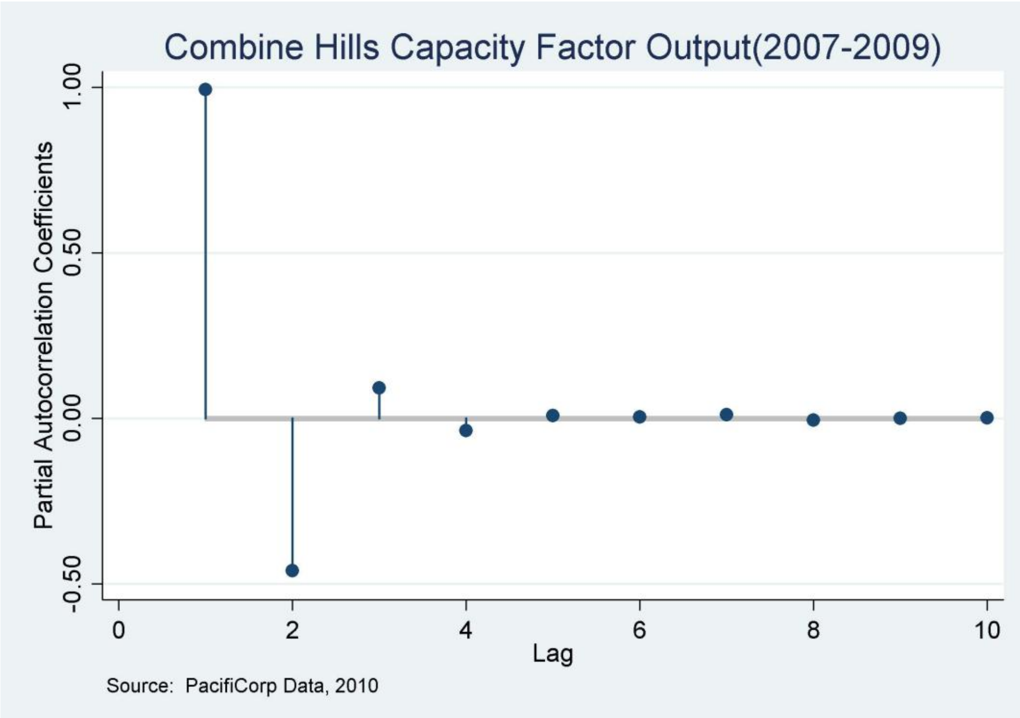


Figure 9A. Partial autocorrelation coefficients for lags in capacity factor for Combine Hills.



A.3 Data Clean-up and Verification

The source wind generation data were characterized by a number of issues that needed data clean-up, verification and, in some cases, adjustments. The first observed issue is that for certain records over various periods of time, the historical wind output data were zero. Those observations covered varying lengths of time and, in some instances, up to a few months. However, we noticed that the zero-value data blocks consistently occurred only at the beginning of a wind project's chronological energy output data and therefore it is suspected that those were probably periods when the plant had not yet been fully commissioned. Thus, those observations are treated as "missing" and excluded them from the historical data set.

Next, through our source data review, we identified that the output of certain plants seemed to have much smaller capacity factors and increased over time. This trend seemed to have extended beyond the natural volatility of wind generation for those wind sites and showed up as a gradual increase over time and reaching a maximum after a number of months. This observation seemed to suggest that the historical data were capturing the build-out of a wind site before it has reached its commercial operation date. As the maximum available capability through wind plant construction on a daily basis was not documented, the decision was made to exclude wind output data for dates prior to the known commercial operation date for each wind site. As a result, the data set used for simulations was limited to include only date ranges that conform to the known commercial operation dates shown in Table 1A.

Table 1A. Summary of wind plant start dates and nameplate capacity.

Plant name	Applied Commercial Operation Date	Nominal Capacity (MW)	Observed Max Output (MW)
Dunlap I	11/1/2010	111	Data Unavailable
Goodnoe Hills	5/31/2008	94	95
Glenrock	1/17/2009	237	232
Glenrock III			
Rolling Hills			
High Plains	9/13/2009	99	148
McFadden Ridge I	10/10/2009	29	29
Leaning Juniper	9/14/2006	101	103
Marengo I	6/26/2008	211	206
Marengo II			
Seven Mile Hill I	12/31/2008	119	123
Seven Mile Hill II			
Combine Hills	6/17/2003	41	41
Wolverine Creek	4/29/2005	65	65
Mountain Wind I	9/29/2008	141	137
Mountain Wind II			
Three Buttes	12/1/2009	99	Data Unavailable
Top of the World	12/31/2010	202	Data Unavailable
Spanish Fork	7/31/2008	19	22
Foote Creek I	4/1/1999	95	137
Foote Creek II			
Foote Creek III			
Foote Creek IV			
Rock River			

The sites that were affected by these revisions were:

- Goodnoe Hills (observations were set to missing for November 2007 through May 2008),
- Marengo (observations were set to missing for February 2007 through May 2008),
- Spanish Fork (observations were set to missing for April 2008 through Jul 2008),
- Mountain Wind (observations were set to missing for April 2008 through September 2008),
- Seven Mile Hill (observation were set to missing for November 2008 through December 2008),
- McFadden Ridge (observations were set to missing for June 2009 through September 2009),
- High Plains (observations were set to missing for February 2009 through August 2009),
- Glenrock (observations were set to missing for November 2008 through December 2008).

- That leaves five wind sites that were not affected by this adjustment —Leaning Juniper, Combine Hills, Stateline, Wolverine Creek, and Foote Creek.

The second clean-up process involved understanding the aggregation of data and the interpretation of the plant size. The data provided to the technical advisor contained single wind output data stream for sites that share the same principal name but are distinguished as individual projects—those include Marengo and Marengo II, Mountain Wind and Mountain Wind II, Seven Mile Hill and Seven Mile Hill II, Glenrock and Glenrock III. The wind output data, which were collected on-site, did not distinguish between separate sharing the same name.

The third clean-up involved the fact that the maximum output levels observed in the wind output data sometimes exceed the capacity officially available to PacifiCorp. The Study team decided to use the maximum output found in each wind profile data stream to be the *de facto* wind site megawatt capacity. We used this capacity level and converted each 10-minute output into a capacity factor value ranging from 0 to 1.[12]

A.4 Wind Data Simulation Methodology

A.4.1 General Description

The overall methodology centered on using available data to estimate the missing data. To do so, the statistical relationships between pairs of sites were studied and those relationships were used to derive or estimate the wind output for periods that historical data are incomplete or missing. For example, if there was a *fully available* set of historical data for site A, but *partially missing* for site B, the overlapping periods during which historical data are available for both sites A and B were used to estimate the statistical relationship using that data. Then the technical advisor employed that statistical relationship and used the available data from site A for the period when site B has missing data to estimate wind data for that period. If site B has *completely missing* data, the technical advisor applied NREL's simulated data (from 2004-2007) to establish the statistical relationship between sites A and B and then applied that estimated relationship to the historical data of site A and again, estimated site B's wind output accordingly.

A.4.2 Wind Generation Estimation Model Specification

In general, the modeling approach is based on the use of contemporaneously available ten-minute wind capacity factor data from *fully available* wind profiles to simulate capacity factor data for profiles with *partially* or *completely missing* wind output. As prior figures demonstrated, ten-minute wind output exhibited a generally volatile profile with several notable features. First, output from previous periods is highly indicative of the current level of output, with the partial autocorrelations significant up to as many as six lags. Second, the diurnal patterns were harder to discern on a consistent basis. Given these characteristics and our preliminary analysis, we

[12] The capacity factor represents the output at a given point in time as a fraction of the maximum possible output for the wind project. For example, a capacity factor of 0.23 indicates that current output is 23% of the total capacity of the wind site.

chose to include six lagged terms in addition to the concurrent wind output term in the model used to estimate the statistical relationship between pairs of sites. We have found that such specification allows us to capture the time-based behavior and time-dependence of the wind data used in the Study. This approach also captures some of the spatial relationship between the two sites—as wind moves from one site to the other, its impact on the other site is delayed in time. The equation below describes the general structure of the model[13]:

$$Site_t^A = \alpha_0 Site_t^B + \alpha_1 Site_{t-1}^B + \alpha_2 Site_{t-2}^B + \alpha_3 Site_{t-3}^B + \alpha_4 Site_{t-4}^B + \alpha_5 Site_{t-5}^B + \alpha_6 Site_{t-6}^B + \varepsilon$$

A.4.3 Wind Generation Estimation Model for Constrained Output

An important challenge in specifying this model is the nature of the capacity factor variables. Capacity factor is used instead of absolute wind output levels to translate between small and large wind plants. By such a construction, the wind output measured in capacity factor terms can only take values between 0 and 1 (or, equivalently 0% and 100%). Attempting to predict a limited dependent variable using a standard linear ordinary least squares (OLS) approach resulted in estimated values for the dependent variable (or sites with *partially missing* and *completely missing* historical data) that are outside the possible value range.

For example, for given mean values of the explanatory variables, the linear OLS model might result in a predicted mean dependent variable value greater than a capacity factor of 100%. This is due to the fact that a linear OLS model does not limit the outcome range for the dependent variable. In the literature, a model whose dependent variable is limited at either one or both upper and lower ends of its range is called a "censored" model.[14] A standard approach for estimating a censored model is to use the *Tobit* regression model. The *Tobit* model was originally developed by James Tobin (1958)[15] and employs an estimation technique, which recognizes the limited ("censored") range of possible values that the *observed* dependent variable can take.[16] As a result, predicted mean values for the dependent variable will behave as expected and not exceed the natural capacity limits of 0 and 1, as specified in our case.

The *Tobit* model uses a maximum likelihood process, which takes into account the probability of obtaining an observation that lies inside the censoring interval. In other words, *Tobit* typically is used to estimate the likelihood of a value to be equal to some expected quantity. The model assumes that the true value of the dependent variable (y*) is explained by a number of independent variables, where the regression error term (epsilon) is normally distributed with a zero mean. In addition, if y* is between 0 and 1 we observe y*, however, if y*<0 we observe 0 and, similarly, if y*>1, we observe 1. The maximum likelihood estimation uses the probability

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[13] We specify a regression model that has no constant term.

[14] Greene, William H., "Econometric Analysis", 5th Ed., Prentice Hall 2003, p. 764.

[15] Gujarati, Damodar N., "Basic Econometrics", McGraw Hill 2003, p. 616; Kennedy, Peter "A Guide to Econometrics," 5th Ed., MIT Press 2003, pp. 289-290.

[16] Ibid.

of each individual observation being censored to estimate the regression coefficients.[17] In other words, the regression coefficients are determined to ensure that their value maximizes the likelihood of obtaining the observed values of y*.[18]

In contrast to linear OLS regression, the *Tobit* regression model does not report an R-squared metric, which typically indicates the explanatory power of the regression model specification (with high R-squared value indicating stronger explanatory power). In other words, in the linear OLS regression, the adjusted R-squared measures the proportion of variance of the dependent variable that has been explained by the independent (right-hand-side) variables. There are a range of so-called "Pseudo R-Squared" metrics that have been proposed in the literature for use with maximum likelihood models, such as the *Tobit* model. However, their interpretation is not equivalent to the R-Squared in OLS. This is because estimates derived using a *Tobit* model are calculated via an iterative process designed to maximize the likelihood of obtaining the observations of the dependent variable, rather than to minimize variance.[19]

The technical advisor used the statistical software package STATA© to perform the regressions using the Tobit model. The model specification uses the chosen explanatory variables and generates a censored prediction of y* where the relevant upper and lower censoring limits are taken into account.[20] An example of the six-lag model the technical advisor settled upon for significance is below:

$$Goodnoe_t^A = \alpha_0 LeaningJuniper_t^B + \alpha_1 LeaningJuniper_{t-1}^B + \alpha_2 LeaningJuniper_{t-2}^B + \\ + \alpha_3 LeaningJuniper_{t-3}^B + \alpha_4 LeaningJuniper_{t-4}^B + \alpha_5 LeaningJuniper_{t-5}^B + \alpha_6 LeaningJuniper_{t-6}^B + \varepsilon$$

A.4.4 Using NREL's Wind Data to Facilitate Wind Simulation for Sites without Historical Information

To simulate wind data of sites with no historical information, the technical advisor used the NREL wind data to estimate the statistical relationship between pairs of sites and then used the estimated relationship to simulate the necessary wind data. For sites with *completely missing* historical wind data, NREL sites are chosen to serve as a proxy wind profiles.

NREL's *Western Wind Dataset* was created by *3TIER* for use in NREL's *Western Wind and Solar Integration Study*. The dataset was synthesized using numerical weather prediction (NWP)

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[17] For example, see "STATA Base Reference Manual Release 11", Stata Corp. pp. 1939-1948; Maddala, G. S., "Limited-Dependent and Qualitative Variables in Econometrics.", Cambridge University Press 1986, pp.159-162.

[18] For more detailed description of the Tobit model, please see Maddala, G. S., "Limited-Dependent and Qualitative Variables in Econometrics", Cambridge University Press 1986, pp.159-162.

[19] For more information, please see: Long, J. Scott. "Regression Models for Categorical and Limited Dependent Variables" Thousand Oaks: Sage Publications, 1997; Freese, Jeremy and J. Scott Long. "Regression Models for Categorical Dependent Variables Using Stata", College Station: Stata Press, 2006.

[20] For more information, please see: Baum, Christopher F., "An Introduction to Modern Econometrics Using Stata", College Station: Stata Press, 2006, p. 264.

models "to recreate the historical weather for the western U.S. for 2004, 2005, and 2006. The modeled data were temporally sampled every 10 minutes and spatially sampled every arc-minute (approximately 2 kilometers)."[21] We refer to this wind data set as the "NREL data".

The first step in using the NREL *Western Wind Dataset* is to identify NREL-modeled sites that are the closest in geographical terms to the relevant PacifiCorp wind sites. These are called the "NREL proxies" for each corresponding PacifiCorp wind site. The technical advisor then estimated the statistical relationship between the pairs of NREL proxies (that correspond to PacifiCorp wind sites) and used the statistical relationship to carry out the rest of the simulation described above. PacifiCorp staff provided the technical advisor with the geographical coordinates (latitude and longitude) for the PacifiCorp wind sites as summarized in Table 2A. In addition, the NREL data contains comprehensive information on the geographical coordinates of all modeled sites.[22] The technical advisor then determined the closest NREL proxy for each of plant.[23]

Table 2A. NREL Proxies selected for pertinent PacifiCorp plants.

PacifiCorp Plant Name	Closest NREL Site ID	Distance (km)
High Plains	16676	0.5
McFadden	16676	0.5
Rock River	31422	0.4
Rolling Hills	23909	2.9
Dunlap	19280	0.8
Three Buttes	23870	5.3
Top of the World	23803	4.8

Table 2A shows each PacifiCorp-NREL pair and the calculated distance between them. We should note that High Plains and McFadden Ridge share the same geographical location and, as a result, are paired with the same NREL-modeled site. As a result, High Plains and McFadden Ridge have identical simulated profiles. (This is a function of the study's approach of simulating wind generation output based on geographical location rather than wind project name—for

[21] http://www.nrel.gov/wind/integrationdatasets/western/methodology.html#methodology [accessed July 1, 2010]

[22] The main web portal for the NREL Western Wind Dataset can be accessed at http://wind.nrel.gov/Web_nrel

[23] Geographical coordinates for two points on the earth's surface can be converted to a straight-line distance using a range of alternative algorithms, which take into consideration the shape of the earth and use trigonometric formulas to project and measure surface distances. For the purposes of this study, the Spherical Law of Cosines was used to calculate the distance between each relevant PacifiCorp wind site and every site in the Western Wind Dataset. Fore more information, please see: Weisstein, Eric W. "Spherical Trigonometry." From MathWorld -- A Wolfram Web Resource. http://mathworld.wolfram.com/SphericalTrigonometry.html [accessed July 1, 2010]

Distance (km) = ArcCos(Sin(Latitude Pacificorp) * Sin(Latitude NREL) + Cos(Latitude Pacificorp) * Cos(Latitude NREL) * Cos(Longitude NREL - Longitude Pacificorp)) * 6371 km example, the same simulated profile is also used to represent the Mountain Wind/Mountain Wind II pair of wind sites.)

After determining the set of NREL sites to be used in the simulation analysis, NREL data were formatted, compiled by site, and labeled using their PacifiCorp counterpart's name. Similar to the earlier approach in formatting the PacifiCorp data, NREL wind output data were converted into capacity factor terms (using a 30 MW capacity value for each site as specified in the NREL description of the dataset).[24]

A.4.5 Pairing of Wind Profiles Used for Regression

Recognizing the monthly seasonality of wind data, each modeled pair required twelve separate regression models per year, one for each month.[25] To ensure the use of observed historical wind data is meaningful, we require that a full year of overlap between a *fully available* wind profile and a *partially missing* wind profile. This means that if the *partially missing* wind profile only had 11 months of historical data, it was treated as a *completely missing* dataset and used the NREL data to help simulate the data from the period without historical data. To simplify the rest of this explanation, the *fully available* wind profile was a *predictor* and a site with *partially missing or completely missing* wind profile was a *predicted* site (because the process effectively used the available profile to "predict" the missing profile).

The Study focused on two methods in estimating monthly regressions. First, for sites with *partially missing* historical wind data that have at least 12 months of historical data, the data from a *fully available* site was employed as the *predictor* (such as Foote Creek, Combine Hills, or Leaning Juniper) to estimate monthly coefficients. From the coefficients derived in the regression estimation, the Study estimated the wind data for all the missing months. Second, for sites with *partially missing* data (and with less than 12 months historical data available) and sites with *completely missing* data, the NREL *closest neighbor* set of wind profiles was employed. The process estimated monthly regression models between the closest NREL site to the *predictor* and the closest NREL site to the *predicted*. Then the coefficients estimated in those regressions were applied to the PacifiCorp *fully available predictor* data to simulate 10-minute output data for the *predicted.* This second approach implicitly assumed that the monthly relationships between the *predictor* and the *predicted* derived from the 2004-2006 period (using available NREL data) were applicable to the Initial Term as represented by the PacifiCorp data. Below in Figure 10A, a flow chart depicts the steps described above. Table 3A depicts the pairs of wind sites with left column containing the *predictor* and the right column containing the *predicted.*

[24] http://www.nrel.gov/wind/integrationdatasets/about.html [accessed July 1, 2010]

[25] For example, if overlapping data for the *predictor* and the *predicted* are available for all of 2008 and 2009, we estimate a regression for January using data for that month from both 2008 and 2009. Then, the estimated coefficients from the regression will be used to predict the output for January of 2007 using the *predictor* 2007 data for that month.

Figure 10A. Wind generation data development flow chart.

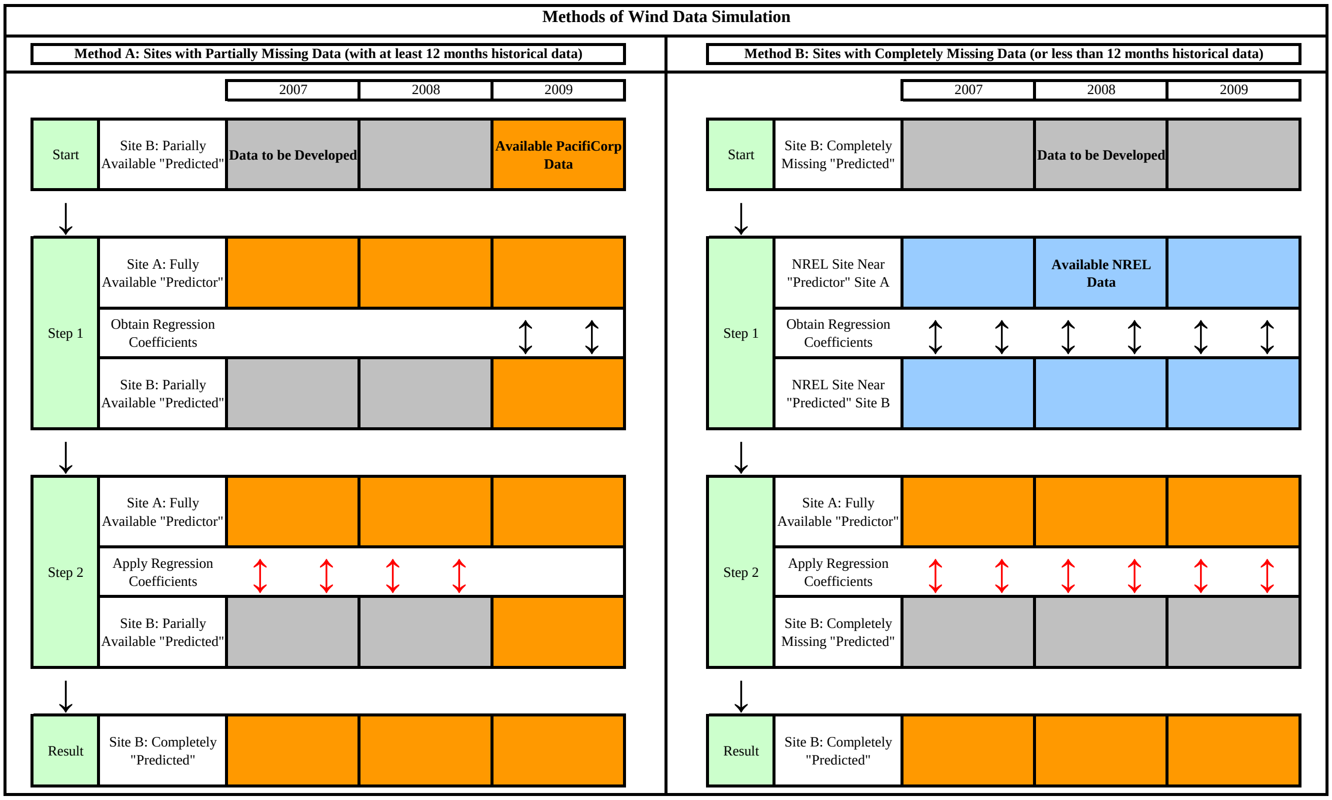


Table 3A. Pairs of wind projects used in data simulation.

Predicted	Predictor	Data Used
High Plains	Foote Creek	NREL/PacifiCorp
McFadden	Foote Creek	NREL/PacifiCorp
Rock River	Foote Creek	NREL/PacifiCorp
Rolling Hills	Foote Creek	NREL/PacifiCorp
Dunlap	Foote Creek	NREL/PacifiCorp
Three Buttes	Foote Creek	NREL/PacifiCorp
Top of the World	Foote Creek	NREL/PacifiCorp
Goodnoe	Leaning Juniper	PacifiCorp
Marengo	Combine Hills	PacifiCorp
Mountain Wind	Foote Creek	PacifiCorp
Seven Mile Hill	Foote Creek	PacifiCorp
Spanish Fork	Foote Creek	PacifiCorp
Glenrock	Foote Creek	PacifiCorp

A.4.6 Regression Analysis

The estimation process of the *Tobit* regressions was identical across all sites—the six-lag model is applied to a *predictor-predicted* pair. After estimation, the resulting coefficients were used to generate data for the *predicted* profile for all missing time periods using the values of the *predictor* in those time periods.[26] A sample of resulting regression coefficients for one month for one pair of wind sites is shown in Table 4A below.

Table 4A. Predictive capacity factor coefficients for the simulation of Goodnoe Hills wind generation using Leaning Juniper actual generation data.

Explanatory Variables	Estimated Coefficients
Capacity Factor Leaning Juniper	0.841***
	(0.0744)
Capacity Factor Leaning Juniper [t-1]	-0.321**
	(0.130)
Capacity Factor Leaning Juniper [t-2]	0.0314
	(0.135)
Capacity Factor Leaning Juniper [t-3]	0.0631
	(0.135)
Capacity Factor Leaning Juniper [t-4]	0.0597
	(0.135)
Capacity Factor Leaning Juniper [t-5]	0.00342
	(0.130)
Capacity Factor Leaning Juniper [t-6]	0.267***
	(0.0744)
Observations	4,464

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

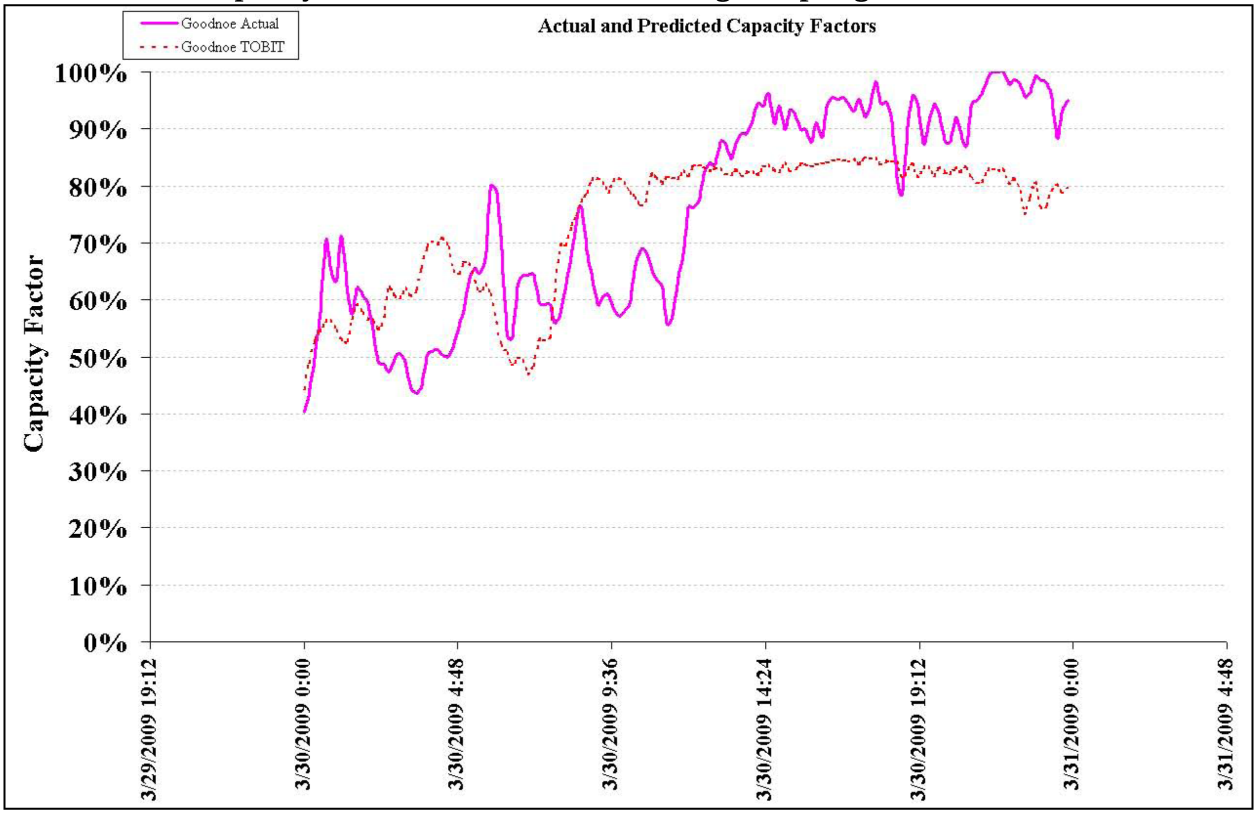
A.4.7 Estimate Mean Values of the Predicted

In general, using the estimated regression coefficients to derive a prediction for the dependent variable is done by using the mean values of the explanatory variables to arrive at the predicted mean value of the dependent variable. In this case, however, we are interested in generating predicted values of the dependent variable (*predicted)* for all individually observed values of the independent variable (*predictor*). As a result, applying the estimated regression coefficients to each individual observation of the explanatory variables will result in predicted values of the *predicted* that are significantly less variable than the true unobserved *predicted* series. This is due to the fact that the regression model assumes that the regression error is zero on average

[26] Again, all estimation procedures and simulations were conducted using the commercially-available statistical software package STATA© (http://www.stata.com)

across the observations, but not in every individual instance. An illustrative comparison of the predicted mean value to the historical actual of the same period is shown in Figure 11A.

Figure 11A. Comparison of actual Goodnoe Hills capacity factors with predicted mean Goodnoe Hills capacity factors derived off of Leaning Juniper generation data.



A.4.8 Calculating the Regression Residuals

To address the loss of variability by simply using the regression coefficients in the estimation, the technical advisor subtracted the predicted values of the dependent variable from their corresponding observed values over the overlapping subset of *predicted/predictor* data used for the regression estimation.[27] This produced a set of regression residuals, which represent the amount by which predicted values for the known (historical) part of the data set were different from the actual observed values of the *predicted.*

Then, each regression residual value was categorized according to the level of predicted output it was originally associated with. The predicted values are then grouped in bins of 10 percentage points to create 10 bins that cover the range of 0% to 100% capacity factor output. For example, all residuals that were associated with a predicted output between 10% and 20% are grouped together. As Figures 12A and 13A show, the distributions of those residuals vary across bins.

[27] In the case of the PacifiCorp sourced data, this is done over the monthly regression data. For the Hybrid approach where NREL data was required, this is done with the NREL data.

Figure 12A. Highly non-normal residuals from bin 5 of the March regression of Goodnoe Hills capacity factor derived from observed Leaning Juniper data.

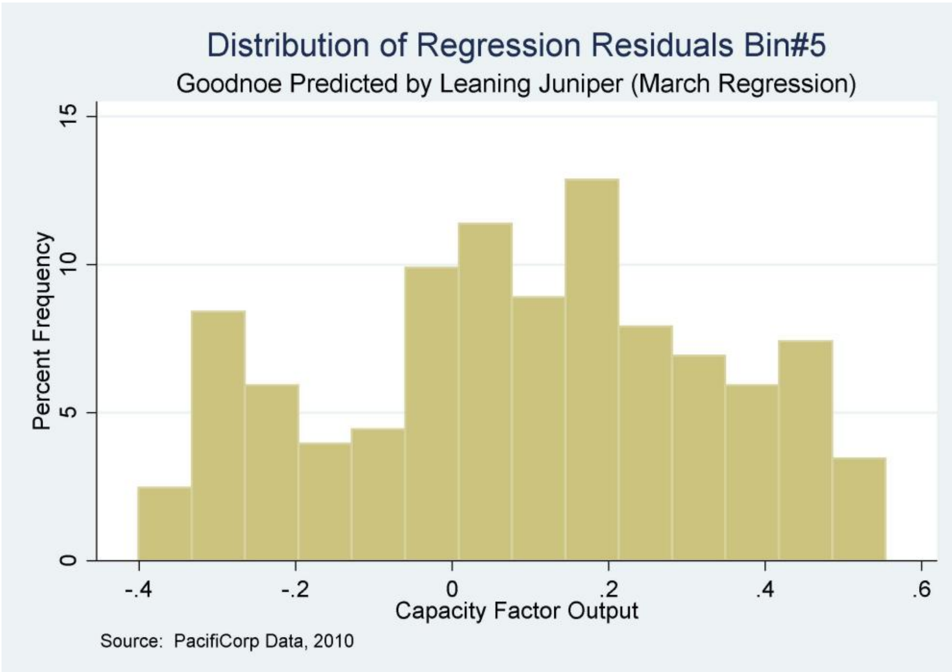
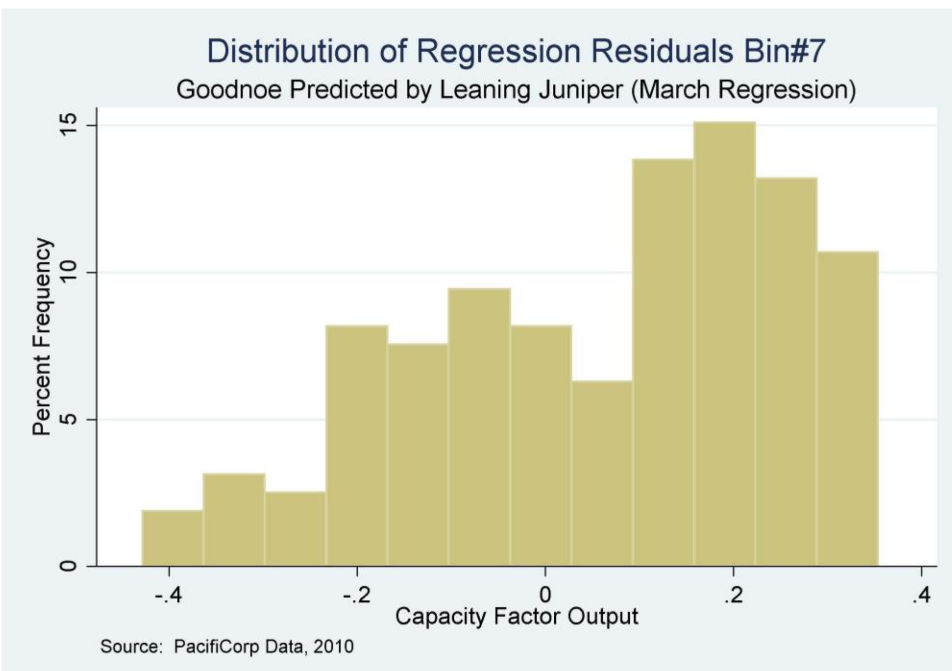


Figure 13A. Highly non-normal residuals from bin 7 of the March regression of Goodnoe Hills capacity factor derived from observed Leaning Juniper data.



A.4.9 Sample of Residuals According to Simulated Output Ranges

The next step involved randomly drawing residuals from the previously defined bins and "adding them back" to the simulated mean 10-minute wind output. The procedure of making random draws from an empirical distribution of residuals is called "bootstrapping" residuals.[28] In the context of this study, the technical advisor applied the bootstrapping procedure by randomly drawing[29] a residual from a corresponding bin and adding it to the predicted mean capacity factor value. For example, if a predicted capacity factor value for a missing data point falls within the 10% to 20% interval, a residual value will be randomly drawn from the bin that contains the residuals of the corresponding capacity factor of the historical data when compared with the simulated (or predicted) mean values.

A.4.10 Application of a Non-Linear 3-Step Median Smoother to the Sampled Residuals

After generating a time-series of bootstrapped residuals, the additional step of applying a non-linear smoother to the series, called the "span-3 median smoother" was taken. The span-3 median smoother is a process by which the median of the current, previous, and next period value — in this case, it is calculated by taking the median of residual(t-1), residual(t), residual(t+1)[30] — and using that median as the residual for the current period. The purpose of this approach is two-fold. Firstly, the median smoother ensures that the time-series of residuals resembles the time behavior of wind more closely, with lags affecting the instantaneous results. Secondly, the span-3 median smoother introduces a time-dependency to the data set, which is known to exist in the original wind data.[31]

The technical advisor then added the smoothed time-series of the randomly drawn residuals to the predicted mean capacity factor values for each ten-minute point; then checking the resulting data to make sure the estimates remained within the 0 – 100% capacity factor range.

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[28] This name alludes to the fact that, absent prior knowledge of the distribution, the researcher has to pull herself by the bootstraps by drawing randomly from the empirically-derived residual data in order to generate residuals.

[29] Random draws are done with replacement as implemented by the STATA© *bsample* procedure.

[30] For example, see "STATA Base Reference Manual Release 11", Stata Corp. p. 1758; Mosteller, F. and Tukey, John W., "Data Analysis and Regression: A Second Course in Statistics", Addison-Wesley: 1977., pp. 52-58.

[31] Although the non-linear smoothing approach does not exactly replicate the auto-regressive behavior of the wind data, it introduces some similar dependency.

Appendix B

Regression Coefficients and Relative Significance

Regression Results by Month for Glenrock Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.347***	0.242	0.460**	0.278	0.0338	0.554***	0.105	0.576***	0.527***	0.597***	0.669***	0.594***
	(0.125)	*(0.160)*	*(0.184)*	*(0.193)*	*(0.181)*	*(0.140)*	*(0.124)*	*(0.104)*	*(0.140)*	*(0.160)*	*(0.160)*	*(0.168)*
Capacity Factor Foote Creek [t-1]	-0.161	-0.131	-0.186	-0.0782	-0.0667	-0.301	0.0168	-0.181	-0.157	-0.246	-0.310	-0.272
	(0.229)	*(0.288)*	*(0.309)*	*(0.334)*	*(0.298)*	*(0.259)*	*(0.209)*	*(0.174)*	*(0.234)*	*(0.283)*	*(0.283)*	*(0.298)*
Capacity Factor Foote Creek [t-2]	0.0830	0.0687	0.0658	0.0437	-0.0228	0.173	0.0738	0.0989	0.0445	0.154	0.126	0.0644
	(0.249)	*(0.304)*	*(0.322)*	*(0.349)*	*(0.306)*	*(0.283)*	*(0.218)*	*(0.182)*	*(0.241)*	*(0.301)*	*(0.299)*	*(0.313)*
Capacity Factor Foote Creek [t-3]	-0.000558	-0.0146	-0.0358	-0.0237	0.0461	0.00166	0.0998	0.0265	-0.0223	0.0128	-0.0828	-0.0207
	(0.252)	*(0.305)*	*(0.323)*	*(0.350)*	*(0.306)*	*(0.285)*	*(0.218)*	*(0.182)*	*(0.242)*	*(0.303)*	*(0.300)*	*(0.313)*
Capacity Factor Foote Creek [t-4]	0.00538	0.0916	0.0701	0.0163	0.0896	0.176	0.0423	0.0703	0.131	0.100	0.144	0.0531
	(0.249)	*(0.304)*	*(0.322)*	*(0.349)*	*(0.307)*	*(0.282)*	*(0.217)*	*(0.182)*	*(0.242)*	*(0.301)*	*(0.299)*	*(0.313)*
Capacity Factor Foote Creek [t-5]	-0.0399	-0.272	-0.0229	-0.0347	-0.121	-0.212	-0.132	-0.0851	-0.149	-0.275	-0.447	-0.280
	(0.229)	*(0.288)*	*(0.309)*	*(0.334)*	*(0.300)*	*(0.258)*	*(0.208)*	*(0.175)*	*(0.234)*	*(0.283)*	*(0.282)*	*(0.298)*
Capacity Factor Foote Creek [t-6]	0.126	0.561***	0.184	0.166	0.387**	0.405***	0.532***	0.245**	0.526***	0.538***	0.976***	0.710***
	(0.126)	*(0.160)*	*(0.184)*	*(0.193)*	*(0.182)*	*(0.140)*	*(0.123)*	*(0.104)*	*(0.140)*	*(0.160)*	*(0.160)*	*(0.169)*
Number of Observations	2,160	4,032	4,464	4,320	4,464	4,320	4,464	4,464	4,320	4,464	4,320	4,464

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Spanish Fork Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.360**	0.215	0.330	0.503**	0.200	0.0481	-0.0363	-0.183	0.259	0.379**	0.147	0.0538
	(0.175)	*(0.232)*	*(0.217)*	*(0.239)*	*(0.242)*	*(0.220)*	*(0.263)*	*(0.179)*	*(0.196)*	*(0.178)*	*(0.184)*	*(0.167)*
Capacity Factor Foote Creek [t-1]	-0.244	-0.184	-0.187	-0.181	-0.0632	-0.0647	-0.0745	0.0931	-0.0370	-0.103	-0.0451	-0.0854
	(0.328)	*(0.415)*	*(0.366)*	*(0.411)*	*(0.400)*	*(0.406)*	*(0.444)*	*(0.300)*	*(0.333)*	*(0.310)*	*(0.328)*	*(0.300)*
Capacity Factor Foote Creek [t-2]	0.0304	0.0212	0.119	0.0537	0.0487	0.0509	0.0109	0.00608	-0.0965	-0.0136	-0.00668	0.0305
	(0.357)	*(0.439)*	*(0.381)*	*(0.428)*	*(0.411)*	*(0.443)*	*(0.462)*	*(0.313)*	*(0.348)*	*(0.325)*	*(0.348)*	*(0.317)*
Capacity Factor Foote Creek [t-3]	0.0500	0.0332	-0.108	-0.0955	-0.0370	-0.0220	-0.115	-0.0282	0.0344	0.0905	-0.0276	-0.0956
	(0.361)	*(0.441)*	*(0.383)*	*(0.431)*	*(0.408)*	*(0.445)*	*(0.459)*	*(0.314)*	*(0.349)*	*(0.326)*	*(0.350)*	*(0.318)*
Capacity Factor Foote Creek [t-4]	-0.0474	0.0102	-0.00785	0.182	-0.0519	0.0244	0.113	-0.00375	-0.0545	-0.0824	0.0572	0.102
	(0.358)	*(0.440)*	*(0.382)*	*(0.430)*	*(0.407)*	*(0.440)*	*(0.458)*	*(0.312)*	*(0.348)*	*(0.325)*	*(0.349)*	*(0.317)*
Capacity Factor Foote Creek [t-5]	0.0972	-0.0666	0.00720	-0.323	0.0195	-0.111	0.00394	-0.0554	-0.115	0.0815	-0.215	-0.321
	(0.328)	*(0.416)*	*(0.367)*	*(0.412)*	*(0.404)*	*(0.402)*	*(0.440)*	*(0.298)*	*(0.333)*	*(0.310)*	*(0.329)*	*(0.300)*
Capacity Factor Foote Creek [t-6]	-0.128	0.199	-0.0310	0.0558	-0.152	0.0713	-0.00857	0.0280	0.218	-0.154	0.302	0.672***
	(0.175)	*(0.232)*	*(0.217)*	*(0.238)*	*(0.247)*	*(0.219)*	*(0.263)*	*(0.178)*	*(0.196)*	*(0.179)*	*(0.185)*	*(0.168)*
Number of Observations	4,464	4,032	4,464	4,320	4,464	4,320	4,608	8,928	8,640	8,928	8,640	8,928

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Seven Mile Hill Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Capacity Factor Foote Creek [t]	0.519***	0.865***	0.521***	0.705***	1.073***	0.833***	0.722***	0.720***	0.716***	0.787***	0.907***	0.872***
	(0.122)	*(0.115)*	*(0.116)*	*(0.100)*	*(0.113)*	*(0.134)*	*(0.0954)*	*(0.0860)*	*(0.0951)*	*(0.120)*	*(0.118)*	*(0.108)*
Capacity Factor Foote Creek [t-1]	-0.309	-0.366*	-0.00258	-0.218	-0.317*	-0.415*	-0.110	-0.0883	-0.0719	-0.323	-0.375*	-0.387**
	(0.228)	*(0.206)*	*(0.195)*	*(0.173)*	*(0.185)*	*(0.247)*	*(0.161)*	*(0.144)*	*(0.159)*	*(0.212)*	*(0.209)*	*(0.191)*
Capacity Factor Foote Creek [t-2]	0.127	0.135	0.0807	0.104	0.0968	0.247	0.124	0.147	0.106	0.164	0.152	0.103
	(0.249)	*(0.218)*	*(0.203)*	*(0.180)*	*(0.188)*	*(0.271)*	*(0.169)*	*(0.150)*	*(0.164)*	*(0.225)*	*(0.221)*	*(0.198)*
Capacity Factor Foote Creek [t-3]	-0.0283	-0.0230	-0.0466	0.00180	0.000586	0.00521	0.161	0.0237	-0.0534	0.00176	-0.0393	-0.0567
	(0.251)	*(0.218)*	*(0.203)*	*(0.180)*	*(0.188)*	*(0.273)*	*(0.169)*	*(0.151)*	*(0.164)*	*(0.227)*	*(0.222)*	*(0.198)*
Capacity Factor Foote Creek [t-4]	0.126	0.120	0.109	0.0881	0.0325	0.140	0.0899	0.0209	0.105	0.0975	0.145	0.0793
	(0.249)	*(0.218)*	*(0.203)*	*(0.180)*	*(0.188)*	*(0.271)*	*(0.169)*	*(0.151)*	*(0.164)*	*(0.225)*	*(0.221)*	*(0.198)*
Capacity Factor Foote Creek [t-5]	-0.302	-0.382*	-0.0425	-0.0821	-0.0763	-0.120	-0.0786	-0.0998	-0.0207	-0.175	-0.295	-0.223
	(0.228)	*(0.206)*	*(0.195)*	*(0.172)*	*(0.184)*	*(0.248)*	*(0.163)*	*(0.145)*	*(0.160)*	*(0.212)*	*(0.209)*	*(0.189)*
Capacity Factor Foote Creek [t-6]	0.519***	0.770***	0.336***	0.453***	0.350***	0.217	0.269***	0.242***	0.337***	0.493***	0.805***	0.521***
	(0.121)	*(0.115)*	*(0.116)*	*(0.100)*	*(0.111)*	*(0.135)*	*(0.0961)*	*(0.0867)*	*(0.0955)*	*(0.120)*	*(0.118)*	*(0.107)*
Number of Observations	4,464	4,032	4,464	4,320	4,464	4,320	4,464	4,464	4,320	4,464	4,320	4,608

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Mountain Wind Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Capacity Factor Foote Creek [t]	0.522***	0.614***	0.639***	0.372**	0.338***	0.303***	0.749***	0.495***	0.435***	0.527***	0.664***	0.806***
	(0.175)	*(0.217)*	*(0.129)*	*(0.160)*	*(0.128)*	*(0.110)*	*(0.138)*	*(0.149)*	*(0.154)*	*(0.123)*	*(0.126)*	*(0.124)*
Capacity Factor Foote Creek [t-1]	-0.333	-0.291	-0.183	-0.146	-0.0689	-0.158	-0.262	-0.184	-0.158	-0.204	-0.263	-0.373*
	(0.329)	*(0.389)*	*(0.217)*	*(0.276)*	*(0.211)*	*(0.202)*	*(0.233)*	*(0.250)*	*(0.257)*	*(0.211)*	*(0.224)*	*(0.222)*
Capacity Factor Foote Creek [t-2]	0.129	0.0805	0.0961	0.0198	0.0127	0.134	0.0493	0.102	0.0790	0.0825	0.135	0.104
	(0.359)	*(0.411)*	*(0.225)*	*(0.288)*	*(0.216)*	*(0.221)*	*(0.243)*	*(0.261)*	*(0.265)*	*(0.220)*	*(0.237)*	*(0.235)*
Capacity Factor Foote Creek [t-3]	-0.0548	-0.0821	-0.0349	-0.0195	0.0322	0.000107	0.137	0.00232	-0.0552	-0.00161	-0.0200	-0.102
	(0.362)	*(0.413)*	*(0.226)*	*(0.289)*	*(0.216)*	*(0.223)*	*(0.243)*	*(0.262)*	*(0.265)*	*(0.221)*	*(0.238)*	*(0.236)*
Capacity Factor Foote Creek [t-4]	0.146	0.0787	0.0767	0.0641	0.0273	0.0867	-0.0219	0.0359	0.118	0.0481	0.0241	0.0787
	(0.359)	*(0.412)*	*(0.225)*	*(0.288)*	*(0.216)*	*(0.221)*	*(0.243)*	*(0.261)*	*(0.265)*	*(0.220)*	*(0.237)*	*(0.235)*
Capacity Factor Foote Creek [t-5]	-0.339	-0.0256	-0.0428	-0.210	-0.0462	-0.0963	0.0567	-0.131	-0.174	-0.131	-0.0237	-0.287
	(0.329)	*(0.390)*	*(0.217)*	*(0.276)*	*(0.211)*	*(0.202)*	*(0.234)*	*(0.251)*	*(0.257)*	*(0.211)*	*(0.224)*	*(0.222)*
Capacity Factor Foote Creek [t-6]	0.545***	0.0835	0.305**	0.445***	0.400***	0.248**	0.0834	0.325**	0.676***	0.314**	0.112	0.580***
	(0.175)	*(0.217)*	*(0.129)*	*(0.160)*	*(0.128)*	*(0.110)*	*(0.138)*	*(0.150)*	*(0.154)*	*(0.123)*	*(0.126)*	*(0.124)*
Number of Observations	4,464	4,032	4,464	4,320	4,464	4,320	4,464	4,464	4,608	8,928	8,640	8,928

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Marengo Predicted by Combine Hills

Explanatory Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	Estimated Coefficients											
Capacity Factor Combine Hills [t]	0.486***	0.372***	0.360***	0.482***	0.487***	0.234***	0.307***	0.295***	0.353***	0.594***	0.493***	0.760***
	(0.182)	*(0.113)*	*(0.0969)*	*(0.122)*	*(0.0869)*	*(0.0862)*	*(0.0803)*	*(0.0722)*	*(0.0805)*	*(0.0868)*	*(0.0903)*	*(0.111)*
Capacity Factor Combine Hills [t-1]	-0.271	-0.109	-0.129	-0.235	-0.226	-0.131	-0.186	-0.146	-0.160	-0.328**	-0.228	-0.336*
	(0.336)	*(0.197)*	*(0.177)*	*(0.219)*	*(0.157)*	*(0.158)*	*(0.145)*	*(0.136)*	*(0.147)*	*(0.161)*	*(0.164)*	*(0.199)*
Capacity Factor Combine Hills [t-2]	0.182	0.151	0.135	0.0636	0.0711	0.0448	0.0484	0.0365	0.0837	0.134	0.113	0.170
	(0.364)	*(0.211)*	*(0.192)*	*(0.230)*	*(0.166)*	*(0.168)*	*(0.150)*	*(0.146)*	*(0.158)*	*(0.173)*	*(0.175)*	*(0.211)*
Capacity Factor Combine Hills [t-3]	-0.00779	-0.0543	-0.165	-0.0483	-0.0264	0.00555	0.0109	-0.00229	-0.128	-0.109	-0.0854	0.0328
	(0.365)	*(0.212)*	*(0.194)*	*(0.231)*	*(0.166)*	*(0.168)*	*(0.150)*	*(0.147)*	*(0.160)*	*(0.174)*	*(0.176)*	*(0.212)*
Capacity Factor Combine Hills [t-4]	0.0761	0.0545	0.243	0.113	0.138	0.0672	-0.0142	0.112	0.198	0.168	0.155	0.116
	(0.364)	*(0.209)*	*(0.192)*	*(0.230)*	*(0.167)*	*(0.166)*	*(0.150)*	*(0.147)*	*(0.158)*	*(0.173)*	*(0.175)*	*(0.211)*
Capacity Factor Combine Hills [t-5]	-0.0275	-0.145	-0.556***	-0.508**	-0.325**	-0.393**	-0.438***	-0.484***	-0.406***	-0.458***	-0.294*	-0.197
	(0.336)	*(0.196)*	*(0.177)*	*(0.219)*	*(0.158)*	*(0.156)*	*(0.145)*	*(0.136)*	*(0.147)*	*(0.161)*	*(0.163)*	*(0.199)*
Capacity Factor Combine Hills [t-6]	0.179	0.452***	1.056***	0.950***	0.752***	0.839***	0.944***	0.879***	0.841***	0.839***	0.719***	0.483***
	(0.181)	*(0.112)*	*(0.0968)*	*(0.122)*	*(0.0872)*	*(0.0853)*	*(0.0800)*	*(0.0720)*	*(0.0801)*	*(0.0867)*	*(0.0901)*	*(0.111)*
Number of Observations	4,464	4,032	4,464	4,320	4,464	5,040	8,928	8,928	8,640	8,928	8,640	8,928

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Goodnoe Predicted by Leaning Juniper

Explanatory Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	Estimated Coefficients											
Capacity Factor Leaning Juniper [t]	0.811***	0.730***	0.841***	0.877***	0.901***	0.762***	0.755***	0.703***	0.805***	0.682***	0.776***	0.748***
	(0.103)	*(0.126)*	*(0.0744)*	*(0.0820)*	*(0.0869)*	*(0.0520)*	*(0.0601)*	*(0.0541)*	*(0.0755)*	*(0.0552)*	*(0.0675)*	*(0.118)*
Capacity Factor Leaning Juniper [t-1]	-0.412**	-0.445*	-0.321**	-0.379***	-0.420***	-0.320***	-0.283***	-0.279***	-0.412***	-0.233**	-0.319***	-0.366*
	(0.189)	*(0.242)*	*(0.130)*	*(0.147)*	*(0.159)*	*(0.0910)*	*(0.103)*	*(0.0953)*	*(0.138)*	*(0.0961)*	*(0.119)*	*(0.217)*
Capacity Factor Leaning Juniper [t-2]	0.222	0.166	0.0314	0.164	0.177	0.0852	0.116	0.167*	0.161	0.120	0.160	0.166
	(0.205)	*(0.267)*	*(0.135)*	*(0.157)*	*(0.171)*	*(0.0956)*	*(0.108)*	*(0.101)*	*(0.148)*	*(0.102)*	*(0.126)*	*(0.233)*
Capacity Factor Leaning Juniper [t-3]	-0.0369	-0.0679	0.0631	0.0348	-0.00515	0.0395	-0.0405	-0.0296	0.0255	0.0218	-0.0387	-0.0299
	(0.206)	*(0.270)*	*(0.135)*	*(0.157)*	*(0.172)*	*(0.0960)*	*(0.108)*	*(0.102)*	*(0.148)*	*(0.102)*	*(0.127)*	*(0.234)*
Capacity Factor Leaning Juniper [t-4]	0.127	0.123	0.0597	0.0691	0.0812	0.0867	0.0846	0.127	0.0876	0.0641	0.106	0.114
	(0.205)	*(0.267)*	*(0.135)*	*(0.157)*	*(0.172)*	*(0.0958)*	*(0.108)*	*(0.101)*	*(0.148)*	*(0.102)*	*(0.126)*	*(0.233)*
Capacity Factor Leaning Juniper [t-5]	-0.130	-0.291	0.00342	-0.127	-0.102	-0.121	-0.135	-0.142	-0.180	-0.0979	-0.122	-0.205
	(0.189)	*(0.242)*	*(0.130)*	*(0.147)*	*(0.161)*	*(0.0914)*	*(0.103)*	*(0.0952)*	*(0.138)*	*(0.0962)*	*(0.119)*	*(0.217)*
Capacity Factor Leaning Juniper [t-6]	0.324***	0.470***	0.267***	0.294***	0.305***	0.291***	0.339***	0.343***	0.360***	0.349***	0.389***	0.400***
	(0.103)	*(0.126)*	*(0.0744)*	*(0.0819)*	*(0.0873)*	*(0.0521)*	*(0.0601)*	*(0.0540)*	*(0.0757)*	*(0.0551)*	*(0.0675)*	*(0.118)*
Number of Observations	4,464	4,032	4,464	4,320	4,608	8,640	8,928	8,928	8,640	8,928	8,640	8,928

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Top of the World Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.368***	0.327***	0.275***	0.194***	0.0788**	0.101***	0.0683***	0.0724***	0.137***	0.202***	0.395***	0.416***
	(0.0643)	*(0.0623)*	*(0.0500)*	*(0.0391)*	*(0.0316)*	*(0.0243)*	*(0.0223)*	*(0.0260)*	*(0.0300)*	*(0.0449)*	*(0.0619)*	*(0.0577)*
Capacity Factor Foote Creek [t-1]	0.0545	0.0482	0.0451	0.00184	0.0524	0.00127	0.0123	-0.0122	0.0202	0.0312	0.103	0.0662
	(0.0843)	*(0.0828)*	*(0.0674)*	*(0.0521)*	*(0.0414)*	*(0.0327)*	*(0.0298)*	*(0.0355)*	*(0.0412)*	*(0.0593)*	*(0.0794)*	*(0.0768)*
Capacity Factor Foote Creek [t-2]	-0.0469	0.0164	-0.0208	0.0212	0.0251	0.0268	7.50e-05	0.0251	0.0246	0.00170	-0.0110	0.00624
	(0.0857)	*(0.0835)*	*(0.0677)*	*(0.0523)*	*(0.0415)*	*(0.0327)*	*(0.0297)*	*(0.0355)*	*(0.0412)*	*(0.0596)*	*(0.0805)*	*(0.0771)*
Capacity Factor Foote Creek [t-3]	-0.0369	-0.0183	-0.00578	0.0170	0.00300	0.0202	0.0107	0.0229	0.00661	0.000210	0.0185	-0.0236
	(0.0855)	*(0.0835)*	*(0.0677)*	*(0.0523)*	*(0.0415)*	*(0.0327)*	*(0.0297)*	*(0.0355)*	*(0.0413)*	*(0.0596)*	*(0.0806)*	*(0.0774)*
Capacity Factor Foote Creek [t-4]	-0.0152	0.00696	-0.00881	0.0368	0.0260	0.0321	0.0133	-0.00532	0.00566	0.0176	-0.0311	-0.00378
	(0.0856)	*(0.0836)*	*(0.0678)*	*(0.0522)*	*(0.0415)*	*(0.0328)*	*(0.0296)*	*(0.0356)*	*(0.0413)*	*(0.0596)*	*(0.0805)*	*(0.0774)*
Capacity Factor Foote Creek [t-5]	0.0884	0.0553	0.0489	0.0240	0.0380	0.0151	-0.0174	0.0350	0.00410	0.0615	0.0477	0.0482
	(0.0844)	*(0.0828)*	*(0.0674)*	*(0.0521)*	*(0.0414)*	*(0.0328)*	*(0.0296)*	*(0.0356)*	*(0.0412)*	*(0.0592)*	*(0.0796)*	*(0.0769)*
Capacity Factor Foote Creek [t-6]	0.365***	0.239***	0.243***	0.238***	0.144***	0.159***	0.0577***	0.125***	0.153***	0.249***	0.266***	0.365***
	(0.0644)	*(0.0624)*	*(0.0500)*	*(0.0391)*	*(0.0316)*	*(0.0243)*	*(0.0222)*	*(0.0261)*	*(0.0300)*	*(0.0448)*	*(0.0620)*	*(0.0578)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Three Buttes Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.347***	0.284***	0.299***	0.201***	0.0910***	0.122***	0.0774***	0.0606**	0.128***	0.184***	0.394***	0.389***
	(0.0602)	*(0.0612)*	*(0.0465)*	*(0.0406)*	*(0.0314)*	*(0.0250)*	*(0.0217)*	*(0.0273)*	*(0.0287)*	*(0.0447)*	*(0.0604)*	*(0.0559)*
Capacity Factor Foote Creek [t-1]	0.0552	0.0508	0.0395	0.00591	0.0290	0.0116	0.00723	0.0320	0.00576	0.0335	0.0977	0.0541
	(0.0789)	*(0.0813)*	*(0.0627)*	*(0.0540)*	*(0.0411)*	*(0.0337)*	*(0.0290)*	*(0.0372)*	*(0.0394)*	*(0.0588)*	*(0.0776)*	*(0.0747)*
Capacity Factor Foote Creek [t-2]	-0.0260	0.00141	-0.00890	0.0211	0.0119	0.0118	0.0286	0.0344	0.0199	0.0135	-0.0355	0.0155
	(0.0801)	*(0.0821)*	*(0.0630)*	*(0.0542)*	*(0.0411)*	*(0.0338)*	*(0.0290)*	*(0.0372)*	*(0.0394)*	*(0.0592)*	*(0.0787)*	*(0.0754)*
Capacity Factor Foote Creek [t-3]	-0.0199	0.0114	0.0108	0.0197	0.0300	0.0244	-0.0105	0.00457	0.0208	0.0216	-0.000275	-0.00758
	(0.0798)	*(0.0820)*	*(0.0631)*	*(0.0542)*	*(0.0411)*	*(0.0338)*	*(0.0290)*	*(0.0372)*	*(0.0394)*	*(0.0592)*	*(0.0787)*	*(0.0755)*
Capacity Factor Foote Creek [t-4]	-0.0358	-0.0225	-0.00289	-0.000622	0.0185	0.0152	0.000939	0.0212	0.00602	0.00727	-0.0350	-0.0196
	(0.0800)	*(0.0821)*	*(0.0630)*	*(0.0542)*	*(0.0412)*	*(0.0338)*	*(0.0289)*	*(0.0372)*	*(0.0394)*	*(0.0593)*	*(0.0788)*	*(0.0755)*
Capacity Factor Foote Creek [t-5]	0.0651	0.0465	0.00235	0.0502	0.0142	0.0313	0.0117	-0.00139	0.00699	0.0327	0.0617	0.0364
	(0.0789)	*(0.0814)*	*(0.0626)*	*(0.0540)*	*(0.0411)*	*(0.0338)*	*(0.0289)*	*(0.0373)*	*(0.0394)*	*(0.0590)*	*(0.0778)*	*(0.0751)*
Capacity Factor Foote Creek [t-6]	0.329***	0.270***	0.206***	0.221***	0.156***	0.162***	0.0388*	0.119***	0.154***	0.244***	0.242***	0.331***
	(0.0603)	*(0.0613)*	*(0.0465)*	*(0.0406)*	*(0.0314)*	*(0.0250)*	*(0.0216)*	*(0.0274)*	*(0.0286)*	*(0.0446)*	*(0.0605)*	*(0.0563)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for Dunlap Predicted by Foote Creek

Explanatory Variables	Estimated Coefficients											
	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Capacity Factor Foote Creek [t]	0.450***	0.292***	0.352***	0.234***	0.114***	0.161***	0.104***	0.134***	0.176***	0.278***	0.408***	0.447***
	(0.0478)	*(0.0441)*	*(0.0378)*	*(0.0285)*	*(0.0237)*	*(0.0186)*	*(0.0140)*	*(0.0168)*	*(0.0214)*	*(0.0366)*	*(0.0458)*	*(0.0488)*
Capacity Factor Foote Creek [t-1]	0.0665	0.0726	0.0582	0.0495	0.0409	0.0313	0.0518***	0.0298	0.0542*	0.0676	0.112*	0.0523
	(0.0624)	*(0.0587)*	*(0.0510)*	*(0.0379)*	*(0.0310)*	*(0.0251)*	*(0.0186)*	*(0.0228)*	*(0.0294)*	*(0.0483)*	*(0.0588)*	*(0.0652)*
Capacity Factor Foote Creek [t-2]	-0.00458	-0.0240	-0.0135	0.0126	0.0678**	0.0369	0.0250	0.0311	0.0447	0.00626	0.00486	0.00843
	(0.0635)	*(0.0592)*	*(0.0513)*	*(0.0381)*	*(0.0311)*	*(0.0251)*	*(0.0186)*	*(0.0228)*	*(0.0294)*	*(0.0486)*	*(0.0596)*	*(0.0655)*
Capacity Factor Foote Creek [t-3]	-0.0151	0.0472	-0.00555	0.00570	0.0440	0.0429*	0.0163	0.0196	0.0232	-0.00101	-0.0307	-0.0148
	(0.0636)	*(0.0591)*	*(0.0513)*	*(0.0381)*	*(0.0311)*	*(0.0251)*	*(0.0186)*	*(0.0228)*	*(0.0294)*	*(0.0486)*	*(0.0595)*	*(0.0656)*
Capacity Factor Foote Creek [t-4]	-0.0355	-0.0389	0.00531	0.0189	0.0356	0.0318	0.0173	0.0247	-0.00119	-0.000509	0.00812	0.0296
	(0.0635)	*(0.0592)*	*(0.0513)*	*(0.0380)*	*(0.0311)*	*(0.0251)*	*(0.0186)*	*(0.0228)*	*(0.0294)*	*(0.0486)*	*(0.0595)*	*(0.0657)*
Capacity Factor Foote Creek [t-5]	0.0849	0.0637	0.00670	0.0516	0.0435	0.0361	-0.00205	0.0201	-0.00276	0.0434	0.0525	0.0145
	(0.0624)	*(0.0587)*	*(0.0509)*	*(0.0379)*	*(0.0310)*	*(0.0251)*	*(0.0186)*	*(0.0228)*	*(0.0294)*	*(0.0484)*	*(0.0588)*	*(0.0652)*
Capacity Factor Foote Creek [t-6]	0.367***	0.385***	0.282***	0.239***	0.150***	0.119***	0.0783***	0.120***	0.147***	0.289***	0.277***	0.388***
	(0.0476)	*(0.0440)*	*(0.0377)*	*(0.0284)*	*(0.0236)*	*(0.0186)*	*(0.0140)*	*(0.0168)*	*(0.0214)*	*(0.0366)*	*(0.0457)*	*(0.0489)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Regression Results by Month for Rolling Hills Predicted by Foote Creek

Explanatory Variables	Estimated Coefficients											
	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Capacity Factor Foote Creek [t]	0.372***	0.334***	0.310***	0.213***	0.0919***	0.119***	0.0854***	0.0756***	0.144***	0.224***	0.392***	0.414***
	(0.0635)	*(0.0631)*	*(0.0490)*	*(0.0405)*	*(0.0318)*	*(0.0252)*	*(0.0223)*	*(0.0267)*	*(0.0303)*	*(0.0457)*	*(0.0619)*	*(0.0590)*
Capacity Factor Foote Creek [t-1]	0.0571	0.0678	0.0577	0.0329	0.0321	0.0383	-0.00870	0.00443	0.0205	0.0232	0.0809	0.0331
	(0.0832)	*(0.0838)*	*(0.0660)*	*(0.0539)*	*(0.0416)*	*(0.0340)*	*(0.0298)*	*(0.0362)*	*(0.0417)*	*(0.0604)*	*(0.0795)*	*(0.0788)*
Capacity Factor Foote Creek [t-2]	-0.0482	-0.00447	-0.0226	0.0145	0.0318	0.0134	0.0186	0.0355	-0.00162	0.0120	0.0158	0.0364
	(0.0846)	*(0.0846)*	*(0.0664)*	*(0.0541)*	*(0.0417)*	*(0.0341)*	*(0.0297)*	*(0.0362)*	*(0.0418)*	*(0.0605)*	*(0.0804)*	*(0.0791)*
Capacity Factor Foote Creek [t-3]	-0.0268	-0.0390	-0.0218	0.0237	0.0244	0.0130	0.0108	0.0189	0.0227	0.00717	-0.0234	-0.00569
	(0.0845)	*(0.0846)*	*(0.0664)*	*(0.0541)*	*(0.0417)*	*(0.0340)*	*(0.0297)*	*(0.0362)*	*(0.0419)*	*(0.0607)*	*(0.0803)*	*(0.0792)*
Capacity Factor Foote Creek [t-4]	-0.0226	-0.00151	-0.0163	0.0253	0.0162	0.0160	0.0123	0.0139	0.00500	0.01000	-0.00365	0.00189
	(0.0844)	*(0.0847)*	*(0.0664)*	*(0.0541)*	*(0.0417)*	*(0.0340)*	*(0.0297)*	*(0.0362)*	*(0.0418)*	*(0.0607)*	*(0.0804)*	*(0.0793)*
Capacity Factor Foote Creek [t-5]	0.0468	0.0350	0.0432	0.0216	0.0334	0.0344	-0.0196	0.0162	0.0129	0.0313	0.0881	0.0672
	(0.0830)	*(0.0838)*	*(0.0659)*	*(0.0539)*	*(0.0416)*	*(0.0340)*	*(0.0297)*	*(0.0362)*	*(0.0417)*	*(0.0604)*	*(0.0796)*	*(0.0788)*
Capacity Factor Foote Creek [t-6]	0.383***	0.279***	0.235***	0.231***	0.150***	0.163***	0.0720***	0.113***	0.162***	0.269***	0.225***	0.312***
	(0.0633)	*(0.0632)*	*(0.0489)*	*(0.0405)*	*(0.0318)*	*(0.0252)*	*(0.0222)*	*(0.0266)*	*(0.0303)*	*(0.0457)*	*(0.0620)*	*(0.0593)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Regression Results by Month for Rock River Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.697***	0.614***	0.723***	0.733***	0.702***	0.708***	0.727***	0.685***	0.746***	0.680***	0.700***	0.681***
	(0.0257)	*(0.0206)*	*(0.0198)*	*(0.0182)*	*(0.0126)*	*(0.0129)*	*(0.0116)*	*(0.0128)*	*(0.0145)*	*(0.0187)*	*(0.0245)*	*(0.0261)*
Capacity Factor Foote Creek [t-1]	0.169***	0.224***	0.190***	0.173***	0.141***	0.105***	0.104***	0.146***	0.127***	0.185***	0.212***	0.167***
	(0.0337)	*(0.0275)*	*(0.0269)*	*(0.0242)*	*(0.0165)*	*(0.0174)*	*(0.0155)*	*(0.0174)*	*(0.0199)*	*(0.0247)*	*(0.0316)*	*(0.0350)*
Capacity Factor Foote Creek [t-2]	0.0506	0.0688**	0.0670**	0.0322	0.0253	0.0207	0.0247	0.0315*	-0.0103	0.0492**	0.0506	0.0486
	(0.0343)	*(0.0278)*	*(0.0271)*	*(0.0244)*	*(0.0165)*	*(0.0174)*	*(0.0155)*	*(0.0174)*	*(0.0199)*	*(0.0248)*	*(0.0320)*	*(0.0354)*
Capacity Factor Foote Creek [t-3]	0.0220	0.0364	0.0287	-0.0120	0.0291*	0.0512***	0.0268*	0.0158	0.0310	0.00557	0.0150	-0.00890
	(0.0344)	*(0.0278)*	*(0.0272)*	*(0.0244)*	*(0.0166)*	*(0.0175)*	*(0.0155)*	*(0.0174)*	*(0.0199)*	*(0.0249)*	*(0.0321)*	*(0.0355)*
Capacity Factor Foote Creek [t-4]	0.000164	-0.0105	0.0138	0.00796	0.0376**	-0.0108	0.00877	0.0250	0.0424**	0.0261	-0.00958	0.0228
	(0.0346)	*(0.0279)*	*(0.0272)*	*(0.0244)*	*(0.0166)*	*(0.0175)*	*(0.0155)*	*(0.0174)*	*(0.0199)*	*(0.0249)*	*(0.0321)*	*(0.0356)*
Capacity Factor Foote Creek [t-5]	0.000294	0.0494*	0.0205	0.00953	0.0165	0.0349**	0.0211	0.0118	0.00483	0.0240	0.00374	0.0274
	(0.0341)	*(0.0278)*	*(0.0273)*	*(0.0243)*	*(0.0166)*	*(0.0175)*	*(0.0155)*	*(0.0175)*	*(0.0199)*	*(0.0248)*	*(0.0318)*	*(0.0356)*
Capacity Factor Foote Creek [t-6]	0.116***	0.0503**	-0.0140	0.0660***	0.0248*	0.0505***	0.0125	0.0255**	0.0436***	0.0427**	0.0719***	0.126***
	(0.0259)	*(0.0209)*	*(0.0203)*	*(0.0183)*	*(0.0126)*	*(0.0130)*	*(0.0117)*	*(0.0129)*	*(0.0145)*	*(0.0189)*	*(0.0247)*	*(0.0268)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for McFadden Predicted by Foote Creek

	Estimated Coefficients											
Explanatory Variables	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Capacity Factor Foote Creek [t]	0.461***	0.329***	0.284***	0.297***	0.196***	0.168***	0.155***	0.177***	0.220***	0.240***	0.297***	0.404***
	(0.0522)	*(0.0429)*	*(0.0363)*	*(0.0304)*	*(0.0216)*	*(0.0205)*	*(0.0196)*	*(0.0221)*	*(0.0231)*	*(0.0322)*	*(0.0484)*	*(0.0446)*
Capacity Factor Foote Creek [t-1]	0.0625	0.0793	0.0563	0.139***	0.141***	0.144***	0.145***	0.106***	0.160***	0.124***	0.122**	0.0597
	(0.0684)	*(0.0571)*	*(0.0490)*	*(0.0405)*	*(0.0283)*	*(0.0276)*	*(0.0260)*	*(0.0301)*	*(0.0317)*	*(0.0424)*	*(0.0622)*	*(0.0596)*
Capacity Factor Foote Creek [t-2]	-0.0579	0.0406	0.0375	0.0891**	0.194***	0.182***	0.202***	0.176***	0.118***	0.110***	0.0247	0.0458
	(0.0696)	*(0.0576)*	*(0.0493)*	*(0.0407)*	*(0.0283)*	*(0.0276)*	*(0.0260)*	*(0.0301)*	*(0.0317)*	*(0.0426)*	*(0.0628)*	*(0.0598)*
Capacity Factor Foote Creek [t-3]	-0.00530	0.0210	0.0248	0.0507	0.0834***	0.130***	0.0969***	0.1000***	0.0786**	0.0880**	0.0279	0.00789
	(0.0695)	*(0.0575)*	*(0.0493)*	*(0.0407)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0629)*	*(0.0600)*
Capacity Factor Foote Creek [t-4]	0.0353	0.00324	0.00366	0.0158	0.0435	0.0303	0.0332	0.0287	0.0465	0.0255	0.0414	-0.0257
	(0.0694)	*(0.0576)*	*(0.0492)*	*(0.0407)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0629)*	*(0.0602)*
Capacity Factor Foote Creek [t-5]	0.0822	0.0794	0.0859*	0.0525	0.0447	0.0170	0.00342	0.0192	0.00913	0.0133	0.0704	0.0689
	(0.0683)	*(0.0571)*	*(0.0489)*	*(0.0405)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0622)*	*(0.0596)*
Capacity Factor Foote Creek [t-6]	0.322***	0.328***	0.377***	0.201***	0.107***	0.0697***	0.0844***	0.0662***	0.0966***	0.228***	0.254***	0.423***
	(0.0520)	*(0.0429)*	*(0.0362)*	*(0.0304)*	*(0.0216)*	*(0.0206)*	*(0.0195)*	*(0.0221)*	*(0.0231)*	*(0.0322)*	*(0.0483)*	*(0.0448)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Regression Results by Month for High Plains Predicted by Foote Creek

Explanatory Variables	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	Estimated Coefficients											
Capacity Factor Foote Creek [t]	0.461***	0.329***	0.284***	0.297***	0.196***	0.168***	0.155***	0.177***	0.220***	0.240***	0.297***	0.404***
	(0.0522)	*(0.0429)*	*(0.0363)*	*(0.0304)*	*(0.0216)*	*(0.0205)*	*(0.0196)*	*(0.0221)*	*(0.0231)*	*(0.0322)*	*(0.0484)*	*(0.0446)*
Capacity Factor Foote Creek [t-1]	0.0625	0.0793	0.0563	0.139***	0.141***	0.144***	0.145***	0.106***	0.160***	0.124***	0.122**	0.0597
	(0.0684)	*(0.0571)*	*(0.0490)*	*(0.0405)*	*(0.0283)*	*(0.0276)*	*(0.0260)*	*(0.0301)*	*(0.0317)*	*(0.0424)*	*(0.0622)*	*(0.0596)*
Capacity Factor Foote Creek [t-2]	-0.0579	0.0406	0.0375	0.0891**	0.194***	0.182***	0.202***	0.176***	0.118***	0.110***	0.0247	0.0458
	(0.0696)	*(0.0576)*	*(0.0493)*	*(0.0407)*	*(0.0283)*	*(0.0276)*	*(0.0260)*	*(0.0301)*	*(0.0317)*	*(0.0426)*	*(0.0628)*	*(0.0598)*
Capacity Factor Foote Creek [t-3]	-0.00530	0.0210	0.0248	0.0507	0.0834***	0.130***	0.0969***	0.1000***	0.0786**	0.0880**	0.0279	0.00789
	(0.0695)	*(0.0575)*	*(0.0493)*	*(0.0407)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0629)*	*(0.0600)*
Capacity Factor Foote Creek [t-4]	0.0353	0.00324	0.00366	0.0158	0.0435	0.0303	0.0332	0.0287	0.0465	0.0255	0.0414	-0.0257
	(0.0694)	*(0.0576)*	*(0.0492)*	*(0.0407)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0629)*	*(0.0602)*
Capacity Factor Foote Creek [t-5]	0.0822	0.0794	0.0859*	0.0525	0.0447	0.0170	0.00342	0.0192	0.00913	0.0133	0.0704	0.0689
	(0.0683)	*(0.0571)*	*(0.0489)*	*(0.0405)*	*(0.0283)*	*(0.0277)*	*(0.0260)*	*(0.0300)*	*(0.0317)*	*(0.0426)*	*(0.0622)*	*(0.0596)*
Capacity Factor Foote Creek [t-6]	0.322***	0.328***	0.377***	0.201***	0.107***	0.0697***	0.0844***	0.0662***	0.0966***	0.228***	0.254***	0.423***
	(0.0520)	*(0.0429)*	*(0.0362)*	*(0.0304)*	*(0.0216)*	*(0.0206)*	*(0.0195)*	*(0.0221)*	*(0.0231)*	*(0.0322)*	*(0.0483)*	*(0.0448)*
Number of Observations	13,386	12,240	13,392	12,960	13,392	12,960	13,392	13,392	12,960	13,392	12,960	13,392

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Appendix C

Operating Reserve Demand Seasonal Detail

This Appendix presents the monthly component operating reserve service demand calculated for the PacifiCorp East and West Balancing Authority Areas in the Study. The 1,372 MW and 1,833 MW penetration scenarios include some simulated wind data; the load-only and 425 MW penetration scenarios do not.

Table C1.West Balancing Authority Area, Load Only

	Load Following		Regulation	
	Up	Down	Up	Down
January	127	129	125	82
February	93	103	111	73
March	114	115	109	77
April	84	87	103	65
May	93	101	95	72
June	82	83	78	63
July	93	96	69	64
August	79	84	65	60
September	96	104	88	64
October	83	83	98	62
November	149	166	127	95
December	125	116	101	86

Table C2.West Balancing Authority Area, 425 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	132	134	131	91
February	104	110	117	82
March	128	124	118	92
April	96	96	110	78
May	108	109	102	84
June	103	96	88	80
July	110	105	78	79
August	98	94	76	77
September	105	107	94	73
October	97	88	104	74
November	157	169	133	103
December	132	121	106	94

Table C3. West Balancing Authority area, 1,372 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	153	150	171	139
February	122	122	152	129
March	160	152	152	140
April	133	122	150	121
May	135	131	136	123
June	131	123	127	118
July	128	122	110	104
August	118	113	103	104
September	125	121	118	101
October	124	105	126	104
November	181	180	152	131
December	159	138	142	131

Table C4. West Balancing Authority area, 1,833 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	153	150	171	139
February	124	124	152	129
March	162	154	152	140
April	136	123	150	121
May	137	133	136	123
June	133	125	127	118
July	129	123	110	104
August	120	115	103	104
September	126	122	118	101
October	125	106	126	104
November	182	180	152	131
December	161	139	142	131

Table C5. East Balancing Authority area, Load Only

	Load Following		Regulation	
	Up	Down	Up	Down
January	127	131	150	110
February	117	122	131	98
March	135	138	122	102
April	105	103	145	95
May	146	145	133	114
June	143	152	134	114
July	157	155	130	112
August	162	162	122	111
September	144	162	127	105
October	139	146	116	97
November	154	164	161	110
December	145	149	182	112

Table C6. East Balancing Authority Area, 425 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	132	135	152	113
February	120	125	134	101
March	139	142	124	105
April	112	107	148	99
May	151	148	137	118
June	148	155	137	118
July	161	157	132	115
August	165	164	124	114
September	149	165	130	109
October	143	150	119	101
November	158	168	163	113
December	150	154	185	116

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Table C7. East Balancing Authority Area, 1,372 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	187	193	201	175
February	201	195	210	189
March	212	209	207	200
April	193	174	212	182
May	204	184	183	179
June	205	192	189	185
July	205	177	170	172
August	204	187	164	166
September	219	203	185	177
October	218	211	202	192
November	230	227	232	197
December	212	228	253	207

Table C8. East Balancing Authority area, 1,833 MW

	Load Following		Regulation	
	Up	Down	Up	Down
January	240	262	250	241
February	256	262	264	247
March	247	247	235	236
April	236	213	243	223
May	228	205	203	202
June	232	210	204	202
July	220	185	177	183
August	216	197	176	179
September	245	222	201	199
October	257	251	235	230
November	276	290	279	259
December	291	299	300	266