

BEFORE THE PUBLIC UTILITIES COMMISSION  
OF THE STATE OF SOUTH DAKOTA

In the Matter of the Complaint by Juhl  
Energy LLC against NorthWestern  
Corporation dba NorthWestern Energy for  
Establishing a Purchase Power Agreement

Docket EL16-021

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**PREFILED REBUTTAL TESTIMONY**

5

**OF LUKE P. HANSEN**

6

**ON BEHALF OF NORTHWESTERN ENERGY**

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9 **Q. Please state your name and business address.**

10 **A. My name is Luke P. Hansen, and my business address is 11 East Park, Butte,**  
11 **Montana 59701.**

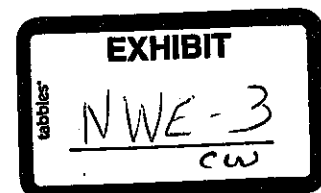
12 **Q. Are you the same Luke Hansen that filed testimony in this docket?**

13 **A. Yes.**

14 **Q. Ms. Maini testified that "NorthWestern's approach relies, in large part, on**  
15 **historical relationships to predict future conditions." Does NorthWestern**  
16 **do anything to validate its approach? (Maini page 15)**

17 **A: Yes, NorthWestern and Ascend Analytics undertake many validation steps in**  
18 **order to verify the modeling results.**

LPH-1



1 **Q. Can you describe the validation steps that NorthWestern and Ascend**  
2 **Analytics perform on the PowerSimm modeling results?**

3 **A.** Yes. After the modeling is completed, NorthWestern analyzes each of the  
4 following inputs to the model: load, renewable generation, commodity prices, and  
5 thermal generation dispatch. First, NorthWestern analyzes the load  
6 determinations from the model to ensure that they are consistent with the  
7 inputted forecasted load. The renewable resources are also analyzed in order to  
8 verify that the generation of each of these resources is consistent with the  
9 inputted generation forecasts. The modeled commodity prices for natural gas,  
10 heavy and light load electricity, and coal, are each reviewed for congruity with the  
11 expected forecast prices. Finally, the generation of the thermal assets is  
12 reviewed to ensure proper economic dispatch of each resource.

13  
14 Ascend also performs a validation process in order to determine that the  
15 modeling results are appropriate. The validation process that Ascend performs  
16 was previously discussed in the 2013 Montana Electricity Supply Resource  
17 Procurement Plan ("2013 Plan"). Below is the discussion of the validation  
18 process that Ascend performs that is taken from the 2013 Plan.

19  
20 **Summary of Simulation Validation Results**

21 Model validation and benchmarking is an essential part of the risk management  
22 and planning process. Ascend has developed tests designed to verify model  
23 calibration to the input data and ensure accuracy and consistency of the

1 PowerSimm simulation output. These validation tests provide insight into the  
2 simulations and build confidence in using the results as tools for informed  
3 decision making.  
4

5 Apart from routine checks of the input data for outliers or other anomalies, the  
6 majority of the validation effort is focused on ensuring that the model output is  
7 appropriately calibrated to the historical input data. The stochastic simulation  
8 methodology used by PowerSimm generates trajectories of future conditions of  
9 weather, load, and market prices, which define ranges of potential future states  
10 over which generation, cost of supply, and other important planning variables are  
11 optimized. To make sure the future states modeled by PowerSimm are feasible,  
12 the simulated distributions of weather, load, forward market prices, and daily and  
13 hourly spot prices are examined in detail to verify consistency with the body of  
14 available historical data. Several additional validation tests also make sure that  
15 important historically-observed relationships, such as the relationships between  
16 weather and load and between load and spot prices, are captured in the model  
17 output.  
18

### 19 **Validation of Simulated Commodity Prices**

20 PowerSimm's forward price module simultaneously simulates multiple commodity  
21 price forecasts into the future, estimating parameters for the stochastic  
22 processes and the covariate factors. The forward price module in PowerSimm  
23 builds a system of simultaneous equations that captures the stochastic

1 component of each individual forward contract while maintaining structural and  
 2 covariate relationship between neighboring contract months, other commodities,  
 3 and other factors. Table 6-3 lists the tests performed to validate forward price  
 4 simulation output.

6 Table 6-3

Forward Price Simulation Validation Criteria			
Test No.	Market Attribute	Information Used to Evaluate	Expectation
1	Uncertainty in Future Prices	Forward Price Confidence Intervals (mean, P5, P95)	<ul style="list-style-type: none"> <li>- Uncertainty grows over time with a conical shape.</li> <li>- Width of confidence intervals will grow for a period and then level off (should not grow indefinitely).</li> <li>- Ranges of prices are consistent with market expectation and historic perspective of forward price uncertainty.</li> </ul>
2	Mean Reversion of Prices	Simulated Price Paths	Simulated price paths match the historically observed mean reversion behavior over the estimated date ranges used to parameterize the model.
3	Correlation of Related Commodities	Heat Rate Confidence Intervals (mean, P5, P95)	<ul style="list-style-type: none"> <li>-Heat rates derived from simulated forward prices have limited growth in uncertainty over time.</li> <li>-The on peak heat rate is greater than or equal to off peak heat rate for all months.</li> <li>-The heat rate distributions change mean and/or spread from month to month due to seasonality.</li> </ul>

7  
 8 Uncertainty in forward price simulations is examined by computing the mean and  
 9 the 5<sup>th</sup> and 95<sup>th</sup> percentiles for the distributions of simulated final evolved  
 10 forward/forecast prices at each delivery date. Figure 6-13 and Figure 6-14 show  
 11 these confidence intervals for monthly Mid-C Heavy Load electricity and AECO

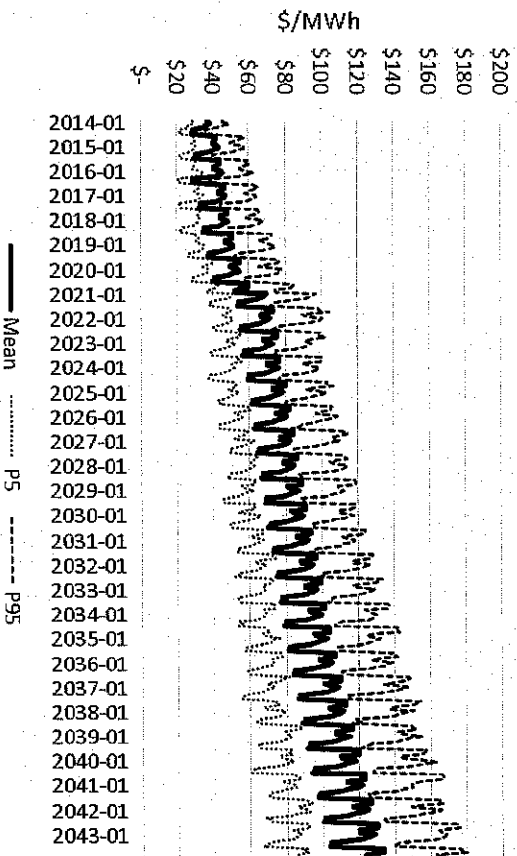
1 gas prices, respectively. These plots reflect a number of historically observed  
2 phenomena regarding the forward/forecast price of both electricity and gas. For  
3 example, strong seasonal components in both contract price and contract  
4 volatility can readily be seen in the simulated output, and are consistent with  
5 observed market trends. A sharp increase in the price of electricity is observed  
6 around the year 2021, reflecting the distribution of future carbon penalties and  
7 their effect on electricity prices. Additionally, uncertainty in the simulated  
8 forward/forecast prices grows as delivery dates range further into the future, a  
9 phenomenon consistent with historical market behavior. Overall, the confidence  
10 interval plots in Figure 6-13 and Figure 6-14 indicate that forward price  
11 simulations in PowerSimm capture an appropriate range of future states of the  
12 market.

13  
14 Reversion of forward contract prices toward the mean is another important  
15 market phenomenon, and can be seen in the forward price simulation confidence  
16 interval plots discussed above, as well as in plots of the final evolved forward  
17 price paths for individual iterations of the forward price simulation. Five such  
18 price paths are plotted by simulation iteration in Figure 6-15, and spikes in the  
19 contract price across neighboring delivery dates can be observed, followed by  
20 reversion of the prices toward the mean.

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Figure 6-13

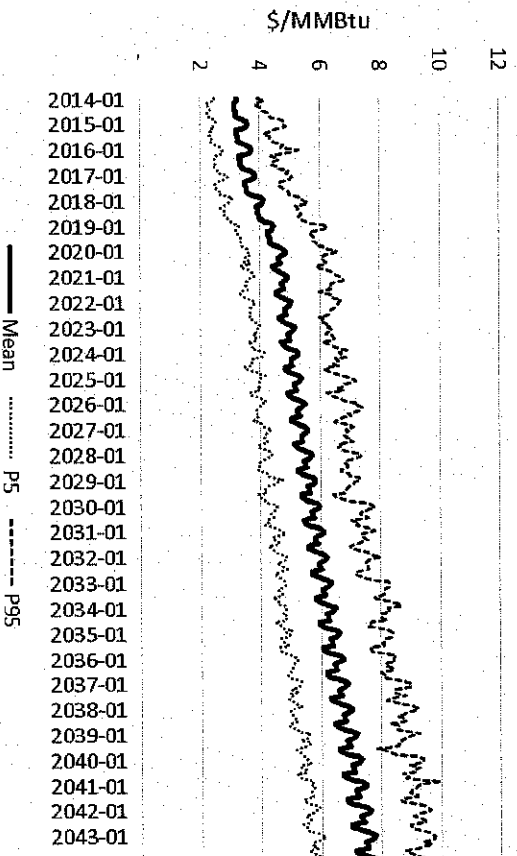
Mid-C Heavy Load Price Confidence Intervals



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Figure 6-14

AECO Price Confidence Intervals

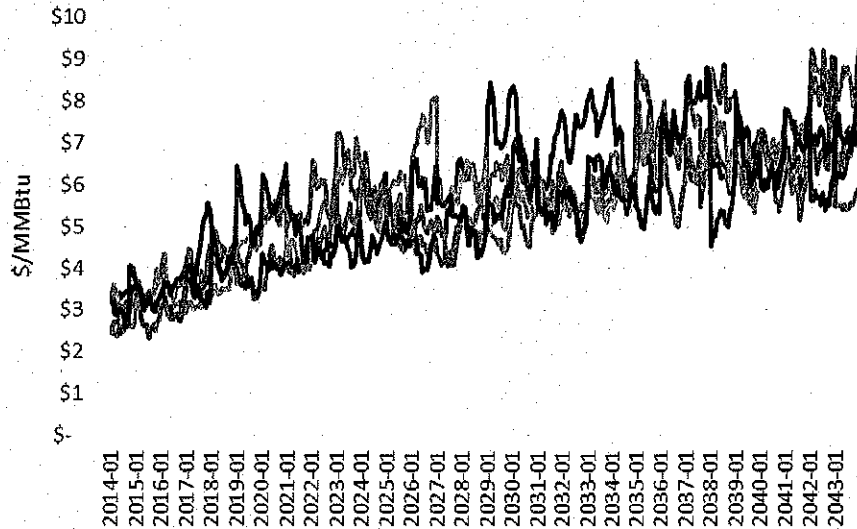


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Figure 6-15

Five Example Paths for AECO Gas Price



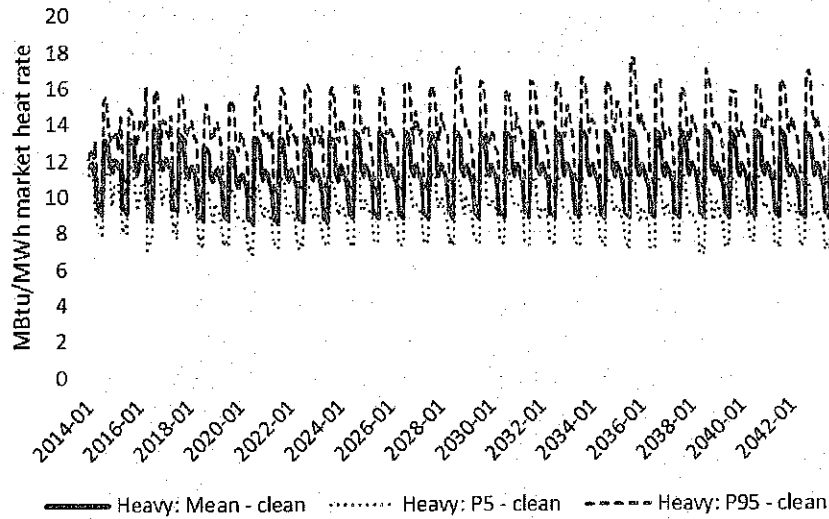
Finally, the structural relationship of forward/forecasted prices for power and gas is investigated via plots of the market implied heat rates.<sup>1</sup> Figure 6-16 and Figure 6-17 show the simulated mean and the 5<sup>th</sup> and 95<sup>th</sup> percentiles for the forward market implied heat rates for Mid-C heavy load and light load, respectively. These heat rates are computed by dividing the forward market price of Mid-C electricity, excluding the impact of any CO<sub>2</sub> price, by the forward price of AECO gas. Notably, despite growth in uncertainty of the individual contract prices, growth in uncertainty of the implied heat rates is limited. Heat rate plots with the impact of CO<sub>2</sub> price added to the power price are shown in Volume 2, Chapter 4. The simulations also show that the implied heat rates for Mid-C heavy load are

<sup>1</sup> The market implied heat rate is the ratio of power prices (\$/MWh) to gas prices (\$/MMBtu) and yields units of generation heat rates of MMBtu/MWh.

1 greater than those for Mid-C light load, which is consistent with market  
2 expectations.

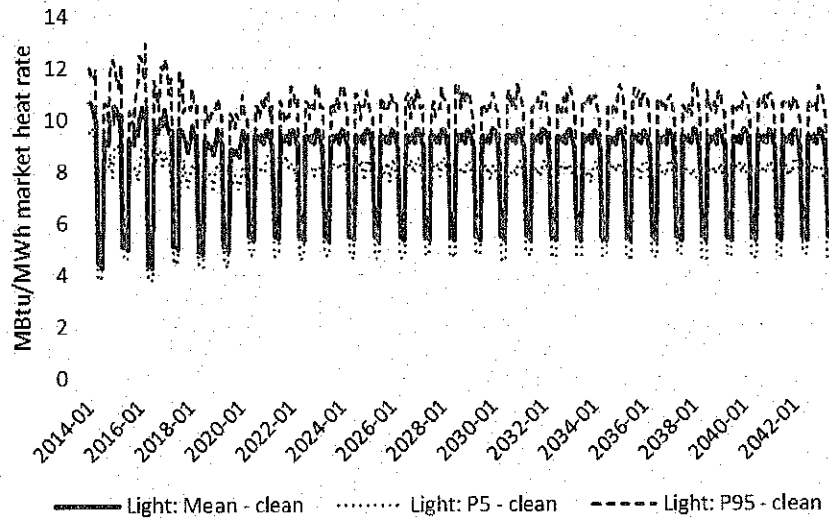
3 Figure 6-16

4 Heavy Load Implied Market Heat Rate Confidence Interval



8 Figure 6-17

Light Load Implied Market Heat Rate Confidence Interval





1 **Validation of Simulated Weather**

2 Weather forecasts are used as inputs into a data preparation procedure that  
3 transforms weather into probability distributions that are fed into the overall  
4 forecasting simulations. The purpose of weather simulation is to provide a set of  
5 outcomes for simulated daily and hourly weather variables across weather stations  
6 in Montana. The criteria used to validate the distributions generated by PowerSimm  
7 weather simulations are summarized in Table 6-4 below.

8  
9 **Table 6-4**

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<b>Weather Simulation Validation Criteria</b>			
<b>Test No.</b>	<b>Attribute</b>	<b>Information Used to Evaluate</b>	<b>Expectation</b>
1	Seasonal Fluctuation in Temperature	Maximum dry bulb temperature confidence intervals by month	Simulated values match historical values, for mean, P5, and P95
2		Maximum dry bulb temperature confidence intervals by day of the year	Simulated values match historical values, for mean, P5, and P95

11

12 Checking the simulated dry bulb temperature distributions on both a monthly and  
13 a daily basis provides verification that the simulations align with historical  
14 distributions across multiple time scales. In particular, these checks ensure that  
15 important monthly and daily variations in weather patterns, which have significant  
16 effects on load and market prices, are present in the simulation output.

17 Validation plots for the monthly and daily simulated dry bulb temperature  
18 confidence intervals are shown in Figure 6-18 and Figure 6-19, respectively.  
19 Simulated values are shown in blue and historical values in red. These plots

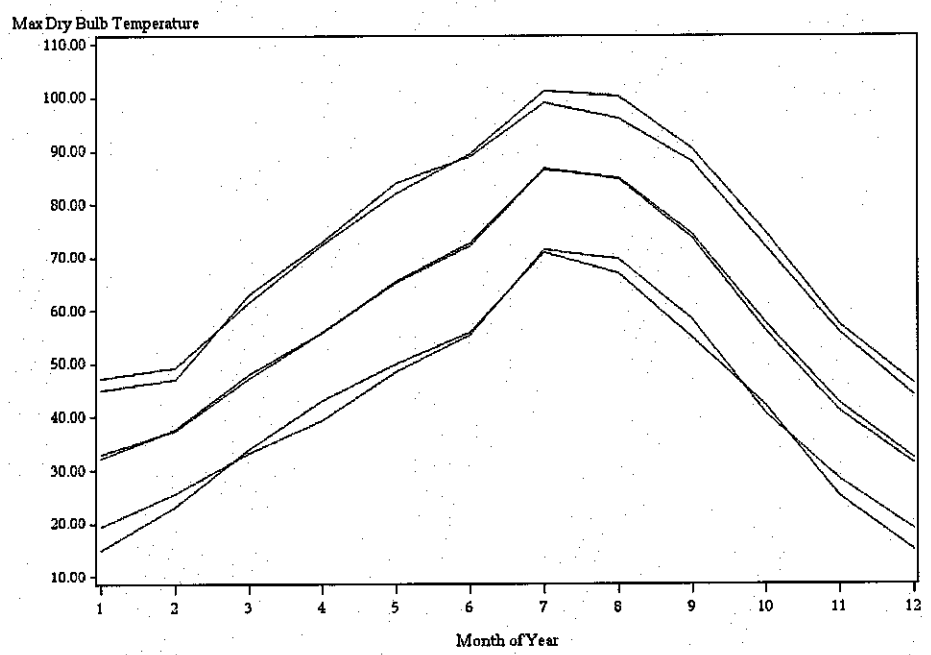
1 illustrate the excellent agreement between simulated weather output and  
2 historical data at the mean and the 5<sup>th</sup> and 95<sup>th</sup> percentiles.

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Figure 6-18

**Actual vs. Simulated Maximum Drybulb Temperatures by Month of Year**  
MISSOULA, MT

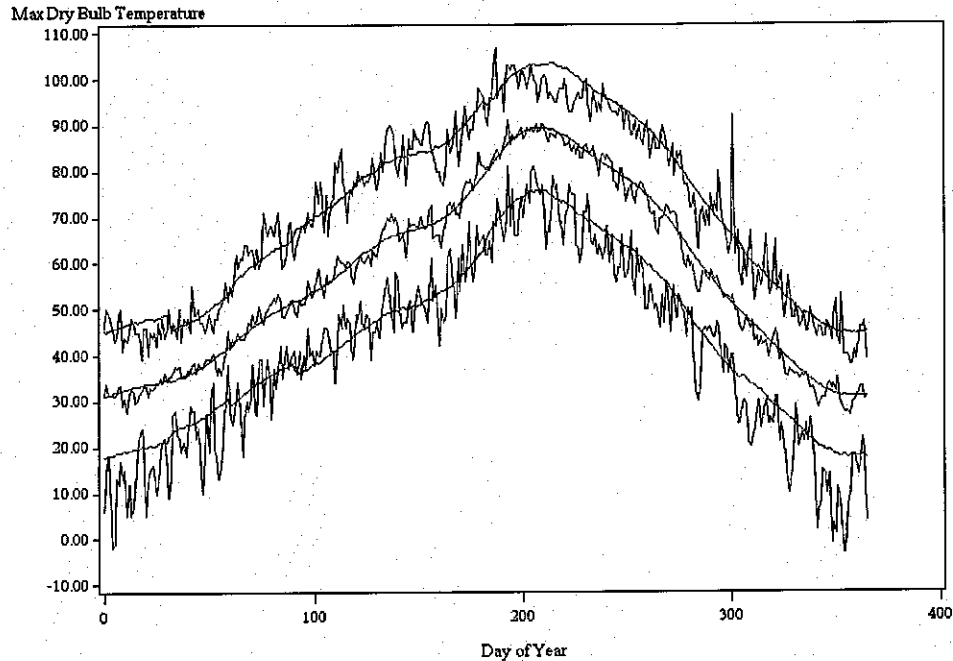


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Figure 6-19

**Actual vs. Simulated Maximum Drybulb Temperatures by Day of Year**  
MISSOULA, MT



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**Validation of Simulated Load**

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Developing accurate electricity load simulations is critical for determining cost of

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service, associated risks, and appropriate hedging strategies. In addition, load

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simulation has significant bearing on electricity prices because of the strong non-

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linear relationship between electricity load and prices. The validation tests listed in

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Table 6-5 are designed to verify accuracy of the load simulations and their

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calibration to the historical data.

Table 6-5

<b>Load Simulation Validation Criteria</b>			
<b>Test No.</b>	<b>Attribute</b>	<b>Information used to evaluate</b>	<b>Expectation</b>
1	Seasonal Fluctuation in Load	Confidence intervals by month (backcast mode)	Simulated values match historical values for mean, P5, and P95
2	Hourly Fluctuation in Load	Confidence intervals by hour (backcast mode)	Simulated values match historical values for mean, P5, and P95
3	Seasonal Fluctuation in Daily Load Profile	Confidence intervals by hour and by month (backcast mode)	Simulated values match historical values for mean, P5, and P95
4	Correlation Between Load and Weather	Weather-Load Scatterplot	Heating and/or cooling loads are demonstrated as applicable for the markets simulated.

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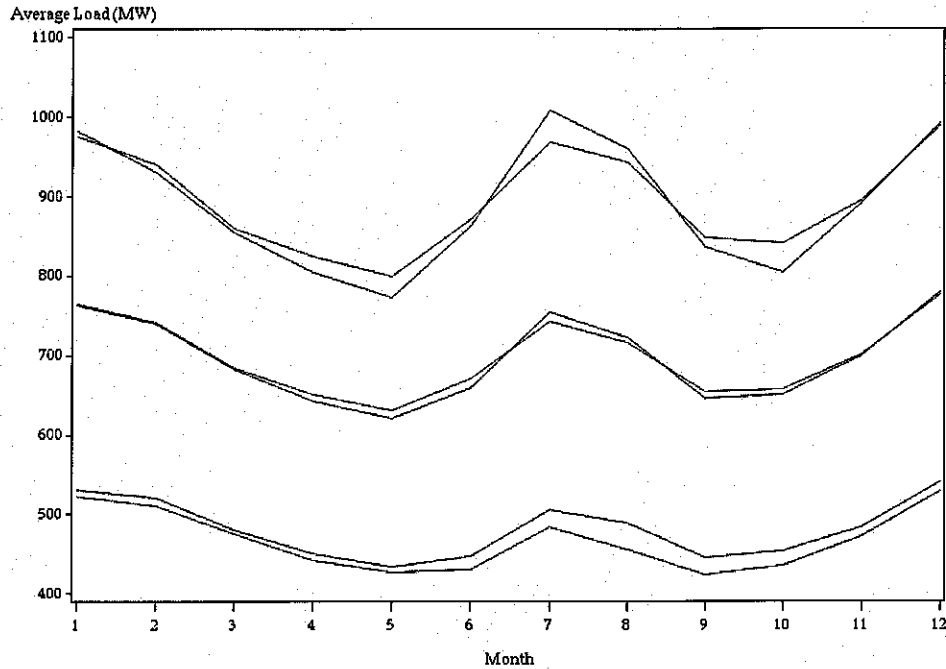
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As with weather, simulated loads are examined across a range of time scales. The monthly confidence intervals at the mean, the 5<sup>th</sup>, and 95<sup>th</sup> percentiles, shown in Figure 6-20, display seasonal variability in the average load; namely, load is generally higher in both the summer and winter than in the spring and fall. This test is run in "backcast mode", in which simulations are performed over a historical time period for comparison with the original historical data. Figure 6-20 demonstrates the excellent agreement between simulated and historical load distributions on a monthly timescale.

Figure 6-20

**Actual vs. Simulated Average Load by Month**  
NWE Load

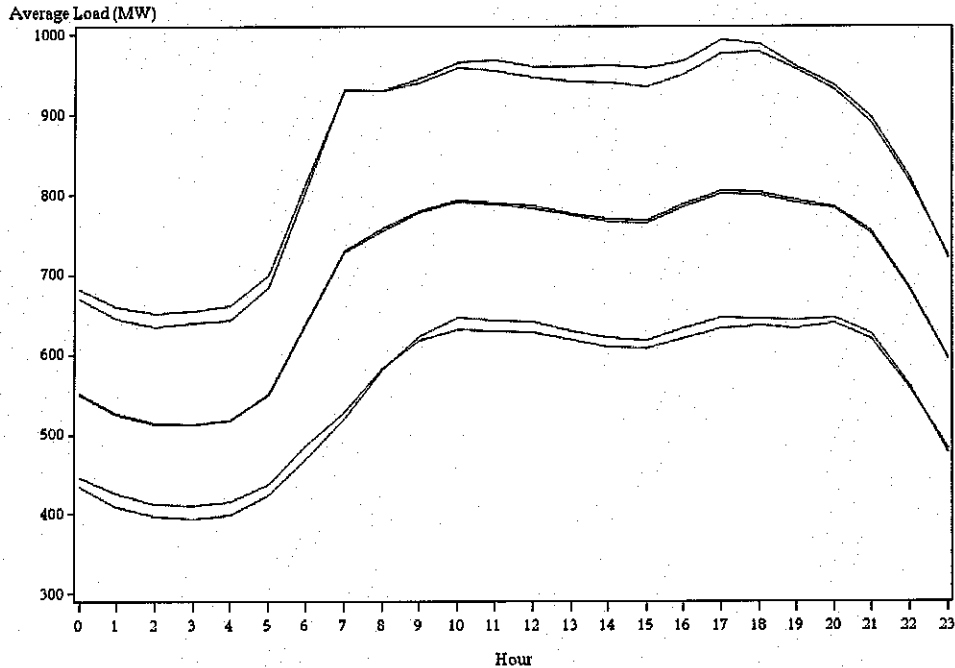


Confidence intervals are also examined for hourly load over the course of a day. Figure 6-21 shows the mean and the 5<sup>th</sup> and 95<sup>th</sup> percentiles of both the historical (red) and simulated (blue) hourly loads. The daily peaking behavior of electric loads is readily observed in this plot. Again, excellent agreement is achieved between the historical data and the simulation output.

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Figure 6-21

**Actual vs. Simulated Average Load by Hour of Day  
NWE Load**



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4 A third confidence interval plot captures the changes in daily peaking behavior on  
5 a monthly basis. Figure 6-22 and Figure 6-23 show the historical (red) and  
6 simulated (blue) mean and the 5<sup>th</sup> and 95<sup>th</sup> percentiles for hourly load by month.  
7 Importantly, the shape of the daily load profile can be seen to change  
8 dramatically by month. In cold months, there is a peak in the early morning  
9 hours, followed by a second peak in the evening, as seen in Figure 6-22 for the  
10 month of February. In warm months, there is a single elongated peak that  
11 reaches a maximum during the hottest hours of the day, as seen Figure 6-23 for  
12 the month of August. Again, simulations match the historical data sets very  
13 closely at the mean, the 5<sup>th</sup>, and 95<sup>th</sup> percentiles.

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Finally, the nonlinear relationship between load and temperature is maintained in

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the simulation output; electric load typically becomes elevated when the

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temperature is either low or high. This relationship is readily observed in both the

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historical data and the simulated output for load and weather, as shown in Figure

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6-24. Historical data points are shown in red and simulations are shown in blue.

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The plot shows that the observed historical relationship is accurately captured by

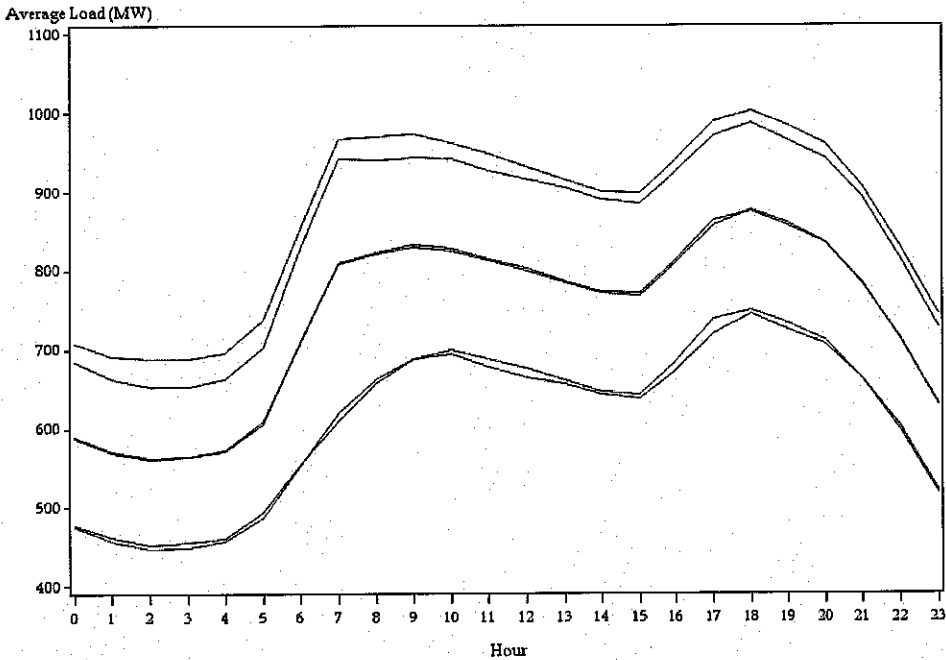
8

the simulation output.

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Figure 6-22

**Actual vs. Simulated Average Load by Hour by Month**  
Load: NWE Load Month: 2



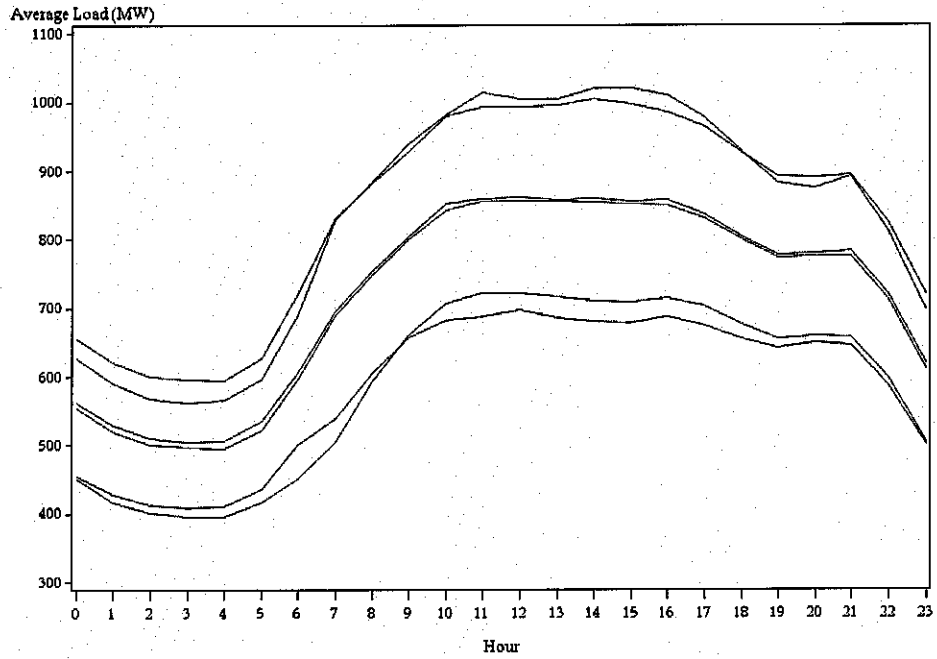
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Figure 6-23

**Actual vs. Simulated Average Load by Hour by Month**  
Load: NWE Load Month: 8



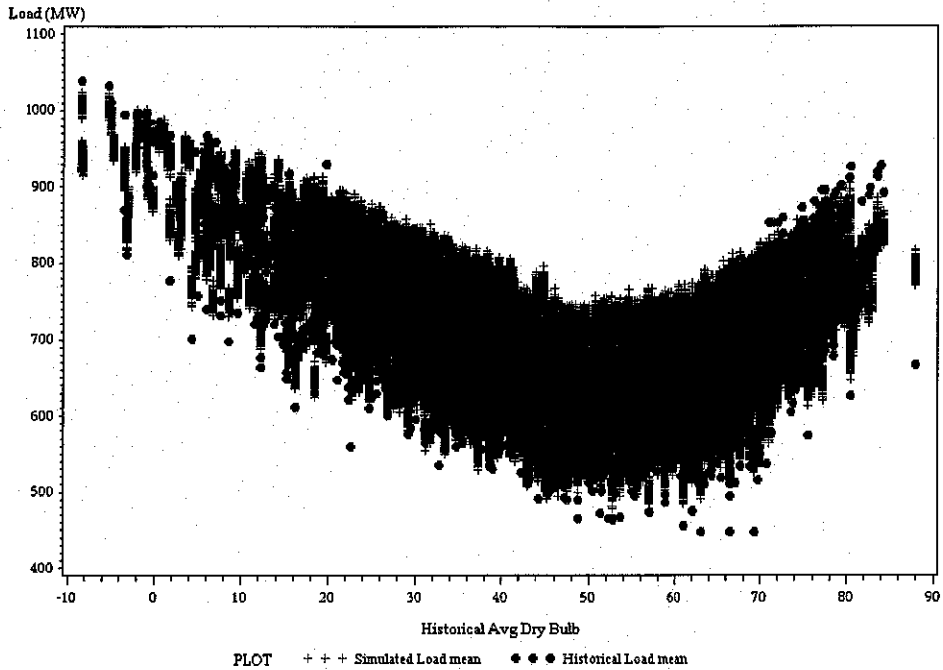
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Figure 6-24

**Actual vs. Simulated Weather-Load Relationship**  
NWE Load



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4 **Validation of Simulated Spot Prices**

5 Simulations of spot prices in PowerSimm incorporate the results of the various  
 6 simulations discussed above, allowing these related model components to affect  
 7 electricity and gas prices on daily and hourly time scales. Relationships between  
 8 fundamental input variables and electricity prices are measured from historical data,  
 9 and simulated variables such as load, hydro generation, imports/exports, reserve  
 10 margins, supply stack, and gas prices are used as explanatory variables for the  
 11 electricity prices through a structural state space model. Table 6-6 lists the tests  
 12 performed to validate the spot price simulation output and ensure its consistency  
 13 and accuracy compared to historical data.

Table 6-6

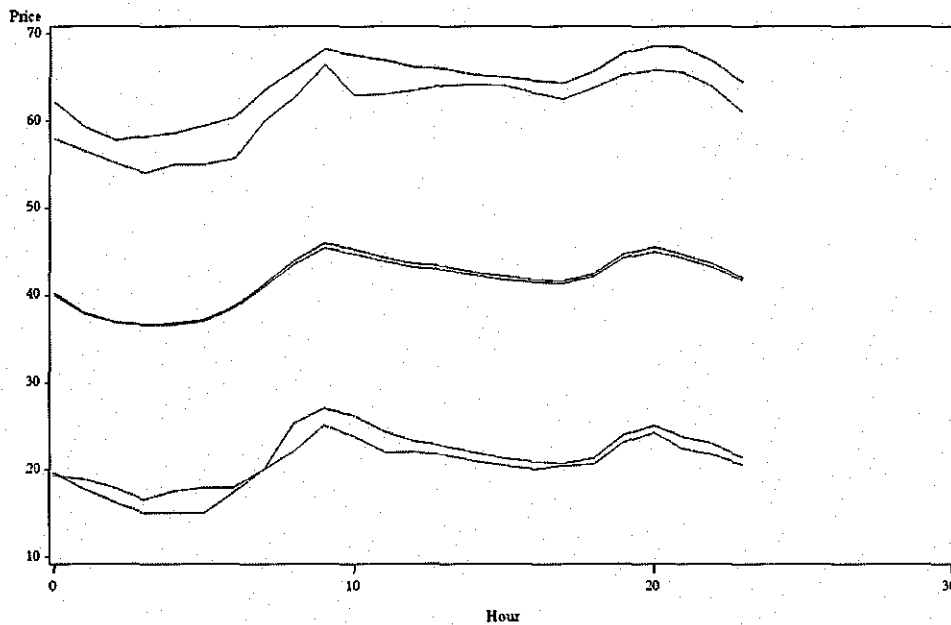
Forward Price Simulation Validation Criteria			
Test No.	Market Attribute	Information Used to Evaluate	Expectation
1	Uncertainty in Electric Prices	Hourly confidence intervals for electric prices by month (mean, P10, P90)	Simulated values consistent with historical values for mean, P10, P90
2	Uncertainty in Gas Prices	Monthly confidence intervals for natural gas (mean, P10, P90)	Simulated values consistent with historical values for mean, P10, P90
3	Electricity Spot Prices Correlate with Load	Load-Spot Scatter Plot	Spot prices increase with system load, in a manner consistent with historical data

Similar to the hourly peaking behavior observed for load above, electricity spot prices also display a significant hourly shape. Figure 6-25 gives an example of this hourly price shape for Mid-C electricity spot prices for the months of February and August, showing the mean and the 10<sup>th</sup> and 90<sup>th</sup> percentiles of both the historical data (red) and the simulation output (blue). The figure illustrates a stark difference between the hourly Mid-C electricity price profiles during the winter and summer: a slight double peak exists in February, as in other cold months, and a single elongated evening peak exists in August, as in other warmer months. The figure further illustrates that, in both cases, the simulation output accurately captures both the shape and magnitude of hourly prices for Mid-C electricity. Similar validation plots for additional months are included in Volume 2, Chapter 4.

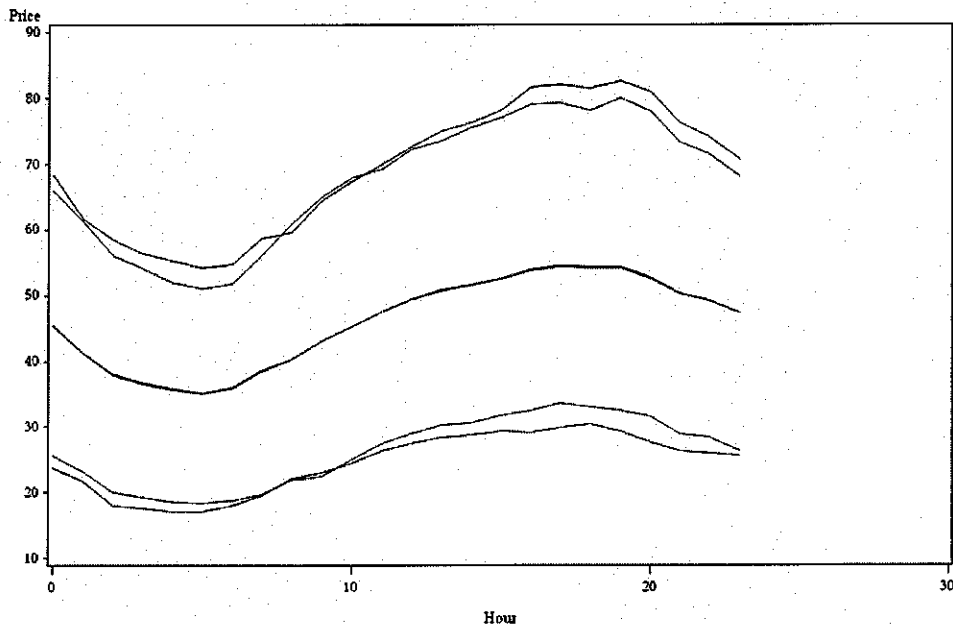
1 For natural gas, important price variations occur on a monthly basis. These  
2 seasonal components of natural gas prices are the result of both simple supply  
3 and demand fundamentals as well as complex interactions between related  
4 commodities and markets. Seasonal components of natural gas prices are the  
5 result of both simple supply and demand fundamentals as well as complex  
6 market and commodity interactions. Figure 6-26 shows the mean and the 10<sup>th</sup>  
7 and 90<sup>th</sup> percentiles for the price of AECO natural gas by month of the year. A  
8 slight increase in the price of gas during late fall and winter can be observed in  
9 both the historical data (red) and the simulation output (blue). Again, the  
10 confidence intervals of the simulations are consistent with those from the  
11 historical data.  
12  
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Figure 6-25

**p10-Mean-p90 Confidence Intervals for Hourly Mid-C Electricity Prices  
Month 2**



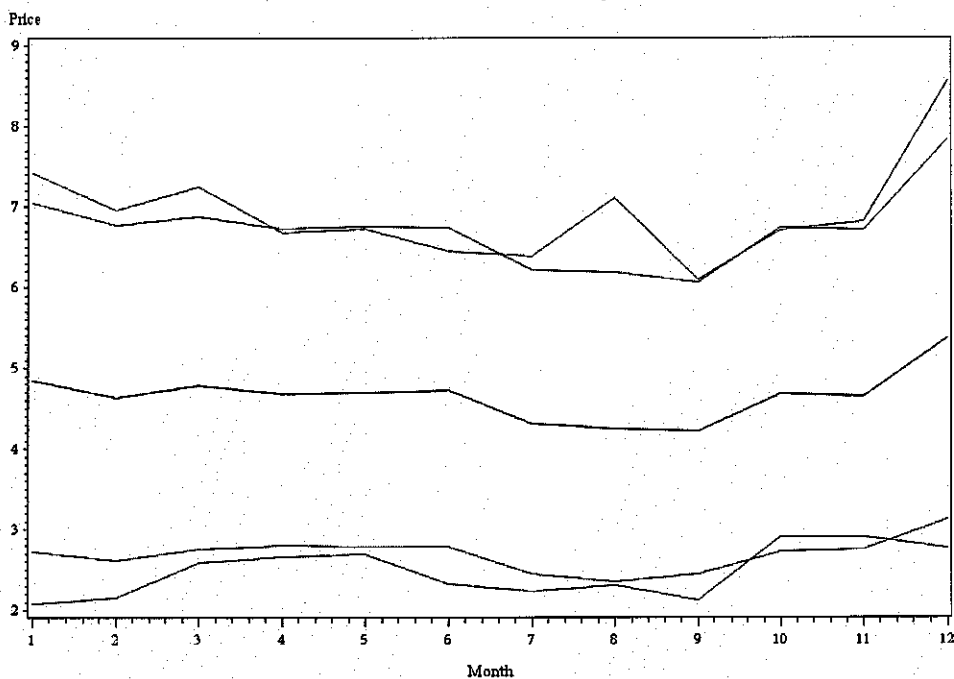
**p10-Mean-p90 Confidence Intervals for Hourly Mid-C Electricity Prices**  
**Month 8**



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**Figure 6-26**

**AECO Gas Confidence Intervals by Month**



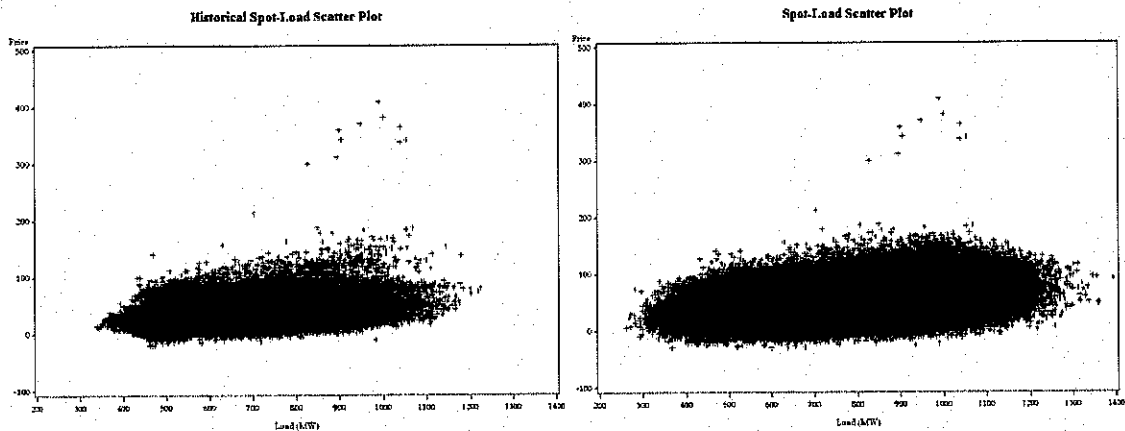
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1 Finally, historical data indicate that there is a significant correlation between the  
2 spot price of electricity and system load. The correlation is generally positive,  
3 though the exact relationship may vary widely by market. For this reason, it is  
4 important to verify that the relationship captured in the simulation output is  
5 consistent with the particular market being modeled. Figure 6-27 shows the price  
6 of Mid-C electricity plotted against the system load, with historical values shown  
7 in red and simulated values in blue. The left pane depicts historical prices only,  
8 and the right pane shows an overlay of historical and simulated prices. The  
9 scatter plot shows that the simulations accurately capture the relationship  
10 between Mid-C electricity prices and load.

11  
12 Figure 6-27

13 (Left) Historical Mid-C Spot Price vs. System Load.

14 (Right) Overlay of Historical (Red) and Simulated (Blue) Mid-C Spot Price  
15 vs. System Load



16

17

1       **Validation of Renewable Generation Levels**

2       Since PowerSimm simulates renewable (hydro and wind) generation along with  
3       weather, load, and prices, it is necessary to validate these simulated outputs as  
4       well. Figure 6-28 shows historical monthly capacity factors for Hydro Acquisition  
5       assets in black, and the mean, P5, and P95 simulation results from the PowerSimm  
6       hydro realizations. The red confidence interval largely encompasses the historical  
7       data, indicating good agreement between the simulation results and prior years'  
8       generation.

Figure 6-28

Historical (Black) and Simulated (Red) Confidence Intervals for Monthly Hydro Capacity

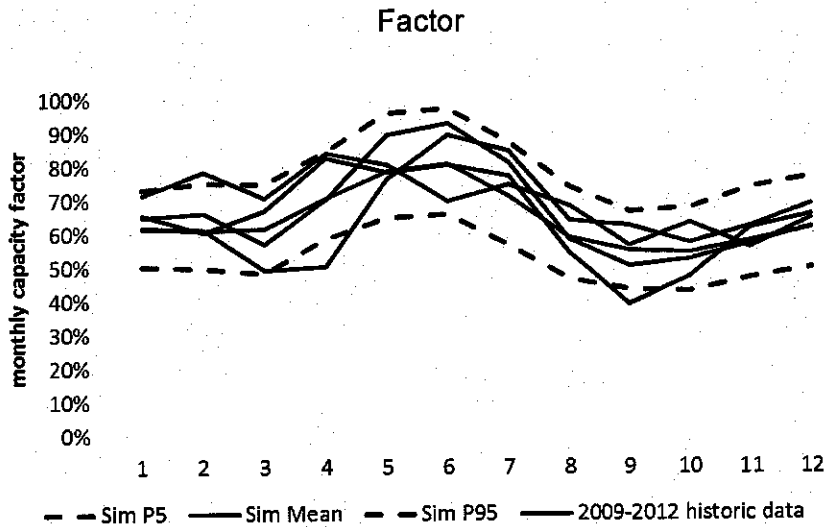
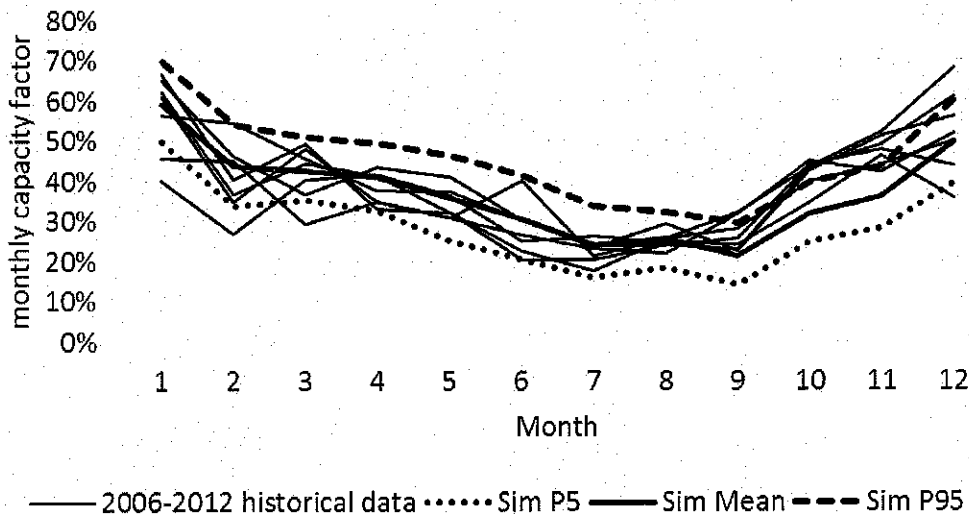


Figure 6-29 shows the equivalent monthly energy validation results for NorthWestern's wind asset generation. Historic monthly capacity factors are largely contained within the P5 and P95 confidence intervals (red) calculated by the PowerSimm simulation engine.

Figure 6-29

Historical (Black) and Simulated (Red) Monthly Wind Capacity Factors



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5 **Q. Ms. Maini stated that NorthWestern's analysis could be enhanced by**  
6 **using the hourly prices to calculate avoided costs instead of**  
7 **externally calculating the costs using monthly prices. Can**  
8 **NorthWestern use hourly prices?**

9 **A.** No. NorthWestern has been working with Ascend to enhance PowerSimm  
10 to allow the calculation of avoided costs to be performed entirely in  
11 PowerSimm. NorthWestern expects PowerSimm to have the ability to  
12 calculate avoided costs on an hourly basis by April.

13 **Q Please describe what NorthWestern has been doing to achieve the**  
14 **functionality that Ms. Maini said would enhance analysis?**

15 **A.** NorthWestern has been working with Ascend to perform the avoided cost  
16 calculations in PowerSimm. Each time changes are made to PowerSimm



1 in order to calculate the avoided cost, model simulations are performed  
2 and the results are validated. NorthWestern needs to be sure that the  
3 hourly calculation can be validated and is consistent with the calculation of  
4 avoided costs.

5 **Q. What inputs have changed since NorthWestern originally calculated**  
6 **the avoided for the Juhl projects in this docket?**

7 **A.** There would be three changes to the inputs. First, NorthWestern would  
8 update the market prices to reflect the current electric and natural gas  
9 prices. Second, the forecasts for the coal contracts would also be updated  
10 to reflect current expectations for the coal costs for Big Stone, Coyote, and  
11 Neal. Finally, the escalation of the commodities would be updated to use  
12 the 2017 Energy Administration Information ("EIA") Annual Energy  
13 Outlook ("AEO") instead of the 2016 EIA AEO.

14 **Q Has NorthWestern calculated the avoided cost using monthly prices**  
15 **with these changes?**

16 **A.** No.

17 **Q. Why not?**

18 **A.** NorthWestern's focus has been working with Ascend to calculate the  
19 avoided cost on an hourly time series in PowerSimm. Also, while  
20 NorthWestern has asserted that Juhl hasn't created a legally enforceable  
21 obligation ("LEO"), NorthWestern will need an order from the Commission  
22 to verify that an LEO hasn't been created and that updating the inputs to  
23 the model is appropriate.

1 **Q. Is NorthWestern willing to calculate avoided cost using monthly**  
2 **prices with these if the Commission requires it to do so?**

3 **A. Yes.**

4 **Q. Does this conclude your testimony?**

5 **A. Yes, it does.**