Exh. DCG-7C
Dockets UE-170033/UG-170034
Witness: David C. Gomez
CONFIDENTIAL VERSION

BEFORE THE WASHINGTON
UTILITIES AND TRANSPORTATION COMMISSION

WASHINGTON UTILITIES AND TRANSPORTATION COMMISSION, **Complainant,** **v.** **PUGET SOUND ENERGY,** **Respondent.**	**DOCKETS UE-170033 and UG-170034 (*Consolidated*)**

EXHIBIT TO
TESTIMONY OF

David C. Gomez

STAFF OF
WASHINGTON UTILITIES AND
TRANSPORTATION COMMISSION

PSE's Response to Staff DR No. 176, Attachments C through F, Vaisala Operational Reforecasts

June 30, 2017

CONFIDENTIAL PER PROTECTIVE ORDER – CONFIDENTIAL VERSION

Vaisala 3TIER Services Operational Reforecast

PROJECT

Wild Horse : Kittitas County, Washington

using 127 Vestas V80-1.8MW wind turbines at $67\,m$

FOR

Puget Sound Energy

DATE

8 October, 2016

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VAISALA

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Contents

1 INTRODUCTION

Vaisala has been retained by Puget Sound Energy to provide an operational reforecast for the Wild Horse wind farm, which is located in Kittitas County, Washington. This project is comprised of 127 Vestas V80-1.8MW turbines for a total project capacity of 228.6 MW.

The operational reforecast is an independent assessment of the future production of an operating project based on the historical production data and the climate. It considers the variability of the climate and the observed production data, including generation and availability data, as reported by the project. Vaisala offers two different Operational Reforecast products: a comprehensive analysis that quality controls the 10-minute SCADA data on a turbine specific basis, and a higher level analysis that relies solely on the monthly-mean operating reports of the project.

Since only monthly-mean production data are considered in this analysis, any potential turbine performance issues in the net metered generation data will be transferred into the operational reforecast process. In essence, it is a simulation of the future assuming the plant performs as it has in the past, making adjustments if it is known that operating conditions are expected to change from the past.

Assuming the plant continues to operate as it has in the past, the operational reforecast yields an estimated long-term potential net energy value of 589.5 GWh. Potential net energy refers to the energy the wind farm would produce if the total site availability is 100% and the curtailment loss is 0%. Total site availability includes machine availability, grid availability, and BOP availability.

For this analysis, results will be shown only in terms of potential net energy. The client will need to apply availability and curtailment losses to determine the expected net energy generation of the Wild Horse wind farm.

Project Size	228.6 MW
Number of Turbines	127
Turbine Type	Vestas V80-1.8MW
Hub Height	67 m
Potential Net Energy Generation	589.5 GWh
Net Energy Generation	–
Aggregate Loss Factor	100.0 %
Standard Error of 20-year Estimate	3.7 %

Table 1: Project Overview

2 PROJECT DESCRIPTION

The Wild Horse project is located in Kittitas County, Washington. The project is comprised of 127 Vestas V80-1.8MW turbines at $67\,m$ hub height for a total project capacity of $228.6\,MW$. The wind farm has been operating since January 2007.

The location of the Wild Horse wind farm is shown below in Figure 1.

Figure 1: Map of the Wild Horse project region.

3 METHODOLOGY

To estimate the future net production values, the following two input data sources are utilized: historic production data, including generation and availability data, and 36 years of Numerical Weather Prediction (NWP) model data. Statistical corrections are applied to the normalized production data, based on a simulated climate index, in order to generate a long-term time series of estimated production values. The historic long-term production provides the basis for estimating future production. An outline of the basic approach follows:

- Production, availability and curtailment data are reviewed for quality and usefulness.
- Normalized production data, i.e. potential net energy data, are created by normalizing the net meter generation data to 100% site availability.
- Long-term climate variability is analyzed to determine an appropriate start date for each of 3 independent reanalysis data sets, assuming each has long-term characteristics consistent with the region.
- Utilizing the Weather Research and Forecasting Model (WRF), reanalysis data are downscaled to a $15\,km$ horizontal resolution.
- Time series data of air density and hub height wind speed are extracted from the WRF data set at a centrally located grid point within the project.
- The time series of hub height wind speeds are corrected to on-site conditions using on-site wind resource measurement data, if available.
- An air density corrected project power curve is used to convert the individual reanalysis-based time series to power. Power values are further scaled to expected long-term generation before aggregating by month. These monthly simulated production time series become climate power indices.
- Monthly observed normalized production data are adjusted for the long-term by applying the ratio of the long-term mean monthly profile derived from the 36 years of simulated data against the monthly profile derived over the short-term operational production period.
- The independent long-term estimates are then weighted by respective coefficients of determination; comparing monthly observed production against the simulated power indices.
- Historic trends of availability and curtailment data are analyzed to determine expected future trends. Turbine availability and curtailments are normalized out of the data set when applying the long-term correction factor. The expected future availability and curtailment are added back as loss factors when computing the reforecasted long-term mean net energy estimate.
- Uncertainty analysis is performed to develop the probability of exceedance values (P75, P90, etc.) of expected net energy generation.

4 DATA VERIFICATION

4.1 On-site Resource Data

For operational projects where stand-alone met towers are waked by operating turbines, a broadly applicable view of the site's wind resource can be determined from the nacelle anemometers in the project. A project average time series of wind speed is determined by averaging the 10-min wind speed readings from every turbine in the project. The averaged time series is interpreted as a point reading at the arithmetic average of the latitude and longitude coordinates of all turbines. The nacelle wind resource time series is then used to validate and correct the raw NWP model data using a process of Model Output Statistics (MOS) correction. MOS uses regression equations to remove bias and adjust the variance of the raw model output to improve the match with the provided observational data. Nacelle wind resource measurement data were provided by the client during the period February 2014 through May 2016.

4.2 Operating Results Summary

A summary of historical park performance over the period January 2007 through June 2016 was provided by the client. The data included monthly generation data and various availability statistics. Specifically relevant for this analysis are the net generation, turbine and grid availability data, and curtailment values. The total site availability factor is calculated inclusive of the following: machine availability, balance of plant availability, and grid availability. Project curtailment is computed as the sum of the environmental curtailment and grid curtailment. Potential net energy generation is then derived by dividing the net metered generation data by the total site availability factor and then adding the total project curtailment. The result is a time series representative of the project with 100% availability and no curtailment.

Project generation data, turbine and grid availability data, curtailment data, and potential net generation data utilized by Vaisala are shown below in Table 2. Newly constructed wind farms typically have a break-in period during which availability, and potentially turbine performance, is lower than what would typically be seen over the long-term. This period often takes place during the first year of operations. When multiple years of operating data are provided, Vaisala identifies this initial stabilization period and removes it from the analysis, so that these data do not bias the long-term adjustment. No explicit stabilization period is visible in the early record. Six months of data have not been considered in the analysis because of low grid availability.

Operational generation data over the period January 2007 through December 2015 are used in the analysis. Months with relatively low total site availability values are not incorporated into the analysis, and so a potential net generation value is not computed for these months.

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2007-Jan	46268	97.3	0.0	47532
2007-Feb	36811	97.6	0.0	37716
2007-Mar	61008	97.4	0.0	62637
2007-Apr	48059	95.8	0.0	50176
2007-May	48639	97.0	0.0	50162
2007-Jun	60992	98.2	0.0	62129
2007-Jul	48299	98.1	0.0	49234
2007-Aug	52559	97.6	0.0	53868
2007-Sep	54682	98.6	0.0	55464
2007-Oct	51187	98.3	0.0	52072
2007-Nov	41988	98.7	0.0	42545
2007-Dec	62360	98.2	0.0	63503
2008-Jan	57896	97.4	0.0	59441
2008-Feb	58982	97.4	0.0	60556
2008-Mar	59883	97.4	0.0	61482
2008-Apr	69554	97.1	0.0	71631
2008-May	62610	97.1	0.0	64480
2008-Jun	63021	96.8	0.0	65104
2008-Jul	66150	96.5	0.0	68549
2008-Aug	58144	97.0	0.0	59942
2008-Sep	33447	97.2	0.0	34410
2008-Oct	46831	97.5	0.0	48032
2008-Nov	50834	98.4	0.0	51661
2008-Dec	54746	96.3	0.0	56849
2009-Jan	58027	96.2	0.0	60319
2009-Feb	30698	98.1	0.0	31293
2009-Mar	63934	98.2	0.0	65106
2009-Apr	57766	97.7	0.0	59126
2009-May	60833	98.2	0.0	61948
2009-Jun	52017	98.5	0.0	52814
2009-Jul	35067	96.9	0.0	36189
2009-Aug	40758	97.2	0.0	41932
2009-Sep	30661	96.2	0.0	31879
2009-Oct	45117	96.2	0.0	46899
2009-Nov	49505	94.6	0.0	52331
2009-Dec	25790	97.0	0.0	26588
2010-Jan	26377	97.6	0.0	27026
2010-Feb	15046	98.8	0.0	15229
2010-Mar	46583	98.7	0.0	47197
2010-Apr	75169	98.0	0.0	76742
2010-May	53161	97.8	0.0	54335
2010-Jun	49428	98.0	0.0	50457
2010-Jul	43286	97.1	0.0	44592
2010-Aug	52841	97.6	0.0	54146
2010-Sep	42987	97.9	0.0	43932
2010-Oct	35680	98.0	0.0	36393
2010-Nov	45267	96.7	0.0	46826
2010-Dec	45993	98.1	0.0	46874

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Wild Horse. (continued on next page)

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UE-170033 and UG-170034

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2011-Jan	59853	97.6	0.0	61312
2011-Feb	47954	97.7	0.0	49078
2011-Mar	51723	97.7	0.0	52933
2011-Apr	75048	98.2	0.0	76455
2011-May	55318	96.7	0.0	57230
2011-Jun	68251	96.4	0.0	70769
2011-Jul	57032	97.9	0.0	58262
2011-Aug	44416	94.8	0.0	46865
2011-Sep	39571	97.1	0.0	40755
2011-Oct	51882	98.3	0.0	52773
2011-Nov	45587	98.3	0.0	46389
2011-Dec	38941	98.6	0.0	39510
2012-Jan	61215	98.5	0.0	62179
2012-Feb	49064	98.5	0.0	49826
2012-Mar	71001	97.6	0.0	72717
2012-Apr	51978	98.5	0.0	52759
2012-May	62931	94.3	0.0	66753
2012-Jun	60068	94.0	0.0	63920
2012-Jul	26974	97.6	0.0	27627
2012-Aug	41722	97.6	0.0	42755
2012-Sep	30965	98.0	0.0	31607
2012-Oct	46513	98.2	0.0	47351
2012-Nov	35091	98.8	0.0	35503
2012-Dec	48176	98.4	0.0	48939
2013-Jan	46690	98.7	0.0	47300
2013-Feb	50524	98.9	0.0	51076
2013-Mar	57676	98.1	0.0	58793
2013-Apr	80559	98.2	0.0	82044
2013-May	36878	98.1	0.0	37586
2013-Jun	46008	97.4	0.0	47256
2013-Jul	44073	96.9	0.0	45504
2013-Aug	26334	99.2	0.0	26538
2013-Sep	41819	97.5	0.0	42904
2013-Oct	33189	97.9	0.0	33894
2013-Nov	40475	95.0	0.0	42626
2013-Dec	69832	97.4	0.0	71686
2014-Jan	26680	73.7	0.0	–
2014-Feb	39748	70.2	0.0	–
2014-Mar	62147	96.5	0.0	64408
2014-Apr	68119	97.1	0.0	70181
2014-May	50936	96.3	0.0	52920
2014-Jun	62099	97.0	0.0	64032
2014-Jul	27873	70.9	0.0	–
2014-Aug	38336	91.3	0.0	41995
2014-Sep	43113	94.2	0.0	45751
2014-Oct	40957	95.6	0.0	42844
2014-Nov	62300	98.0	0.0	63597
2014-Dec	44372	98.9	0.0	44856

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Wild Horse. (continued on next page)

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Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2015-Jan	27405	75.3	0.0	–
2015-Feb	42773	73.7	0.0	–
2015-Mar	48093	97.0	0.0	49574
2015-Apr	53418	97.7	0.0	54680
2015-May	27792	97.7	0.0	28440
2015-Jun	43884	98.1	0.0	44725
2015-Jul	55498	71.1	0.0	–
2015-Aug	49822	90.4	0.0	55126
2015-Sep	47777	96.7	0.0	49409
2015-Oct	44970	99.0	0.0	45433
2015-Nov	48370	99.1	0.0	48834
2015-Dec	43551	98.6	0.0	44173
2016-Jan	34758	98.9	0.0	35137
2016-Feb	46667	99.3	0.0	46987
2016-Mar	65740	98.3	0.0	66870
2016-Apr	43345	95.7	0.0	45281
2016-May	61762	98.9	0.0	62462
2016-Jun	56417	98.1	0.0	57504

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Wild Horse. Months with relatively low total site availability are not incorporated into the analysis and potential net generation is not computed. For these months the potential net generation data are shown as missing values.

5 CLIMATE REVIEW

In order to place the production data into the climatological context, Vaisala performed a review of several long-term climate data sources. Vaisala primarily relies on global reanalysis data sets for understanding the long-term climate variability. The reanalysis data sets are derived from thousands of global observations, including ground-based weather stations, ocean surface buoys, satellites, and weather balloons. Vaisala uses three major reanalysis data sets that are each produced independently by different institutions. The data sets reviewed for this analysis are shown below in Table 3.

Data Set	Explained Variance (R^2)	Start Year	End Year
ECMWF ERA-I	0.88	1980	2015
MERRA	0.91	1981	2015
NCEP/NCAR	0.86	1988	2015

Table 3: Monthly explained variance with production data and reference period utilized for each reanalysis data set.

Vaisala considers each reanalysis data set when assessing the long-term climate and results using each data set are weighted by their correlation to observed project performance. Figure 2 shows the annual-mean wind speed values extracted from each reanalysis data set across the period of record. The reference period for each data set is optimized by taking into consideration how representative the entire record is of the recent climate at the site. The utilized reference period and correlation with observed project performance for each reanalysis data set is provided in Table 3.

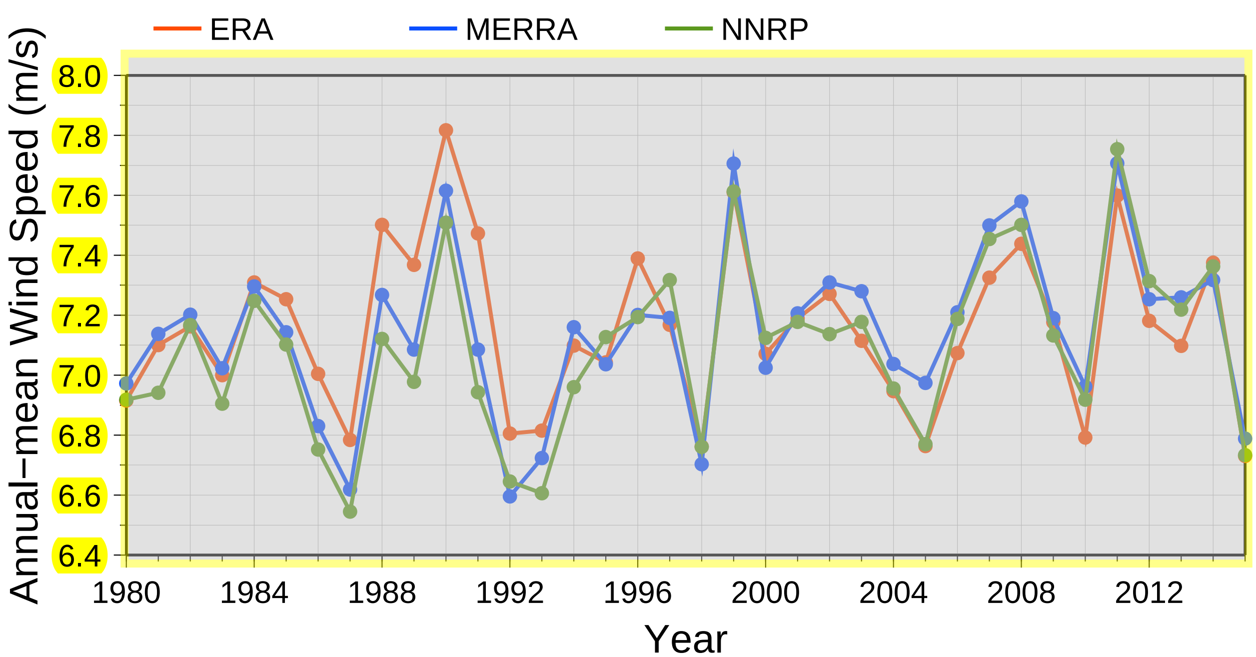

Figure 2: Annual-mean time series plot of considered reanalysis data sets.

6 REFORECAST RESULTS

The 113 months of utilized normalized observed production are independently indexed against the 36 years of simulated power from each reanalysis data set. Concurrent months are binned by calendar month to arrive at a short-term monthly average for both the normalized production data and the three sets of simulated data. The ratio of monthly long-term energy over the short-term (observed) energy from a reanalysis data set is used as an adjustment factor for each mean calendar month for the observed, normalized production data and then annualized for a long-term annual-mean generation. The three independent long-term estimates are combined by weighting each value against the coefficient of determination between the 113 months of observed, normalized production data, and respective reanalysis power data set.

This analysis is presenting results only in terms of the potential net energy generation, and thus is not considering the availability or curtailment loss factors. The long-term mean potential net energy generation estimate for the Wild Horse wind farm is estimated to be 589.5 GWh.

	Wildhorse
Potential Net Energy Generation (GWh)	589.5
Nameplate Capacity (MW)	228.6
Loss Factors	
Total Site Availability	100.0 %
Curtailment	100.0 %
Aggregate Loss Factor	100.0 %
Net Energy Generation (GWh)	–

Table 4: Net energy generation results.

6.1 Long-term Variability

The long-term variability of the simulated potential net energy is shown within this section. Figure 3 shows the long-term mean seasonality via a box-and-whisker plot of the monthly-mean potential net energy data. The shaded boxes are bounded by the P25 and P75 values for each month, and the whiskers denote the minimum and maximum values. The median for each month is denote by the black line within the shaded box. Table 5 shows the numerical values plotted within Figure 3.

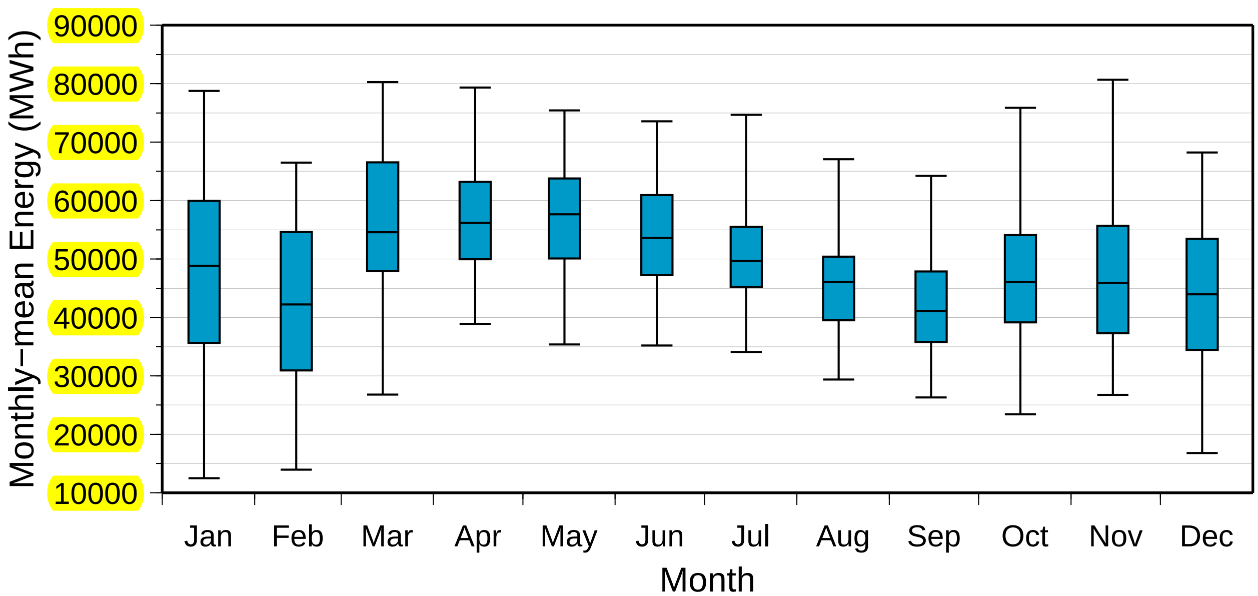

Figure 3: Box-and-whisker plot of monthly-mean simulated potential net energy. This figure displays the expected variability of the monthly-mean data. Median values are denoted by the solid line within each shaded box. Upper and lower boundaries of the shaded box correspond to the 75% and 25% quartiles, while the whiskers denote the maximum and minimum monthly-mean potential net energy values.

	Minimum	P75	Median	P25	Maximum
Jan	12475.3	35643.5	48852.3	59953.9	78752.1
Feb	13957.8	30928.8	42230.1	54605.4	66507.3
Mar	26810.1	47917.7	54574.0	66535.5	80281.2
Apr	38879.7	49961.5	56171.0	63208.9	79322.1
May	35388.1	50098.9	57647.3	63794.2	75400.2
Jun	35205.5	47222.6	53579.2	60927.5	73561.7
Jul	34077.7	45265.5	49685.6	55512.9	74669.9
Aug	29358.5	39524.2	46100.9	50400.1	67083.8
Sep	26326.3	35756.2	41057.5	47886.1	64206.3
Oct	23440.5	39150.3	46087.4	54100.3	75870.0
Nov	26740.9	37296.8	45895.0	55710.9	80661.2
Dec	16807.6	34452.3	43961.7	53473.4	68226.8

Table 5: Minimum, P75, median, P25, and maximum potential net energy values (MWh) for each calendar month.

6.2 Seasonal Profile

The operational reforecast of the Wild Horse annual profile is detailed in this section. Because the reforecast methodology is indexed against individual calendar months, the operational reforecast can illuminate the project's annual profile. Table 6 shows the annual profile in terms of the potential net energy for Wild Horse.

	Potential Net Energy Generation (MWh)	% of Annual Production
Jan	47183.0	8.0 %
Feb	42401.8	7.2 %
Mar	55936.1	9.5 %
Apr	56689.9	9.6 %
May	56383.9	9.6 %
Jun	54195.5	9.2 %
Jul	50104.6	8.5 %
Aug	45829.3	7.8 %
Sep	41911.8	7.1 %
Oct	47907.9	8.1 %
Nov	46605.4	7.9 %
Dec	44359.3	7.5 %

Table 6: Long-term monthly-mean estimates of potential net energy (MWh) and % of annual production.

7 UNCERTAINTY ANALYSIS

The following types of uncertainty are analyzed and incorporated into the analysis: production normalization, climate variability, and model uncertainty.

7.1 Production Normalization Uncertainty

The production normalization uncertainty covers the uncertainty associated with adjusting the net production data for plant availability and curtailment. The long-term analysis is based on the potential power production data, i.e. the production data normalized by the plant availability and curtailment. The uncertainty of the potential power production data is directly related to the plant availability and curtailment, since the potential production values are unknown during periods when the wind plant was not available for producing power. Thus, lower plant availability leads to higher production data uncertainty. In addition, this also covers the uncertainties associated with future changes to turbine efficiencies and availabilities.

7.2 Climate Variability Uncertainty

The climate variability includes two components: temporal variation and future changes in climate.

Temporal uncertainty is based on the inter-annual variability (standard deviation) of the annual-mean energy-based NWP time series corresponding long-term means. It is assumed that each year of the annual-mean potential power time series is independent from the next.

Future changes in climate includes the possibility of future climate varying from the historic climate. Climate change is associated with potential shifts in the climate over the next twenty years. Change in the climate may have positive or negative impacts to the production data. The magnitude of climate change uncertainty is based on how the most recent five years of data compares to the prior long-term record. Based on these factors, a climate change uncertainty value is assessed.

7.3 Model Uncertainty

The model uncertainty describes the uncertainty associated with estimating the long-term MOS-corrected potential net generation time series. The model uncertainty is derived from four components: the quality of the production data, the period of record of the production data, the error of the MOS-corrected data during the production period, and the sensitivity of the MOS calculation.

The uncertainty associated with the quality of the production data is a function of the averaging period of the generation data incorporated into the analysis. Generally speaking, using data with a longer averaging period will increase this uncertainty, e.g. monthly generation data will have higher uncertainty than 10-minute SCADA data.

Based on prior split-sample validation analyses performed by Vaisala, it is known that the uncertainty of the MOS algorithm decreases as the period of the training data increases. Therefore, the training period component of the model uncertainty is determined by the length of record of the production data. To understand the error of the MOS calculation, the root mean squared error (RMSE) is computed between the monthly-mean MOS-corrected data and the observed production data over concurrent time periods. And lastly, the sensitivity component of model uncertainty is derived by computing multiple iterations of MOS, using perturbed input data, and computing the standard deviation of error across the resulting time series. The four components of model uncertainty are statistically aggregated together yielding the total model uncertainty for a 20-year return period.

7.4 Pooled Uncertainty

A quadratic sum is computed of the individual uncertainty values described above to derive the total uncertainty value for the Wild Horse Wind Farm. Table 7 summarizes these calculations.

Project Uncertainty	1-year	5-year	10-year	20-year
Production Normalization	0.7	0.7	0.7	0.7
Climate Variability	10.3	4.7	3.4	2.5
Model	2.7	2.7	2.7	2.7
Total Uncertainty	**10.7**	**5.5**	**4.4**	**3.7**

Table 7: Standard error of future production estimate (%) at Wild Horse.

7.5 Probability of Exceedances

Based on the estimated total project uncertainties, Table 8 presents the probability of exceedance levels associated with the P50 project estimate for the 1-year, 5-year, 10-year, and 20-year cases.

P-level	1-year	5-year	10-year	20-year
P50	589.5	589.5	589.5	589.5
P75	547.1	567.8	572.1	574.6
P90	509.0	548.3	556.3	561.3
P95	486.1	536.7	546.9	553.2
P99	443.3	514.8	529.3	538.2

Table 8: Probability of exceedance values (GWh) at Wild Horse.

8 CONCLUSION

Vaisala has conducted an operational reforecast of the Wild Horse wind farm within Kittitas County, Washington. The reforecast is based on the client provided historical monthly summaries of production, availability, and curtailment data in combination with Vaisala's long-term NWP model data. A power index derived from three NWP model simulations driven by independent reanalysis data sets was utilized to adjust the normalized production data for the long-term. The expected long-term mean potential net annual energy production value, i.e. the net P50, is estimated to be 589.5 GWh. Using the uncertainty assessment results, probability of exceedance values were calculated. The 20-year P90 potential net energy value for the Wild Horse project is 561.3 GWh.

Vaisala 3TIER Services Operational Reforecast

PROJECT

Whiskey Ridge : Kittitas County, Washington

using 22 Vestas V80-2.0MW wind turbines at $67\,m$

FOR

Puget Sound Energy

DATE

7 October, 2016

CONTACT

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Contents

1 INTRODUCTION

Vaisala has been retained by Puget Sound Energy to provide an operational reforecast for the Whiskey Ridge wind farm, which is located in Kittitas County, Washington. This project is comprised of 22 Vestas V80-2.0MW turbines for a total project capacity of $44.0\,MW$.

The operational reforecast is an independent assessment of the future production of an operating project based on the historical production data and the climate. It considers the variability of the climate and the observed production data, including generation and availability data, as reported by the project. Vaisala offers two different Operational Reforecast products: a comprehensive analysis that quality controls the 10-minute SCADA data on a turbine specific basis, and a higher level analysis that relies solely on the monthly-mean operating reports of the project.

Since only monthly-mean production data are considered in this analysis, any potential turbine performance issues in the net metered generation data will be transferred into the operational reforecast process. In essence, it is a simulation of the future assuming the plant performs as it has in the past, making adjustments if it is known that operating conditions are expected to change from the past.

Assuming the plant continues to operate as it has in the past, the operational reforecast yields an estimated long-term potential net energy value of 90.7 GWh. Potential net energy refers to the energy the wind farm would produce if the total site availability is 100% and the curtailment loss is 0%. Total site availability includes machine availability, grid availability, and BOP availability.

For this analysis, results will be shown only in terms of potential net energy. The client will need to apply availability and curtailment losses to determine the expected net energy generation of the Whiskey Ridge wind farm.

Project Size	$44.0\,MW$
Number of Turbines	22
Turbine Type	Vestas V80-2.0MW
Hub Height	$67\,m$
Potential Net Energy Generation	90.7 GWh
Net Energy Generation	–
Aggregate Loss Factor	100.0 %
Standard Error of 20-year Estimate	3.9 %

Table 1: Project Overview

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UE-170033 and UG-170034

2 PROJECT DESCRIPTION

The Whiskey Ridge project is located in Kittitas County, Washington. The project is comprised of 22 Vestas V80-2.0MW turbines at $67\,m$ hub height for a total project capacity of $44.0\,MW$. The wind farm has been operating since January 2010.

The location of the Whiskey Ridge wind farm is shown below in Figure 1.

Figure 1: Map of the Whiskey Ridge project region.

3 METHODOLOGY

To estimate the future net production values, the following two input data sources are utilized: historic production data, including generation and availability data, and 36 years of Numerical Weather Prediction (NWP) model data. Statistical corrections are applied to the normalized production data, based on a simulated climate index, in order to generate a long-term time series of estimated production values. The historic long-term production provides the basis for estimating future production. An outline of the basic approach follows:

- Production, availability and curtailment data are reviewed for quality and usefulness.
- Normalized production data, i.e. potential net energy data, are created by normalizing the net meter generation data to 100% site availability.
- Long-term climate variability is analyzed to determine an appropriate start date for each of 3 independent reanalysis data sets, assuming each has long-term characteristics consistent with the region.
- Utilizing the Weather Research and Forecasting Model (WRF), reanalysis data are downscaled to a $15\,km$ horizontal resolution.
- Time series data of air density and hub height wind speed are extracted from the WRF data set at a centrally located grid point within the project.
- The time series of hub height wind speeds are corrected to on-site conditions using on-site wind resource measurement data, if available.
- An air density corrected project power curve is used to convert the individual reanalysis-based time series to power. Power values are further scaled to expected long-term generation before aggregating by month. These monthly simulated production time series become climate power indices.
- Monthly observed normalized production data are adjusted for the long-term by applying the ratio of the long-term mean monthly profile derived from the 36 years of simulated data against the monthly profile derived over the short-term operational production period.
- The independent long-term estimates are then weighted by respective coefficients of determination; comparing monthly observed production against the simulated power indices.
- Historic trends of availability and curtailment data are analyzed to determine expected future trends. Turbine availability and curtailments are normalized out of the data set when applying the long-term correction factor. The expected future availability and curtailment are added back as loss factors when computing the reforecasted long-term mean net energy estimate.
- Uncertainty analysis is performed to develop the probability of exceedance values (P75, P90, etc.) of expected net energy generation.

4 DATA VERIFICATION

4.1 On-site Resource Data

For operational projects where stand-alone met towers are waked by operating turbines, a broadly applicable view of the site's wind resource can be determined from the nacelle anemometers in the project. A project average time series of wind speed is determined by averaging the 10-min wind speed readings from every turbine in the project. The averaged time series is interpreted as a point reading at the arithmetic average of the latitude and longitude coordinates of all turbines. The nacelle wind resource time series is then used to validate and correct the raw NWP model data using a process of Model Output Statistics (MOS) correction. MOS uses regression equations to remove bias and adjust the variance of the raw model output to improve the match with the provided observational data. Nacelle wind resource measurement data were provided by the client during the period January 2011 through September 2014.

4.2 Operating Results Summary

A summary of historical park performance over the period January 2010 through June 2016 was provided by the client. The data included monthly generation data and various availability statistics. Specifically relevant for this analysis are the net generation, turbine and grid availability data, and curtailment values. The total site availability factor is calculated inclusive of the following: machine availability, balance of plant availability, and grid availability. Project curtailment is computed as the sum of the environmental curtailment and grid curtailment. Potential net energy generation is then derived by dividing the net metered generation data by the total site availability factor and then adding the total project curtailment. The result is a time series representative of the project with 100% availability and no curtailment.

Project generation data, turbine and grid availability data, curtailment data, and potential net generation data utilized by Vaisala are shown below in Table 2. Newly constructed wind farms typically have a break-in period during which availability, and potentially turbine performance, is lower than what would typically be seen over the long-term. This period often takes place during the first year of operations. When multiple years of operating data are provided, Vaisala identifies this initial stabilization period and removes it from the analysis, so that these data do not bias the long-term adjustment. No explicit stabilization period is visible in the early record. Eight months of data have not been considered in the analysis because of low grid availability.

Operational generation data over the period January 2010 through June 2016 are used in the analysis. Months with relatively low total site availability values are not incorporated into the analysis, and so a potential net generation value is not computed for these months.

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2010-Jan	4440	96.7	0.0	4593
2010-Feb	2667	97.4	0.0	2740
2010-Mar	5372	99.1	0.0	5420
2010-Apr	12177	98.3	0.0	12383
2010-May	8159	98.1	0.0	8315
2010-Jun	6515	98.7	0.0	6602
2010-Jul	6492	98.7	0.0	6581
2010-Aug	7459	99.3	0.0	7511
2010-Sep	6164	97.1	0.0	6347
2010-Oct	5240	95.9	0.0	5467
2010-Nov	6883	96.0	0.0	7170
2010-Dec	7358	97.2	0.0	7569
2011-Jan	10428	96.7	0.0	10780
2011-Feb	7758	96.3	0.0	8056
2011-Mar	8279	96.3	0.0	8600
2011-Apr	12080	98.3	0.0	12285
2011-May	8859	98.2	0.0	9022
2011-Jun	9933	99.0	0.0	10037
2011-Jul	7559	98.7	0.0	7659
2011-Aug	5380	99.3	0.0	5417
2011-Sep	6091	97.8	0.0	6231
2011-Oct	8042	96.9	0.0	8303
2011-Nov	6656	97.8	0.0	6804
2011-Dec	6369	98.9	0.0	6441
2012-Jan	9785	98.2	0.0	9966
2012-Feb	8219	97.8	0.0	8402
2012-Mar	11929	98.2	0.0	12148
2012-Apr	8786	98.8	0.0	8891
2012-May	10153	94.4	0.0	10755
2012-Jun	10048	97.3	0.0	10331
2012-Jul	5006	99.1	0.0	5054
2012-Aug	5244	98.9	0.0	5301
2012-Sep	4336	98.5	0.0	4404
2012-Oct	7710	98.5	0.0	7825
2012-Nov	6153	98.5	0.0	6250
2012-Dec	6834	96.4	0.0	7087
2013-Jan	8077	97.4	0.0	8290
2013-Feb	7372	97.0	0.0	7600
2013-Mar	9424	97.2	0.0	9691
2013-Apr	12737	98.6	0.0	12913
2013-May	5363	98.9	0.0	5423
2013-Jun	6533	96.7	0.0	6759
2013-Jul	5870	97.3	0.0	6033
2013-Aug	3348	96.1	0.0	3485
2013-Sep	6461	98.1	0.0	6586
2013-Oct	5493	98.1	0.0	5598
2013-Nov	6966	92.9	0.0	7496
2013-Dec	11352	91.9	0.0	12358

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Whiskey Ridge. (continued on next page)

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2014-Jan	4314	70.8	0.0	–
2014-Feb	7229	71.6	0.0	–
2014-Mar	9745	94.9	0.0	10273
2014-Apr	10610	94.3	0.0	11250
2014-May	7030	99.0	0.0	7102
2014-Jun	8591	94.3	0.0	9106
2014-Jul	3176	67.7	0.0	–
2014-Aug	5022	86.7	0.0	–
2014-Sep	6860	94.9	0.0	7228
2014-Oct	6285	94.2	0.0	6672
2014-Nov	9507	94.5	0.0	10060
2014-Dec	6764	98.2	0.0	6891
2015-Jan	4490	72.5	0.0	–
2015-Feb	5959	71.5	0.0	–
2015-Mar	7072	91.4	0.0	7739
2015-Apr	8750	99.0	0.0	8839
2015-May	4455	99.5	0.0	4476
2015-Jun	6154	98.0	0.0	6280
2015-Jul	7539	73.4	0.0	–
2015-Aug	7067	87.9	0.0	–
2015-Sep	7520	96.6	0.0	7782
2015-Oct	5740	91.8	0.0	6251
2015-Nov	7135	95.8	0.0	7449
2015-Dec	6504	98.8	0.0	6584
2016-Jan	6037	99.4	0.0	6073
2016-Feb	7736	96.9	0.0	7988
2016-Mar	10780	97.7	0.0	11036
2016-Apr	5966	94.8	0.0	6291
2016-May	9763	98.4	0.0	9921
2016-Jun	8418	95.3	0.0	8835

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Whiskey Ridge. Months with relatively low total site availability are not incorporated into the analysis and potential net generation is not computed. For these months the potential net generation data are shown as missing values.

5 CLIMATE REVIEW

In order to place the production data into the climatological context, Vaisala performed a review of several long-term climate data sources. Vaisala primarily relies on global reanalysis data sets for understanding the long-term climate variability. The reanalysis data sets are derived from thousands of global observations, including ground-based weather stations, ocean surface buoys, satellites, and weather balloons. Vaisala uses three major reanalysis data sets that are each produced independently by different institutions. The data sets reviewed for this analysis are shown below in Table 3.

Data Set	Explained Variance (R^2)	Start Year	End Year
ECMWF ERA-I	0.87	1980	2015
MERRA	0.82	1980	2015
NCEP/NCAR	0.75	1988	2015

Table 3: Monthly explained variance with production data and reference period utilized for each reanalysis data set.

Vaisala considers each reanalysis data set when assessing the long-term climate and results using each data set are weighted by their correlation to observed project performance. Figure 2 shows the annual-mean wind speed values extracted from each reanalysis data set across the period of record. The reference period for each data set is optimized by taking into consideration how representative the entire record is of the recent climate at the site. The utilized reference period and correlation with observed project performance for each reanalysis data set is provided in Table 3.

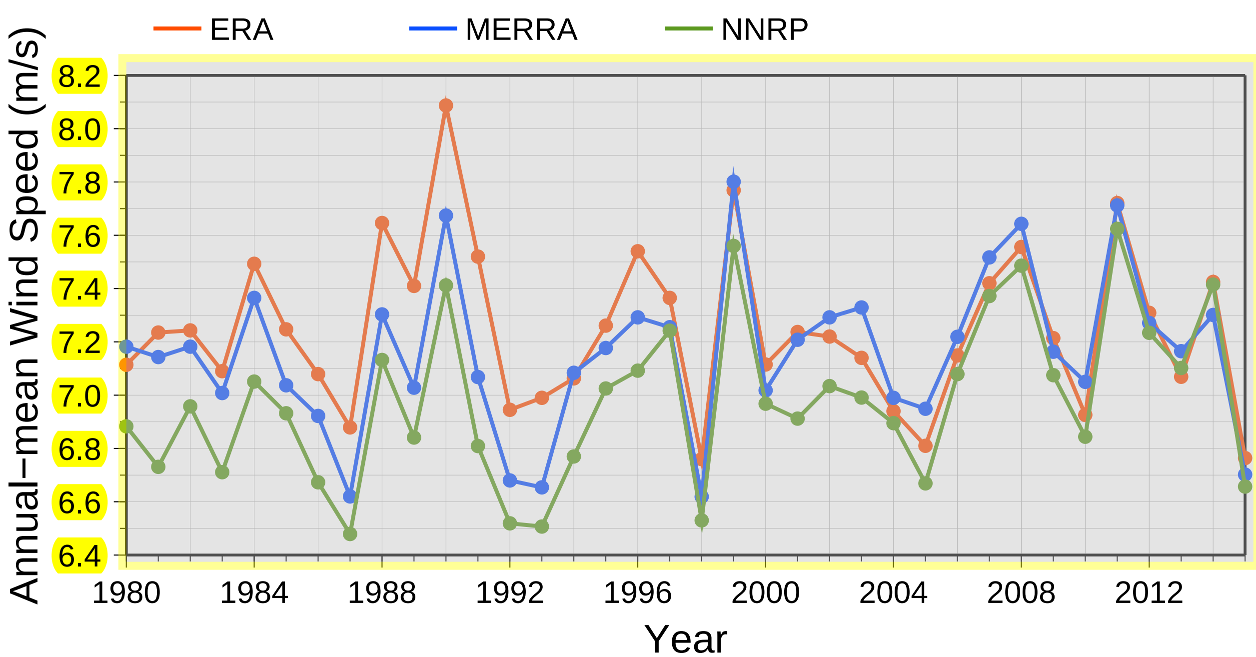

Figure 2: Annual-mean time series plot of considered reanalysis data sets.

6 REFORECAST RESULTS

The 78 months of utilized normalized observed production are independently indexed against the 36 years of simulated power from each reanalysis data set. Concurrent months are binned by calendar month to arrive at a short-term monthly average for both the normalized production data and the three sets of simulated data. The ratio of monthly long-term energy over the short-term (observed) energy from a reanalysis data set is used as an adjustment factor for each mean calendar month for the observed, normalized production data and then annualized for a long-term annual-mean generation. The three independent long-term estimates are combined by weighting each value against the coefficient of determination between the 78 months of observed, normalized production data, and respective reanalysis power data set.

This analysis is presenting results only in terms of the potential net energy generation, and thus is not considering the availability or curtailment loss factors. The long-term mean potential net energy generation estimate for the Whiskey Ridge wind farm is estimated to be 90.7 GWh.

	Whiskeyridge
Potential Net Energy Generation (GWh)	90.7
Nameplate Capacity (MW)	44.0
Loss Factors	
Total Site Availability	100.0 %
Curtailment	100.0 %
Aggregate Loss Factor	100.0 %
Net Energy Generation (GWh)	–

Table 4: Net energy generation results.

6.1 Long-term Variability

The long-term variability of the simulated potential net energy is shown within this section. Figure 3 shows the long-term mean seasonality via a box-and-whisker plot of the monthly-mean potential net energy data. The shaded boxes are bounded by the P25 and P75 values for each month, and the whiskers denote the minimum and maximum values. The median for each month is denote by the black line within the shaded box. Table 5 shows the numerical values plotted within Figure 3.

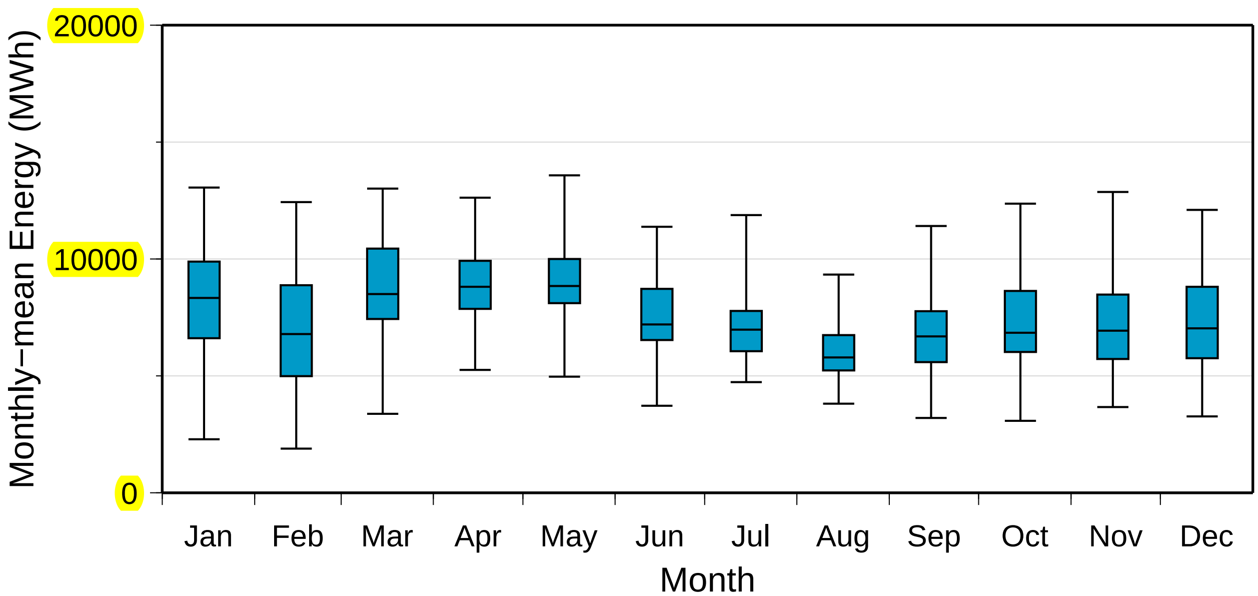

Figure 3: Box-and-whisker plot of monthly-mean simulated potential net energy. This figure displays the expected variability of the monthly-mean data. Median values are denoted by the solid line within each shaded box. Upper and lower boundaries of the shaded box correspond to the 75% and 25% quartiles, while the whiskers denote the maximum and minimum monthly-mean potential net energy values.

	Minimum	P75	Median	P25	Maximum
Jan	2289.8	6606.2	8335.5	9890.4	13058.2
Feb	1886.6	4992.7	6785.6	8877.3	12434.5
Mar	3381.9	7431.2	8503.0	10446.7	13012.3
Apr	5253.1	7866.6	8809.9	9920.3	12627.4
May	4969.3	8110.9	8840.8	10002.3	13576.4
Jun	3717.7	6535.8	7201.2	8718.4	11373.4
Jul	4738.2	6058.4	6978.9	7781.4	11873.7
Aug	3807.8	5238.5	5793.6	6739.0	9327.8
Sep	3198.4	5589.5	6692.8	7765.7	11416.1
Oct	3074.3	6026.9	6846.2	8628.4	12371.1
Nov	3670.5	5717.7	6932.5	8474.4	12862.7
Dec	3265.4	5759.2	7031.6	8806.1	12096.7

Table 5: Minimum, P75, median, P25, and maximum potential net energy values (MWh) for each calendar month.

6.2 Seasonal Profile

The operational reforecast of the Whiskey Ridge annual profile is detailed in this section. Because the reforecast methodology is indexed against individual calendar months, the operational reforecast can illuminate the project's annual profile. Table 6 shows the annual profile in terms of the potential net energy for Whiskey Ridge.

	Potential Net Energy Generation (MWh)	% of Annual Production
Jan	8061.1	8.9 %
Feb	6973.8	7.7 %
Mar	8851.4	9.8 %
Apr	8926.4	9.8 %
May	8842.0	9.8 %
Jun	7534.9	8.3 %
Jul	7048.3	7.8 %
Aug	6037.6	6.7 %
Sep	6671.7	7.4 %
Oct	7341.1	8.1 %
Nov	7102.4	7.8 %
Dec	7290.4	8.0 %

Table 6: Long-term monthly-mean estimates of potential net energy (MWh) and % of annual production.

7 UNCERTAINTY ANALYSIS

The following types of uncertainty are analyzed and incorporated into the analysis: production normalization, climate variability, and model uncertainty.

7.1 Production Normalization Uncertainty

The production normalization uncertainty covers the uncertainty associated with adjusting the net production data for plant availability and curtailment. The long-term analysis is based on the potential power production data, i.e. the production data normalized by the plant availability and curtailment. The uncertainty of the potential power production data is directly related to the plant availability and curtailment, since the potential production values are unknown during periods when the wind plant was not available for producing power. Thus, lower plant availability leads to higher production data uncertainty. In addition, this also covers the uncertainties associated with future changes to turbine efficiencies and availabilities.

7.2 Climate Variability Uncertainty

The climate variability includes two components: temporal variation and future changes in climate.

Temporal uncertainty is based on the inter-annual variability (standard deviation) of the annual-mean energy-based NWP time series corresponding long-term means. It is assumed that each year of the annual-mean potential power time series is independent from the next.

Future changes in climate includes the possibility of future climate varying from the historic climate. Climate change is associated with potential shifts in the climate over the next twenty years. Change in the climate may have positive or negative impacts to the production data. The magnitude of climate change uncertainty is based on how the most recent five years of data compares to the prior long-term record. Based on these factors, a climate change uncertainty value is assessed.

7.3 Model Uncertainty

The model uncertainty describes the uncertainty associated with estimating the long-term MOS-corrected potential net generation time series. The model uncertainty is derived from four components: the quality of the production data, the period of record of the production data, the error of the MOS-corrected data during the production period, and the sensitivity of the MOS calculation.

The uncertainty associated with the quality of the production data is a function of the averaging period of the generation data incorporated into the analysis. Generally speaking, using data with a longer averaging period will increase this uncertainty, e.g. monthly generation data will have higher uncertainty than 10-minute SCADA data.

Based on prior split-sample validation analyses performed by Vaisala, it is known that the uncertainty of the MOS algorithm decreases as the period of the training data increases. Therefore, the training period component of the model uncertainty is determined by the length of record of the production data. To understand the error of the MOS calculation, the root mean squared error (RMSE) is computed between the monthly-mean MOS-corrected data and the observed production data over concurrent time periods. And lastly, the sensitivity component of model uncertainty is derived by computing multiple iterations of MOS, using perturbed input data, and computing the standard deviation of error across the resulting time series. The four components of model uncertainty are statistically aggregated together yielding the total model uncertainty for a 20-year return period.

7.4 Pooled Uncertainty

A quadratic sum is computed of the individual uncertainty values described above to derive the total uncertainty value for the Whiskey Ridge Wind Farm. Table 7 summarizes these calculations.

Project Uncertainty	1-year	5-year	10-year	20-year
Production Normalization	0.7	0.7	0.7	0.7
Climate Variability	11.3	5.1	3.7	2.7
Model	2.8	2.8	2.8	2.8
Total Uncertainty	**11.7**	**5.9**	**4.7**	**3.9**

Table 7: Standard error of future production estimate (%) at Whiskey Ridge.

7.5 Probability of Exceedances

Based on the estimated total project uncertainties, Table 8 presents the probability of exceedance levels associated with the P50 project estimate for the 1-year, 5-year, 10-year, and 20-year cases.

P-level	1-year	5-year	10-year	20-year
P50	90.7	90.7	90.7	90.7
P75	83.5	87.1	87.8	88.3
P90	77.1	83.9	85.3	86.1
P95	73.3	81.9	83.7	84.8
P99	66.1	78.3	80.8	82.4

Table 8: Probability of exceedance values (GWh) at Whiskey Ridge.

8 CONCLUSION

Vaisala has conducted an operational reforecast of the Whiskey Ridge wind farm within Kittitas County, Washington. The reforecast is based on the client provided historical monthly summaries of production, availability, and curtailment data in combination with Vaisala's long-term NWP model data. A power index derived from three NWP model simulations driven by independent reanalysis data sets was utilized to adjust the normalized production data for the long-term. The expected long-term mean potential net annual energy production value, i.e. the net P50, is estimated to be 90.7 GWh. Using the uncertainty assessment results, probability of exceedance values were calculated. The 20-year P90 potential net energy value for the Whiskey Ridge project is 86.1 GWh.

Vaisala 3TIER Services Operational Reforecast

PROJECT

Lower Snake River : Garfield County, Washington

using 149 Siemens SWT 101-2.3MW wind turbines at $80\,m$

FOR

Puget Sound Energy

DATE

8 October, 2016

CONTACT

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Contents

1 INTRODUCTION

Vaisala has been retained by Puget Sound Energy to provide an operational reforecast for the Lower Snake River wind farm, which is located in Garfield County, Washington. This project is comprised of 149 Siemens SWT 101-2.3MW turbines for a total project capacity of 342.7 MW.

The operational reforecast is an independent assessment of the future production of an operating project based on the historical production data and the climate. It considers the variability of the climate and the observed production data, including generation and availability data, as reported by the project. Vaisala offers two different Operational Reforecast products: a comprehensive analysis that quality controls the 10-minute SCADA data on a turbine specific basis, and a higher level analysis that relies solely on the monthly-mean operating reports of the project.

Since only monthly-mean production data are considered in this analysis, any potential turbine performance issues in the net metered generation data will be transferred into the operational reforecast process. In essence, it is a simulation of the future assuming the plant performs as it has in the past, making adjustments if it is known that operating conditions are expected to change from the past.

Assuming the plant continues to operate as it has in the past, the operational reforecast yields an estimated long-term potential net energy value of 849.9 GWh. Potential net energy refers to the energy the wind farm would produce if the total site availability is 100% and the curtailment loss is 0%. Total site availability includes machine availability, grid availability, and BOP availability.

For this analysis, results will be shown only in terms of potential net energy. The client will need to apply availability and curtailment losses to determine the expected net energy generation of the Lower Snake River wind farm.

Project Size	342.7 MW
Number of Turbines	149
Turbine Type	Siemens SWT 101-2.3MW
Hub Height	80 m
Potential Net Energy Generation	849.9 GWh
Net Energy Generation	–
Aggregate Loss Factor	100.0 %
Standard Error of 20-year Estimate	4.7 %

Table 1: Project Overview

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2 PROJECT DESCRIPTION

The Lower Snake River project is located in Garfield County, Washington. The project is comprised of 149 Siemens SWT 101-2.3MW turbines at $80\,m$ hub height for a total project capacity of $342.7\,MW$. The wind farm has been operating since March 2012.

The location of the Lower Snake River wind farm is shown below in Figure 1.

Figure 1: Map of the Lower Snake River project region.

3 METHODOLOGY

To estimate the future net production values, the following two input data sources are utilized: historic production data, including generation and availability data, and 36 years of Numerical Weather Prediction (NWP) model data. Statistical corrections are applied to the normalized production data, based on a simulated climate index, in order to generate a long-term time series of estimated production values. The historic long-term production provides the basis for estimating future production. An outline of the basic approach follows:

- Production, availability and curtailment data are reviewed for quality and usefulness.
- Normalized production data, i.e. potential net energy data, are created by normalizing the net meter generation data to 100% site availability.
- Long-term climate variability is analyzed to determine an appropriate start date for each of 3 independent reanalysis data sets, assuming each has long-term characteristics consistent with the region.
- Utilizing the Weather Research and Forecasting Model (WRF), reanalysis data are downscaled to a $15\,km$ horizontal resolution.
- Time series data of air density and hub height wind speed are extracted from the WRF data set at a centrally located grid point within the project.
- The time series of hub height wind speeds are corrected to on-site conditions using on-site wind resource measurement data, if available.
- An air density corrected project power curve is used to convert the individual reanalysis-based time series to power. Power values are further scaled to expected long-term generation before aggregating by month. These monthly simulated production time series become climate power indices.
- Monthly observed normalized production data are adjusted for the long-term by applying the ratio of the long-term mean monthly profile derived from the 36 years of simulated data against the monthly profile derived over the short-term operational production period.
- The independent long-term estimates are then weighted by respective coefficients of determination; comparing monthly observed production against the simulated power indices.
- Historic trends of availability and curtailment data are analyzed to determine expected future trends. Turbine availability and curtailments are normalized out of the data set when applying the long-term correction factor. The expected future availability and curtailment are added back as loss factors when computing the reforecasted long-term mean net energy estimate.
- Uncertainty analysis is performed to develop the probability of exceedance values (P75, P90, etc.) of expected net energy generation.

4 DATA VERIFICATION

4.1 On-site Resource Data

For operational projects where stand-alone met towers are waked by operating turbines, a broadly applicable view of the site's wind resource can be determined from the nacelle anemometers in the project. A project average time series of wind speed is determined by averaging the 10-min wind speed readings from every turbine in the project. The averaged time series is interpreted as a point reading at the arithmetic average of the latitude and longitude coordinates of all turbines. The nacelle wind resource time series is then used to validate and correct the raw NWP model data using a process of Model Output Statistics (MOS) correction. MOS uses regression equations to remove bias and adjust the variance of the raw model output to improve the match with the provided observational data. Nacelle wind resource measurement data were provided by the client during the period January 2013 through December 2015.

4.2 Operating Results Summary

A summary of historical park performance over the period March 2012 through July 2016 was provided by the client. The data included monthly generation data and various availability statistics. Specifically relevant for this analysis are the net generation, turbine and grid availability data, and curtailment values. The total site availability factor is calculated inclusive of the following: machine availability, balance of plant availability, and grid availability. Project curtailment is computed as the sum of the environmental curtailment and grid curtailment. Potential net energy generation is then derived by dividing the net metered generation data by the total site availability factor and then adding the total project curtailment. The result is a time series representative of the project with 100% availability and no curtailment.

Project generation data, turbine and grid availability data, curtailment data, and potential net generation data utilized by Vaisala are shown below in Table 2. Newly constructed wind farms typically have a break-in period during which availability, and potentially turbine performance, is lower than what would typically be seen over the long-term. This period often takes place during the first year of operations. When multiple years of operating data are provided, Vaisala identifies this initial stabilization period and removes it from the analysis, so that these data do not bias the long-term adjustment. No explicit stabilization period is apparent in the data record, but the first month of operational data is not considered in the analysis. One additional month is also not incorporated into the analysis because of relatively low plant availability.

Operational generation data over the period April 2012 through December 2015 are used in the analysis. Months with relatively low total site availability values are not incorporated into the analysis, and so a potential net generation value is not computed for these months.

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2012-Mar	102609	91.7	0.0	–
2012-Apr	79175	97.9	0.0	80878
2012-May	87058	97.9	0.0	88921
2012-Jun	89650	98.4	0.0	91108
2012-Jul	44790	98.6	0.0	45426
2012-Aug	52218	98.7	0.0	52895
2012-Sep	34743	99.6	0.0	34872
2012-Oct	76772	99.1	0.0	77445
2012-Nov	48222	98.0	0.0	49191
2012-Dec	95703	98.6	0.0	97069
2013-Jan	59055	99.1	0.0	59573
2013-Feb	90724	99.2	0.0	91502
2013-Mar	82204	99.4	0.0	82700
2013-Apr	114961	98.0	0.0	117354
2013-May	64236	94.7	0.0	67860
2013-Jun	60163	99.6	0.0	60417
2013-Jul	55843	99.0	0.0	56384
2013-Aug	44519	98.9	0.0	45010
2013-Sep	76883	99.0	0.0	77660
2013-Oct	39763	99.1	0.0	40127
2013-Nov	64955	99.3	0.0	65413
2013-Dec	63590	98.9	0.0	64310
2014-Jan	55436	98.6	0.0	56217
2014-Feb	76969	99.2	0.0	77574
2014-Mar	100437	98.7	0.0	101718
2014-Apr	88666	99.3	0.0	89336
2014-May	72416	97.6	0.0	74209
2014-Jun	88017	99.1	0.0	88860
2014-Jul	67202	98.0	0.0	68598
2014-Aug	52474	94.5	0.0	55527
2014-Sep	61895	99.0	0.0	62520
2014-Oct	71146	99.5	0.0	71504
2014-Nov	87896	97.6	0.0	90081
2014-Dec	60922	98.9	0.0	61612
2015-Jan	32036	99.3	0.0	32262
2015-Feb	52174	99.6	0.0	52384
2015-Mar	59595	99.5	0.0	59900
2015-Apr	81457	99.6	0.0	81800
2015-May	49520	99.6	0.0	49744
2015-Jun	44969	81.2	0.0	–
2015-Jul	81232	99.0	0.0	82094
2015-Aug	71943	96.4	0.0	74614
2015-Sep	56583	97.4	0.0	58082
2015-Oct	60385	95.4	0.0	63276
2015-Nov	65239	98.1	0.0	66526
2015-Dec	86635	98.2	0.0	88231
2016-Jan	51038	99.0	0.0	51569
2016-Feb	78705	99.2	0.0	79364

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Lower Snake River. (continued on next page)

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2016-Mar	98590	99.0	0.0	99546
2016-Apr	75704	99.5	0.0	76061
2016-May	78598	99.5	0.0	78993
2016-Jun	79016	98.9	0.0	79895
2016-Jul	76309	99.3	0.0	76847

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Lower Snake River. Months with relatively low total site availability are not incorporated into the analysis and potential net generation is not computed. For these months the potential net generation data are shown as missing values.

5 CLIMATE REVIEW

In order to place the production data into the climatological context, Vaisala performed a review of several long-term climate data sources. Vaisala primarily relies on global reanalysis data sets for understanding the long-term climate variability. The reanalysis data sets are derived from thousands of global observations, including ground-based weather stations, ocean surface buoys, satellites, and weather balloons. Vaisala uses three major reanalysis data sets that are each produced independently by different institutions. The data sets reviewed for this analysis are shown below in Table 3.

Data Set	Explained Variance (R^2)	Start Year	End Year
ECMWF ERA-I	0.85	1997	2015
MERRA	0.89	1997	2015
NCEP/NCAR	0.86	1997	2015

Table 3: Monthly explained variance with production data and reference period utilized for each reanalysis data set.

Vaisala considers each reanalysis data set when assessing the long-term climate and results using each data set are weighted by their correlation to observed project performance. Figure 2 shows the annual-mean wind speed values extracted from each reanalysis data set across the period of record. The reference period for each data set is optimized by taking into consideration how representative the entire record is of the recent climate at the site. The utilized reference period and correlation with observed project performance for each reanalysis data set is provided in Table 3.

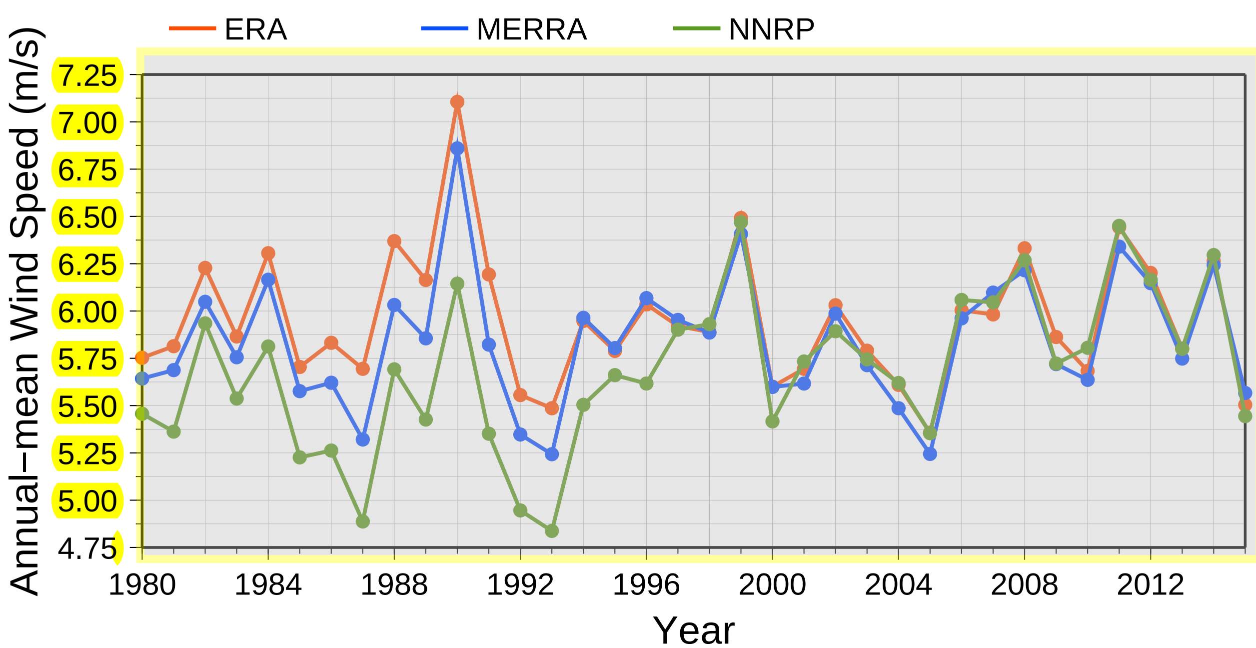

Figure 2: Annual-mean time series plot of considered reanalysis data sets.

6 REFORECAST RESULTS

The 52 months of utilized normalized observed production are independently indexed against the 36 years of simulated power from each reanalysis data set. Concurrent months are binned by calendar month to arrive at a short-term monthly average for both the normalized production data and the three sets of simulated data. The ratio of monthly long-term energy over the short-term (observed) energy from a reanalysis data set is used as an adjustment factor for each mean calendar month for the observed, normalized production data and then annualized for a long-term annual-mean generation. The three independent long-term estimates are combined by weighting each value against the coefficient of determination between the 52 months of observed, normalized production data, and respective reanalysis power data set.

This analysis is presenting results only in terms of the potential net energy generation, and thus is not considering the availability or curtailment loss factors. The long-term mean potential net energy generation estimate for the Lower Snake River wind farm is estimated to be $849.9\,GWh$.

	Lowersnakeriver
Potential Net Energy Generation (GWh)	849.9
Nameplate Capacity (MW)	342.7
Loss Factors	
Total Site Availability	100.0 %
Curtailment	100.0 %
Aggregate Loss Factor	100.0 %
Net Energy Generation (GWh)	–

Table 4: Net energy generation results.

6.1 Long-term Variability

The long-term variability of the simulated potential net energy is shown within this section. Figure 3 shows the long-term mean seasonality via a box-and-whisker plot of the monthly-mean potential net energy data. The shaded boxes are bounded by the P25 and P75 values for each month, and the whiskers denote the minimum and maximum values. The median for each month is denote by the black line within the shaded box. Table 5 shows the numerical values plotted within Figure 3.

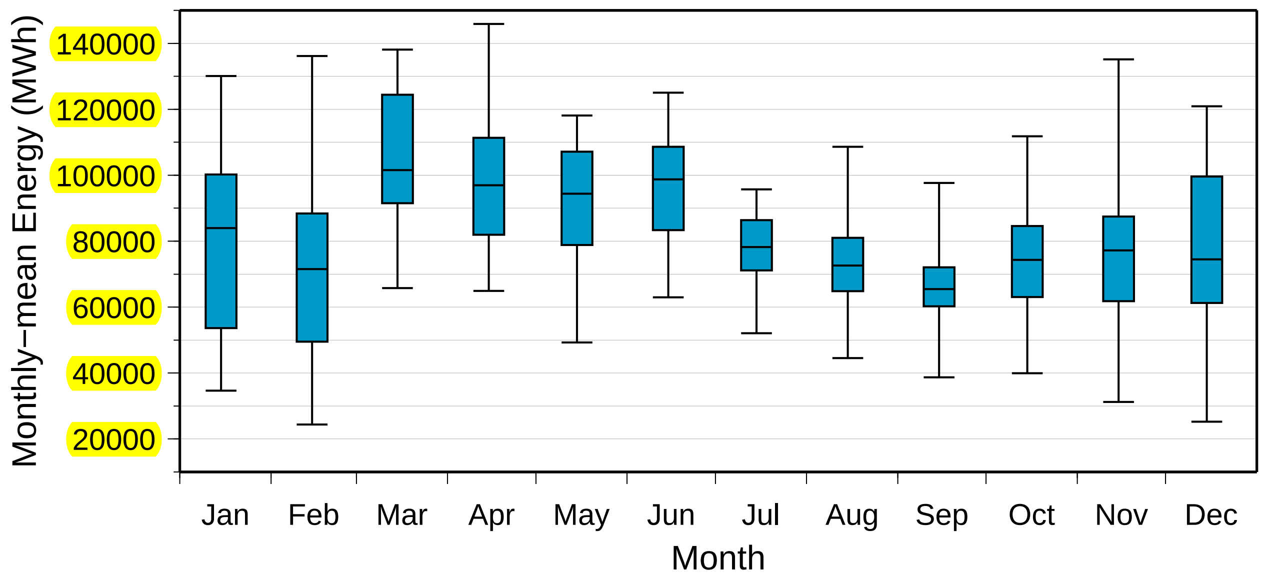

Figure 3: Box-and-whisker plot of monthly-mean simulated potential net energy. This figure displays the expected variability of the monthly-mean data. Median values are denoted by the solid line within each shaded box. Upper and lower boundaries of the shaded box correspond to the 75% and 25% quartiles, while the whiskers denote the maximum and minimum monthly-mean potential net energy values.

	Minimum	P75	Median	P25	Maximum
Jan	26941.7	42849.5	65262.8	79967.2	103991.3
Feb	21613.5	44768.4	64604.5	79942.1	121534.3
Mar	56316.9	79418.0	87466.8	108361.6	118843.3
Apr	53396.8	67456.2	80054.7	91636.9	122540.7
May	43957.1	66105.6	81665.4	90122.4	102290.5
Jun	53810.9	71251.1	79470.1	89408.1	99964.0
Jul	46232.5	61338.4	67699.3	71194.7	84081.3
Aug	43472.4	57815.1	67064.3	72493.9	95471.6
Sep	35925.3	56112.3	60815.8	68584.5	88630.1
Oct	38523.3	58951.0	68718.9	77762.7	104618.1
Nov	25188.7	50990.3	62568.0	72235.0	110917.3
Dec	22395.4	54552.7	66016.7	89268.5	108130.6

Table 5: Minimum, P75, median, P25, and maximum potential net energy values (MWh) for each calendar month.

6.2 Seasonal Profile

The operational reforecast of the Lower Snake River annual profile is detailed in this section. Because the reforecast methodology is indexed against individual calendar months, the operational reforecast can illuminate the project's annual profile. Table 6 shows the annual profile in terms of the potential net energy for Lower Snake River.

	Potential Net Energy Generation (MWh)	% of Annual Production
Jan	64025.8	7.5 %
Feb	62369.3	7.3 %
Mar	90824.0	10.7 %
Apr	81351.1	9.6 %
May	78508.2	9.2 %
Jun	78841.2	9.3 %
Jul	65957.5	7.8 %
Aug	65654.7	7.7 %
Sep	61595.2	7.2 %
Oct	68400.8	8.0 %
Nov	63729.1	7.5 %
Dec	68684.7	8.1 %

Table 6: Long-term monthly-mean estimates of potential net energy (MWh) and % of annual production.

7 UNCERTAINTY ANALYSIS

The following types of uncertainty are analyzed and incorporated into the analysis: production normalization, climate variability, and model uncertainty.

7.1 Production Normalization Uncertainty

The production normalization uncertainty covers the uncertainty associated with adjusting the net production data for plant availability and curtailment. The long-term analysis is based on the potential power production data, i.e. the production data normalized by the plant availability and curtailment. The uncertainty of the potential power production data is directly related to the plant availability and curtailment, since the potential production values are unknown during periods when the wind plant was not available for producing power. Thus, lower plant availability leads to higher production data uncertainty. In addition, this also covers the uncertainties associated with future changes to turbine efficiencies and availabilities.

7.2 Climate Variability Uncertainty

The climate variability includes two components: temporal variation and future changes in climate.

Temporal uncertainty is based on the inter-annual variability (standard deviation) of the annual-mean energy-based NWP time series corresponding long-term means. It is assumed that each year of the annual-mean potential power time series is independent from the next.

Future changes in climate includes the possibility of future climate varying from the historic climate. Climate change is associated with potential shifts in the climate over the next twenty years. Change in the climate may have positive or negative impacts to the production data. The magnitude of climate change uncertainty is based on how the most recent five years of data compares to the prior long-term record. Based on these factors, a climate change uncertainty value is assessed.

7.3 Model Uncertainty

The model uncertainty describes the uncertainty associated with estimating the long-term MOS-corrected potential net generation time series. The model uncertainty is derived from four components: the quality of the production data, the period of record of the production data, the error of the MOS-corrected data during the production period, and the sensitivity of the MOS calculation.

The uncertainty associated with the quality of the production data is a function of the averaging period of the generation data incorporated into the analysis. Generally speaking, using data with a longer averaging period will increase this uncertainty, e.g. monthly generation data will have higher uncertainty than 10-minute SCADA data.

Based on prior split-sample validation analyses performed by Vaisala, it is known that the uncertainty of the MOS algorithm decreases as the period of the training data increases. Therefore, the training period component of the model uncertainty is determined by the length of record of the production data. To understand the error of the MOS calculation, the root mean squared error (RMSE) is computed between the monthly-mean MOS-corrected data and the observed production data over concurrent time periods. And lastly, the sensitivity component of model uncertainty is derived by computing multiple iterations of MOS, using perturbed input data, and computing the standard deviation of error across the resulting time series. The four components of model uncertainty are statistically aggregated together yielding the total model uncertainty for a 20-year return period.

7.4 Pooled Uncertainty

A quadratic sum is computed of the individual uncertainty values described above to derive the total uncertainty value for the Lower Snake River Wind Farm. Table 7 summarizes these calculations.

Project Uncertainty	1-year	5-year	10-year	20-year
Production Normalization	0.4	0.4	0.4	0.4
Climate Variability	13.6	6.2	4.4	3.2
Model	3.5	3.5	3.5	3.5
Total Uncertainty	**14.1**	**7.1**	**5.6**	**4.7**

Table 7: Standard error of future production estimate (%) at Lower Snake River.

7.5 Probability of Exceedances

Based on the estimated total project uncertainties, Table 8 presents the probability of exceedance levels associated with the P50 project estimate for the 1-year, 5-year, 10-year, and 20-year cases.

P-level	1-year	5-year	10-year	20-year
P50	849.9	849.9	849.9	849.9
P75	769.2	809.4	817.7	822.8
P90	696.6	772.8	788.7	798.4
P95	653.1	751.0	771.4	783.8
P99	571.5	710.0	738.8	756.4

Table 8: Probability of exceedance values (GWh) at Lower Snake River.

8 CONCLUSION

Vaisala has conducted an operational reforecast of the Lower Snake River wind farm within Garfield County, Washington. The reforecast is based on the client provided historical monthly summaries of production, availability, and curtailment data in combination with Vaisala's long-term NWP model data. A power index derived from three NWP model simulations driven by independent reanalysis data sets was utilized to adjust the normalized production data for the long-term. The expected long-term mean potential net annual energy production value, i.e. the net P50, is estimated to be 849.9 GWh. Using the uncertainty assessment results, probability of exceedance values were calculated. The 20-year P90 potential net energy value for the Lower Snake River project is 798.4 GWh.

Vaisala 3TIER Services Operational Reforecast

PROJECT

Hopkinsridge : Columbia County, Washington

using 87 Vestas V80-1.8MW wind turbines at $67\,m$

FOR

Puget Sound Energy

DATE

8 October, 2016

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Contents

1 INTRODUCTION

Vaisala has been retained by Puget Sound Energy to provide an operational reforecast for the Hopkinsridge wind farm, which is located in Columbia County, Washington. This project is comprised of 87 Vestas V80-1.8MW turbines for a total project capacity of $156.6\,MW$.

The operational reforecast is an independent assessment of the future production of an operating project based on the historical production data and the climate. It considers the variability of the climate and the observed production data, including generation and availability data, as reported by the project. Vaisala offers two different Operational Reforecast products: a comprehensive analysis that quality controls the 10-minute SCADA data on a turbine specific basis, and a higher level analysis that relies solely on the monthly-mean operating reports of the project.

Since only monthly-mean production data are considered in this analysis, any potential turbine performance issues in the net metered generation data will be transferred into the operational reforecast process. In essence, it is a simulation of the future assuming the plant performs as it has in the past, making adjustments if it is known that operating conditions are expected to change from the past.

Assuming the plant continues to operate as it has in the past, the operational reforecast yields an estimated long-term potential net energy value of 412.8 GWh. Potential net energy refers to the energy the wind farm would produce if the total site availability is 100% and the curtailment loss is 0%. Total site availability includes machine availability, grid availability, and BOP availability.

For this analysis, results will be shown only in terms of potential net energy. The client will need to apply availability and curtailment losses to determine the expected net energy generation of the Hopkinsridge wind farm.

Project Size	$156.6\,MW$
Number of Turbines	87
Turbine Type	Vestas V80-1.8MW
Hub Height	$67\,m$
Potential Net Energy Generation	412.8 GWh
Net Energy Generation	–
Aggregate Loss Factor	100.0 %
Standard Error of 20-year Estimate	4.0 %

Table 1: Project Overview

Designated Information is CONFIDENTIAL per Protective Order in Dockets

UE-170033 and UG-170034

2 PROJECT DESCRIPTION

The Hopkinsridge project is located in Columbia County, Washington. The project is comprised of 87 Vestas V80-1.8MW turbines at $67\,m$ hub height for a total project capacity of $156.6\,MW$. The wind farm has been operating since December 2005.

The location of the Hopkinsridge wind farm is shown below in Figure 1.

Figure 1: Map of the Hopkinsridge project region.

3 METHODOLOGY

To estimate the future net production values, the following two input data sources are utilized: historic production data, including generation and availability data, and 36 years of Numerical Weather Prediction (NWP) model data. Statistical corrections are applied to the normalized production data, based on a simulated climate index, in order to generate a long-term time series of estimated production values. The historic long-term production provides the basis for estimating future production. An outline of the basic approach follows:

- Production, availability and curtailment data are reviewed for quality and usefulness.
- Normalized production data, i.e. potential net energy data, are created by normalizing the net meter generation data to 100% site availability.
- Long-term climate variability is analyzed to determine an appropriate start date for each of 3 independent reanalysis data sets, assuming each has long-term characteristics consistent with the region.
- Utilizing the Weather Research and Forecasting Model (WRF), reanalysis data are downscaled to a $15\,km$ horizontal resolution.
- Time series data of air density and hub height wind speed are extracted from the WRF data set at a centrally located grid point within the project.
- The time series of hub height wind speeds are corrected to on-site conditions using on-site wind resource measurement data, if available.
- An air density corrected project power curve is used to convert the individual reanalysis-based time series to power. Power values are further scaled to expected long-term generation before aggregating by month. These monthly simulated production time series become climate power indices.
- Monthly observed normalized production data are adjusted for the long-term by applying the ratio of the long-term mean monthly profile derived from the 36 years of simulated data against the monthly profile derived over the short-term operational production period.
- The independent long-term estimates are then weighted by respective coefficients of determination; comparing monthly observed production against the simulated power indices.
- Historic trends of availability and curtailment data are analyzed to determine expected future trends. Turbine availability and curtailments are normalized out of the data set when applying the long-term correction factor. The expected future availability and curtailment are added back as loss factors when computing the reforecasted long-term mean net energy estimate.
- Uncertainty analysis is performed to develop the probability of exceedance values (P75, P90, etc.) of expected net energy generation.

4 DATA VERIFICATION

4.1 On-site Resource Data

For operational projects where stand-alone met towers are waked by operating turbines, a broadly applicable view of the site's wind resource can be determined from the nacelle anemometers in the project. A project average time series of wind speed is determined by averaging the 10-min wind speed readings from every turbine in the project. The averaged time series is interpreted as a point reading at the arithmetic average of the latitude and longitude coordinates of all turbines. The nacelle wind resource time series is then used to validate and correct the raw NWP model data using a process of Model Output Statistics (MOS) correction. MOS uses regression equations to remove bias and adjust the variance of the raw model output to improve the match with the provided observational data. Nacelle wind resource measurement data were provided by the client during the period January 2009 through December 2010.

4.2 Operating Results Summary

A summary of historical park performance over the period December 2005 through July 2016 was provided by the client. The data included monthly generation data and various availability statistics. Specifically relevant for this analysis are the net generation, turbine and grid availability data, and curtailment values. The total site availability factor is calculated inclusive of the following: machine availability, balance of plant availability, and grid availability. Project curtailment is computed as the sum of the environmental curtailment and grid curtailment. Potential net energy generation is then derived by dividing the net metered generation data by the total site availability factor and then adding the total project curtailment. The result is a time series representative of the project with 100% availability and no curtailment.

Project generation data, turbine and grid availability data, curtailment data, and potential net generation data utilized by Vaisala are shown below in Table 2. Newly constructed wind farms typically have a break-in period during which availability, and potentially turbine performance, is lower than what would typically be seen over the long-term. This period often takes place during the first year of operations. When multiple years of operating data are provided, Vaisala identifies this initial stabilization period and removes it from the analysis, so that these data do not bias the long-term adjustment. A stabilization period from December 2005 through July 2006 is identified in the data record. An additional 15 months of data have not been considered in the analysis because of low plant availability.

Operational generation data over the period August 2006 through December 2015 are used in the analysis. Months with relatively low total site availability values are not incorporated into the analysis, and so a potential net generation value is not computed for these months.

Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2005-Dec	24394	87.6	0.0	–
2006-Jan	64182	91.5	0.0	–
2006-Feb	34792	92.9	0.0	–
2006-Mar	35752	93.2	0.0	–
2006-Apr	33054	93.8	0.0	–
2006-May	26857	90.2	0.0	–
2006-Jun	18009	94.3	0.0	–
2006-Jul	20575	94.1	0.0	–
2006-Aug	12581	94.7	0.0	13287
2006-Sep	15772	95.1	0.0	16588
2006-Oct	20798	97.9	0.0	21244
2006-Nov	55848	97.2	0.0	57456
2006-Dec	23367	98.4	0.0	23738
2007-Jan	28105	97.2	0.0	28915
2007-Feb	34149	97.8	0.0	34901
2007-Mar	40150	98.7	0.0	40687
2007-Apr	41485	98.2	0.0	42237
2007-May	36812	98.1	0.0	37517
2007-Jun	35194	93.7	0.0	37554
2007-Jul	25396	97.3	0.0	26112
2007-Aug	30768	97.0	0.0	31734
2007-Sep	33718	93.5	0.0	36055
2007-Oct	25907	79.2	0.0	–
2007-Nov	22627	90.1	0.0	25107
2007-Dec	48154	92.3	0.0	52151
2008-Jan	40101	86.8	0.0	–
2008-Feb	35693	96.3	0.0	37080
2008-Mar	51316	95.6	0.0	53661
2008-Apr	47106	93.6	0.0	50334
2008-May	33440	93.4	0.0	35814
2008-Jun	44006	99.2	0.0	44383
2008-Jul	28956	97.1	0.0	29824
2008-Aug	34223	98.2	0.0	34836
2008-Sep	18275	98.6	0.0	18544
2008-Oct	25795	98.3	0.0	26236
2008-Nov	27144	96.5	0.0	28117
2008-Dec	39268	97.2	0.0	40420
2009-Jan	42012	94.7	0.0	44358
2009-Feb	15144	99.1	0.0	15281
2009-Mar	48171	96.4	0.0	49958
2009-Apr	35969	88.7	0.0	–
2009-May	39572	86.9	0.0	–
2009-Jun	33283	92.8	0.0	35876
2009-Jul	21839	71.4	0.0	–
2009-Aug	28596	83.3	0.0	–
2009-Sep	29697	92.8	0.0	31993
2009-Oct	30772	90.6	0.0	33952
2009-Nov	38074	86.8	0.0	–

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Hopkinsridge. (continued on next page)

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Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2009-Dec	18093	89.3	0.0	20251
2010-Jan	20374	93.7	0.0	21735
2010-Feb	12772	95.5	0.0	13375
2010-Mar	36626	98.5	0.0	37197
2010-Apr	54069	97.4	0.0	55526
2010-May	43376	96.9	0.0	44777
2010-Jun	41995	98.1	0.0	42812
2010-Jul	22670	97.9	0.0	23149
2010-Aug	31651	94.1	0.0	33643
2010-Sep	25177	88.0	0.0	–
2010-Oct	27646	97.0	0.0	28513
2010-Nov	32314	98.7	0.0	32727
2010-Dec	32600	97.8	0.0	33334
2011-Jan	42681	98.6	0.0	43309
2011-Feb	39566	98.0	0.0	40394
2011-Mar	48089	97.8	0.0	49151
2011-Apr	57622	98.3	0.0	58636
2011-May	34807	81.5	0.0	–
2011-Jun	30558	63.0	0.0	–
2011-Jul	23157	73.7	0.0	–
2011-Aug	31703	96.1	0.0	32977
2011-Sep	21716	98.3	0.0	22091
2011-Oct	37426	97.7	0.0	38307
2011-Nov	42876	96.2	0.0	44593
2011-Dec	22886	98.3	0.0	23282
2012-Jan	43498	95.0	0.0	45768
2012-Feb	28720	91.3	0.0	31461
2012-Mar	53687	98.4	0.0	54576
2012-Apr	37477	97.0	0.0	38643
2012-May	41655	97.0	0.0	42925
2012-Jun	44330	96.8	0.0	45788
2012-Jul	23147	92.9	0.0	24925
2012-Aug	25130	98.3	0.0	25565
2012-Sep	18307	98.7	0.0	18548
2012-Oct	34869	97.2	0.0	35862
2012-Nov	26327	98.0	0.0	26870
2012-Dec	53493	98.0	0.0	54574
2013-Jan	31152	98.8	0.0	31546
2013-Feb	45431	98.6	0.0	46090
2013-Mar	41985	99.0	0.0	42425
2013-Apr	54071	99.0	0.0	54639
2013-May	32606	97.0	0.0	33618
2013-Jun	27945	97.8	0.0	28573
2013-Jul	28977	96.8	0.0	29922
2013-Aug	22126	98.3	0.0	22504
2013-Sep	35390	97.8	0.0	36193
2013-Oct	19421	96.7	0.0	20078
2013-Nov	31432	96.8	0.0	32470

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Hopkinsridge. (continued on next page)

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Date	Net Metered Generation (MWh)	Total Plant Availability (%)	Curtailment (MWh)	Potential Net Generation (MWh)
2013-Dec	36062	95.2	0.0	37877
2014-Jan	29251	83.2	0.0	–
2014-Feb	32655	87.9	0.0	–
2014-Mar	51561	94.4	0.0	54613
2014-Apr	50939	96.3	0.0	52902
2014-May	44729	97.0	0.0	46109
2014-Jun	44659	98.0	0.0	45574
2014-Jul	29929	97.1	0.0	30832
2014-Aug	27765	95.8	0.0	28976
2014-Sep	26837	92.8	0.0	28905
2014-Oct	30053	98.5	0.0	30517
2014-Nov	42993	99.0	0.0	43410
2014-Dec	25930	86.2	0.0	–
2015-Jan	13610	79.6	0.0	–
2015-Feb	27553	97.8	0.0	28167
2015-Mar	30922	98.0	0.0	31543
2015-Apr	36772	97.5	0.0	37723
2015-May	22553	98.0	0.0	23023
2015-Jun	26192	97.2	0.0	26958
2015-Jul	35469	98.8	0.0	35900
2015-Aug	34059	98.3	0.0	34655
2015-Sep	26830	92.3	0.0	29077
2015-Oct	31518	97.9	0.0	32203
2015-Nov	34567	98.9	0.0	34944
2015-Dec	46357	97.7	0.0	47453
2016-Jan	29015	98.8	0.0	29376
2016-Feb	38998	97.9	0.0	39829
2016-Mar	44384	97.1	0.0	45714
2016-Apr	33713	94.4	0.0	35731
2016-May	37061	98.8	0.0	37511
2016-Jun	35493	98.7	0.0	35949
2016-Jul	34608	98.2	0.0	35260

Table 2: Observed net metered generation, plant availability, curtailment, and potential net generation data for Hopkinsridge. Months with relatively low total site availability are not incorporated into the analysis and potential net generation is not computed. For these months the potential net generation data are shown as missing values.

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5 CLIMATE REVIEW

In order to place the production data into the climatological context, Vaisala performed a review of several long-term climate data sources. Vaisala primarily relies on global reanalysis data sets for understanding the long-term climate variability. The reanalysis data sets are derived from thousands of global observations, including ground-based weather stations, ocean surface buoys, satellites, and weather balloons. Vaisala uses three major reanalysis data sets that are each produced independently by different institutions. The data sets reviewed for this analysis are shown below in Table 3.

Data Set	Explained Variance (R^2)	Start Year	End Year
ECMWF ERA-I	0.87	1997	2015
MERRA	0.86	1997	2015
NCEP/NCAR	0.84	1997	2015

Table 3: Monthly explained variance with production data and reference period utilized for each reanalysis data set.

Vaisala considers each reanalysis data set when assessing the long-term climate and results using each data set are weighted by their correlation to observed project performance. Figure 2 shows the annual-mean wind speed values extracted from each reanalysis data set across the period of record. The reference period for each data set is optimized by taking into consideration how representative the entire record is of the recent climate at the site. The utilized reference period and correlation with observed project performance for each reanalysis data set is provided in Table 3.

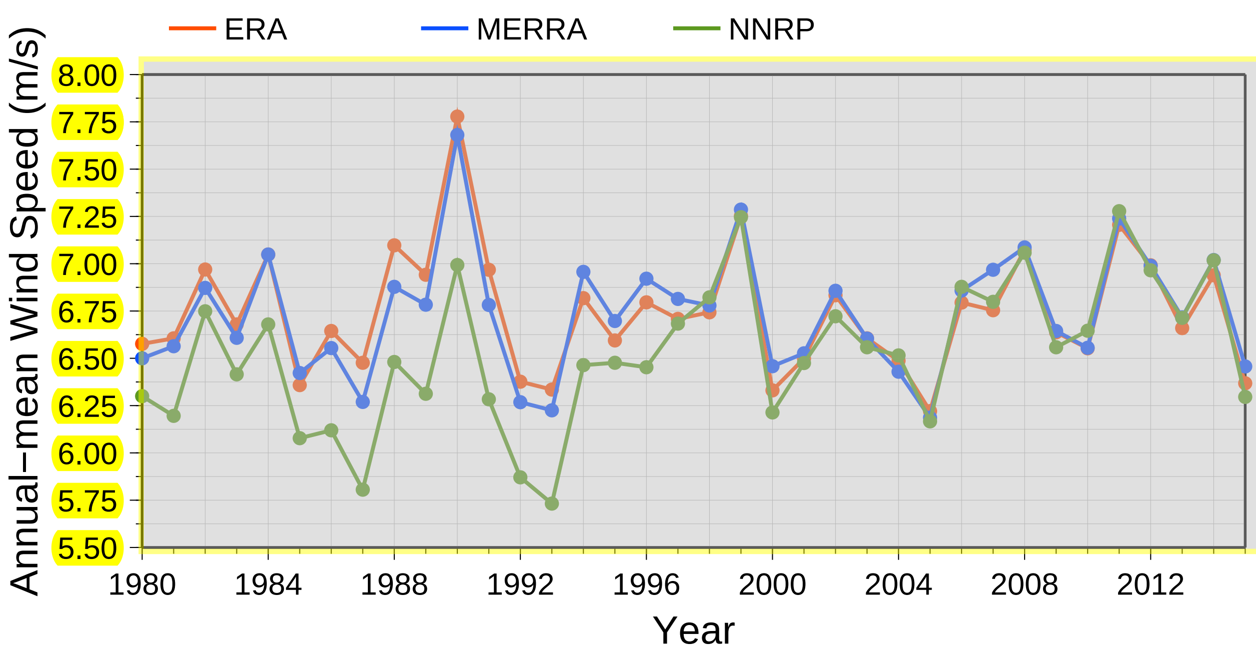

Figure 2: Annual-mean time series plot of considered reanalysis data sets.

6 REFORECAST RESULTS

The 80 months of utilized normalized observed production are independently indexed against the 36 years of simulated power from each reanalysis data set. Concurrent months are binned by calendar month to arrive at a short-term monthly average for both the normalized production data and the three sets of simulated data. The ratio of monthly long-term energy over the short-term (observed) energy from a reanalysis data set is used as an adjustment factor for each mean calendar month for the observed, normalized production data and then annualized for a long-term annual-mean generation. The three independent long-term estimates are combined by weighting each value against the coefficient of determination between the 80 months of observed, normalized production data, and respective reanalysis power data set.

This analysis is presenting results only in terms of the potential net energy generation, and thus is not considering the availability or curtailment loss factors. The long-term mean potential net energy generation estimate for the Hopkinsridge wind farm is estimated to be 412.8 GWh.

	Hopkinsridge
Potential Net Energy Generation (GWh)	412.8
Nameplate Capacity (MW)	156.6
Loss Factors	
Total Site Availability	100.0 %
Curtailment	100.0 %
Aggregate Loss Factor	100.0 %
Net Energy Generation (GWh)	–

Table 4: Net energy generation results.

6.1 Long-term Variability

The long-term variability of the simulated potential net energy is shown within this section. Figure 3 shows the long-term mean seasonality via a box-and-whisker plot of the monthly-mean potential net energy data. The shaded boxes are bounded by the P25 and P75 values for each month, and the whiskers denote the minimum and maximum values. The median for each month is denote by the black line within the shaded box. Table 5 shows the numerical values plotted within Figure 3.

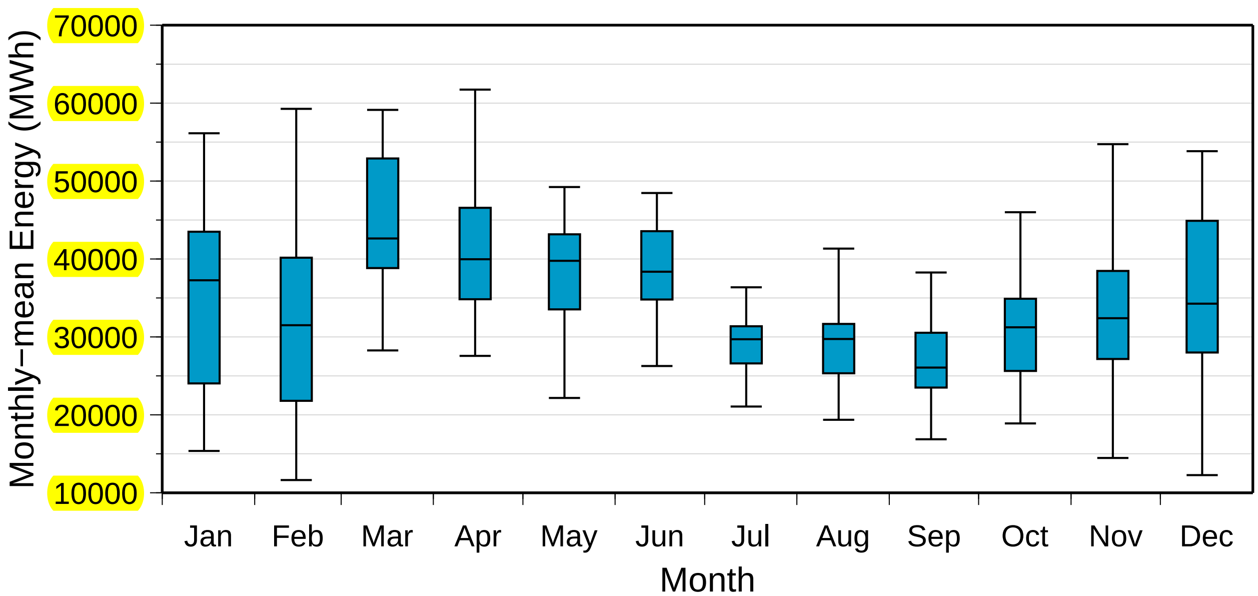

Figure 3: Box-and-whisker plot of monthly-mean simulated potential net energy. This figure displays the expected variability of the monthly-mean data. Median values are denoted by the solid line within each shaded box. Upper and lower boundaries of the shaded box correspond to the 75% and 25% quartiles, while the whiskers denote the maximum and minimum monthly-mean potential net energy values.

	Minimum	P75	Median	P25	Maximum
Jan	15366.2	24026.0	37280.3	43487.9	56136.9
Feb	11628.0	21793.8	31492.2	40175.3	59283.3
Mar	28250.7	38840.4	42626.4	52888.9	59118.6
Apr	27566.9	34846.8	39959.4	46573.4	61732.2
May	22151.0	33538.4	39752.3	43154.6	49240.3
Jun	26257.8	34813.3	38362.1	43551.6	48455.9
Jul	21056.9	26612.0	29687.9	31355.5	36353.4
Aug	19383.0	25328.0	29746.5	31660.4	41342.1
Sep	16873.1	23495.5	26061.7	30549.9	38266.8
Oct	18889.4	25631.5	31233.9	34883.6	45999.9
Nov	14453.7	27166.4	32412.7	38464.9	54722.1
Dec	12267.2	27993.9	34256.0	44900.2	53845.3

Table 5: Minimum, P75, median, P25, and maximum potential net energy values (MWh) for each calendar month.

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6.2 Seasonal Profile

The operational reforecast of the Hopkinsridge annual profile is detailed in this section. Because the reforecast methodology is indexed against individual calendar months, the operational reforecast can illuminate the project's annual profile. Table 6 shows the annual profile in terms of the potential net energy for Hopkinsridge.

	Potential Net Energy Generation (MWh)	% of Annual Production
Jan	35254.1	8.5 %
Feb	31223.0	7.6 %
Mar	44742.2	10.8 %
Apr	41078.1	10.0 %
May	38650.7	9.4 %
Jun	38256.8	9.3 %
Jul	29124.1	7.1 %
Aug	28860.5	7.0 %
Sep	26780.8	6.5 %
Oct	30789.8	7.5 %
Nov	33101.3	8.0 %
Dec	34900.2	8.5 %

Table 6: Long-term monthly-mean estimates of potential net energy (MWh) and % of annual production.

7 UNCERTAINTY ANALYSIS

The following types of uncertainty are analyzed and incorporated into the analysis: production normalization, climate variability, and model uncertainty.

7.1 Production Normalization Uncertainty

The production normalization uncertainty covers the uncertainty associated with adjusting the net production data for plant availability and curtailment. The long-term analysis is based on the potential power production data, i.e. the production data normalized by the plant availability and curtailment. The uncertainty of the potential power production data is directly related to the plant availability and curtailment, since the potential production values are unknown during periods when the wind plant was not available for producing power. Thus, lower plant availability leads to higher production data uncertainty. In addition, this also covers the uncertainties associated with future changes to turbine efficiencies and availabilities.

7.2 Climate Variability Uncertainty

The climate variability includes two components: temporal variation and future changes in climate.

Temporal uncertainty is based on the inter-annual variability (standard deviation) of the annual-mean energy-based NWP time series corresponding long-term means. It is assumed that each year of the annual-mean potential power time series is independent from the next.

Future changes in climate includes the possibility of future climate varying from the historic climate. Climate change is associated with potential shifts in the climate over the next twenty years. Change in the climate may have positive or negative impacts to the production data. The magnitude of climate change uncertainty is based on how the most recent five years of data compares to the prior long-term record. Based on these factors, a climate change uncertainty value is assessed.

7.3 Model Uncertainty

The model uncertainty describes the uncertainty associated with estimating the long-term MOS-corrected potential net generation time series. The model uncertainty is derived from four components: the quality of the production data, the period of record of the production data, the error of the MOS-corrected data during the production period, and the sensitivity of the MOS calculation.

The uncertainty associated with the quality of the production data is a function of the averaging period of the generation data incorporated into the analysis. Generally speaking, using data with a longer averaging period will increase this uncertainty, e.g. monthly generation data will have higher uncertainty than 10-minute SCADA data.

Based on prior split-sample validation analyses performed by Vaisala, it is known that the uncertainty of the MOS algorithm decreases as the period of the training data increases. Therefore, the training period component of the model uncertainty is determined by the length of record of the production data. To understand the error of the MOS calculation, the root mean squared error (RMSE) is computed between the monthly-mean MOS-corrected data and the observed production data over concurrent time periods. And lastly, the sensitivity component of model uncertainty is derived by computing multiple iterations of MOS, using perturbed input data, and computing the standard deviation of error across the resulting time series. The four components of model uncertainty are statistically aggregated together yielding the total model uncertainty for a 20-year return period.

7.4 Pooled Uncertainty

A quadratic sum is computed of the individual uncertainty values described above to derive the total uncertainty value for the Hopkinsridge Wind Farm. Table 7 summarizes these calculations.

Project Uncertainty	1-year	5-year	10-year	20-year
Production Normalization	0.8	0.8	0.8	0.8
Climate Variability	10.0	4.6	3.3	2.4
Model	3.1	3.1	3.1	3.1
Total Uncertainty	**10.5**	**5.6**	**4.6**	**4.0**

Table 7: Standard error of future production estimate (%) at Hopkinsridge.

7.5 Probability of Exceedances

Based on the estimated total project uncertainties, Table 8 presents the probability of exceedance levels associated with the P50 project estimate for the 1-year, 5-year, 10-year, and 20-year cases.

P-level	1-year	5-year	10-year	20-year
P50	412.8	412.8	412.8	412.8
P75	383.4	397.2	399.9	401.5
P90	357.1	383.2	388.4	391.4
P95	341.3	374.8	381.5	385.4
P99	311.6	359.1	368.5	374.1

Table 8: Probability of exceedance values (GWh) at Hopkinsridge.

8 CONCLUSION

Vaisala has conducted an operational reforecast of the Hopkinsridge wind farm within Columbia County, Washington. The reforecast is based on the client provided historical monthly summaries of production, availability, and curtailment data in combination with Vaisala's long-term NWP model data. A power index derived from three NWP model simulations driven by independent reanalysis data sets was utilized to adjust the normalized production data for the long-term. The expected long-term mean potential net annual energy production value, i.e. the net P50, is estimated to be 412.8 GWh. Using the uncertainty assessment results, probability of exceedance values were calculated. The 20-year P90 potential net energy value for the Hopkinsridge project is 391.4 GWh.