PROJECT PERFORMANCE REPORT
METHODOLOGIES

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CONTENTS

GLOSSARY

Anticipated Annual Energy Production (Anticipated AEP): The preliminary annual energy production that is uses a project average Scale Factor to estimate a fully-burdened production value. Only used within the Prospecting phase.

Anticipated Capacity Factor: The ratio of the Anticipated AEP to the theoretical energy production if the turbine(s) were running at rated capacity for the entire year. Only used within the Prospecting phase of a project.

Balance of Plant (BOP): All supporting components and auxiliary systems of the wind turbine generator needed to deliver the energy.

Capacity Factor: The ratio of the actual power output over a period of time to the theoretical maximum output if generation was at rated capacity continuously for the same period of time.

Composite Performance Distribution: The resulting distribution after combining all performance factor distributions. This Composite Performance Distribution then allows for energy production value altering.

Curtailment: An occasion when wind resource is available for energy production, but the turbine operator does not allow for generation.

ECMWF Reanalysis 5th Gen. (ERA5): A long-term reanalysis dataset provided by the European Center for Medium-Range Weather Forecasts (ECMWF). Contains 30+ years of global hourly reanalysis data, which include wind speed, direction, surface wind gusts, and temperature.

Exceedance Table: The Composite Performance Distribution is applied to the Net Annual Energy Production. The Exceedance Table lists the resulting P-values of the energy production.

Gross Annual Energy Production (Gross AEP): The total amount of energy generated by the turbine(s) in one year before any Wake Loss or Performance Factors are considered. Only the wind resource affects the Gross AEP.

Gross Capacity Factor: The ratio of the Gross AEP to the theoretical energy production if the turbine were running at its rated capacity for the entire year.

Icing: An event in which ice buildup occurs on a turbine blade.

Ice Shedding: An event in which the ice buildup on a turbine blade is released and falls from the structure.

LiDAR: A remote sensing instrument used to collect wind data, short for Light Detection and Ranging. The data collected by LiDARs are volume measurements as opposed to point measurements.

Long-Term: Describes a consecutive period of the most recent 30 years.

Measure-Correlate-Predict (MCP): A statistical technique that is used to create a simulated, long-term dataset by relating a concurrent short, measured target dataset to a long-term reference dataset.

Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA2): A satellite-derived long-term reanalysis data source from NASA. Contains 30+ years of global hourly reanalysis data, which include wind speed, direction, and temperature.

Meteorological Towers (MET): Set of instrumentation used to collect wind data, including speed, direction, and temperature at typically three different heights, typically on a tower. These are point measurements as opposed to volume measurements.

Near-site Data: Data that has been collected within 20 miles of the project site.

Net Capacity Factor: The ratio of the Net AEP to the theoretical energy production if the turbine were running at its rated capacity for an entire year.

Net Annual Energy Production (Net AEP): Gross AEP minus any Wake Loss effects. No other Performance Factors are included in the Net Annual Energy Production calculation.

On-site Data: Data that has been collected on the project site or customer property.

Original Equipment Manufacturer (OEM): The manufacturer that makes components used in other companies' products.

P50 Annual Energy Production (P50 AEP): The estimated energy delivered to the point of revenue metering during an average year while the project is in operation.

P50 Capacity Factor: The ratio of the P50 AEP to the theoretical energy production if the turbine were running at its rated capacity for an entire year.

P-value: Exceedance Probabilities for a given variable. For example, a P90 energy production value denotes the production level predicted to be exceeded 90% of the time period.

Performance Factors: Individual distributions of various elements that determine the variability of the energy production. Examples include electrical loss, power curve degradation, measurement and modeling, etc.

Point Dataset: Any chosen short-term MET or LiDAR dataset in the near vicinity of a project. It is only representative of its measurement location. A Point Dataset can be, but will not always be, a Site Dataset.

Point MCP Dataset: An MCP dataset created with a Point Dataset and the reanalysis grid-point closest to the Point Dataset measurement location.

Power Curve: The relationship between the wind speed and power output of a specific wind turbine.

Project Performance Report (PPR): Includes the summary from the Wind Resource Assessment Report and its main outcome values (Gross Annual Energy Production and Net Annual Energy Production), explanations of Performance Factors, the Composite Performance Distribution, and the Exceedance Table.

Prospecting Phase: The initial stage of project development. The result includes an Initial Evaluation document sent to potential customers.

Prudent Wind Industry Practices: The practices, methods, specifications and standards of safety, performance, quality, dependability, efficiency, and economy generally recognized by industry members in the US as good and proper. Other practices, methods, or acts which, in the exercise of reasonable judgment by those reasonably experienced in the industry in light of the specific projects and facts known at the time a decision is made, would be expected to accomplish the result intended at a reasonable cost and consistent with applicable laws, reliability, safety, and expedition. Prudent Wind Industry Practices are not intended to be limited to the optimum practices, methods, or acts to the exclusion of all others, but rather to be a spectrum of good and proper practices, methods, and acts.

Reanalysis Data: A modeled dataset with measured observations assimilated into forecast models; typically long-term, globally complete, and consistent timestamps.

Site Dataset: The most representative Point Dataset of the project site. A Site Dataset will always be a Point Dataset.

Site MCP Dataset: A long-term MCP dataset created with the Site Dataset and the closest available reanalysis grid-point to the site.

TAILS 3.0: One Energy's proprietary software used to model turbine icing, shadow flicker, and wake loss.

Wake Loss: When obstacles upwind create a wake that reduces the wind available at the downwind wind turbines. Wake loss results in a reduction of energy production.

Waked Sector: The directional sector(s) in which wake will affect a turbine.

Wind Resource Assessment Report (WRA): Includes the site wind resource analysis, Gross AEP, and Wake Loss. The outcome is the Net Annual Energy Production.

1. INTRODUCTION

A Project Performance Report (PPR) is conducted as part of the pre-construction development of a Wind for Industry project. The PPR is completed after the Wind Resource Assessment (WRA) and applies project-specific losses and uncertainties associated to the Net Annual Energy Production (AEP) estimates for the proposed project. The PPR methodology contains a Monte Carlo-based model that uses 20 specific Performance Factors with differing probability density functions (PDF) that will model the losses and uncertainties of energy production. Not all Performance Factors are applicable to all projects; additional Performance Factors may be added as necessary. The Performance Factor PDFs include natural and artificial distributions and allow for specific "caps" that are based on contractual, natural, or insurance-based boundaries. One hundred thousand random combinations of all the Performance Factor PDFs are combined and the result is a cumulative density function (CDF) called the Composite Density Function. An Exceedance Table that represents the specific site is also derived from the best methods currently available to statisticians. This Exceedance Table shows various P-Value energy production estimates which can indicate the energy production spread associated with the project.

The objective of this methodology is to allow for explanation and derivation of each section within One Energy's PPR. Included in each section are the deliverables of analysis for guidance in understanding the report within the Project Due Diligence Package **Appendix 2: Project Performance Report**. The deliverables within the formal PPR from each section are designated in bold text throughout this document.

This Project Performance Report Methodology is version 2021.1.

2. PROJECT INFORMATION

An overview of the specific project is presented within this section, including project siting and a summary of the Gross and Net AEP values. These are shown for reference and are the same as within the WRA document.

A. SITE LAYOUT

The following information is presented in PPR Section 2A – Site Layout:

1) **Image with turbine siting and surrounding land**
2) **Table with the project wind turbine(s) latitude, longitude, and elevation**

B. WRA SUMMARY

The following information is presented in PPR Section 2B – WRA Summary:

1) **A table with the Annual Net Energy Production and capacity factors by turbine and full project**
2) **A table with the Monthly Net Energy Productions by turbine and full project**

3. PERFORMANCE FACTORS

One Energy has developed a method to more accurately predict real-world events that can alter uncertainty and losses in energy production than current industry standards. The standard variables that are considered uncertainty or losses within the industry are addressed, but in a different and purely statistical fashion. A Performance Factor is defined as an individual variable with a distribution that determines the variability of the energy production. Each Performance Factor has one PDF that describes the probability of affecting the energy production. The majority of the Performance Factor distributions are assumed normal, but specific distributions are derived from real-world data and imported directly. Performance Factors may have multiple distributions combined and weighted appropriately to create the single PDF. Based on real-world data from previous projects, it is not assumed that a Performance Factor effect can only result in a straight loss.

The x-axis of all the Performance Factor distributions is representative of change in Net AEP with 100% indicating no change. Values higher than 100% indicate an increase in Net AEP and values lower than 100% indicate a decrease in Net AEP. A mean of 100% indicates there is no bias with the sought-after Performance Factor. The area under each Performance Factor PDF must equal 1 to be a true PDF. Upper and lower bounds may be placed on the distribution for each PDF based on contractual, natural, or insurance reasons. If these bounds are placed, a linear scaling factor is applied to adjust the distribution to establish a true PDF with the area under the distribution equal to 1. Figure 1 shows a Performance Factor with a mean of 100% and a standard deviation of 7%.

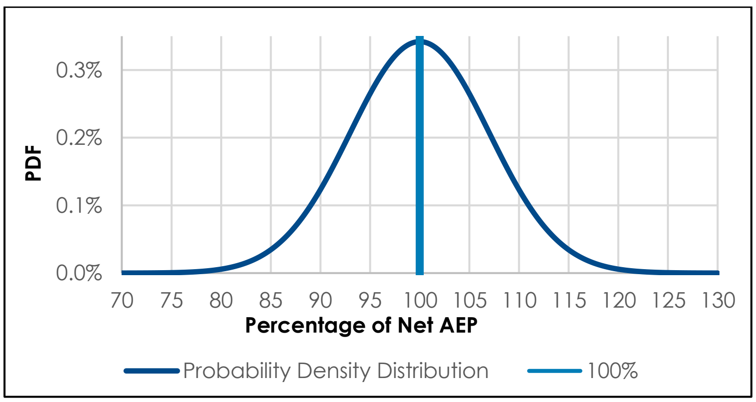

Figure 1: Performance Factor example with mean 100% and standard deviation

Table 1 is a list of the current Performance Factors included in One Energy's project performance analysis. Also included is an indication if the x-axis on the PDF of the specified Performance Factor can exceed 100%. It must be noted that additional Performance Factors may be added if a specific project requires it.

PERFORMANCE FACTOR	PDF CAN BE GREATER THAN 100%
Annual Wind Variability	Yes
Balance of Plant	No
Catastrophic Events	No
Curtailment	No
Data Measurement	Yes
Electrical Collection Line	No
Extreme Temperature Downtime	No
Extreme Wind Speed Downtime	No
Grid	No
Icing Downtime	No
Measure-Correlate-Predict (MCP)	Yes
Owner/Operator Turbine Availability	No
OEM Turbine Availability	No
Parasitic	No
Power Curve	Yes
Power Curve Degradation	No
Shear Extrapolation	Yes
Wake Loss Model	Yes
Wind Flow Model	Yes
Wind Rose Sensitivity	Yes

Table 1: Performance Factors

The distributions of each Performance Factor will vary at each site due to turbine manufacturer, data source types, and specific site characteristics. A CDF is created for each Performance Factor along with the distribution.

It is important to note that all Performance Factors are in terms of energy production, not wind speed. A model was created to develop a relationship between the average site wind speed and the energy production to then convert the wind-speed uncertainty into energy-production uncertainty. This relationship is determined by using a simulated time series created by running an MCP of a measured target dataset with a long-term reanalysis dataset. The power curve provided by the Original Equipment Manufacturer (OEM) is used to convert the simulated data into yearly energy productions. Each year is normalized to the long-term average for both wind speed and energy production. These values are then plotted against each other and the best linear fit is found. The slope of the linear fit is determined to be the wind speed-to-energy sensitivity factor and is multiplied by the wind-speed uncertainty value previously found to obtain the energy production uncertainty. This wind speed-to-energy sensitivity factor varies depending on the site and is recalculated for each project.

It is also important to note that some Performance Factors are time sensitive. An assumption is made that all hours are equal in energy production to create a ratio, to then produce the mean and standard deviations. For example: twelve annual hours of downtime creates 8,748 hours of uptime, where then the ratio $\frac{8,748}{8,760}$ is multiplied by the Net AEP. The resulting AEP is then normalized to the full Net AEP to create the value to use within the Performance Factor.

The following information is specified in PPR Section 3 – Performance Factors:

1) **Individual Performance Factors' mean and standard deviations, or a table of the imported PDF**
2) **Plot of the distribution, along with the CDF**

A. ANNUAL WIND VARIABILITY

The Annual Wind Variability Performance Factor considers how annual wind-speed fluctuation affects the energy production over a long period of time. This Performance Factor is calculated by using the Site MCP dataset. This is the same dataset that is used in wake loss calculations and should be used regardless of the chosen WRA method. The energy production is calculated by applying the manufacturer-provided power curve to the Site MCP dataset. The energy production for each year is used to create a true distribution of the yearly energy production. The distribution is used as the PDF and converted to a CDF for the Performance Factor.

It is assumed that there is only one turbine and that wake loss is not taken into consideration. This Performance Factor is site specific.

B. BALANCE OF PLANT

The Balance of Plant Performance Factor considers the risk for the turbines being down for repair of project equipment not including components covered under warranty. This includes, but is not limited to, transformers, Control Equipment Enclosures, and switchgears. This risk includes major equipment issues, such as needing a new transformer, and includes the time it takes to obtain the new parts, whether domestic or international. It does not include grid downtime, planned maintenance, or OEM downtime. A 10% chance is assumed for a 10-day event which is part of the Balance of Plant Performance Factor. The Balance of Plant Performance Factor is fixed and does not change for different sites.

C. CATASTROPHIC EVENTS

The Catastrophic Event Performance Factor involves the probabilities of a major event that would render the turbine out of commission for 30 or more days. This includes tornadoes rated EF-3 or higher, earthquakes with a magnitude of 6.0 or higher, and other large and unpredictable events. It is assumed that there is a 1:1000 chance of one of these catastrophic events impacting a project. With this assumption, the distribution for the Catastrophic Event Performance Factor is a combination of two curves.

The first curve accounts for the 1:1000 chance a catastrophic event occurs. Its mean is 87% due to insurance policies, with a standard deviation of 0 and a weight of 0.1%. The second curve accounts for the probability of no catastrophic events occurring. Its mean is 100%, with a standard deviation of 0 and a weight of 99.9%. These two curves are then combined. The Catastrophic Event Performance Factor is fixed and does not change for different sites.

D. CURTAILMENT

The Curtailment Performance Factor is associated with shutting down the turbines while wind speeds are sufficient for power generation. Grid curtailment is an issue for large wind farms, but typically not for *Wind for Industry*® projects. *Wind for Industry*® projects do not put enough energy back onto the grid (if any energy is put back on the grid at all, depending on the project) for the export to be higher than the baseload of the grid. An OEM may also require curtailment for sector management, or State regulations may require curtailment for environmental factors such as migratory paths.

If no curtailment of any type is expected, the Curtailment Performance Factor is a normal distribution with a mean of 100% and a standard deviation of zero. Depending on the project, OEM or regulatory curtailment may occur and will be addressed in this Performance Factor. In general, grid curtailment is not expected at any *Wind for Industry®* project.

E. DATA MEASUREMENT

The Data Measurement Performance Factor is based on the best available industry knowledge of the errors and uncertainty associated with measuring wind speed. These variables are used within the Wind Resource Assessment and the uncertainty must be taken into consideration. The primary measurement instrument for the Wind Resource Assessment is the determining metric for what uncertainty values to use within the Data Measurement Performance Factor. Additional modes may be added within this Performance Factor when multiple datasets are used to estimate energy production.

MET tower measurement distribution is determined from industry standards and through relevant studies conducted. A mean of 100% is used to indicate there is no bias in the measurements. The instrumentation group Renewable NRG Systems conducted a study to determine the uncertainty and accuracy of a variety of anemometers, as seen in their Application Note [1]. The standard deviation used for the Data Measurement Performance Factor, if the main measurement tool are anemometers, is determined by using the table in the NRG Application Note for the specific anemometer and the class of anemometer. This uncertainty in the table is in wind speed, so a conversion to annual energy production is performed.

If a LiDAR dataset is used, the Data Measurement Performance Factor is a normal distribution with a mean of 100% to indicate there is no bias in the measurements, and uses the accuracy provided by the LiDAR manufacturer as the standard deviation. These standard deviations are typically measured in wind speed, so a conversion to annual energy production is necessary. This Performance Factor is site specific.

F. ELECTRICIAL COLLECTION LINE

The Electrical Collection Line Performance Factor models the amount of power lost through transmission lines and electrical components to determine the estimated loss from the turbine to the interconnection point.

One Energy utilizes the electrical modeling software EasyPower® for collection line losses. This software does not have an associated uncertainty therefore One Energy designed an internal study to estimate the uncertainty by comparing the EasyPower® model to actual losses using operational data. Using this internal study, it was determined that the uncertainty for the model is 1.1%.

The Electrical Collection Line Performance Factor is assumed normal with the mean as the output from the EasyPower® model and a standard deviation of 1.1%, with an upper bound of 100%. This Performance Factor is site specific. The uncertainty value is evaluated annually as more operational data becomes available.

For additional information and validation of this Performance Factor, see One Energy white paper "*Electrical Line Losses and Uncertainty*" [2].

G. EXTREME TEMPERATURE DOWNTIME

For the Extreme Temperature Downtime Performance Factor, long-term data from either a re-analysis grid-point dataset representative of the site or a nearby airport are examined. The number of hours that exceed the temperature thresholds are counted on a per-year basis and normalized per hours in a year. These values for each year create the extreme temperature dataset. The mean and standard deviation are calculated from this extreme temperature dataset and the curve is assumed to be normal. This Performance Factor is site specific.

H. EXTREME WIND SPEED DOWNTIME

The Extreme Wind Speed Downtime Performance Factor is associated with the downtime related to extreme meteorological wind events that cause the turbine(s) to shut down. To calculate the distribution of anticipated amount of downtime associated with high wind events, a 10-year dataset of National Weather Service (NWS) nationwide Watch/Warnings is used.

For each year of Watch/Warnings, the data is spatially filtered within ArcGIS to only include the county the project is within and the counties that are adjacent. From that spatially filtered Watch/Warning dataset, it is filtered to only include the following alert types:

- Severe Thunderstorm Warning
- Tornado Warning
- High Wind Warning
- Hurricane Force Wind Warning
- Blizzard Warning
- Extreme Wind Warning.

For the entire dataset, a single event is determined using the duration of the previous issued alert. If the next alert in chronological order starts before the end of the previous issued alert, then it is not considered an event. If the next alert is issued after the end of the previous issued alert, then it is considered an event. This is done to prevent overlapping time periods of alerts.

For all the determined alert events, the average duration of alert by type is calculated, and the number of events by alert type is counted. The number of specific alert-type events are then multiplied by its respective average duration to obtain the number of hours within the year for the specific alert type. This is repeated for all alert types.

The number of hours by alert are then summed to create the total number of hours of alerts for one specific year. This entire process is repeated for the most recent 10 years of Watch/Warning datasets, each creating the total number of applicable alert hours by year. From the 10-year number of alert hours dataset, an average and standard deviation is calculated. This average and standard deviation is then converted into a percentage of year and used for the Performance Factor. The Extreme Wind Speed Downtime Performance Factor is assumed to be normal and is site specific.

For additional information and validation of this Performance Factor, see One Energy white paper "*Extreme Wind Speed Downtime Performance Factor Using NWS Alert Data*" [3].

One Energy acknowledges high wind hysteresis as an industry concern. Because One Energy is the owner/operator for most of its projects, the turbine(s) are manually shut down during these events in relation to severe thunderstorms and high gusts. The turbine(s) are turned back on after the On-Call Meteorologist deems the high wind event is over, thereby mitigating the concern for hysteresis.

I. GRID

The Grid Performance Factor considers the time the grid itself is down or causes a turbine fault. Because *Wind for Industry®* projects are located behind-the-meter, they must trip when the grid trips. This Performance Factor accounts for the length of blackout periods as well as grid availability. This Performance Factor is assumed the be normally distributed, with the mean and standard deviation determined using utility reliability data from the EIA Form 861 [4].

The Customer Average Interruption Duration Index (CAIDI) data from utilities that report using the Institute of Electrical and Electronics Engineers (IEEE) standards is averaged by state within the EIA Form 861. This gives an estimate of the minutes of interruption per grid event that would be experienced in any given state. A minimum of the seven most recent years of CAIDI data is obtained for the state the project is located in. An average year assumes a total of four grid events per year, based on One Energy's operating fleet data, and an additional three hours of downtime is added to each event to account for additional time to assess a grid event and access the site if needed. For each year within the CAIDI data, the grid interruption minutes is added to the three hours, and then multiplied by four to get the year's downtime associated with the grid.

The yearly minutes of grid downtime are averaged across all years and used to calculate the percentage of the year the project is available, which is then taken as the Performance Factor mean. The standard deviation of the yearly minutes of grid downtime across all years of data is taken as the Performance Factor standard deviation.

For additional information and validation of this Performance Factor, see One Energy white paper "*United States Electricity Grid Affecting Turbine Uptime*" [5].

J. ICING DOWNTIME

Two main forms of icing must be considered when calculating the Icing Downtime Performance Factor: precipitation icing and in-cloud icing. These two components will be determined separately and then combined to create the Performance Factor. This Performance Factor will only consider project downtime due to icing and will not consider power curve degradation due to icing.

Precipitation Icing

To estimate the annual downtime associated with precipitation icing, ten years of NCDC airport data is used. NCDC airport data provides weather codes that are used to indicate precipitation types, including freezing precipitation. The number of freezing rain and freezing drizzle events are counted, where events are not counted if the event is less than 12 hours after another event being considered. Each event considered is assumed to be 12 hours of downtime. Total downtime is then summed annually and, using the summed annual hours of downtime, the average and standard deviation is found. The mean and standard deviation are then divided by the total hours in a year to find the loss percentage.

If no suitable NCDC airport data is available, a contour map from relevant literature that indicates freezing rain days across the contiguous United States is used [Figure 2; 6]. The contour map shows the average annual number of days with freezing rain. The mean of the precipitation icing downtime is found by identifying the days with freezing rain and dividing by the total number of days in the year. The standard deviation is determined to be $\frac{3}{8}$ of the mean.

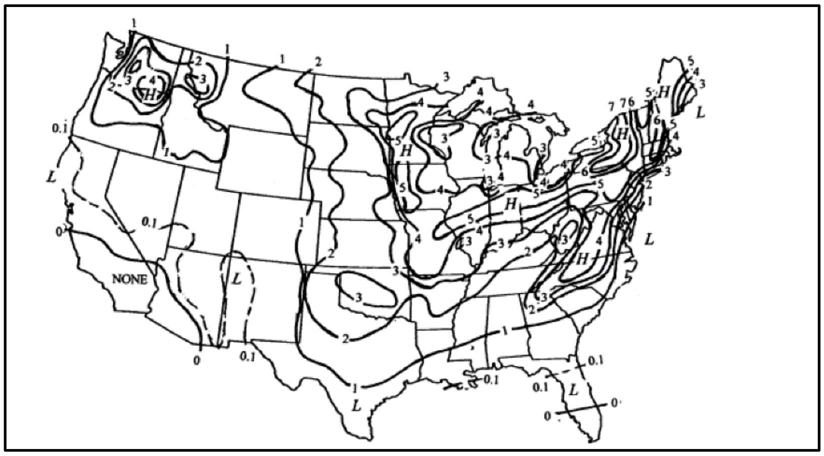

Figure 2: Spatial Variations of Freezing Rain, Changnon and Karl (2003) [6]

In-Cloud Icing

To estimate the annual downtime associated with in-cloud icing, a publicly available in-cloud ice map from VTT is used [7]. VTT's WIceAtlas Map consists of 4,000+ globally spaced datasets with over 20 years of data each. The map uses temperature and cloud base height data to identify in-cloud ice conditions and correlates it with the International Energy Agency (IEA) Ice Classes [8]. The project location is found on the map (Figure 3), and the IEA Ice Class is determined from Table 2. It is important to note that, because the publicly available map combines IEA Classes 3 through 5 into one class, One Energy assumes IEA Class 3 any time Classes 3-5 are indicated within the contiguous United States.

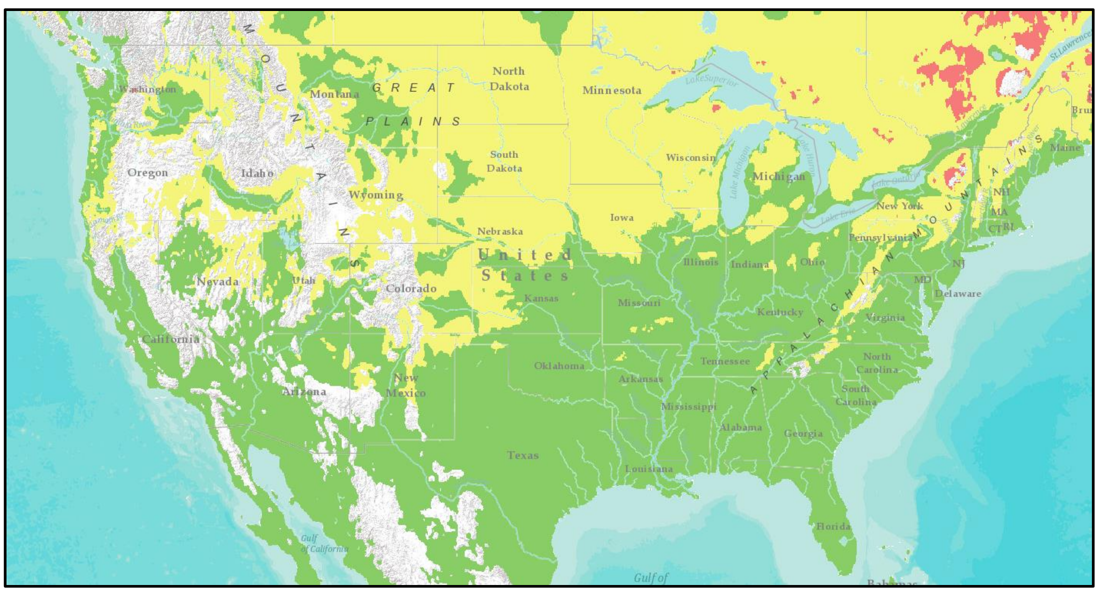

Figure 3: VTT WIceAtlas Map [7]

IEA ICE CLASS	METEOROLOGICAL ICING (% OF YEAR)	INSTRUMENTAL ICING (% OF YEAR)	AEP LOSS (% OF GROSS AEP)	PUBLIC WICEATLAS MAP
5	>10	>20	>20	
4	5-10	10-30	10-25	
3	3-5	6-15	3-12	
2	0.5-3	1-9	0.5-5	
1	0-0.5	<1.5	0-0.5	

Table 2: IEA Ice Class [8]

Once the IEA Ice Class is identified, the instrumental icing is used to estimate annual downtime from in-cloud icing. The average percentage loss is taken to be the center of the instrumental icing frequency range of the identified Ice Class, while the upper and lower bounds of the range are defined as two standard deviations from the mean.

Combining Precipitation and In-Cloud

The two calculated portions of the Icing Downtime Performance Factor, precipitation icing and in-cloud icing, can be combined to form a single normal distribution representative of the Icing Performance Factor. Assuming normal distributions and variable independence, the loss means are added together to create the total loss percentage and the two standard deviations are combined as follows:

$$\sigma = \sqrt{\sigma_p^2 + \sigma_{ic}^2}$$

Equation 1

where σ is the Performance Factor uncertainty, σ_p is the precipitation icing standard deviation, and σ_{ic} is the in-cloud icing standard deviation.

The complement of the total loss is taken as the mean of this Performance Factor. The distribution is assumed normal, has a maximum value of 100%, and is site specific.

If no data exists for the in-cloud icing component or if the turbine will not be shut down for icing events, site-specific analysis may be required.

For additional information and validation of this Performance Factor, see One Energy white paper "*Project Icing Downtime*" [9].

K. OEM TURBINE AVAILABILITY

The OEM Turbine Availability Performance Factor is primarily based on an OEM-provided value within the signed contract as well as historical turbine availability data. This Performance Factor considers turbine downtime due to OEM events, not including scheduled turbine maintenance. Using previous projects' availability data by month, an actual distribution is created. Only full years of data are used to reduce seasonality bias, beginning with the first month of data availability (i.e. a year can be from March-February). To be included in the dataset, a turbine must have two years of operational data. All annual datapoints must be at or above the minimum warranted availability based on the contract provided by the OEM. From these datapoints, a CDF is created. An upper bound is placed for a maximum availability of 100%.

This Performance Factor will be updated every twelve months as more turbine availability data is collected and does not change between different sites. In the absence of turbine-specific availability data, One Energy considers their operating fleet's availability data to be representative of any manufacturer's availability.

L. OWNER/OPERATOR TURBINE AVAILABILITY

The Owner/Operator Turbine Availability Performance Factor is based on historical availability data. This Performance Factor considers turbine downtime due to Owner/Operator events and scheduled maintenance; downtime due to OEM events is not included. Using previous projects' availability data by month, an actual distribution is created. Only full years of data are used for each turbine, beginning with the first month of data availability (i.e. a year can be from March to February). Turbines with less than two full years of operational data are not included in the dataset so the commissioning period is not over-weighted. The uptime is converted to a percentage by comparing the available time to the theoretical maximum time the turbine could be operational. Any turbine month with 10 consecutive days of downtime related to a BOP event (e.g. transformer, collection line, etc.) is considered to be accounted for within the BOP performance factor. This event is removed from the dataset and the remaining availability is calculated (e.g. a 30-day month with a 10-day event would have the availability calculated with a theoretical maximum operational time of 20 days). An upper bound is placed for a maximum availability of 100%.

This Performance Factor will be updated every 12 months as more turbine availability data is collected and does not change between different sites. This performance factor is not turbine-model specific, as One Energy's operating procedures will not change with a different turbine model.

M. PARASITIC

The Parasitic Performance Factor accounts for parasitic power losses while the turbine is not generating electricity. The turbine loses power when it is not generating because it needs to keep the turbine controls online for items such as remote starting or braking, FAA lighting, and data collection.

One Energy uses the current turbine downtime energy consumption average of 5.85 kilowatt-hours (kWh) per hour per turbine, its standard deviation of 1.7 kWh per hour per turbine, along with the expected system availability and the Site MCP Dataset to estimate annual average downtime hours. To obtain the system availability, the following site-specific Performance Factors are combined using a Monte Carlo method to create the median downtime unavailability value in percentage:

- Icing downtime
- Extreme temperature downtime
- Extreme wind speed downtime
- Balance of plant
- Grid downtime
- Owner/Operator turbine availability
- OEM turbine availability

The Site MCP Dataset is then used to calculate the annual average number of hours the wind speed will be below cut-in wind speed. The downtime in hours is the unavailability due to low wind speeds.

The downtime unavailability is multiplied by the wind speed unavailability (to assume independence) to obtain the downtime expected at the site in percentage. This expected downtime is then converted into hours per year. The number of expected downtime hours is then multiplied by the 5.85 kWh loss per hour, then multiplied by the number of turbines within the project to obtain the total kilowatt-hours of parasitic loss. This energy loss is then divided by the Net AEP of the site to create the mean for this Performance Factor. The standard deviation is calculated by multiplying the 1.7 kWh per hour by the number of expected downtime hours and number of turbines, then dividing by the Net AEP.

This Performance Factor is site-specific and assumed to be normal. The standard deviation is as explained above and the distribution has a maximum upper bound of 100%.

For more information and validation of this Performance Factor, see One Energy white paper "*Parasitic Energy Losses and Uncertainty*" [10].

N. POWER CURVE

Each OEM must provide a contractual power curve with the intended turbine for purchase. The contractual power curve is the normalized value within the Power Curve Performance Factor. The Performance Factor associated with the power curve is a normal distribution of the actual observed power curves from past projects. The observed power curves are normalized against the manufacturer's power curve at an air density representative of the site, with the mean and standard deviation of these observed power curves becoming the mean and standard deviation of the Power Curve Performance Factor distribution, explained below. The upper bound for the Power Curve Performance Factor is the highest observed data point from the observed power curves, and the lower bound cut-off is based on the OEM's value in the contract of what percentage of time the turbines must be producing at the contractual power curve or higher.

A LiDAR deployment is conducted to create the measured power curves in accordance with IEC 61400-12. The distance between the wind-speed measurements gathered from the LiDAR and the turbine tested must be between two- and four-times the rotor diameter. Sectors of waked data from nearby towers within 10D are not used within the power curve measurement dataset. Periods of time when the turbine was not operational, as determined by turbine downtime logs, are not used within the dataset. The resulting data is binned in 0.5 m/s centered bins, from 1 m/s below cut-in wind speed to 1.5-times the wind speed at 85% of rated power. For example, for the Goldwind 87-1500 turbine, the bin ranges between 2 - 14 m/s. The IEC 61400-12 indicates that a dataset is complete when a minimum of 30 minutes in each wind-speed bin is filled, the entire dataset has a minimum of 180 hours, and the data collection period spans at least 3 months. The measured wind-speed data, along with corresponding turbine production data for the same period, are used to create the raw measured power curve. The average power output for each wind-speed bin is used to create the average measured power curve.

The average measured power curves from the tested turbines are used and compared to the manufacturer-provided power curve to determine differences in estimated AEP. Using wind-speed distributions from nearby MET or LiDAR data, estimates are created for wind speed distribution by applying the measured power curves determined from the LiDAR deployment and the manufacturer-provided power curve. For each wind speed distribution, the percent difference found from comparing the corresponding measured power curve AEP estimates to the OEM power curve AEP estimate are recorded. Each of the recorded percentages may then be used to find the average percent difference and standard deviation.

This average percent difference in estimated AEP between measured and OEM power curves is used as the mean value for the Power Curve Performance Factor. The associated standard deviation of these percent differences is standard deviation for the Performance Factor. A lower bound is placed at the warrantied value, and no upper bound is placed. This distribution is assumed to be normal. For additional information and validation of this Performance Factor, see One Energy white paper "*Results of Power Curve Measurements at NFWC Using ZephIR LiDAR*" [11].

Should a turbine model be considered that One Energy does not have operational data for, One Energy will attempt to work with the OEM to acquire operational data for this analysis. If this is not possible, the performance factor will be a normal distribution with a mean of 100% and standard deviation determined from a study performed by AWS Truepower [12]. This study included an IEC-compliant power curve test for 24 turbines of varying manufacturers and reported the average difference between the AEP based on measured and advertised power curves. The average loss value reported from the study is used as 95th percentile within the assumed normal distribution (2x standard deviation). The standard deviation is then computed from that assumption and used within the Performance Factor. The distribution is assumed normal, a lower bound is placed at the warrantied value, and no upper bound is placed. This value is not site specific.

O. POWER CURVE DEGRADATION

The wear on turbine blades and other moving parts can potentially degrade turbine efficiency. The Power Curve Degradation Performance Factor takes this into consideration. An article from WindPower Monthly examined how capacity factor changed over time with wind turbines in Denmark [13]. The findings in this article are the basis for the Power Curve Degradation Performance Factor distribution. The result of this analysis was that the capacity factor decreases by 0.7 percentage points over the 20-year lifetime of the turbine for onshore turbines.

Using this information, a model is created to convert the project-specific Gross Annual Energy Production capacity factor that is determined from the WRA into a uniform distribution using the range of the 0.7 percentage-point decrease into percentage of annual energy production. The Power Curve Degradation Performance Factor is site specific and is not a normal distribution.

P. SHEAR EXTRAPOLATION

The Shear Extrapolation Performance Factor accounts for using the power law shear profile to extrapolate wind speeds measured at lower heights up to hub height. This extrapolation brings an uncertainty into the data and should be accounted for. If data is measured at hub height and no extrapolation is necessary, this Performance Factor is determined to have a mean of 100% and a standard deviation of 0%.

If data is not measured at hub height, whether from a MET or a LiDAR, extrapolation using the power law is conducted. This Performance Factor is assumed normal and has a mean of 100% to indicate no bias. An external white paper examined an experiment performed to determine the uncertainty associated with using the power law and log law to extrapolate wind speeds [14]. Depending on the extrapolation method and the terrain of the measurement site, the uncertainty value is taken from Table 3.

VERTICAL EXTRAPOLATION SUMMARY AEP COMPARISONS		
	Measured vs Power Law Extrap.	Measured vs Log Law Extrap
	Standard Deviation	Standard Deviation
All Sites	4.2%	3.0%
Flat Sites	1.8%	1.9%
Forested Sites	7.0%	5.0%
Hilly/Ridgeline Sites	3.6%	2.5%

Table 3: Vertical Extrapolation Uncertainty [8]

The Shear Extrapolation Performance Factor uses the associated uncertainty from Table 3 as the standard deviation if wind speeds are extrapolated to hub height. This Performance Factor is site specific.

Q. SHORT-TERM MEASURE-CORRELATE-PREDICT (MCP)

The Measure-Correlate-Predict (MCP) Performance Factor is quantifies the uncertainty in correlating a short-term on- or near-site target dataset to a long-term reference dataset to predict long-term wind-speed estimates at a project site. An internal study was conducted to determine the uncertainty associated with different lengths of short-term on-site data. For the MCP Performance Factor, a mean of 100% is used, indicating no bias, and the standard deviation is based on the length of the short-term target dataset. The uncertainty is determined from Table 4, which is a result from the internal study and number of months of target data.

For additional information and validation of this Performance Factor, see One Energy white paper "*Quantifying MCP AEP Uncertainty*" [15].

MONTHS	AEP UNCERT. EST.
1	8.96%
2	5.98%
3	4.41%
4	3.44%
5	2.67%
6	2.23%
7	1.81%
8	1.50%
9	1.31%
10	1.11%
11	0.93%
12	0.84%
13	0.88%
14	0.87%
15	0.92%
16	0.87%
17	0.82%
18	0.69%
19	0.45%
20	0.34%
21	0.23%
22	0.26%
23	0.20%

Table 4: MCP Length Uncertainty

R. WAKE LOSS MODEL

When modeling wake loss, there is uncertainty in the generated estimates due to the model and simplifying assumptions inherent to the model. Currently, One Energy uses its proprietary wake loss software to estimate the wake loss at the proposed sites when more than one turbine is sited. This software utilizes the N.O. Jensen Model, which is a simple, yet effective, wake loss model within the industry.

There is a 15% model uncertainty in the wake loss estimate from the Jensen model [16]. To determine the standard deviation for this Performance Factor, the determined wake loss estimate, which is in percentage loss of energy production, is multiplied by 15%. The total wake loss for the entire project is used as opposed to the individual turbine wake loss percentages. The mean is 100%, which is indicative of no bias. This Performance Factor is site specific and is only applicable when more than one turbine is being assessed. Should another wake loss model be used, a similar process will be used to calculate the Performance Factor.

S. WIND FLOW MODEL

For some WRAs, a wind flow model may be used to estimate the wind resource variability across the project area and to generate energy production estimates at each turbine location. If a wind flow model was used, an associated wind flow model uncertainty should be used for the Wind Flow Model Performance Factor. The Wind Flow Model Performance Factor depends on the specific wind flow model used and the modeled site. Each wind flow model will need its own uncertainty distribution.

One Energy uses the Continuum wind flow model and has documented the uncertainty values associated with the model within an internal study.

For more information and validation, see One Energy white paper "*Estimating Continuum Wind Flow Model Uncertainty*" [17].

T. WIND ROSE SENSITIVITY

The Wind Rose Sensitivity Performance Factor accounts for the annual variability in wake loss from upwind turbines. This Performance Factor is only applicable when more than one turbine is being assessed.

Using the Site MCP dataset, a wind direction distribution for each year is calculated. These wind direction distributions are then put through the Jensen wake loss model to calculate expected wake at each turbine within the project. For each year, the average wake loss at each turbine is calculated and then averaged across the entire project.

Using each year of project average wake loss, a standard deviation is calculated. The Wind Rose Sensitivity Performance factor is assumed normal with a mean of 100% to indicate no bias. This Performance Factor is site-specific.

4. COMPOSITE PERFORMANCE DISTRIBUTION

A probability dataset is created for each Performance Factor by utilizing a Monte Carlo Method. One hundred thousand trials are performed. Each Performance Factor is considered independent and a unique random number is generated for each throughout each trial. The random number is determined to be the CDF value for that sample, and the probability of the energy production percentage related to the random CDF value is compiled into a probability dataset for each Performance Factor.

Within the individual trial, the effect of each Performance Factor is calculated and then is combined with the other Performance Factors by the statistical rule of multiplication, assuming independence, to find the total effect on energy production. This same process is completed for the full number of trials. A new probability dataset encompassing the results of all trials is created, and a new distribution is determined, called the Composite Performance Distribution.

The following information is presented in PPR Section 3 – Composite Performance Distribution:

1) **Plot of the Composite Performance Distribution**

5. FULLY-BURDENED AEP & EXCEEDANCE VALUES

From the Composite Performance Distribution, a cumulative density function is derived. At each integer interval from the CDF of the Composite Performance Distribution from 1 through 99, a Scale Factor is found. Each integer interval corresponds to a P-Value (i.e. interval 40 is representative of P40) with its associated Scale Factor. The Scale Factor for each P-Value integer is applied to the Net Energy Production (determined in the WRA) to obtain the exceedance energy production value for the specific P-Value.

A. PRODUCTION P-VALUES

One Energy calculates all energy production P-Values from P1 through P99. Only specific P-Values are shown within the PPR document: P1, P10, P50, P75, P90, P95, and P99. These P-Values are explicitly shown to demonstrate energy production spread and full uncertainty estimates in line with the industry. The end result is a fully-burdened P50 energy production value and the spread associated with site-specific uncertainties.

The following information is presented in PPR Section 4A – Production P-Values:

1) **Table with the Net AEP Scale Factors**
2) **Table with annual energy productions values at P1, P10, P50, P75, P90, P95, and P99**
3) **Table with annual capacity factors at P1, P10, P50, P75, P90, P95, and P99**
4) **Table with monthly energy production at P1, P10, P50, P75, P90, P95, and P99**

B. P50 ANNUAL ENERGY PRODUCTION 12X24

A 12x24 energy production table shows diurnal and seasonal trends expected from the site-specific project. A Net AEP 12x24 is displayed within the WRA and only contains wake effects. This P50 Energy Production 12x24 includes both wake and all other factors that affect production, as included within this document.

A Scaling Ratio is found between each month's P50 energy production and the corresponding monthly Net AEP. This Scaling Ratio is applied to all hours of the day within the specified month of the Net AEP 12x24 and repeated for each month. All hours within a single month are scaled using the same ratio and the ratios are not adjusted diurnally.

The following information is presented in PPR Section 4B –P50 12x24:

1) **Table of the fully burdened P50 Energy Production 12x24**

6. PROSPECTING ANTICIPATED ENERGY PRODUCTION

During the Prospecting (Initial Evaluation) stage of project development, a Preliminary Site Wind Assessment is conducted. As detailed in the Wind Resource Assessment methodology Section 10: Prospecting Wind Assessment, a Baseline AEP with wake loss is determined.

A region-appropriate average P50 Scale Factor is applied to the Baseline AEP with wake loss to create the Anticipated AEP and Anticipated Capacity Factor. Past project P50 Scale Factors are used to create the region-appropriate average P50 Scale Factor. If there is no region-appropriate average P50 Scale Factor, a preliminary Composite Performance Distribution is created with reasonable estimates of each Performance Factor and the P50 Scale Factor from that is used.

This Anticipated AEP is a preliminary production estimate used within financial modeling for the project.

7. CONCLUSION

One Energy conducts a project performance analysis that is necessary for energy production estimates for a proposed project. In the PPR, the following are included: Performance Factors and their distribution information, figures of each Performance Factor probability density function, the Composite Performance Distribution, the range of P-values for annual energy production, and the exceedance table for a site-specific project. The result of the PPR is a fully burdened annual P50 energy production.

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