GE
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Pan-Canadian Wind Integration Study (PCWIS)

Section 3: Wind Data Development

Prepared for: Canadian Wind Energy Association (CanWEA)

Prepared by: GE Energy Consulting / Vaisala

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imagination at work

Legal Notices

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Technical Advisory Committee Members:

- Alberta Electric System Operator (AESO)
- BC Hydro
- Hydro Quebec
- Independent Electricity System Operator (IESO)
- ISO-New England (ISO-NE)
- Manitoba Hydro
- Midcontinent Independent System Operator (MISO)
- National Renewable Energy Laboratory (NREL)
- New York Independent System Operator (NYISO)
- SaskPower
- Utility Variable-Generation Integration Group (UVIG)
- Western Electricity Coordinating Council (WECC)

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Acronyms and Nomenclatures

Base Scenarios

5% BAU	5% Wind Penetration – Business-As-Usual
20% DISP	20% Dispersed Wind Penetration
20% CONC	20% Concentrated Wind Penetration
35% TRGT	35% Targeted Wind Penetration

Unit Types

CC-GAS	Combined Cycle Gas Turbine
COGEN	Cogeneration Plant
DPV	Distributed Photovoltaic
HYDRO	Hydropower / Hydroelectric plant
NUCLEAR	Nuclear Power Plant
OTHER	Includes Biomass, Waste-To-Energy, Etc.
PEAKER	SC-GAS and RE/IC
PSH	Pumped Storage Hydro
PV	Photovoltaic
RE/IC	Reciprocating Engine/Internal Combustion Unit
SC-GAS	Simple Cycle Gas Turbine
SOLAR	Solar Power Plant
ST-COAL	Steam Coal
ST-GAS	Steam Gas
WIND	Wind Power Plant

Canadian Provinces in PCWIS

AB	Alberta
BC	British Columbia

MB	Manitoba
NB	New Brunswick
ON	Ontario
QC	Quebec
MAR	Maritime
NL	Newfoundland and Labrador
NS	Nova Scotia
PE	Prince Edward Island
SK	Saskatchewan

USA Pools in PCWIS

BAS	Basin
CAL	California ISO
DSW	Desert Southwest
FRCC	Florida Reliability Coordinating Council
ISONE	ISO New England
MISO	Midcontinent ISO
NWP	Northwest Power Pool
NYISO	New York ISO
PJM	PJM Interconnection
RMP	Rocky Mountain Pool
SERC-E	SERC Reliability Corporation- East
SERC-N	SERC Reliability Corporation- North
SERC-S	SERC Reliability Corporation- South
SERC-W	SERC Reliability Corporation- West
SPP	Southwest Power Pool Regional Entity

General Glossary

AESO	Alberta Electric System Operator

BAA	Balancing Area Authority
Btu	British thermal unit
CanWEA	Canadian Wind Energy Association
CF	Capacity Factor
CO_2	Carbon Dioxide
DA	Day-Ahead
DNV GL	DNV GL Group
DPV	Distributed PV
DR	Demand Response
EI	Eastern Interconnection
ELCC	Effective Load Carrying Capability
EUE	Expected Un-served Energy
ERGIS	Eastern Renewable Generation Integration Study
EV	Electric Vehicle
EWITS	Eastern Wind Integration and Transmission Study
FERC	Federal Energy Regulatory Commission
FOM	Fixed Operations and Maintenance
GE	GE Energy Consulting
GEII	General Electric International, Inc.
GE EC	GE Energy Consulting
GE MAPS	GE's "Multi Area Production Simulation" Software
GE MARS	GE's "Multi Area Reliability Simulation" Software
GE PSLF	GE's "Positive Sequence Load Flow" Software
GT	Gas Turbine
GW	Gigawatt
GWh	Gigawatt Hour
HA	Hour-Ahead
HR	Heat Rate
IEC	International Electrotechnical Commission

IESO	Independent Electricity System Operator
IPP	Independent Power Producers
IRP	Integrated Resource Planning
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt Hour
lbs.	Pounds (British Imperial Mass Unit)
LDC	Load Duration Curve
LMP	Locational Marginal Prices
LNR	Load Net of Renewable Energy
LOLE	Loss of Load Expectation
MAE	Mean-Absolute Error
MMBtu	Millions of BTU
MMT	Million Metric Tons
MVA	Megavolt Ampere
MW	Megawatts
MWh	Megawatt Hour
NERC	North American Electric Reliability Corporation
NO_X	Nitrogen Oxides
NRCan	Natural Resources Canada
NREL	National Renewable Energy Laboratory
O&M	Operational & Maintenance
PCWIS	Pan-Canadian Wind Integration Study
PPA	Power Purchase Agreement
REC	Renewable Energy Credit
RPS	Renewable Portfolio Standard
RT	Real-Time
RTEP	Regional Transmission Expansion Plan
SCUC	Security Constrained Unit Commitment

SCEC	Security Constrained Economic Dispatch
SO_2	Sulfur Dioxide
SO_X	Sulfur Oxides
ST	Steam Turbine
TW	Terawatts
TWh	Terawatt Hour
UTC	Coordinated Universal Time
VOC	Variable Operating Cost
VOM	Variable Operations and Maintenance
WECC	Western Electricity Coordinating Council
WI	Western Interconnection

3 Wind Data Development

Section Acknowledgement:

Sub-section 3-1 was written by the Environment and Climate Change Canada team[1].

Sub-section 3-2 and the following sub-sections were written by the Vaisala team.

3.1 Mesoscale Modeling of Wind Speed Time Series

3.1.1 Introduction

The objective of this project was to generate multi-year time series of surface-layer meteorological fields as part of the Pan-Canadian Wind Integration Study (PCWIS). The Canadian Wind Energy Association (CanWEA) has a target of generating 20% of Canada's electricity by 2025 from wind energy. In this regard, CanWEA will analyze the time series generate by this project for devising a viable strategy for such large-scale integration of wind energy within the Canadian power grids.

The project was mandated to generate the relevant time series using a three-dimensional mesoscale atmospheric model with 2-km horizontal grid spacing and 10 min time resolution, over all of Canada (south of 70° N). Mandatory outputs for the project include wind speed and direction, air temperature, specific humidity at 80, 100, and 120 m above ground level along with surface pressure.

3.1.2 Methodology

Mesoscale simulations for this project were carried out using the limited-area configuration of the Global Environmental Multiscale (GEM) atmospheric model (GEM-LAM hereafter). In general, the GEM model works by first solving a set of dynamical equations directly on the model grid. Physical processes including atmospheric radiation, fluxes from different land-surface components, boundary-layer turbulent mixing as well as clouds and precipitation are not directly resolved at the grid scale. These subgrid-scale processes are accounted for in the model by supplementing the solutions of the dynamical equations with parameterized tendencies associated with the pertinent physical processes.

[1] "Mesoscale Modeling Of Wind Speed Time Series, A Summary Report", Prepared by: W. Yu, S. Z. Husain, L. Separovic, and D. Fernig, Atmospheric Numerical Weather Prediction Research Section, Meteorological Research Division, Atmospheric Science and Technology Directorate, Environment and Climate Change Canada, 2121 TransCanada Highway, Dorval (Quebec), Canada H9P 1J3, "Funding for this project (RENI 546) was provided by the ecoENERGY Innovation Initiative (ecoEII) of Canada, March 16, 2015

Large-scale atmospheric features in the meteorological fields simulated with limited-area models are susceptible to deviations from the generally coarse-resolution driving fields over time, particularly for large continental-scale spatial domains. A major scientific challenge for this project was, therefore, to determine the appropriate strategy to address the issue of large-scale deviations for multi-year simulations.

In order to minimize the impact of large-scale deviations associated with a large spatial domain over extended-range simulations, the problem may be separated into multiple periods of sufficiently short time-frames. Construction of a final continuous time-series of any meteorological variable in this approach however suffers from abrupt changes due to temporal blending. Furthermore, individual shorter integration requires time for spin-up of clouds that are not analyzed in the regional analysis files from the Meteorological Service of Canada (MSC). The spin-up issue would therefore increase the computational cost of the project.

Dividing the problem into multiple mesoscale simulations over smaller domains each running for extended time-periods (from weeks to months) followed by spatial blending of the end results on the other hand results in spatial discontinuities in the meteorological fields, particularly along the lateral boundaries of the smaller domains. Furthermore, existing literature shows that the nested simulation domains cannot be arbitrarily small in order to permit proper development of small scales.

Based on the aforementioned adverse implications associated with temporal and spatial blending, a continuous temporal integration over the entire spatial domain appears to be the most suitable approach for this project, provided a mechanism is put in place to restrict large-scale deviations in the simulated fields. Large-scale atmospheric deviations are controlled by spectrally nudging the model outputs to the driving fields. Spectral nudging of the atmospheric large scales, as implemented in this project, is found to effectively control any undesirable deviation without considerable suppression of the small scales. The research conducted during this project have shown that simple temporal interpolation to derive the reference fields, in between two analysis hours, can lead to mesoscale variance deficiency in the spectrally-nudged simulated fields. Two different strategies have been proposed and examined during this project to deal with such variance deficiencies. One option is to use a time-varying nudging coefficient that puts the maximum weight on the analyses fields only when the simulation time is very close to the time for which valid analyses fields are available. The other approach, which has been demonstrated to be more effective, is to produce hourly estimates of analyses by running 6-hour forecasts initialized with the analyses and assuming a linear growth of forecast error within the first 6 hours of model simulation. The later approach is found to effectively eliminate any variance deficiency associated with the temporally-interpolated analysis fields. Furthermore, different spectral nudging approaches, including the appropriate nudging length scales as well as the vertical profiles and temporal relaxations for nudging, have been investigated to determine the optimal nudging strategy. Analysis conducted during the course of this project has shown that specific humidity is well constrained during extended-range simulations when only temperature and wind speed are controlled by nudging. As a result, only the simulated temperature and horizontal wind speed fields were selected for nudging in this project. Further details regarding the spectral nudging approach developed for this project are provided in (Husain et al., 2014).

Although controlling the evolution of the atmospheric large scales generally improves the outputs of high-resolution mesoscale simulations within the surface layer, the prognostically evolving surface fields can nevertheless deviate from their expected values leading to significant inaccuracies in the predicted surface-layer meteorology. A forcing strategy based on grid nudging of the different surface fields, including surface temperature, soil-moisture, and snow conditions, towards their expected values obtained from a high-resolution offline surface scheme was therefore developed to limit any considerable deviation. The offline surface scheme used to downscale the surface fields (surface temperature, soil moisture, snow depth, and snow density) is known as the Surface Prediction System (SPS) which is based on the ISBA (Interactions between Soil, Biosphere, and Atmosphere) land-surface scheme. The standard implementation of the SPS scheme was considerably modified in the course of this project to include weighted blending of the driving forecasts fields to remove abrupt changes during switching between the driving forecast fields. Furthermore, a large-scale relaxation scheme for the evolving soil moisture field towards its regional analysis counterpart was implemented to restrict intermittent large-scale deviations. Additional details on the land-surface component of this project are provided in (Separovic et al., 2014).

3.1.3 Simulation Strategy

The basic simulation followed a two-stage strategy. First, the MSC's regional analysis fields, available every 6 hours (0000, 0600, 1200 and 1800 UTC, where UTC denotes the Coordinated Universal Time), were used to initialize and drive a GEM-LAM simulation involving 15 km horizontal grid spacing over the entire simulation domain over the entire time period (2008-2010). The 15-km GEM-LAM (LAM-15 hereafter) simulation included large-scale nudging of horizontal wind speed and temperature toward the operational regional analysis fields. The relevant surface fields in LAM-15 simulation were also nudged towards to SPS-generated reference fields. The purpose of the LAM-15- simulation was to produce three-dimensional meteorological fields with large scales features closely resembling those embedded in the driving analysis fields, but available more frequently (every 20 min) to force the second-stage 2-km GEM-LAM (LAM-2 hereafter) simulation. The LAM-2 simulation also involved atmospheric and surface nudging towards the appropriate reference fields to produce the final desired outputs.

3.1.4 Verification of Strategy

Outputs of the LAM-15 and LAM-2 simulations were extensively analyzed to verify the validity of the strategy developed during the course of this project. The verifications that were conducted during this project are provided below.

I. Similarity between the large-scales of the driving and the simulated field were compared to determine the impact of different atmospheric nudging configurations and to identify the most appropriate nudging strategy. Similarity of large-scales is compared for both LAM-15 and LAM-2 simulations that were forced with the operation regional analysis and LAM-15 outputs, respectively.

II. The ratios of spectral variance between the driving and analysis fields for different length scales and at different vertical levels were compared to study the impact of different nudging configurations. It helped to identify the appropriate nudging length scales. Variance spectra ratio was analyzed for both LAM-15 and LAM-2 simulation outputs. It was also useful in determining the impact of surface nudging.

III. Simulated fields are compared at the screen level (2-m temperature and dew point, and 10 m wind speed) against those obtained from ground-based stations spread all across Canada. In addition to the entire domain, screen-level statistical scores (bias, root-mean-square error, standard error) were compared for individual regions. The results have shown that both LAM-15 and LAM-2 simulations coupled with atmospheric and surface nudging resulted in improved screen-level temperature compared to the operational regional forecast while wind speed scores were also found to be equivalent. Over complex terrain, e.g., over British Columbia, LAM-2 simulations were found to result in improved scores for wind speed.

IV. Simulated fields were also compared against the limited wind turbine data that were available. For those limited number of stations, the simulated fields demonstrated improved statistical score compared to the operational forecasts. Moreover, the results for the optimal LAM-2 simulation were found to clearly outperform the optimally configured LAM-15 simulation.

3.1.5 Conclusions

A dynamical downscaling strategy based on high-resolution mesoscale simulations over a large continental-scale spatial domain and an extended time-period has been developed within the course of this project. Continuous temporal integration over the entire domain, as opposed to extended integrations over smaller spatial domains or multiple simulations with shorter time periods over larger domains followed by spatiotemporal blending, was found to be the most suitable approach for accomplishing the high-resolution downscaling objectives of the project.

The developed scheme was employed during the project to generate the multi-year time series of meteorological variables for CanWEA as a contribution to the broader PCWIS.

In order to improve the impact of spectral-nudging two novel methods have been developed that reduces or eliminates variance deficiency in the simulated fields. This includes the concept of time-varying nudging increment and the method of computing frequent analysis estimates. Extensive sensitivity studies have been carried out to identify the optimal nudging configuration in terms of the shape of nudging vertical profile, nudging length-scales and the type of temporal relaxation.

Large-scale spectral nudging of horizontal wind speed and temperature was found to adequately control large-scale deviations in specific humidity. In order to overcome intermittent deviations the surface fields were nudged towards some reliable reference dataset obtained from the modified SPS external surface model. Results show that compared to the coarse-resolution regional analysis fields, the SPS fields when used as reference for surface nudging clearly led to improved screen-level scores for both temperature and dew point. Nudging of the surface fields was however found to be neutral for the screen-level wind speed. Increasing the strength of surface nudging was found to improve screen-level scores further.

Meteorological fields obtained through high resolution LAM-2 simulations following the nudging strategy adopted in this project is able to maintain large-scale similarity with the driving LAM-15 fields, while adding substantially increased spatial variance for the smaller scales (less than 200 km). In terms of screen-level score, LAM-2 simulations were, in general, found to be equivalent compared to the LAM-15 simulations over the entire domain, although over BC and the North, where orography-induced spatial variance is more influential, LAM-2 simulations were found to improve both screen-level temperature and wind speed. Performance of different atmospheric nudging configurations for both LAM-15 and LAM-2 simulations was also evaluated against 80-m wind and temperature data obtained from three wind farm locations. For all three stations, LAM-2 simulation with its optimal nudging configuration was found to deliver better statistical accuracy for both wind speed and temperature over its LAM-15 counterpart.

3.1.6 References

- Husain, S.Z., Separovic, L., Yu, W., and Fernig, D. (2014): Extended-range high-resolution dynamical downscaling over a continental-scale spatial domain with atmospheric and surface nudging. Journal of Geophysical Research – Atmospheres, 119(24): 13720-13750.

- Separovic, L., Husain, S.Z., Yu, W., and Fernig, D. (2014): High-resolution surface analysis for extended-range downscaling with limited-area atmospheric models. Journal of Geophysical Research – Atmospheres, 119(24): 13651-13682.

3.2 Wind Integration Dataset

3.2.1 Introduction

Vaisala was retained to produce an integration dataset in support of the PCWIS. An integration dataset provides the simulated raw production and forecasts that act as inputs to the models and scenarios used in an integration study. A primary focus of integration datasets is to attain realistic properties of wind energy generating facilities, and realistic forecast levels of forecast skill in the simulated retrospective forecasts.

The PCWIS is an integration study intended to cover a broad swath of southern Canada. The main components of the dataset delivered by Vaisala are a synthetic history for more than 50,000 hypothetical wind energy locations consisting of simulated 10-minute production, and simulated hourly energy production forecasts for the hour-ahead, four hour-ahead, six hour-ahead, and 24 hour-ahead forecast horizons for each of the locations over a three-year period from 2008 through 2010. The wind production dataset uses the meteorological dataset described above as provided by Environment and Climate Change Canada as its basis, with algorithms to convert the meteorology into time series of synthetic energy generation developed and applied by Vaisala. The production estimates include losses specially formulated for the Canadian domain and parameters of the wind integration study, and include dynamic wake losses, icing losses, and low temperature losses.

Because of the importance of transmission interconnects to the United States, attempts were made where possible to follow the procedures established during the creation of the US Wind Integration National Dataset (Draxl et al, 2015), which Vaisala created in collaboration with the U.S. National Renewable Energy Laboratory.

3.2.2 Meteorological Datasets

Two independent meteorological datasets were used for the creation of production and forecasted production data, and these were produced by Environment and Climate Change Canada and Vaisala, respectively.

3.2.2.1 Simulated Production

Environment and Climate Change Canada generated the meteorological dataset that provided the basis for simulated energy production, using a limited area mesoscale numerical weather prediction (NWP) model, run at a horizontal grid resolution of 2km as described previously. Variables provided at each of the cell locations were: wind speed at 80m (m/s), 100m (m/s), and 120m (m/s), wind direction at 100m (degrees), temperature at 80m (Celsius), 100m (Celsius), and 120m (Celsius), humidity at 100m (kg/kg), and surface pressure (hPa). The output interval was 10 minutes, and data was delivered for the period from January 1, 2008 through December 31, 2010.

3.2.2.2 Simulated Forecasts

Vaisala produced a second, independent meteorological dataset that provided the basis for the simulated energy production forecasts. The fundamental tool employed in the creation of the meteorological dataset was the Weather Research and Forecasting (WRF) modeling framework. WRF is maintained by the U.S. National Center for Atmospheric Research (NCAR), but includes contributions from institutions worldwide. Specifically, version 3.4.1 of the WRF Advanced Research and Weather (ARW) model was used.

Vaisala's base simulation consisted of 41 full eta levels and had the following configuration:

- Planetary Boundary Layer Scheme - YSU model
- Surface Parameterization - Monin-Obukhov similarity model
- Land-surface option – NOAH LSM
- Scale selective nudging

Nested domains of 54km, 18km, and 6km were used. The model was initialized once per day at 0000 UTC, with no spin-up period. The 1-degree NOAA GEFS Reforecast 2 (Hamill et al, 2013) control simulation was used to specify initial and lateral boundary conditions. Each forecast simulation was run out 48 hours to ensure that the day-ahead (i.e. next day) period was covered. The output interval was 60 minutes.

3.2.3 The Wind Hourly Production Dataset

3.2.3.1 Cell selection

The initial target for the total number of sites in PCWIS was 50,000, distributed across the various provinces in proportions determined in coordination with the steering committee. Varying proportions of onshore and offshore sites on a per-province basis were specified, depending on the feasibility of offshore production and quality of wind resource. A maximum of 15% offshore penetration was considered for the Maritimes, Ontario, Quebec, and British Columbia, leading to an overall offshore penetration of roughly 10% for all of Canada. Hudson Bay was considered unfeasible. Provinces with no access to large open bodies of water had zero offshore sites.

In total, 54,846 onshore and offshore cells were prescribed. A cell in the context of this project refers to a point location and hypothetical wind development site in the Canadian domain collocated with a numerical weather prediction (NWP) grid point. Each cell represents four square kilometers, with a presumed maximum installation capacity of eight 2MW modern utility-scale wind turbines. Each cell therefore has a maximum rated capacity of 16MW. The turbine density specification was identical to that in the US Wind Integration National Dataset, and is based on examination of turbine density within modern North American wind projects.

While each cell has a maximum rated capacity of 16MW, individual cell power curves are one of four available classes, based on the simulated 2008 annual average wind speed at each cell. Specifics of the power curves are described below.

The strategy for cell selection was to grossly oversample the potential number of cells required for the integration study, in order to provide maximum flexibility during the selection of scenarios. Due to technical restrictions at Environment and Climate Change Canada, all cells needed to be selected before any modeling could begin. Starting with a list of all cells within each province, many cells were excluded according to criteria developed in collaboration with the steering committee. Specifically, areas that were excluded from the site selection process met at least one of the following conditions:

- An area with a terrain slope of greater than 20°
- Surface elevation of greater than 2000m
- Area within a Provincial park or Wilderness
- Populated areas
- Aboriginal and Indian Areas
- Major lakes and rivers

After these areas were excluded, the remaining cells were sorted by annual mean wind speed at 80m, and the windiest cells were included. In order to meet the target numbers for each province, different lower threshold values for wind speed were developed for each province. These, along with the resultant number of grid cells, are shown in Table 3-1.

Table 3-1: Initial Set Of Onshore Site Selection by Province

Province	Wind speed cutoff (m/s)	Selected onshore sites
British Columbia	8.2	4,935
Alberta	7.1	9.314
Saskatchewan	7.9	2,949
Manitoba	7.4	2,987
Ontario	6.9	9,511
Quebec	7.9	13,663
Maritimes (NB,NS, PEI)	8.7	2,203
ALL CANADA ONSHORE		**45,562**

Working from this initial list, additional sites were added to represent all existing known and planned wind energy installations, and hand-selected offshore locations. Offshore sites are situated between 10 and 50 km from shorelines, and locations were chosen in coordination with the steering committee. The final set of 54,846 selected cell locations is shown in

Figure 1, and the full list of locations, along with their geographic coordinates, is available as a comma separated values (CSV) file (to be made available through CanWEA PCWIS website).

Figure 3-1: Selected PCWIS Sites.

3.2.3.2 Power production profiles

Power production profiles were generated for each site by applying a power curve to the 100m winds for every 10-minute time period in the meteorological dataset. The power curves used were taken from the Eastern Renewable Generation Integration Study (ERGIS) (Bloom et al, 2015), and are shown in Figure 2. There is a different power curve for each of the IEC classes 1, 2, and 3, and a special power curve was applied for offshore locations. These power curves represent composite curves for existing and in-development utility-scale wind turbines. A density correction (proportional to the cube root of the ratio of the modeled density to the turbine reference density) was applied to estimate an effective wind speed at the turbine reference density. A high wind speed cut-out of 20 m/s was used for class 3, and 25 m/s for the other classes. Hysteresis cut-in values were set to be 5 m/s below the high wind cut-out values.

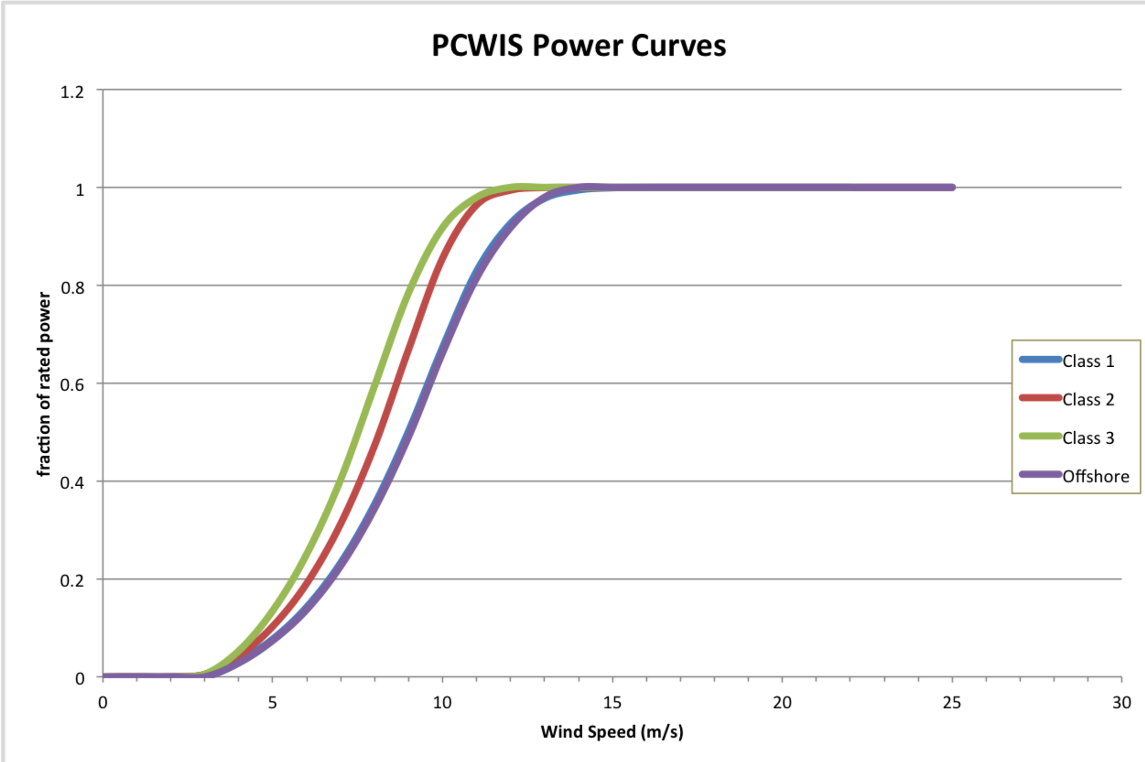

Figure 3-2: PCWIS Power Curves

3.2.3.3 Production losses

Several loss types were implemented in the simulated production dataset. These were array losses, icing losses, and low temperature losses. Loss targets were established by the PCWIS steering committee. Losses were tested and formulated on the simulated production data, then applied consistently to both simulated production and simulated forecasts.

Array Losses

Array losses depend on the size and layout of the array. Based on industry experience, the combined turbulence and wake loss factor was estimated to be 10% for the average size in plant used in this study (270MW). The same loss factor was applied to all wind plants in all study scenarios. The PCWIS steering committee identified a target array loss that would result in system-wide power reduced by 10%. To achieve this loss, a factor was applied to wind speed at each cell. This modified wind speed was used to generate cell-specific power profiles that were summed to calculate the differential impact on the power at the system level. Applying a correction to the wind speed allows wind turbines to still reach rated power.

The process of identifying the appropriate wind speed correction factor was an iterative one that first determined the baseline system-wide annual power production with no array losses. Subsequent iterations, as shown in Table 3-2, applied progressively conservative correction until system-wide power production for all hours of 2008 had been reduced by 10% of the baseline. It was found that a loss factor of 6.5% applied to wind speed at all times resulted in a 10% reduction in system-wide power. This loss factor was then applied in a similar manner to 2009 and 2010 wind speeds.

Table 3-2: Iterations of Array Losses

PWCIS Array Losses Iteration Experiments			
Wind Speed Correction Factor	0.93	0.94	0.935
System Wide Power Production Reduction	11%	9%	10%

Icing Losses Overview

Icing losses are complex in nature, and there are significant differences between operational and meteorological icing conditions. For the PCWIS dataset, only simple icing losses that depend on relative humidity and temperature were considered. Nonetheless, this represents a novel consideration for an integration study.

Icing losses in PCWIS wind hourly dataset

Based on a review of previous icing studies and the meteorological fields available from Environment and Climate Change Canada, Vaisala recommended modeling the energy reduction as a function of time during which temperature was below zero (T < 0 °C) and relative humidity exceeded a threshold value (RH > 88%). This value is quite low as a threshold for icing, and may be a result of biases with Environment and Climate Change Canada's model. Whenever these conditions were met in a grid cell, production in that cell was set to zero and a data flag was set to indicate that icing was in effect. This ensured that periods of cold conditions, and no production, would not be mistaken for icing if the relative humidity criterion was not met. In addition, it allowed for simple accounting of the system-wide number of icing hours. The PCWIS steering committee suggested a targeted icing loss in terms of system-wide icing hours per annum of between 5-10%. An iterative approach to threshold selection was used. The iterative process took place on the simulated production meteorology for 2008 provided by Environment and Climate Change Canada. Temperature at 100m, pressure at the surface, and the specific humidity were used to produce a value for relative humidity. The temperature criterion was held constant at 0 °C, while the relative humidity threshold was varied. After several iterations, it was found that a relative humidity threshold of 88% resulted in 8.1% hours affected by icing conditions annually. This value is quite low as a threshold for icing, and I was flagged as an issue that was not further investigated. Figure 3-3 shows the seasonal variation in the percentage of hours affected by icing. Naturally the numbers peak in winter, though there was no obvious reason for the sharp difference between December and January. The relative humidity threshold was applied to simulated production and simulated production forecasts for the remaining years.

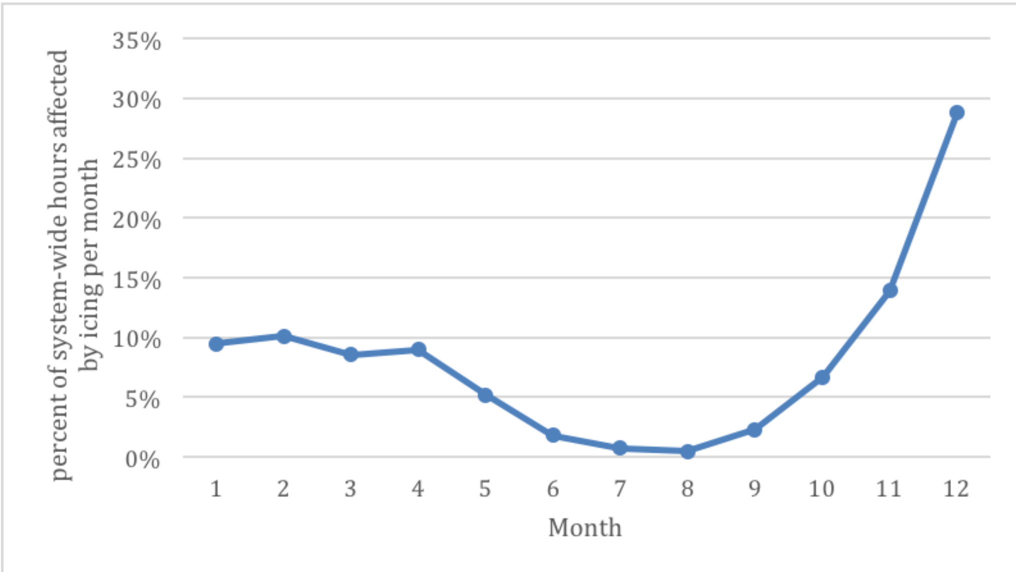

Figure 3-3: Percent of System-Wide Hours Affected By Icing per Month

Low Temperature Losses

A wind turbine will shut down when the air temperature falls below a threshold value, to avoid risk of mechanical system damage. For this study, wind turbine generators are assumed to have cold weather operation packages with a low-temperature cutout of -35°C, including 5° of hysteresis. Therefore, the wind turbine generators will shut down when the air temperature falls to -35°C and return to operation when the temperature rises to -30°C. For this study, Vaisala set generation to zero for each cell any time that the temperature dropped below -35°C, and production was kept at zero until the temperature for the cell returned to -30°C. However, while the 100% shut-off may not actually happen, this assumption was deemed satisfactory.

3.2.4 Simulated Wind Energy Production Forecast Data

A key requirement for wind energy integration work is the availability of wind energy forecasts to go with the modeled estimates of production. These forecasts were designed to have error characteristics similar to the current state of the art of operational wind forecasting.

Power forecasts at 1, 4, 6, and 24-hour lead times were produced to correspond to each hour of the wind power production dataset. A mesoscale NWP model-based approach was used to realistically capture the natural spatiotemporal correlations between the wind sites, i.e. to ensure that neighbouring sites have forecast errors in the same direction and of similar magnitudes. Each power forecast contains a deterministic, best-estimate value.

3.2.4.1 24-hour lead-time forecasts

The WRF model was used to create the meteorological data set to achieve reasonable 24-hour lead-time forecasts. The model was run over Canada with progressively finer nested domains of 54km, 18km, and 6km. The model was initialized once per day at 0000 UTC, with no spin-up period. The 1-degree NOAA Reforecast2 GEFS Control simulation was used to specify initial and lateral boundary conditions. Each forecast simulation was run out 48 hours to ensure that the day-ahead (i.e. next day) period was covered. The output interval was 60 minutes.

Due to computational limits, the forecast NWP simulations were initialized only once per day (at 00Z). Forecast errors are relatively flat during the 24-48 hour period, but there is a discontinuity in the forecast properties as a result.

Forecasts of simulated actuals are often overly skillful, because many of the same observations go into both the global reanalysis datasets used to create the simulated actuals, and the global reforecast datasets used to create the historical forecasts. In this case, the use of GEFS boundary conditions and reduced resolutions resulted in forecasts that had sufficient error to proceed. To adjust this error further, as described below, Vaisala used a combination of time series smoothing and “truth” blending, which is simply a weighted average of the raw forecast and the simulated actual value at a given time. This mimicked operational model output statistics (MOS) by reducing bias and improving skill, but not by too much. At the same time, it was computationally efficient relative to running full MOS at all of the sites.

Vaisala used an iterative approach to the statistics; adjusting smoothing and blending amounts upward until forecast time series and error histograms appeared reasonable and bulk error metrics were similar to state-of-the-art day-ahead forecasts.

From experience with previous integration work, the 24-hour-ahead noise and error statistics were deemed appropriate when the forecast was a result of an 80%/20% mixture of a 13-hour centered moving average of the raw NWP forecasts and 13 hour centered moving average of the simulated actuals, respectively. In this context, the simulated actuals were treated as “truth”. The mixture of simulated actuals into the raw NWP forecast is what is meant by “truth” blending.

Table 3-3 describes the subjective characteristics of forecast error tuning throughout the iterative process of choosing the right weighting of smoothed raw NWP forecast and smoothed “truthful” simulated actuals. With the underlying goal of mimicking appropriate typical operational forecasts, Vaisala tested various configurations of raw NWP forecast smoothing windows, simulated actual smoothing windows, and blending weights. Based on industry experience with operational forecasts, Vaisala identified appropriate error statistics.

Table 3-3: Iterations of Day-Ahead Forecasting Smoothing

Forecast Smoothing	Observation Smoothing	Observation Weight	Subjective Character	Subjective Bias	Subjective Skill
3 h	N/A	N/A	Too Noisy	Too Large	Too Low
3 h	1 h	10%	Too Noisy	A Bit Large	Too Low
3 h	3 h	10%	Noisy, But Less So	A Bit Large	Too Low
7 h	7 h	10%	A Little Noisy	A Bit Large	A Bit Low
13 h	7 h	10%	About Right	A Bit Large	About Right
7 h	7 h	30%	A Little Noisy	Much Lower	Too High
13 h	13 h	20%	About Right	Acceptable	About Right

Forecast Production Bias Correction

One of the potential effects of conducting analysis on datasets produced by different numerical weather prediction models is systematic bias arising from differences in model physics and discretization. A unique challenge for PCWIS was that Environment and Climate Change Canada used a model for the simulated actuals that was not available for the simulated forecasting.

Initial comparison of the simulated actuals and simulated forecasts for a selection of aggregated sites for the year of 2008 by the project team showed significant forecast bias in the day-ahead forecasts. In independent analysis, Vaisala was able to reproduce the bias on the same selection of aggregated sites. Since bias was found in the aggregated sites it was assumed that the bias applied system wide.

To correct for the system-wide bias between the simulated actuals and simulated forecasts, Vaisala implemented a cell-based wind speed scaling of the forecast wind speeds, based on the ratio of the mean 2008 wind speeds in the production and forecast datasets. In other words, for each cell the 2008 annual mean wind speed ratio between the simulated actuals and simulated forecasts was applied to the simulated forecast. This one-time cell-based correction was applied across 2009 and 2010. In other words, new annual wind speed bias correction factors were not reproduced for 2009 and 2010. However, the project team was able to confirm that this correction had a satisfactory effect.

Correction of Under-Forecast Production Due to Conservative Icing

During a secondary phase of the dataset creation, after losses were applied, subsequent analysis found that the forecasted production for an aggregation of cells was again showing under-production. The simulated forecasts were, on an annual basis, predicting significantly less power than the simulated actuals. Vaisala found this to be due to an excess amount of icing losses in the forecast dataset. The likely reason for the differences in icing conditions between the simulated actual production and simulated forecasted production is due to the different manner in which atmospheric moisture content is derived by the different NWP models. WRF alone has more than 6 moisture models to choose from.

Vaisala addressed the difference in icing losses by applying a correction that eliminated the condition where it was possible to have zero-forecasted production and non-zero actual production, retaining the conditions where zero forecasted production and zero actual production existed, and where non-zero forecasted production and zero actual production existed. This had the effect of eliminating false positive icing conditions and suitably corrected the forecasted under-production.

3.2.4.2 Short lead-time forecasts

Statistical forecasts were generated for each site for the short lead-time (1, 4, and 6 hour) forecasts, based on a dispersive persistence method. Vaisala's operational short lead-time forecasts outperform a simple persistence forecast through sophisticated statistical methods not employable for this dataset, therefore special approximations were used with the simulated actuals to approximate the error statistics of operational short lead-time forecasts. The selected mechanism used shortened persistence lead times to increase the skill of the forecasts to the desired level, using the two parameters of persistence interval and lead-time, as described below.

The most basic persistence forecast uses the current value as a prediction for some future value. The length of the time between the observation and the predicted time is referred to as the 'lead time', and the length of the lead time has a significant impact on the skill of the forecaster. In the present convention, period-ending time was used. The enhanced skill of operational forecasts can be approximated using lead times shorter than would be available in a real time system, but using a constant lead time does not properly characterize the distribution of events in time – the errors are not properly dispersed.

For this dataset, the lead-time parameter was randomly sampled from a normally distributed population of 8,760 10-minute interval lead times, with a range of 0-80 minutes and a mean of 40 minutes. In other words, the population contains lead times of 0, 10, and 20 minutes, and so on up to 80 minutes. The most common lead time is 40 minutes. The effect of the mean 40-minute lead time is to improve average forecast skill.

The second parameter was the persistence interval. The persistence interval is the length of time over which the simulated actual (observed) data is averaged, and in the case of high-resolution (e.g. 1-minute) observations can be used to resample the observed data to a longer period, for instance from 1 minute to 10 minutes. However, for this study since the simulated actuals were only available every 10 minutes, the persistence parameter was held constant.

Two examples along with figures of the algorithm are given below:

Example #1: As shown in Figure 3-4, if the present time is T_0 and we are tasked with producing a forecast valid from T_{+60} to T_{+120} and a 40-minute lead time is sampled, then the algorithm takes the value at T_{+20} and selects this value as the forecast.

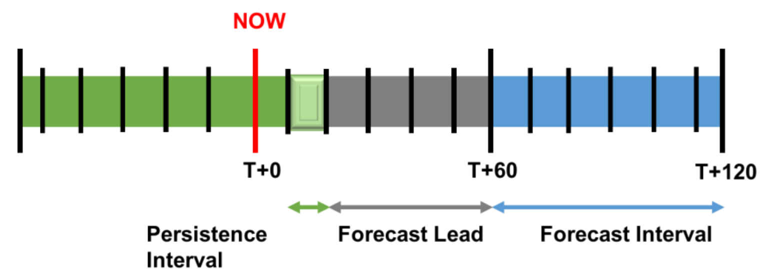

Figure 3-4: Graphical Example of Forecast Algorithm: 40min Lead Time

Example #2: As shown in Figure 3-5, if the present time is T_0 and we are tasked with producing a forecast valid from T_{+60} to T_{+120} and an 80-minute lead time is sampled, then the algorithm takes the value at T_{-20} and selects this value as the forecast.

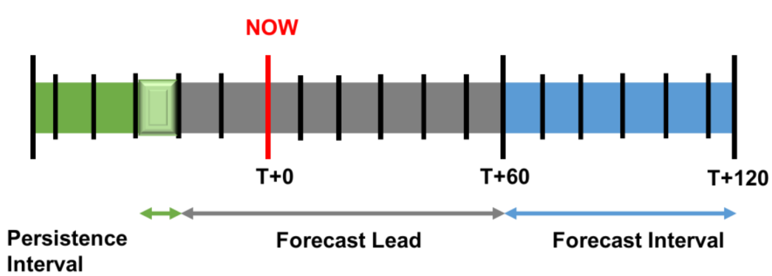

Figure 3-5: Graphical Example of Forecast Algorithm: 80min Lead Time

An iterative procedure similar to that of the 24-hour lead-time forecasts was followed, starting with a 1-hour forecast comprised of 10-min persistence at 40-min lead. This was adjusted until the improvement over persistence was similar to current operational forecasts, as shown in Table 3-4.

In practice, the long-term statistics of short lead-time forecasts show a greater skill than a simple persistence forecast, however at any given time, it is possible for such a forecast to be more skillful than normal, or less skillful than normal. A range of lead-times ensured a varying measure of success in the 1-hour forecasts.

Table 3-4: Iterations of Short-Term Forecast Parameters

Persistence Interval	Mean Lead Time	Lead Time Range	Auto-Correlation	Subjective Skill
10 min	40 min	N/A	N/A	A Bit High
10 min	45 min	0-90 min	0.9	A Bit Low
10 min	40 min	0-80 min	0.9	Barely High
10 min	40 min	0-80 min	0.9	Just Right

After parameters for the 1-hour forecasts were determined, the 4-hour lead-time forecasts were computed using an 80% to 20% blending of the 24-hour and 1-hour forecasts, and the 6-hour lead-time forecasts were computed using a 90% to 10% blending of the 24-hour and 1-hour forecasts. The equations used to calculate 4 (F_4) and 6 (F_6) hour-ahead forecasts are as follows:

$$F_4 = 0.8(F_{24}) + 0.2(F_1)$$

$$F_6 = 0.9(F_{24}) + 0.1(F_1)$$

3.2.5 Epilogue

The objective of the wind data production task was to generate synthetic wind production data and associated forecasts in support of the PCWIS. Where possible, methodologies consistent with the creation of the US Wind Integration National Dataset were employed. Several challenges emerged during the work described above: notably consistency issues between the meteorological dataset created by Environment and Climate Change Canada and the forecasting dataset created by Vaisala. Nonetheless, good communication between the project team, CanWEA and its consultants, and the Technical Advisory Committee made it possible to address issues as they arose, and it is the project team's view that the resulting production and forecasting datasets address the needs of the integration study.

3.2.6 References

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