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Emerging Technologies of Short-Term Wind Power Forecasting

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Executive Summary

Due to the increasing energy demand and pressing environmental issues, wind energy as one of the fastest growing renewable energy sources of electricity in Canada has been significantly developed in recent years. However, due to the natural variability of wind, the integration of wind energy into electrical power systems is challenging. Variable and fluctuating wind power causes numerous problems in power quality, system stability, and energy dispatch. These problems become more severe as the penetration level of wind energy increases. Therefore, the demand for accurate and reliable wind power forecasts has continued to grow in the electric power industry. Utilities, system operators and regional transmission organizations become increasingly reliant on these forecasts to efficiently operate power systems with large wind power penetrations.

Accordingly, the University of New Brunswick (UNB) was contracted by Natural Resources Canada (NRCan) to conduct a project on development and validation of advanced and integrated wind forecasting methods, aiming for applications in utilities and wind farms. The main objectives of this project are:

- To evaluate and improve short term wind forecasts from the Environment Canada (EC) wind forecast model;
- To develop and implement icing forecasting methods using the EC's forecasting model;
- To develop and test a wind ramp forecasting algorithm that can be combined with the EC wind forecast model to form a comprehensive wind forecasting package; and
- To study the benefit of bulk energy storage for wind plant operation to alleviate residual forecast error and uncertainty.

In accordance with these objectives, all required research tasks including data collection and acquisition, assessment of EC wind forecasting model, assessment of wind power production based on EC wind forecast model, development of icing forecasting model, development of wind power ramp forecasting method, study of bulk energy storage for wind plant operation, an interim report detailing the methodology and approach for the wind power forecasting technologies, and development, assessment and demonstrations of an integrated wind power forecasting package have been successfully completed in this project by March 31, 2022.

This white paper primarily focuses on the short-term wind power production forecast and wind power ramp forecast, providing a review of the state-of-the-art of forecasting methods, detailing the methodologies and performance of wind forecasting technologies developed by the UNB team during this project, and discussing on challenges and opportunities of wind forecast in future grid operation.

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1 Review on Short-term Wind Forecating Technologies

With the global increase of wind power generation in power systems, the importance of wind forecasting on a short-term time frame basis has grown tremendously. These developed forecasting models must be able to deal with all the unforeseen weather changes that impact both the stability and the economic yield of the modelled power systems. Over the last few decades, many short- term methods have been developed to accurately predict wind forecasts to mitigate risk for utility companies when scheduling wind energy in the electricity market. This section reviews recent short-term wind power forecasting methods, looking into the availability and structure of various methods in support vector machines (SVM), neural networks (NN) and hybrid schemes. Furthermore, this review also compares the methods in each category to determine the most viable of all methods to help further advance the developed wind power forecasting modules in this project.

1.1 Introduction

Wind power is one of the biggest forms of green electrical sources globally, generating clean, non- polluting renewable electricity with a global net capacity of 60.18GW in 2019 [1]. However, wind power production prediction of wind energy conversion systems (WECS) remains a challenge due to the inherent variation caused by wind energy. As a result, these uncertainties prevent WECS from being fully dispatch-able, posing a mounting challenge to the system operator and utilities alike and discourages large-scale wind power implementation and integration. Therefore, the ability to accurately quantify and predict wind power generation, in addition to its uncertainties, will have a profound impact on wind farm integration into the grid. Furthermore, accurate predictions will aid in the overall optimization of power system operation, such as generation scheduling, fuel purchasing scheduling, maintenance scheduling, investment scheduling, and security analysis. Various wind power forecasting methodologies are classified based on timescales with all power prediction methods can be separated based on the prediction horizon into three categories [2], [3] as:

- Immediate-short-term (6 hours-8hours ahead) forecasting.
- Short-term (day-ahead, 48 hours) forecasting.
- Long-term (multiple-days-ahead) forecasting.

The exact time windows for immediate-short-term, short-term and long-term predictions are set by utilities and/or system operators. Regardless of which time horizon the wind power prediction algorithm is categorized in, all wind power forecasting models can be classified into two major groups which [4-7]:

- Forecast future power values through statistics, leveraging time series data, considering historical behavior of target wind farm power.
- Predict wind power through adaptation of forecasted values from a physical model like the Numerical Weather Prediction (NWP) model.

Over the last two decades, several approaches have been developed to attempt to predict an accurate forecasting for immediate and short-term wind power (STWP) prediction forecasting [8- 15]. The main approaches utilized for STWP forecasting can be split into three categories: Neural Networks (NN)[12], [14], [16-23] and support vector machines (SVM) [13], [24-29] or a hybrid combination of several NN or SVM or both [8], [15], [19], [22], [25], [30-32]. With the advent of data analytics, STWP and STWS forecasting processes have begun incorporating data driven models in further aiding wind power prediction [6], [8], [10]. Regardless of implementation, the important fact remains that no matter which models and algorithms are adopted into STWP forecasts, the focus of all research efforts is to ensure the forecasted wind power production matches the actual generation as much as possible (e.g., wind power production forecasts achieved by wind speed forecasting methods with power curve models). Accordingly, it should be noted that wind speed forecasting methods will be referred to a short-term wind speed (STWS) forecasts and wind power will be referred to as short term wind power (STWP) forecasts throughout this section.

This white paper presents a detailed review on existing approaches used in wind power prediction over the STWP methodologies (up to day-ahead), focusing on SVM, NN and Hybrid techniques used to obtain the wind power prediction. Furthermore, this paper aims to further identify possible developments in future work based on the reviewed models. Each major category is compared based on the accuracy of prediction models using specific error quantification to numerically verify the feasibility and effectiveness of the methods in a WECS environment. Five typical statistical metrics, mean error (ME) or bias (Bias), root mean squared errors (RMSE), mean absolute errors (MAE), mean absolute percentage errors (MAPE), and adaptive mean absolute percentage errors (AMAPE), have been utilized for performance evaluation.

Bias or Mean Error refers to consistent differences between actual measurements and generated forecasts of those quantities which can be loosely described as a tendency to either over-forecast or under-forecast, expressed as

$$Bias = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (e_i) \qquad (1.1)$$

where N is the number of test points during the forecasting period and ei represents the forecast error between the observed (yi) and forecasted (y-i) values at a discrete time i.

RMSE provides another global error measure during the entire forecasting period which is a good estimator of the accuracy of mean forecasts. Its nonlinear form penalizes larger errors as it becomes larger upon the existence of large errors. It is given by

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (e_i)^2} \qquad (1.2)$$

MAE has been widely used in regression problems and by the renewable energy industry to evaluate forecasting performance. Unlike the RMSE metric, MAE weights all values equally and thus do not add additional weight to extreme forecasting events. It can be expressed as

$$MAE = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} |e_i| \qquad (1.3)$$

MAPE as another one of the most common measure of forecast error expresses the forecast accuracy in a percentage term. MAPE functions best when there are no extremes to the data. It can be given by

$$MAPE = \frac{100}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{|e_i|}{|y_i|} \quad (1.4)$$

AMAPE is a variation on the MAPE that is calculated using the average of the absolute value of the actual and the absolute values of the forecasts ($|\bar{y}_{\mathrm{i}}|$) in the denominator instead of the instantaneous measurements y_i. This statistic is preferred to be used as accuracy measure in wind power production forecast. It can be given by

$$MAPE = \frac{100}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{|e_i|}{|\bar{y}_{\mathrm{i}}|} \quad (1.5)$$

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1.2 Support Vector Machine Solutions (SVM)

SVM approaches have been for short-term wind forecasting methods for quite some time, with one of the most popular SVM used being the support vector regression (SVR) variant which is utilized in both linear and non-linear approaches [13], [24-29]. An STWP method used in [13] combines the SVM modelling with a wavelet transform in using hour ahead wind farm data. The paper outlines two methodology approaches using the WT-SVM approach. The first method utilizes the WT to decompose the incoming data stream into frequency components and then passing them into a piecewise SVM (PSVM). The second method uses WT as a kernel function inside the SVM as a replacement to the radial basis function (RBF). Each method is tested using a 30-day set of data in April 2008 from a wind farm in Texas on a one-hour, two-hour and three- hour ahead basis. The first method is the most superior, having accuracy and faster calculating speed when compared to the kernel WT in method 2 due to WT serving as a filter to the input data which changes any nonlinear signal into fixed frequency components with a recurring interval [13].

The STWP method utilized in [7]also utilizes wavelet SVM solution which is comprised of three major components: a preprocessing stage which normalizes the data and extracts features, the WSVM itself which runs a wind speed prediction where the wind-speed is converted to wind power based on the denormalization and the power curve. The method utilizes a Gaussian kernel function to change behaviours. The data used was the Western Dataset which comprises of weather models used in the western US between 2004-2006 sampled every ten minutes for ever two kilometers using 680 similar wind turbines ten miles west of Denver, Colorado.

An STWS method used in [26] utilizes augmented Lagrangian multiplier (ALM) and stochastic gradient descend (SGD) to take the heterotactic noise into account that is commonly present in wind speed forecasts. This method was created to curb the downsides of more traditional SVR techniques which assume that the error distribution is Gaussian with the same variance and zero mean. The method utilizes data from 47520 samples as a training set which consists of 11 months of wind speed records, followed by 4320 samples as the test sample based on 30 days of wind speed data from Jilin and Gansu, China [27]. The data is then subjected to 30 min, 60 min and 120 min prediction horizons, monitoring MAE, RMSE, MAPE and standard error of prediction (SEP) whilst being compared to other methods (GNSVR, GN-KRR, Feed

Forward, RNN, LR and Persistence). Although being able to successfully implement the method and account for some heterotactic noise, the method proved to have similar errors to neural network approaches. Table 1 summarizes the SVM methods explored in this subsection.

Table 1- SVM-based short-term wind forecasting methods

SVM Method/Type	**Datasets**	**Performance Results**	**Advantages**	**Disadvantages**
WT–SVM STWP [13]	Farm located in Texas with a time of 30 days in April 2008 based on the statistical error measurements	1hr ahead: MRE=7.97%, RMSE=11.52kW. 2hr ahead: MRE = 4.08%, RMSE=6.22kW. 3hr ahead: MRE = 4.76%, RMSE=7.02kW	The WT decomposition scale and translation factors allow for better prediction of SVM while still maintaining a fast convergence time	Only has one method of comparison (RBF -SVM)
WSVM STWP [7]	set of 3-year wind data sampled every 10 min for 680 wind Turbines in Denver Colorado	1hr ahead: MAE=1.12MW, Std=2.05MW, MAPE=3.74%. 2hr ahead: MAE= 2.31MW, Std= 3.86MW, MAPE= 7.71%. 3hr ahead: MAE=3.23MW, Std= 4.95MW, MAPE=10.76%.	More accurate results in WSVM than physical models and RBF-SVM	Error evaluation was only performed on a smaller one week set with only the normalized error present for the whole dataset
HGN-SVR STWS [26]	Two sets of 1-year wind speed datasets from Jilin and Gansu, China, on a 10 min sample basis	30 min ahead: MAE=0.69m/s, RMSE = 0.93m/s, MAPE=14.17%, SEP=13.1%. 1hr ahead: MAE=0.92m/s, RMSE=1.22m/s, MAPE= 19.65%, SEP=17.14%. 2hr ahead: MAE=1.21m/s, RMSE=1.57m/s, MAPE=28.4%, SEP=20.29%	Simple implementation with more accurate results in STWS than physical models; HGN-SVR is able to account for some heterotactic noise	At 2-hour intervals, some Neural Network overtake the HGN-SVR in MAPE

From the methods summarized in Table 1, it can be observed that each method has its own respective drawbacks, which may cause poor forecasting performance if used on different datasets. However, the WT-SVM model in [13] has the least amount of seasonal variance compared to the HGN-SVR has more seasonal data variety incorporated into the model as it is based on a full year of wind data[26] as well as the WSVM in [7] had more seasonal data variety incorporated into the model as it is based on the three years of wind data it used in one of its tests. Furthermore, the HGN-SVR was tested on more models for verification (GNSVR, GN-KRR, Feed Forward, RNN, LR and Persistence) when compared to the developed WT-SVM model (RBF-SVM) and the WSVM (persistence and RBF-SVM). When looking into the overall prediction error of each method used, the WT-SVM has lower losses at higher prediction windows whereas the WSVM has lower losses at smaller prediction windows.

1.3 Neural Network Methodologies

Neural Networks have been used extensively for STWP solutions over the last two decades with numerous approaches based both on modeling of the physical processes of the boundary layer and historic data with relative ignorance of the underlying processes. Early attempts at utilizing NN in an STWP environment were met with over-fitting issues as well as size issues due to the inherent nature of neural networks growing rapidly with the increase in the numbers of input variables parameters, layers (hidden or otherwise) or nodes (hidden or otherwise). With the advent of deep neural networks (DNN), great strides have been made in several fields including but not limited to computer vision, natural language processing, and speech recognition.

The NN approach in [16], utilized in STWS forecasting, introduces a convolutional neural network (CNN) with data from wind speed data of both early constructed and newly constructed wind farms are employed to train the model. The approach observes similar patterns from existing wind farms and migrates them to the new wind farms using transfer learning [16]. The developed approaches use data from a six-month period (Jul 2016-Dec 2016) of three wind farms on a 10 min sample basis with a wind speed range between 0 and 26.02 m/s. The CNN method uses the data and patterns of two wind farms to predict similar patterns of the third wind farm, using the third wind farm's data set for verification. Furthermore, the conducted testing was performed in a single step (10 min interval) fashion using five different configuration steps to find the optimal matrix setup for the CNN which results in the lowest possible error. Although effective in reduced tail losses, the MAE and MSE values are similar to the compared SVM and Kernel Ridge Regression (KRR) models [16].

Reference [12] utilizes a NN as an STWP forecaster with a wavelet transform (WNN) in order to decompose the nonlinearities present in wind power historical data. The method was also developed without the use of numerical weather prediction (NWP), utilizing the WNN together with the single forecast model to reduce historical data requirements while maintaining accuracy [12]. A wavelet decomposition stage is added before the NN with reconstruction stages added before creating the wind power forecast using Db2 wavelets. The method utilizes two years of data (2013 and 2014) for a day ahead prediction with 15-minute intervals where 15 days of data (1440 data points) are used for training purposes and two days of data (192 data points) are used as validation of the neural network. Testing results use normalized MAE (NMAE) which is normalized to the plant installed capacity, with the developed WNN model having an average NMAE of 2.04% across all 24 months (ranging between 0.53% and 4.56%) and NRMSE = 3.34% (between 0% and 14%) whereas the NN exhibited an NMAE average of 3.09% (ranging between 1.01% and 8.72%) and NRMSE = 7.4% (between 0% and 35%), that indicates better accuracy for the developed WNN. However, this method is computationally intensive.

The UNB-developed CNN-based wind power ramp forecasting method [14], [33] provides day- ahead ramp event forecasts to minimize risks when scheduling wind energy in electricity markets. The forecaster utilizes K-means clustering together with CNN-based pattern identification techniques to obtain similarity measures for time series data comparison with a sliding window [14]. Furthermore, an empirical probability density function (PDF) is used to build a direct link between the wind speed forecasts and ramp event predictions. In addition, a tolerance (TOL) value is implemented to determine the best forecasting accuracy. The UNB module uses data from six wind farms from a period of 2017 to 2019. A TOL value of 0.45 is implemented a resultant method of 65% effectiveness when predicting wind power ramps versus the actual recorded ramp events. In addition, NARX-based UNB short-term wind power production methods [33] shows an average MAE of 0.11 (between 0.08 and 0.14), RMSE of 0.15 (between 0.11 to 0.18) AMAPE of 26.74% (between 24.69% and 29.77%) among six investigated wind farms. The approaches highlighted in this subsection are summarized in Table 2 as:

Table 2- NN-based short-term wind forecasting methods

NN Method/Type	**Datasets**	**Performance Results**	**Advantages**	**Disadvantages**
STWS CNN Forecaster [16]	three commercial wind farms between July 1, 2016, to December 31, 2016	Simple CNN: MSE=0.58m/s , MAE=0.57m/s. Transfer Learning CNN: MSE= 0.52m/s, MAE =0.5258m/s	Incorporate Transfer Lear- ning into short term load forecasts to reduce the number of computations caused by traditional physical systems like NWP	The speed data from the target farm are one month behind Farm 1 and Farm 2.
STWP WNN [12]	2 years/15 min interval from 2013 and 2014, 15 days (1440 data points) for training and two days of data (192 datapoints) for validation of the neural network	WNN: NMAE=2.04%, NRMSE=3.34%, normalized to plant capacity	Day ahead forecast with 15-minutes interval summer, monsoon and winter season with reduced historic data requirements. The wavelet transform reduces the error caused by variability	More computationally intensive then methods that utilize physical modelling techniques
STWP UNB-developed modules [14] [33]	a full year of wind farm data for 2016 sample dataset with a 2017-2019 dataset for the same wind farms being used as verification	STWP hours-ahead: MAE= 0.11, RMSE= 0.15, AMAPE= 26.74%. day-ahead: MAE=0.12, RMSE= 0.17, AMAPE= 28.85%	Ramps events retrieved from the data are recorded in order to evaluate prediction accuracy of ramp events empirical PDF in order to quantify uncertainty	Large amount of historical data requirement for success rate

From the data variety standpoint of the Neural Network methods compared in Table 2, all methods have at least one year of data, with UNB modules having the most data used, meaning multiple seasonal variations across various years. From a performance metrics standpoint, the UNB- developed forecasters are the better solution when looking at rampant change in power demands for both hours ahead and day ahead forecasting when compared to the other forecasting methods. All methods compared here require vast amounts of data which is inherent to NN behavior even if the method deviates from NWP [12].

1.4 Hybid Forecasting Approaches

Since individual statistical methodologies have their drawbacks, many of the most recent most of the recent
Since individual statistical methodologies have their drawbacks, many of the most recent most of the recent
STWP approaches have explored the hybrid modelling sphere involving combination of several NN, SVM, or other statistical approaches together [5], [8-11], [15], [19], [21], [22], [25], [30], [31], [32], [34]. These hybrid schemes were developed in an effort to combine the strengths of a singular statistical approach through multiple models of the same statistical method or several statistical approaches while reducing the disadvantages provided by those methods.

However, today's methodologies are more complex, for instance, the DNN STWP approach used in [10] utilizes DNN, together with data driven methodologies, to predict the wind power using historical data from WECS. The method employs Gated Recurrent Neural Networks (GRNN) which was previously used in speech recognition and traffic predictions to predict the wind power. The data utilized in the STWP method comes from SCADA datasets from a nine-month period between July 1st until March 31st, 2019, of a 7MW WECS in Levenmuth, Fife, Scotland, UK resampled every 10 minutes. The algorithm uses recursive feature elimination in order to identify and eliminate outliers throughout the samples by comparing them to the power curve of the wind turbine. The model is then compared to LSTM methodology and showed improved accuracy with lesser training time for using the raw data directly with an MSE of 0.010 MW with an accuracy of 89.93% and reduced training time 131.29s for the GRNN when compared to the LSTM structure which has an MSE of 0.070 MW, accuracy=73.36% and training time 207.54s. When using an input filter on both the GRNN and the LSTM, the GRNN shows an MSE of 0.0035 MW with an accuracy of 94.06% and reduced training time 96.25s while the LSTM shows an MSE of 0.0053, accuracy=92.74% and training time 159.48s. Although this method proves effective, it has only been tested on a singular WECS and not an entire wind farm with varying WECS.

The STWP method used in [9] uses a RNN model utilizes meteorological data as time series with a two-stage attention mechanism to predict wind power. The attention mechanisms are described by an encoder and decoder stage where the encoder utilizes an LSTM structure to achieve input feature extraction. The decoder is based on a time window approach and functions to compare the output of the encoder for each moment in time. The proposed approach in [10] then combines both mechanisms in order to achieve its wind power prediction. The dataset comes from WECS between 2007 to 2012 in hourly resolution using the National Renewable Energy Laboratory data, where first five years of the six-year data is used as the training dataset, the first half of 2012 is used as the verification dataset, whereas the second half is used as the test dataset [9]. The method is then compared to a random forest algorithm as well as a more LSTM method without their implementations in a 24-hour window comparison. The resultant error MAPE 2.66% and MAE 131.11kW is much lower than the other compared methods which are 14.13% and 1495kW for the random forest while being 14.32% and 260.60kW for the LSTM method without the attention mechanisms.

Reference [15] introduces a hybrid STWP approach using the multi-objective moth-flame optimization (MOMFO) method can obtain high accuracy and stability for wind energy prediction with single-step and multi-step wind energy prediction. This method also implements improved ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) to get rid of noise and extract the main features of wind power time series. The algorithm uses 10 min interval data from a wind farm in Spain with 1500 data points for 4 datasets (6000 points in total). The method is compared to other models including GRNN, WNN, CEEMD-WNN, CEEMD-MFOWNN and CEEMD-MOMFO-WNN. Results show a lower MAE and MAPE and RSME for the developed method in [15] compared to the other datasets.

The STWP approach used in [11] utilizes stacked auto encoder (SAE) and NN for backpropagation (BP) for short term wind forecasting. The SAE-BP method utilized SAE with sparse constraints and random noise is used for feature extraction on historical data, which is than implemented into a BP network for regression analysis. Then Particle Swarm Optimization (PSO) is used to optimize the learning rate of each AE in an effort to further improve the forecasting accuracy. The selected method uses 15 min interval data from the EirGrid data set, of which the data samples from 1 May 2014 to 21 June 2014 are selected for training purposes in order to establish the forecasting model and ideal parameters. Data from 22 June 2014 to 1 July 2014 is selected for verification, where PSO is adopted to arrive at the best fitness value. The resultant model is then used to predict wind power using multi-step ahead in 15 min increments. the muti-step predictions are then compared to BP and SVM schemes. Compared to the BP and SVM methods, the SAEBP approach generally outperforms with an MAPE of 14.71% for 3 day and an average MAPE 15.96% for one to nine steps ahead compared to a MAPE of 47.33% (BP) and 27.88% (SVM). Though the method has proven effective it has not been tested against other NN methods.

The STWP method in [8] designs a data-driven multi-model methodology with deep feature selection process for short-term wind forecasting. The data driven input consists of Humidity, wind speed, direction, pressure, and temperature and is then passed through the deep feature selector which generates an input vector based on component analysis, causality testing, autocorrelation, and recursive feature elimination. The input vector is then passed through a multi-model method which consists of NN, SVM, Gradient Boosting Machine (GBM) and Random Forest methods which a cumulatively grouped into a Forecast layer before being ran through an ensemble algorithm. The method uses a year’s worth of data from 2015 with a one-hour sample interval of seven different sites. All methods encompassed within the multi-model structure are then compared to one another in terms of NMAE and NRMSE with the poly SVM method coming out on top on average NMAE of 4.41% over all seven sites compared to 4.53% for persistence, 4.62% for linear SVM, 4.58% for GBM and 4.64% for the random forest. For the NRMSE is averaged to be around 6.21% for the poly SVM compared to the 6.41% for persistence, 6.91% for linear SVM, 6.55% for GBM and 6.56% for the random forest.

The method employed in [31] utilizes a fuzzy time series and multi objective optimization for wind in a Multi-Objective Differential Evolution (MODE) algorithm for STWS purposes together with an ensemble empirical mode decomposition (EEMD) and fuzzy time series (FTS). The MODE algorithm searches the optimal cut points and weights for forecasting using the fuzzy logic provided by the FTS. The FTS constructs several fuzzy sets of continuous values and discrete values according to the cut points obtained by MODE. The algorithm then constructs a matrix of weights based on the constructed values by the MODE-FTS where defuzzification is performed in order to obtain the forecast result. The wind farm data used is 10min intervals between January 1st to 20th January 2011. The developed EEMD-MODE-FTS is then compared to an equal width (EW) variant (EEMD-EW-FTS) as well as an equal frequency (EF) variant (EEMD-EF-FTS). With superior MAPE, MAE and RMSE as well as Theil inequality coefficient (TIC) Variance of the forecasting error (VAR) and Direction Accuracy (DA) [31].

The differential Evolution (DE) STWS algorithm presented in [34] were designed to optimize the number of hidden layers in each Long Short-Term Memory (LSTM) with neuron count in each hidden layer of LSTM for trade-off between learning performance and model complexity. Furthermore, the method utilizes extreme learning machines (ELM) which are a single-hidden layer feed-forward neural network (SLFFNN). The developed nonlinear hybrid Long Short-Term Memory Differential Evolution algorithm with Hysteretic Extreme Learning Machines (LSTMDE-HELM) utilizes the LSTM network, together with HELM, and DE. The DE algorithm optimizes three different kinds of LSTM networks, while three different types of HELMS, with varying numbers of neurons in each hidden layer, are applied separately to learn of wind speed time series behaviour. Then, a nonlinear combination of LSTM network optimized by the DE will aggregate the forecasted results of the six individual predictors [34]. The developed method showed great MAE, RMSE, MAPE when compared to ARIMA, ANN, SVR, ELM and LSTM approaches but is more computationally extensive.

The STWS method in [19] creates a combination method for wind speed prediction using a two- layer nonlinear combination method. The first layer is based on Elman neural network (ENN), ELM and LSTM to separately forecast wind speed by making use of their merits of calculation speed or strong ability in forecasting and obtain three forecasting results. The second layer consists of an ELM-based nonlinear aggregated mechanism to alleviate the inherent weakness of single method and linear combinations. The created EELELM is used for short-term wind speed prediction problems such as 10-min ahead and 1-hour ahead. The method is then compared to the backpropagation (BP) method, WNN method, and the deep belief network (DBN) method. Results show a lower MAE and MAPE for the hybrid EEL-ELM approach when compared to ELM, ENN, and LSTM.

The hybrid model using variational mode decomposition together with phase space reconstruction and wavelet neural network optimized by genetic algorithm VMD-PSR-GAWNN model [32]. The VMD decomposes the signal into several modes which are then passed through the GAWNN using phase space recognition. The GAWNN is then aggregated into one forecast result. The VMD-PSR- GAWNN method is then compared to the Persistence method PSR-BPNN, PSR-WNN, PSR- GAWNN, EEMD-PSR-GAWNN with a superior MAPE, MAE and RMSE [32]. Table 3 compares all hybrid approaches discussed above.

Table 3- Hybrid approaches for short-term wind forecasting

Hybrid Method	**Datasets**	**Performance Results**	**Advantages**	**Disadvantages**
GRNN STWP [10]	7MW WECS in Levenmuth, Fife, Scotland, UK, July 1st, 2018- March 31st, 2019, resampled every 10 minutes	10 min with Raw data: MSE: 0.01, Accuracy :89.93%, 10 min with input filter MSE:0.0035, accuracy of 94.06%	GRNN implementation is faster and generates less error compared to the LSTM. Furthermore, is architectural fewer components than a standard LSTM setup	Data was only tested on a singular WECS
RNN STWP [9]	National Renewable Energy Laboratory data between 2007 and 2012. First five years were used to train while the first half of 2012 is used as verification while the second half is used as the test set	24-hour ahead: MAPE: 2.66%, MAE 131.11kW	Attention mechanism implementation generates less error compared to the LSTM scheme	Unsure of the value of the attention weight as everything within the designed attention weight rests on the wind speed which eliminates the need for having an attention mechanism in place and instead focus directly on the wind speed
ICEEMDAN-MOMFO-WNN STWP [15]	Sotavento wind farm in North-western Spain 10 min intervals presented in four case studies.	10-min ahead: MAE=0.056, RMSE=0.079, MAPE=5.002%	Offer comparisons to decomposition (Case 2), multi-objective algorithms (Case 3) as well as other forecasting methods (Case 4). Shows error results based on one, two and three steps ahead	Multi-objective multi-verse optimization (ICEEMDAN-MOMVO-WNN) and, multi-objective whale optimization Algorithm (ICEEMDAN-MOWOA-WNN) surpass the ICEEMDAN MOMFO-WNN in certain cases
SAE_BP STWP [11]	EirGrid dataset May 1st to July 1st at 15-minute intervals	Average MAPE between one to nine steps ahead (15min to 135 min):15.96%	Combining SAE with BP and PSO provides a more accurate solution over most multi-step ahead windows compared to SVM and BP	SVM outperforms the SAE_BP at the 15 min (1 step) and 75min (6 steps) mark. Furthermore, the SAE_BP method has not been tested on other NN methods than BP

DD-STWP [8]	one year's worth of data (2015) of seven different sites with a one-hour sample rate	Poly SVM 1-hour ahead: NMAE 4.41% and NRMSE 6.21%	Developed method proved accurate forecasting with low error ratings	Not compared to any other methods other than the unique models used in the multi model stage
LSTMDE-HELM model STWS [34]	wind speed with 10-min interval based out of wind farm data	Case Study 1 (10-min ahead): MAE= 0.47m/s,	DE enhances the performance of the LSTM	Computationally taxing, long training time

From the methods described in Table 3, it can be discerned that the following hybrid algorithms are best executed for a certain time window based on the performance results:

- 10-min ahead:
  - LSTMDE-HELM model STWS [35] has the lowest MAPE =4.85%
  - ICEEMDAN-MOMFO-WNN in [16] has the lowest RMSE = 0.079 and MAE = 0.056
- 1-hour ahead:
  - SAE_BP STWP [12] has the lowest MAPE =12.81%
  - VMD-PSR-GAWN [33] has the lowest RMSE = 0.23 and MAE = 0.18
  - DD-SWTP has the lowest NMAE 4.41% and NRMSE 6.21%
- 6-hour ahead:
  - NN multistep [22] has the lowest MAPE =10.19%
  - VMD-PSR-GAWN [33] has the lowest RMSE = 0.35 and MAE = 0.27

It should be noted that some models analyzed were for the immediate short term (< 1hr) [15], while others extended to day-ahead [9], [20], [22], [23], [33], [35] as well.

Overall Hybrid methods are powerful tools, drawing that benefit from advantageous features of several different types of algorithms. As a result, it allows hybrid methods to obtain better prediction accuracy than other models that are purely artificial, statistical, or physical. The main problem with hybrid models arises from the fact that hybrid models are designed for very specific problems with very promising results under the right conditions. However, applying hybrid model on different datasets may tank the overall performance. Another drawback is that hybrid approaches can be computationally taxing, compared to single NN or SVM methods.

1.5 Conclusion and Discussion

Many recent wind forecasting methods have been reviewed and discussed in this section with respect to SVM, NN or a combination of several of each or both. Through analysis of each respective subsections, the following drawbacks can be seen from these methods:

- SVM
  - Overall, less accurate than ANN in longer time windows
  - Requires a good kernel design to encompass linear and non-linear behavior.
- ANN

    - Overall, less accurate than SVM in shorter time windows
    - Requires a considerable amount if data to be trained and function properly
    - Need proper over and underfitting
    - g prevention mechanisms
- Hybrid
    - Tend to be uniquely tailored for the unique problem it is designed for.
    - More difficult to optimize and reduce errors due to the nature of having multiple different models at once.
    - Computationally intensive as it requires the running of multiple NNs and/or SVMs to obtain the optimal forecast solution.

However, these approaches also have their distinct advantages highlighted below as:

- SVM
    - Fast acting method requiring much less data than ANN
    - Ideal for usage in short time windows where data can only change by a certain amount
- ANN
    - With good tuning ANN methods beat SVM at higher time windows and even shorter ones given proper weighting
    - With the increase in computational power of devices, ANN aims to surpass SVM in short term given the amount of computations GPU computing can accomplish
    - DNN, although more computationally intensive, is a great tool in forecasting wind power and speed based on its architecture and deeper understanding of the behavior of WECS given enough data and training
- Hybrid
    - Able to combine both SVM or ANN or multiple combination of each.
    - Allow curtailment of certain functions to only act in certain time windows (i.e., selecting SVM for short term and NN for long term, etc.)

Although each category approach has its benefits and drawbacks, most methods in the last decade tend to go toward hybrid methods in order to exploit the advantages of both SVM and NN while reducing or eliminating their downsides.

With wind power generation increasing in power systems, the importance of accurate short term wind forecasting takes precedence. This white paper reviewed a variety of developed short-term wind forecasting methodologies that are being utilized in either wind power or wind speed forecasting. The various forecasting models were categorized as SVM, NN, and hybrid methodologies, with each model within a certain category having its own set of characteristics. In addition, emphasis was given on the accuracy of prediction models using error performance metrics. Furthermore, no forecasting model can be perfect for any condition and therefore it is difficult to evaluate the performance of various models, as the existing applications were using different datasets. Nevertheless, the compared methods discussed in this paper provide a glimpse of the approaches that are currently being used in WECS on a short-term basis and serve as a guide to further enhance the developed wind forecasting model.

2 UNB-Developed Short-Term Wind Power Forecasting Methods

Wind as one of the most promising renewable energy sources has sustained a steady growth for Canada's electricity generation in the past few years. However, due to the natural variability of wind, the integration of wind energy into electrical power systems is challenging. Accurate wind power forecasts in the next minutes, hours or days enable utilities, system operators, and other market players to reduce the risks of the uncertainty of wind generation, thereby maximizing the wind energy integration, improving power system operation, and optimizing economic dispatch.

Since 2016, the UNB Team has been working on exploring innovations in advanced wind forecasting technologies involving collaboration with Natural Resources Canada (NRCan), Environment and Climate Change Canada (ECCC), Nergica and Wind Energy Institute of Canada (WEICan) to provide wind forecasting services of short-term wind power production forecasts, wind power ramp prediction and icing forecasts for utilities, system operators and wind farm owners in Canada. Methodologies, approaches and preliminary results for the developed wind forecasting technologies have been detailed in previous annual reports. This white paper focuses on wind power forecasting technologies, including data sources used for forecasting models and performance verification, UNB-developed algorithms of the short-term wind power production forecasting and wind ramp event forecasting, and a standalone wind power forecasting package integrated with the advanced wind power forecasting technologies developed in this project.

2.1 Datasets

Data is always important for developing wind forecasting techniques. In this project, the inputs of short-term wind power production forecasting and wind power ramp forecasting models come from the high-resolution deterministic prediction system (HRDPS) of Environment Canada (EC), which provides hourly weather forecasts up to the following 48 hours, including weather variables of wind speed, wind direction, temperature and relative humidity at 80m.

Additionally, there are a total of six wind farms which maintain the data repositories with the UNB Team for more than four years to support the research in this project. Three wind farms are located in New Brunswick (314MW installed capacity totally), two wind farms in Prince Edward Island (PEI) (129MW) and another one in northern Maine US (42 MW). All the data here has been used for model training, verification and performance evaluation, respectively. Also, the forecasting services from another well-established commercial wind forecasting vender (RF) have been also investigated as a benchmark for assessment and evaluation of technologies developed in this project. A summary of available datasets is presented in Table 4.

Table 4- Dataset summary

Dataset	Available Data	Resolution & Frequency	Available Period
EC Weather Forecast data (HRDPS GRIB2)	Wind Speed @ 80m, Wind Direction @ 80m, Temperature @ 80m, Humidity @ 80m, Surface air pressure	Hourly data & Update 4 times a day (00Z, 06Z, 12Z, 18Z). Look ahead to 48 hours	2015 to 2021[α]
Utility telemetry data (WF-1 – WF-6)	Wind Speed @ 80m, Wind Direction @ 80m, Temperature @ 80m, Wind Power Production, Available Capacity	Every 5-minute data & update hourly.	2015 to 2021[α, β]
Reference Wind Forecast Data (RF)	Wind Speed @ hub Height, Wind Direction @ hub Height, Temperature @ hub Height, Wind Power Production	Day-ahead forecast: Every 15-minute data & Update 5 times a day (05Z, 11Z, 15Z, 17Z, 23Z). Look ahead to 45 hours Hours-ahead forecast: Every 5-minute data & Update hourly. Look ahead to 6.5 hours	2015 to 2020

[α]: The data collection has been stopped in September 2021, due to upgrades of the EC model.

[β]: There has been no correct data collected for WF-5 (a wind farm in Maine, US) since 2020.

2.2 Forecast Accuracy Metrics

In this project, three wind power forecasting modules have primarily been designed and developed based on the EC HRDPS model, including

a) Day-ahead wind power production forecasting: provides hourly wind power production forecasts for the next 48 hours.
b) Hours-ahead wind power production forecasting: predicts the wind power production for look ahead times ranging from 30 minutes to six and a hour hours with 5-minute time steps.
c) Day-ahead wind power ramp forecasting: offers probabilistic forecasts for customized wind ramp events up to the following 48 hours.

In order to assess and validate of these developed forecasting modules, the following metrics have been utilized with the operation data of the investigated wind farms in this project. Four statistical metrics, mean error (ME) or bias (Bias), root mean squared errors (RMSE), mean absolute errors (MAE) and adaptive mean absolute percentage errors (AMAPE), have been adopted in the project to evaluate the forecasting performance of both the day-ahead and hours-ahead wind power production forecasting models. The global averaged values of these metrics and error distributions could give detail assessment of the forecasting accuracy.

Meanwhile, there are some other metrics developed by the UNB Team to measure the performance of the wind power ramp forecast in this report, including ACC, “Hit” rate, and “Timing Effective” rate.

ACC represents the accuracy of wind ramp event forecast, which can be expressed as

$$ACC = \frac{\#\ of\ hit\ events}{\#\ of\ observed\ ramp\ events} \tag{2.1}$$

where "Hit events" represent ramps that are forecasted and occurred as forecasted in terms of both timing and amplitude. In addition, "Timing Effective" is labeled when an actual ramp is occurred in a ± 1 hour range of the forecasted point in time series. "Mag. Error" represents the group of ramps whose estimated magnitudes exceeds 80% - 120% of the measurements. "False Alarm" are the ramps which are forecasted but not occurred. And "Miss" means that a ramp has not been detected by the forecast but is observed.

2.3 Day-Ahead Wind Power Production Forecast

A day-ahead wind power production forecast has been carried out based on a UNB developed power transfer model with an input using EC wind speed forecasts. The power transfer model has developed a non-linear auto-regressive exogenous (NARX) neural network to characterize the relationship between the EC wind speed forecasts and power production of each investigated wind farm. The measurement data of the wind farms are used as an exogenous input to improve the model's accuracy and robustness. The power transfer model is shown in Figure 1.

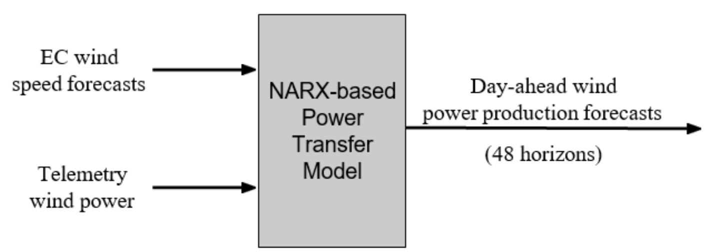


Figure 1- NARX-based power transfer model

As EC provides hourly wind forecasts including wind speed, wind direction and other weather information for the next 48 hours four times each day, the day-ahead wind production forecasts in a real operation environment have been overlapped (eight forecasting values) for each forecasted horizon, which is shown in Figure 2. Thus, global metrics are required to evaluate the forecasting accuracy using either average or median values. In this report, average forecasted values have been selected for the performance assessment. Using average forecasts can help understand the error variations during the actual operation. Also, from Figure 2, there is no significant difference when using average or median values of forecasts for performance assessment.

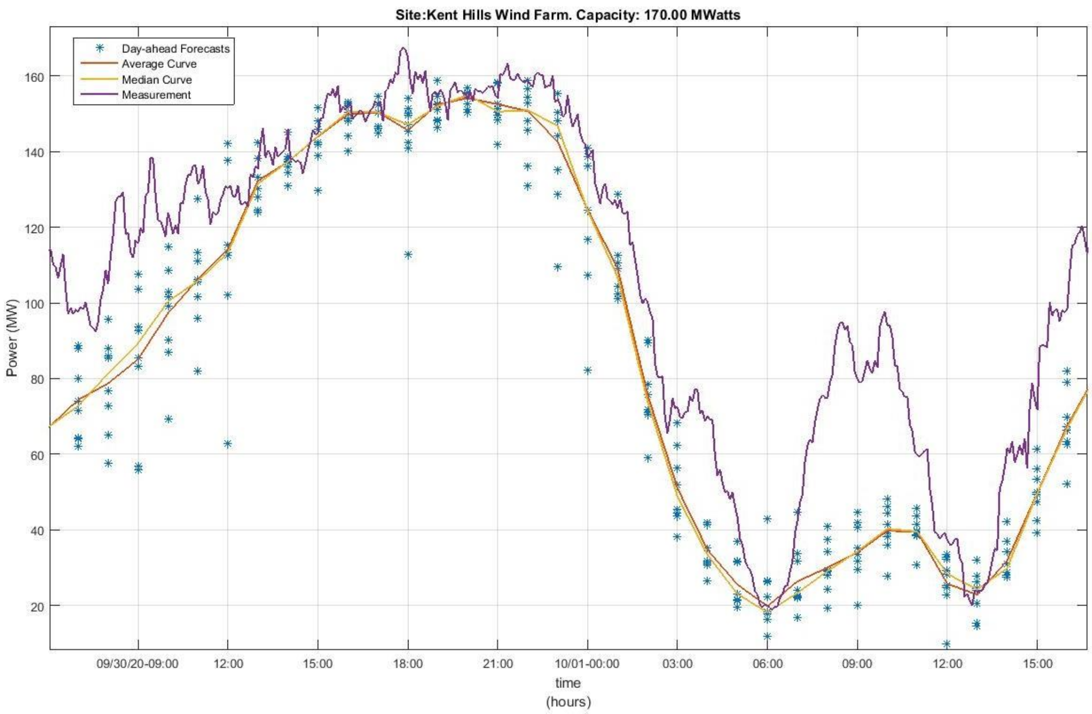


Figure 2- Day-ahead wind power production forecast in a real operation environment

2.3.1 Metric evaluation

The analyses here have been performed with hourly average values for all telemetry data, EC wind forecasts and RF forecasts for metric calculation. Table 5 shows the values of Bias, MAE, RMSE and AMAPE of the day-ahead wind power production forecast generated by both the UNB- developed model and a reference forecaster (RF). The data used for this study is from June 2015 to September 2021, where the data from June 2015 to December 2016 was used for training the models and the remainder for this performance assessment. The forecast errors presented here are the ones normalized by the installed capacity for comparison among errors referring to different wind farms.

Table 5- Metric values of UNB day-ahead wind power production forecast (2015 – 2021)*

Wind Farm	UNB Model				Reference Forecaster (RF)			
	Bias	MAE	RMSE	AMAPE (%)	Bias	MAE	RMSE	AMAPE (%)
WF-1	-0.11	0.13	0.17	26.33	0.09	0.13	0.20	30.60
WF-2	-0.07	0.11	0.16	26.34	-0.08	0.11	0.17	28.02
WF-3	0.02	0.09	0.14	24.26	0.03	0.12	0.19	26.14
WF-4	0.09	0.13	0.19	27.81	0.04	0.12	0.17	25.17
WF-5	-0.10	0.14	0.21	29.88	-0.04	0.13	0.20	27.31
WF-6	0.07	0.13	0.20	29.71	0.06	0.15	0.19	29.02
Average	-0.02	0.12	0.19	27.39	0.02	0.13	0.19	27.71

*: The RF data is from 2015 to 2020.

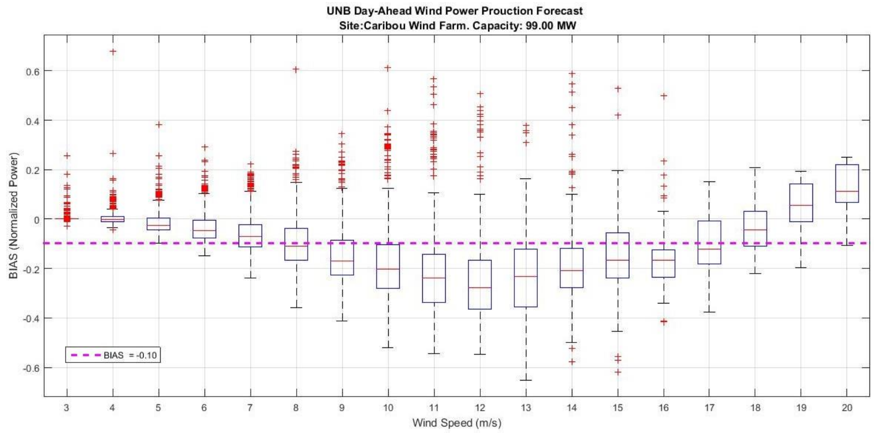
The comparison result illustrates that compared with the forecasting service offered by RF, the UNB day-ahead wind power production forecasting model provides a slight better forecasting accuracy for all investigated wind farms, particularly when looking into MAE and RMSE values. There is no one-size-fits-all indicator for measuring forecasting accuracy, but MAE and RMSE are two of the most important ones. Smaller MAE could protect outliers, whereas lower RMSE values assure a low biased forecast. Thus, the discussion of the performance of short-term wind power production forecast will mainly focus on these two metrics.

2.3.2 Error distributions

Error distributions are another key performance indicator (KPI) that demonstrates the performance of time-series forecasting models. In this subsection, distributions of Bias and MAE of day-ahead wind power production forecasts by both wind speed and forecasting horizons are discussed. The analysis of forecasting error distributions for wind speed can be helpful to evaluate the performance in predicting wind power between the cut-in and rated wind speeds of the turbines. Here we focus on a wind speed range from 3m/s to 20m/s.

Figure 3 and Figure 4 show distributions of forecasting Bias and MAE for WF-1 by different wind speed, respectively. Even though Bias and MAE values of forecasting models provided by UNB and RF are similar, there are slightly difference between their error distributions. RF shows a consistent performance for most of wind speed except high winds, but the average error for each wind speed is relatively large. While the UNB model presents small error variations for different speed and good quality against outliers. Forecasting for other wind farms gives a very similar performance as well.

Figure 5 and Figure 6 show distributions of forecasting Bias and MAE for WF-1 by different forecasting horizons. As the UNB forecasting model and RF model provide day-ahead wind power production forecasts for a look-ahead time of 48 hours and 45 hours, respectively, the analysis of error distribution by forecasting time horizons could help to verify the forecasting performance in a time series framework. As expected and inferable from the metric values, both models show comparable performance. However, compared with RF which had better result in the first couple of horizons, the UNB model provides a more consistent forecast among all the forecasting timescales.



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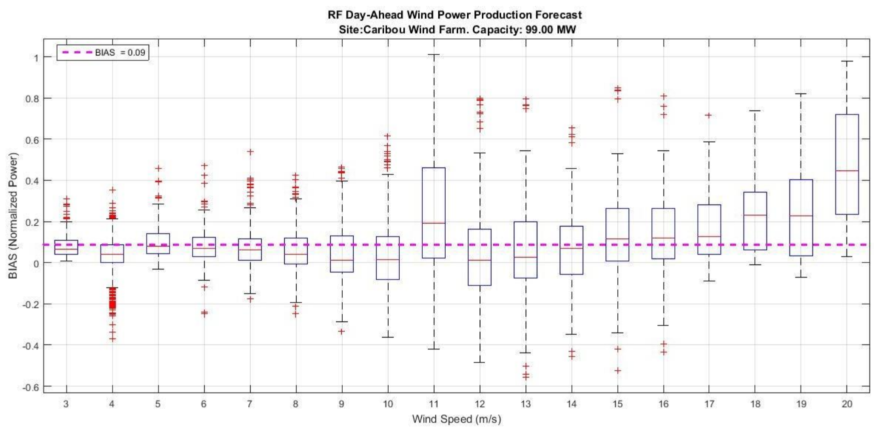
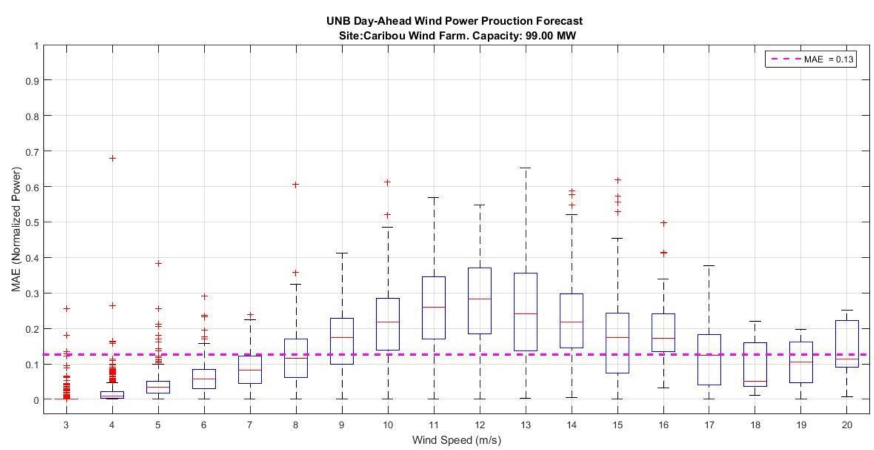


(b)

Figure 3-Bias distribution of day-ahead wind power production forecast by wind speed (a) UNB model (b) RF model



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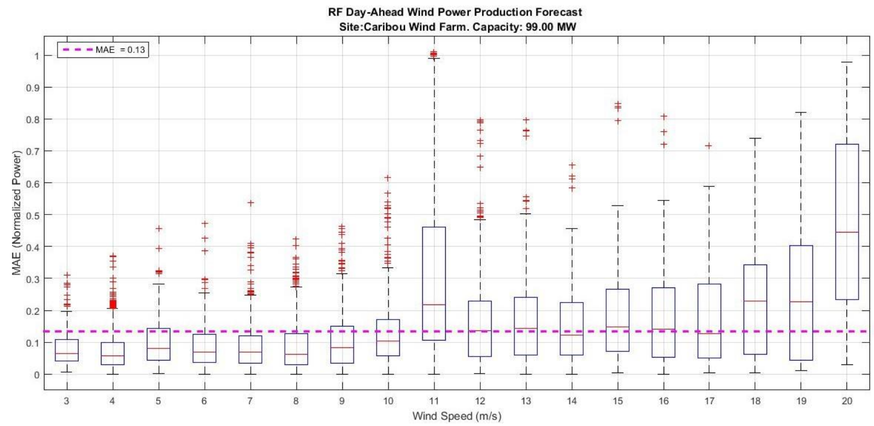
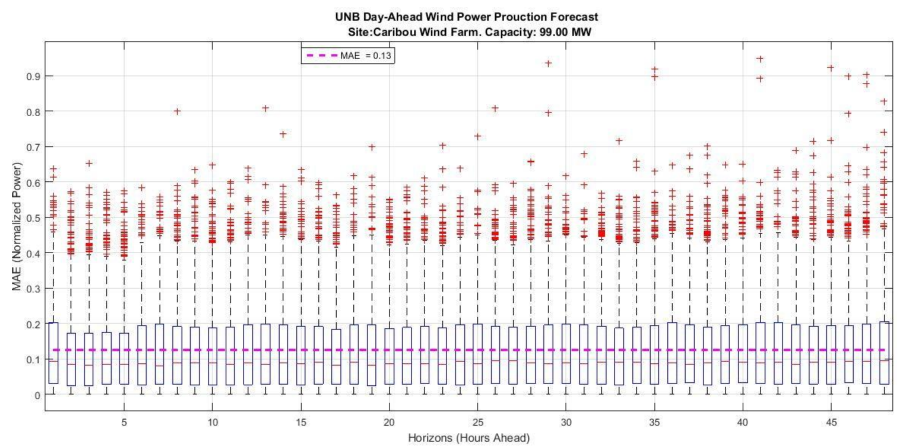


(b)

Figure 4- MAE distribution of day-ahead wind power production forecast by wind speed (a) UNB model (b) RF model



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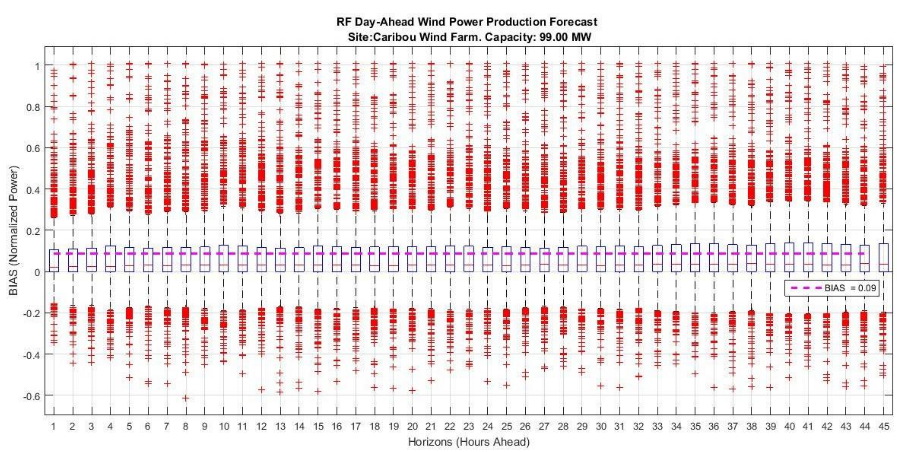
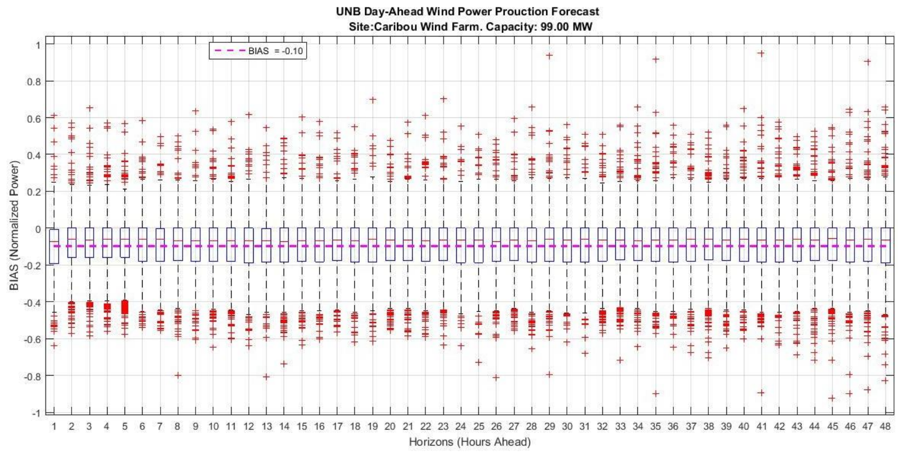
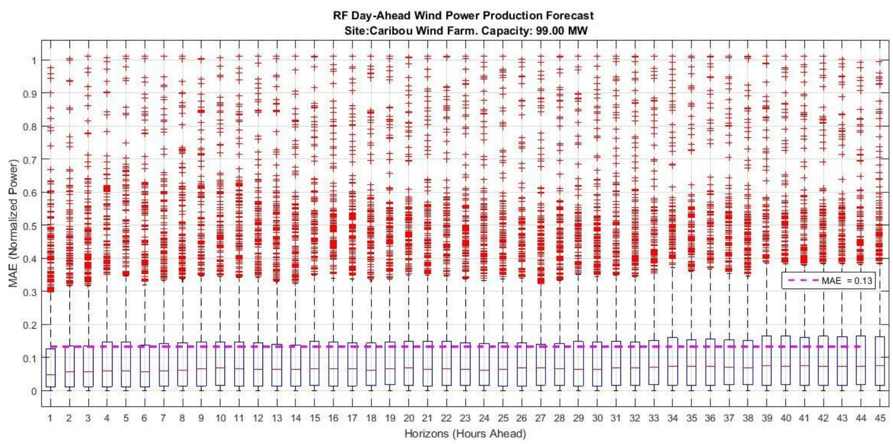


(b)

Figure 5- Bias distribution of day-ahead wind power production forecast by forecasting horizons (a) UNB model (b) RF model



(a)



(b)

Figure 6- MAE distribution of day-ahead wind power production forecast by forecasting horizons (a) UNB model (b) RF model

2.3.3 Post-Forecast Weighing Algorithm

As the developed day-ahead wind power production forecasting module provides hourly forecasts of the next 48 hours every 6-hour, resulting a maximum of eight forecasting values in any given hour, shown as Figure 2. These overlapped forecasts can be utilized to further improve the forecasting accuracy through a proposed fast acting post-forecast weighting algorithm without changes of current forecasting mechanism. The detailed step-by-step process of this method is highlighted below as

STEP 1: Initialize the algorithm through reading the recent power measurement of the investigated wind farm *x* ($x \in X$), P_x^{t-1}, and the power predictions from the day-ahead wind power production forecasting module from the current time step, t_0, which can be represented as FCP_x^{t}. Here, t is a given forecasting horizon from $(t_0 + 1)$ to $(t_0 + 48)$. For each look-ahead time t, there are serval wind power forecasts up to eight

STEP 2: Obtain all the available wind power production forecasts at each time step t ($t \in [(t_0 + 1), (t_0 + 48)]$), $FCP_x^{t,n}$, where n is an index of the available forecasts, and find out the latest forecasts at t, $FCP_x^{t,n}$ which is the most recently available forecast.

STEP 3: Calculate the power deviation in each forecasting horizon, expressed as

s $$\Delta(P_n^t)_{WF_x} = FCP_x^{t,n} - FCP_x^{t,N} \qquad (n = 1, 2, \ldots, 8) \qquad (2.2)$$

Here, if the amount of the available forecasts at t are three or higher, the proposed algorithm will throw out the largest power deviation either negative or positive.

STEP 4: Calculate the corrected wind power production forecast at t using the following equation:

$$P_{WFx}^t = P_x^{t-1} + \frac{1}{N\prime} \sum_{n=1}^{N\prime} \Delta(P_n^t)_{WF_x} \qquad (2.3)$$

When P_x^{t-1} is not available for the given t, P_x^{t-1} can be estimated by P_{WFx}^{t-1} obtained from (2.3).

Figure 7 and Figure 8 shows an example of forecasting performance with and without the post- forecast weighting algorithm in WF-1 using the data from October 15 to November 6, 2020. When using data of 2020, an average MAE improvement for all six wind farms is about 11%.

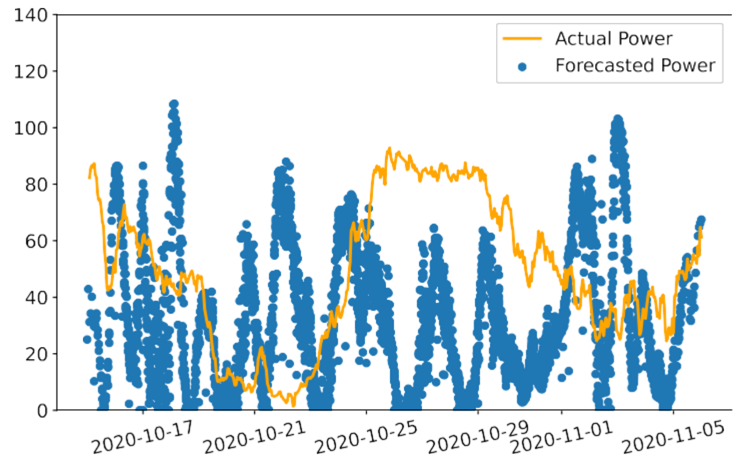


Figure 7- Original day-ahead wind power production forecast for WF-1

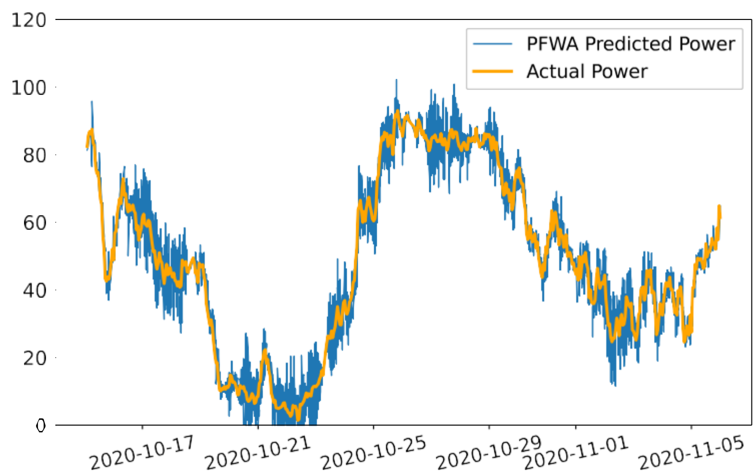


Figure 8- Day-ahead wind power production forecast with post-forecast weighting algorithm for WF-1

2.4 Hours-Ahead Wind Power Production Forecast

The UNB hours-ahead wind power production forecast has been developed through employing a fusion approach to generate forecasts for look-ahead times ranging from 30 minutes up to six and a half hours with 5-min time steps. The model is composed of three independent forecasters combined using a neural network. The three forecasters include a persistence model and two multilayer perceptron (MLP) models. The schematic of this hours-ahead wind production model is shown in Figure 9.

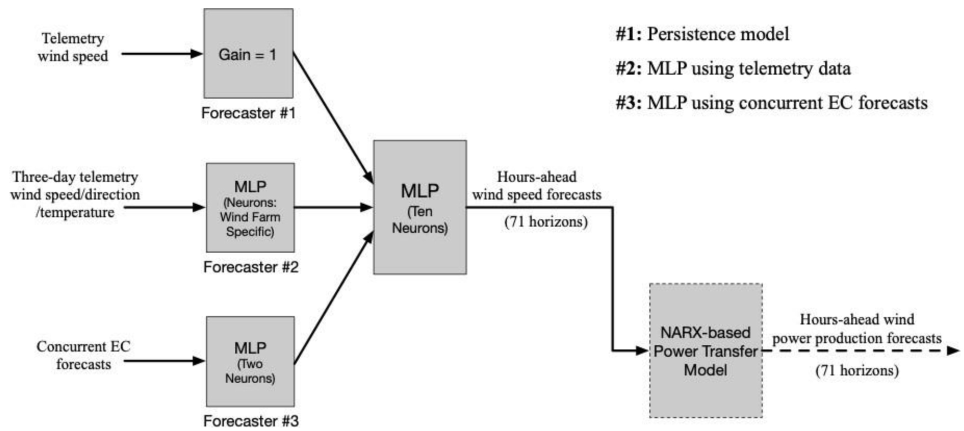


Figure 9- UNB hours-ahead wind power production forecasting model

2.4.1 Metric evaluation

Table 6 lists the values of Bias, MAE, RMSE and AMAPE of the hours-ahead wind power production forecasts developed by the UNB Team. Comparison of the power production forecasting results using both the UNB model and RF service demonstrated a similar range of performance of the two methods. Forecasts generated by the UNB model have relative low MAE values for most of investigated wind farms (except WF-3 & WF-4), but present slightly higher RMSEs than RF's. Lower MAEs mean a better accuracy for a wide range of inputs, while a lower RMSE value indicates the forecast is more correct on average.

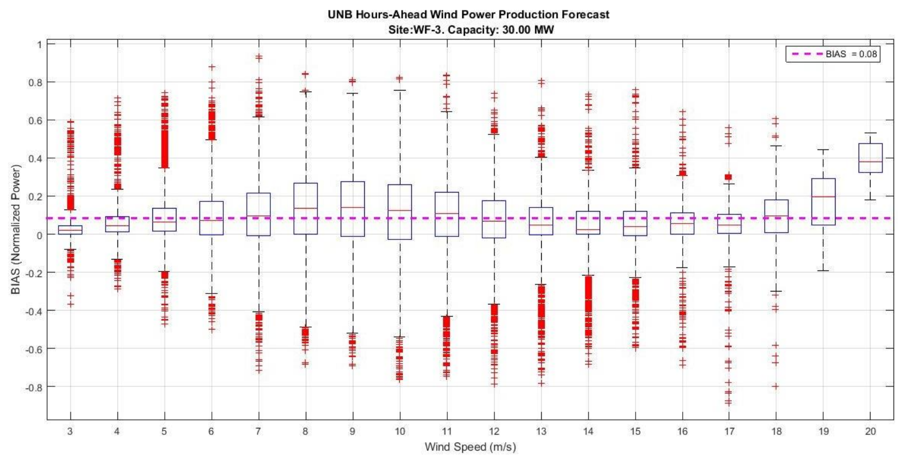
Table 6- Metric values of UNB hours-ahead wind power production forecast (2015 – 2021)*

Wind Farm	UNB Model				Reference Forecaster (RF)			
	Bias	MAE	RMSE	AMAPE (%)	Bias	MAE	RMSE	AMAPE (%)
WF-1	-0.04	0.10	0.13	21.11	0.10	0.13	0.19	28.35
WF-2	-0.05	0.10	0.12	23.09	0.05	0.08	0.10	27.84
WF-3	0.08	0.15	0.18	26.53	0.01	0.10	0.14	24.14
WF-4	0.12	0.13	0.17	27.24	0.04	0.12	0.16	22.17
WF-5	0.10	0.12	0.19	25.35	-0.04	0.13	0.17	23.31
WF-6	0.10	0.13	0.19	26.02	0.06	0.15	0.19	26.02
Average	0.07	0.12	0.17	25.75	0.04	0.12	0.16	25.30

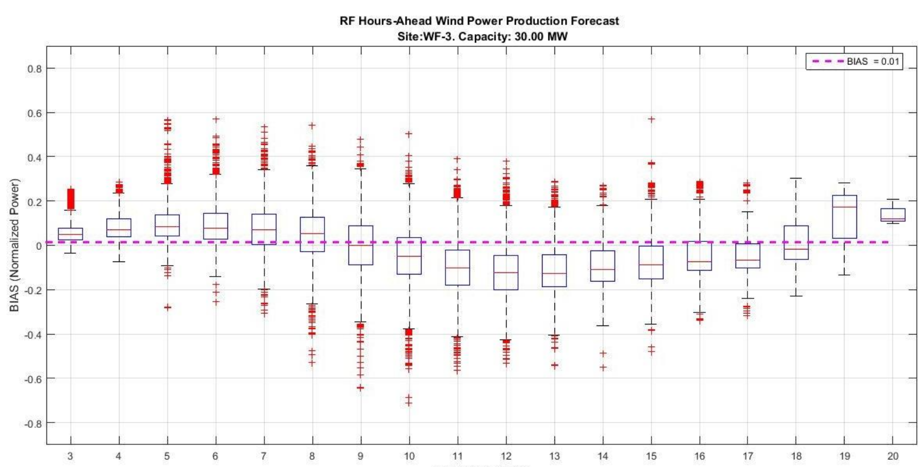
*: The RF data is from 2015 to 2020.

2.4.2 Error distributions

Figure 7 and 8 show distributions of forecasting Bias and MAE by different wind speed for WF-3 which gives the highest metric errors among all the wind farms. It is clear that the high errors in high wind speed region result in a high MAE. Figure 10 and 11 give distributions of forecasting Bias and MAE for WF-3 by different forecasting horizons. From that, we can find that compared with the day-ahead wind power production forecast, the tendency of forecasting errors to increase over time becomes clearer in the hours-ahead production forecast. Both UNB and RF models show high quality forecasting performance of hours-ahead power production forecasting.

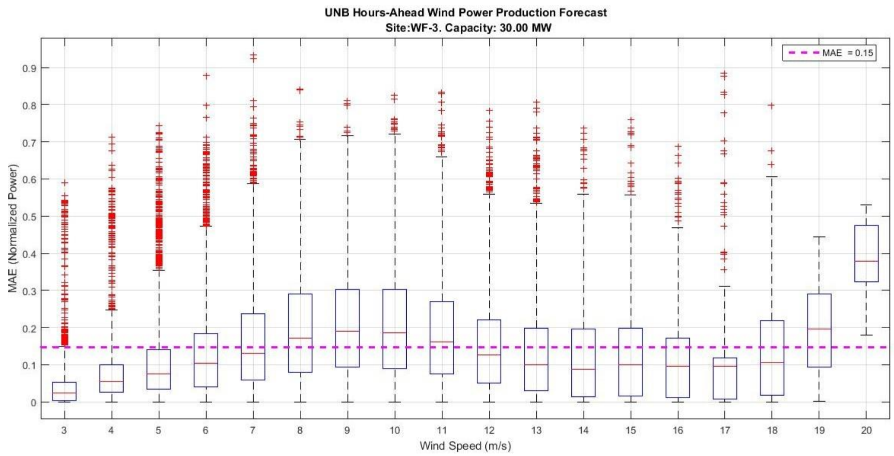


(a)

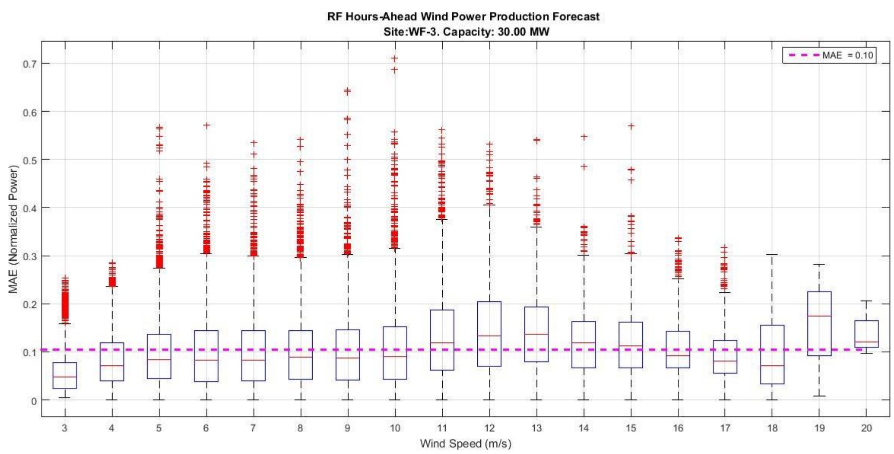


(b)

Figure 10- Bias distribution of hours-ahead wind power production forecast by wind speed (a) UNB model

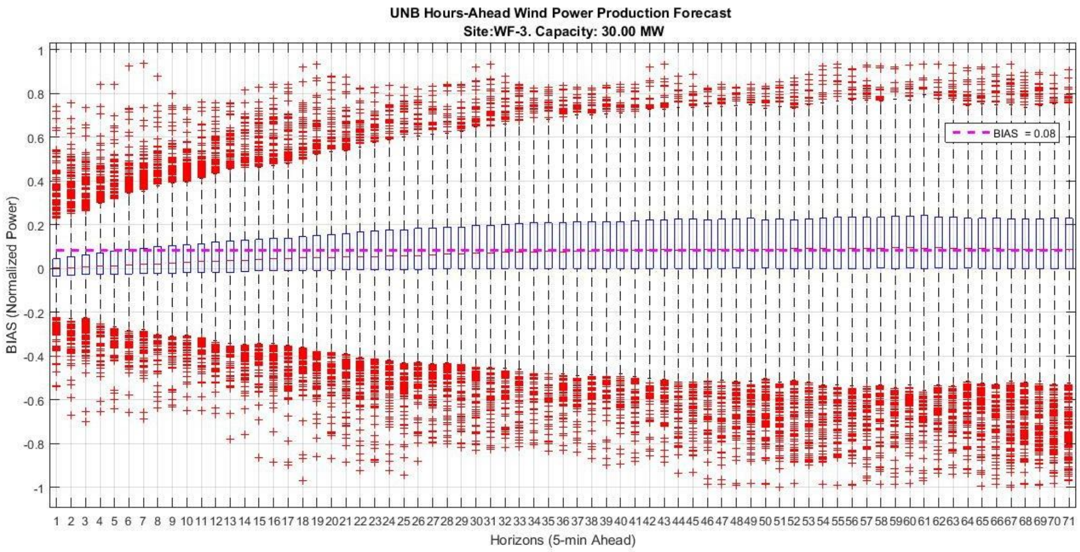


(a)

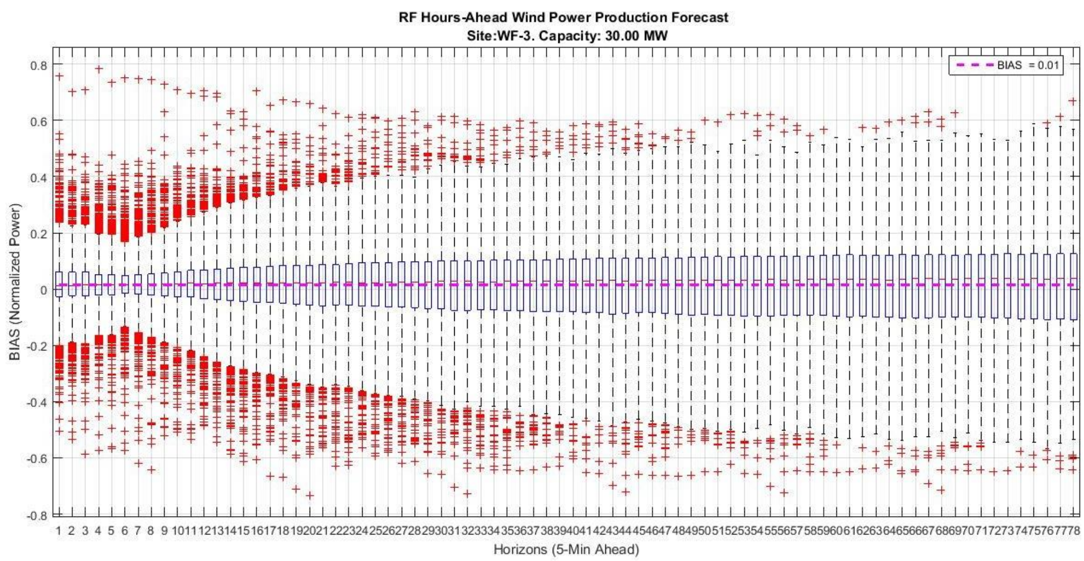


(b)

Figure 11- MAE distribution of hours-ahead wind power production forecast by wind speed (a) UNB model

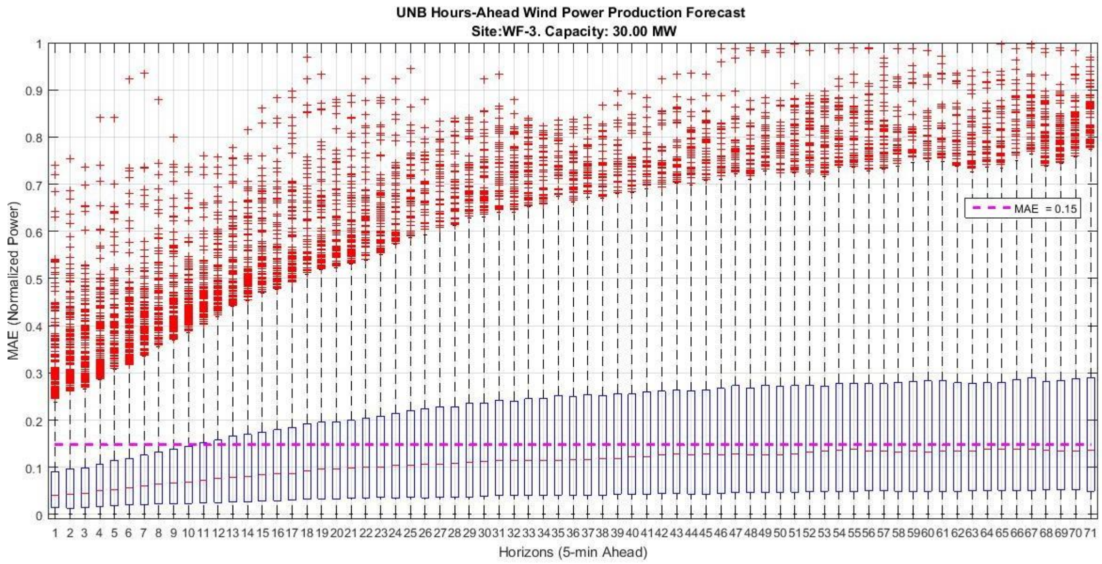


(a)

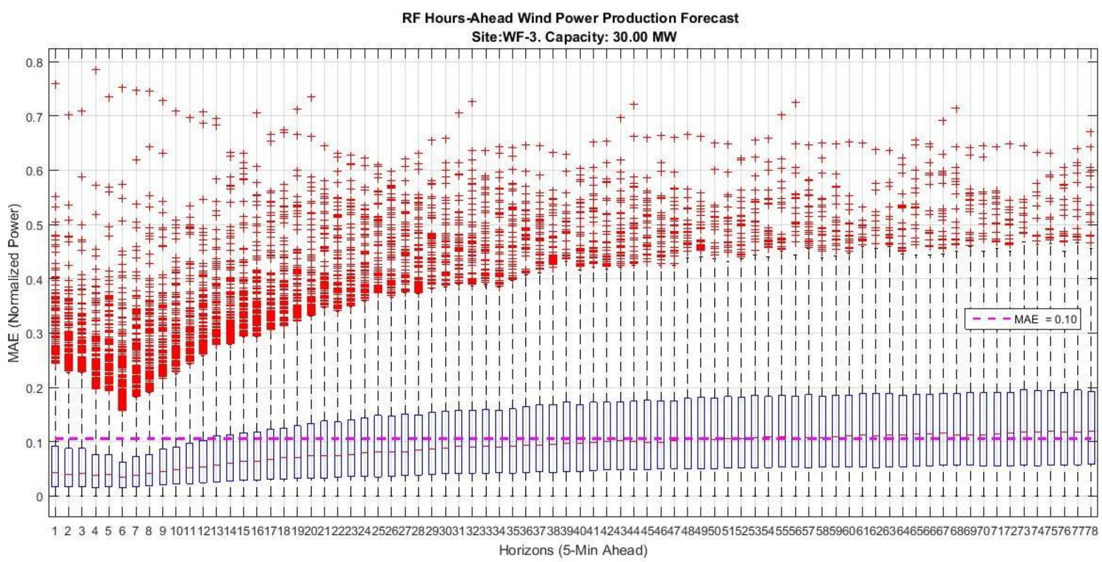


(b)

Figure 12- Bias distribution of hours-ahead wind power production forecast by forecasting horizons (a) UNB model (b) RF model



(a)



(b)

Figure 13- MAE distribution of hours-ahead wind power production forecast by forecasting horizons (a) UNB model (b) RF model

2.5 Day-ahead Wind Power Ramp Forecast

In recent years, wind ramp events caused by the sudden weather changes and even extreme weather conditions raise more concerns due to their significantly impact on the system economics and stability. Accordingly, the UNB Team developed a day-ahead wind power ramp forecasting model in this project using an advanced similarity search method with an empirical probability estimation. Compared with traditional ramp event forecasting methods in the current wind forecasting service market which identify the large ramps from the scenario power production forecasts, the developed method can effectively reduce the impact of the uncertainty from both the wind power production forecast model and the ramp identification process by employing the similarity measure to establish a direct connection between the wind speed forecasts and the wind power ramp prediction. The proposed wind power ramp forecasting scheme is shown in Figure 14.

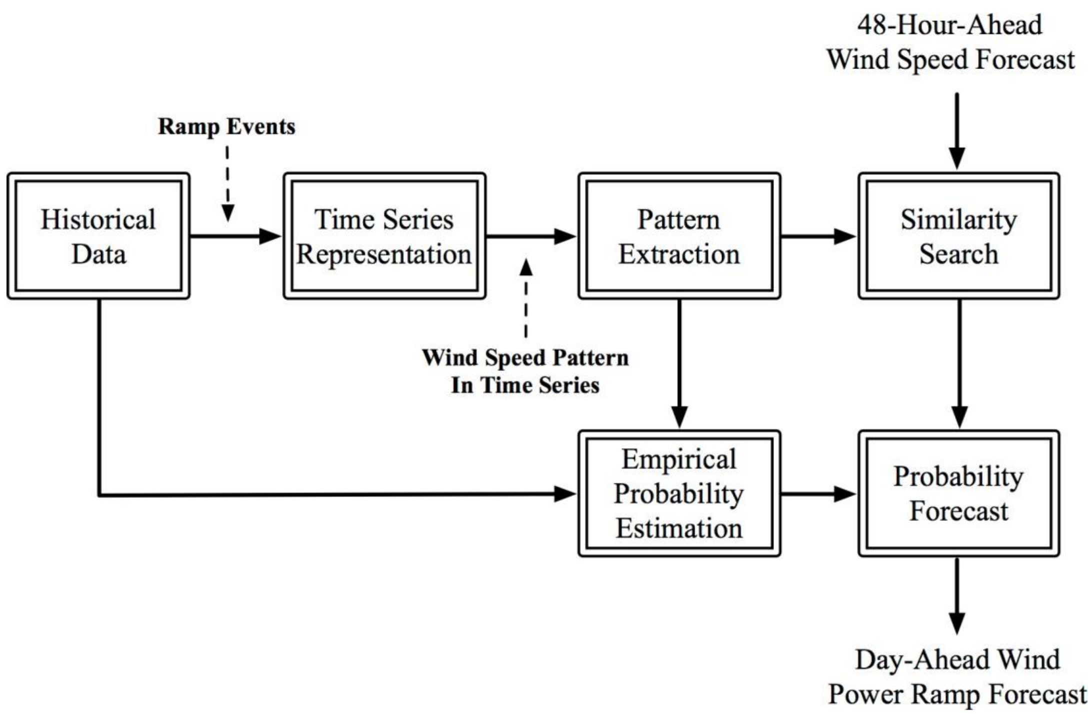


Figure 14- Scheme of UNB-developed wind power ramp forecasting

2.5.1 Grayscale Image-based pattern extraction

A CNN-based autoencoder has been developed for feature extraction of investigated ramp events, which are represented by innovative grayscale images, shown as Figure 15. In a grayscale image- based time series representation, the background color indicates the average wind speed in a sliding window period, the shape in the image represents the wind speed forecast variation responded to the investigated wind ramp event, and the color of the image illustrates the absolute wind speed information based on the color bar map on the side. This method can help for ramp pattern recognition through combining with more details and factors of wind speed forecast profiles and benefit from the implementation of deep learning techniques for pattern clustering and similarity search when dealing with a ramp event as an image.

The design of the CNN-based autoencoder purposefully builds a feature extraction model of the transformed grayscale images. Once the autoencoder is trained, the reconstruction part of the model (i.e., the decoder) can be discarded. The architecture of the encoder model of the proposed autoencoder (CNN-Encoder) is shown in Figure 16. The model consists of a sequence of convolutions layers with filters of varying size and a fixed stride of 1. A rectified linear (ReLU) activation function is adopted in every convolutional layer. The units in the last convolutions layer are flattened into an array of 10 feature vectors for further pattern clustering and similarity measurement.

Figure 2.16
CNN

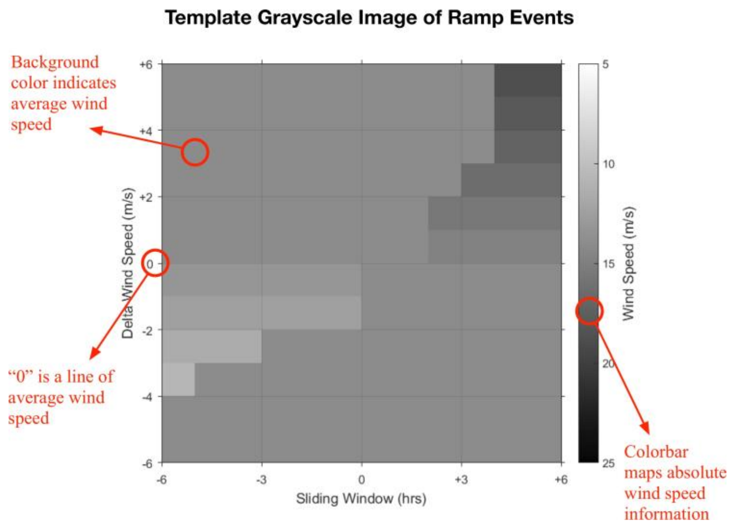


Figure 15- Grayscale image-based time series representation of wind power ramps

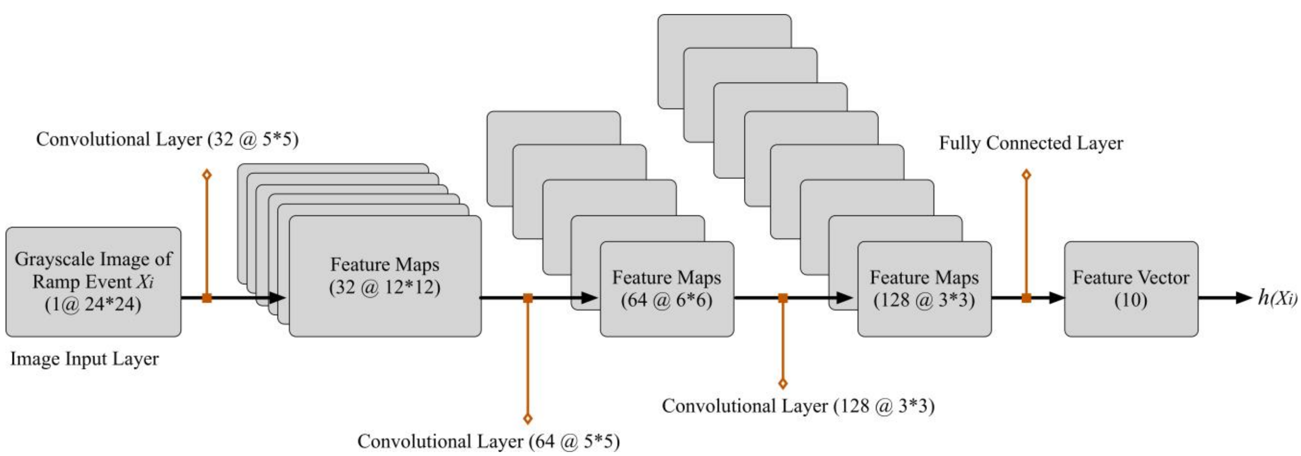


Figure 16- CNN architecture for pattern extraction

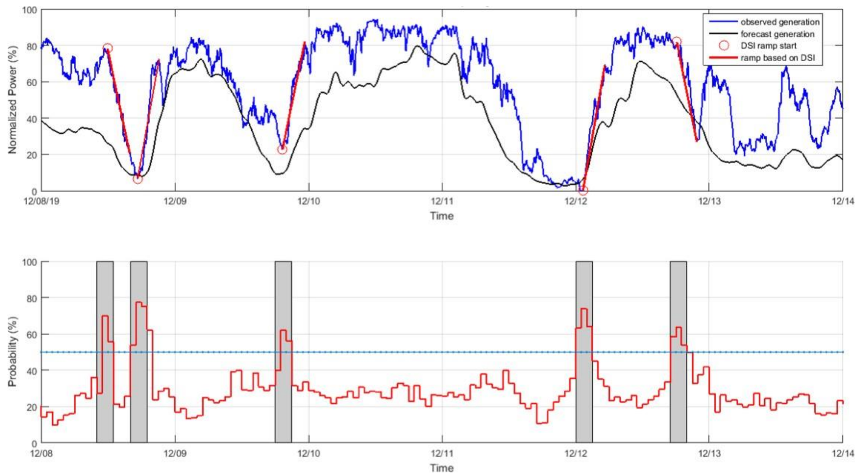


Figure 17- An example (WF-1) of the developed wind power ramp forecast

Figure 17 illustrates the ramp event forecasting for a 7-day period as an example, where the red line indicates the probability of the ramp occurrence, the shadow parts represent the timing effective zone which is limited to ± 1-hour error and the dashed line represents the tolerance (TOL) value optimized explicitly for any given wind farm to achieve the best forecasting accuracy. Here, a success forecast is confirmed when reported within one hour of the actual event.

2.5.2 Metric evaluation

Table 7 lists the results of ramp event forecasts during this test period from January 1, 2020 to December 31, 2020. Any wind power change with a magnitude over 50% of the installed capacity within a time span of four hours or less is defined as a wind ramp event in this report. And different tolerance (TOL) which is adopted for decision-making is optimized for each wind farm to achieve the best forecasting accuracy.

Table 7- Result of UNB ramp event forecasting algorithm (2020)

Wind Farm	Ramp Event	TOL	ACC	Hit		Timing Effective		Mag. Error	False Alarm	Miss
WF-1	187	45%	81.82%	153	66.81%	159	85.03%	6	70	28
WF-2	380	50%	77.89%	296	67.27%	337	88.68%	41	103	43
WF-3	416	60%	79.57%	331	62.10%	368	88.46%	37	165	48
WF-4	510	70%	82.75%	422	67.95%	453	88.82%	31	168	57
WF-5*	382	60%	79.06%	302	65.65%	346	90.58%	44	114	55
WF-6	493	65%	77.48%	382	67.37%	421	85.40%	39	146	72

*:WF-5 used the data from Jan to Dec 2019.

Figure 18 shows how the ACC performs when the training dataset becomes larger. Compared with training a model for either day-ahead or hours-ahead wind power production forecasting models that there exists an option to have an optimal dataset size through trading off between the amount of data and the forecasting accuracy, the ramp event forecasting expects more and more data for training to map the ramp probability with the wind speed forecast.

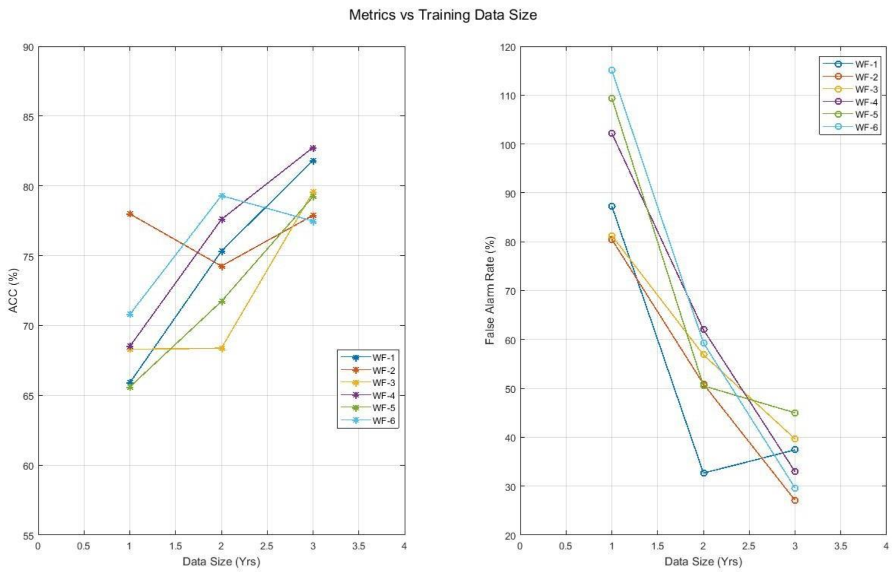


Figure 18- Metric performance with different sizes of training data for wind power ramp forecasting model

2.6 Conclusions

In this project, three wind power forecasting modules have been developed by the UNB team with comprehensive tests for performance evaluation using the data from EC and utility partners, including day-ahead and hours-ahead wind power production forecasting models, and another day- ahead wind power ramp forecasting model. All these forecasting methods are developed based on EC HRDPS model established and maintained for the public good.

With an input of wind speed forecasts generated by HRDPS, a day-ahead wind power production forecasting model has been built to provide hourly power production forecasts for the next 48 hours based on a UNB developed power transfer model, which adopts a NARX neural network to convert EC wind speed forecasts into wind power production predictions with low forecast errors and narrow error dispersion. While the hours-ahead wind power production forecasting method has been developed using a high-tech fusion approach combining three independent forecasters to predict the wind power production for look-ahead times ranging from 30 minutes to six and a half hours with 5-min time steps to meet the forecast delivery requirement of end-users in the electricity markets.

In addition, an innovative wind power ramp forecasting algorithm has also been developed by the UNB team based on a similarity search technology with a grayscale image-based representative of time series wind speed forecast data. Compared with the traditional ramp event forecasting techniques which identify the ramps from scenarios of the short-term wind power production forecasts, the proposed algorithm predicts the ramp events directly from the wind speed forecasts, taking advantage of non-parametric model requirement and uncertainty estimation for both the forecasting model and model transition. Moreover, a transformation from the wind speed profile to a grayscale image not only includes more information about the weather environment, but also supports in implementation of advanced data analysis approaches which can further help for feature extraction, pattern clustering and similarity measurement to improve the performance of ramp event forecasting. All these three forecasting models have been validated completely by a statistical analysis based on accuracy metrics using operational data over six years from six wind farms across Canada.

The performance of the UNB-developed day-ahead and hours-ahead wind power production forecasting models have been validated by taking the approaches of accuracy metrics comparison and error distribution analysis. The better overall values of metrics of Bias, MAE, RMSE and AMAPE by comparison with those from the commercial reference forecasting provider have verified the forecasting performance of the proposed UNB models. Meanwhile, the novel wind power ramp forecasting method can effectively identify the ramp events while reducing the false alarms through employing a CNN-based pattern extraction function block. According to the forecasting results in 2020, more than 65% of the ramp forecasts have been verified to be effective which reported close to 80% of actual event observations in a day-ahead time framework.

3 UNB Wind Power Forecasting Package

A forecast provides value only when end-users can receive the information in a manner that is useful and have the necessary resources and mechanisms in place that enable them to take actions in response to the forecast. Thus, the UNB team developed a Windows desktop application of a comprehensive wind power forecasting package in the end of 2018 integrated with day-ahead/ hours-ahead wind power production forecasting and wind power ramp forecasting algorithms served for utilities, system operators, wind farm owners, and other sector players.

3.1 Wind Power Forecasting Services

The package consists mainly of a core forecast engine integrated with the UNB-developed day- ahead and hours-ahead wind power production forecasting methods as well as a probabilistic wind power ramp prediction algorithm to offer the utility companies and wind farm operators a comprehensive wind power forecast service including:

- Day-ahead wind power production forecast: it provides hourly power production forecasts of the investigated wind farm for the next 48 hours, which are updated four times per day.
- Hours-ahead wind power production forecast: it predicts the power production of the investigated wind farm for look-ahead times ranging from 30 minutes to six and a half hours with 5-minute time steps, which are updated every one hour.
- Wind power ramp forecast: it is implemented within an alert and notification system to provide probabilistic wind power ramp forecasts up to 48 hours ahead.In addition,

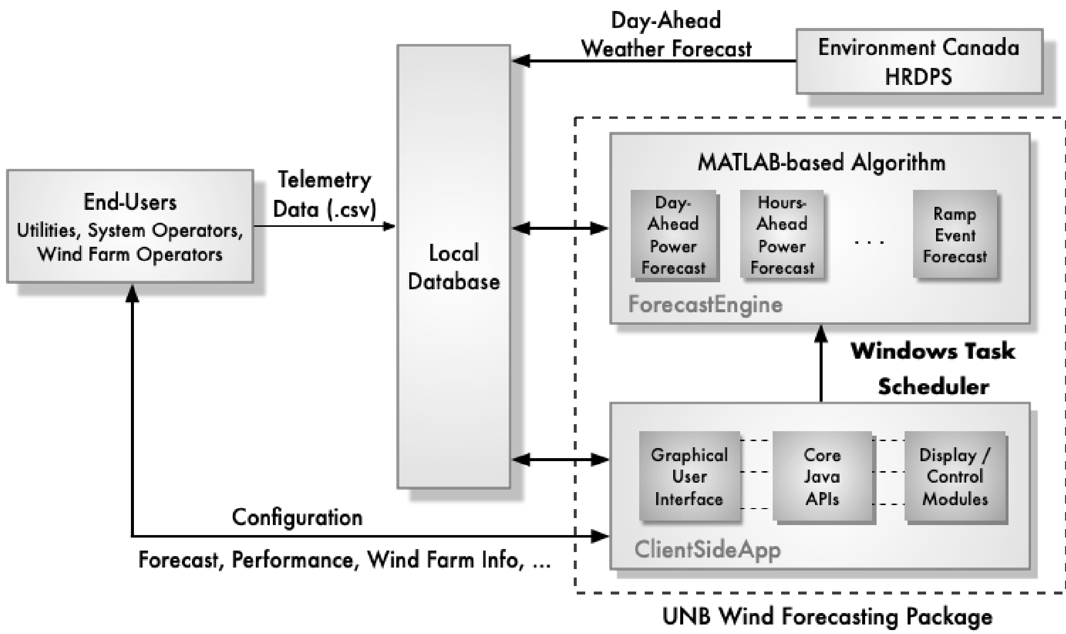


Figure 19- Function block of UNB wind power forecasting package

The proposed wind power forecasting package also provides real-time operating and environmental information of the investigated wind farm, performance evaluation using historical forecast and telemetry data saved in the database server, and an interface to deliver generated forecast to end-users' operation platforms.

The function block of the wind forecasting package being proposed is shown in Figure 19. A local database has been utilized as a data hub which collects telemetry data from end-users and weather forecast information from EC, and then send them to the wind forecasting package to generate the forecasts and populate the environment and operation information of the investigated wind farm. And a task scheduler tool (e.g. Windows Task Scheduler for Windows systems) has been selected to make the package running as scheduled in a real-time operation environment. The client-side application of the wind power forecasting package is designed to provide a clear and effective GUI with a focus on user experience. A screenshot of Dashboard of the UNB wind power forecasting package is shown in below, as an example.

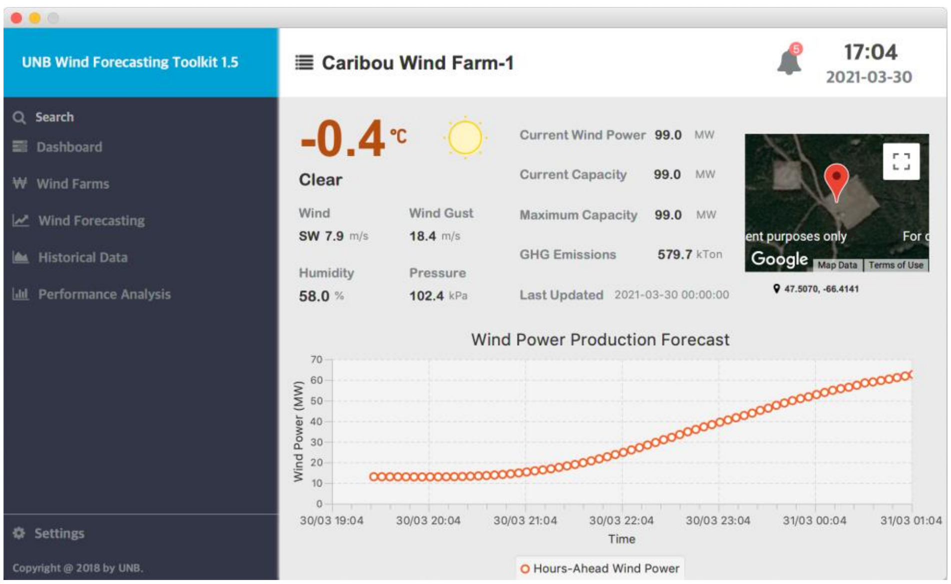


Figure 20- Dashboard screenshot of UNB wind power forecasting package

3.2 Demonstrations

This package has been tested completely at UNB and demonstrated in a real wind farm operation environment at WEICan in 2019 and 2021, respectively. In addition, the UNB team, on behalf of NB Power has also run and tested the package with the six investigated win farms since 2019, which shows the identical performance of the individual wind power forecasting models in the previous section. The detailed design, development and test reports of this wind power forecasting have been presented in the UNB progress report of 2019-2021. Some updates of the wind power forecasting package have been made during the demonstrations with feedback and suggestion from WEICan, primarily including:

- ➢ Simplifying the installation and configuration process using pre-edited batch files.
- ➢ Providing overview information of the total wind power production forecast, the operation status, etc. for all available wind farms supervised by the customer (see Figure 21)
- ➢ Improving the update frequency of wind ramp forecasts up to every 30 minutes.
- ➢ Fixing bugs, such as clock display, default units in the population of real-time weather information, etc.

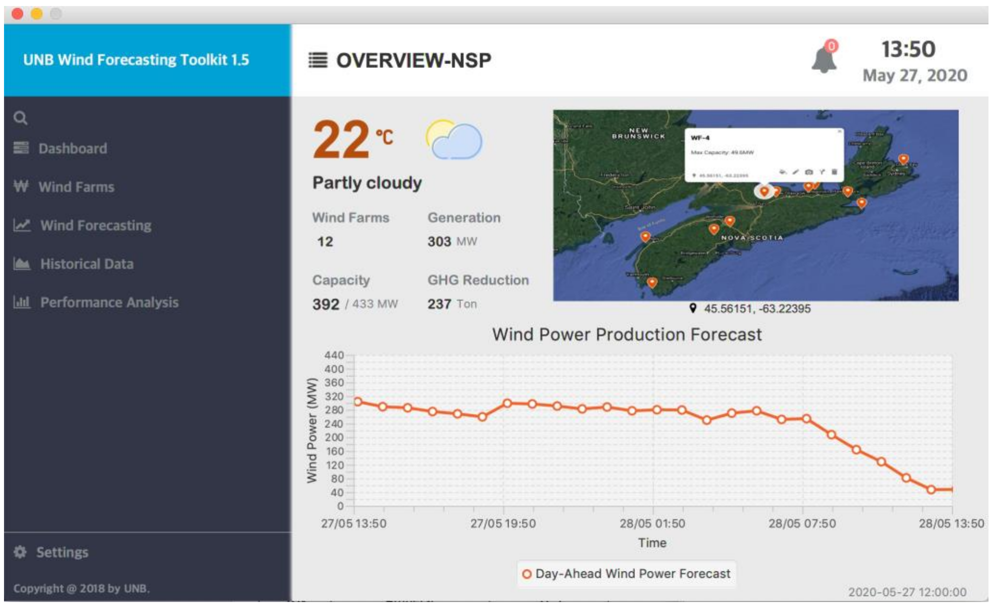


Figure 21- Overview page in Dashboard window

However, even though the UNB wind power forecasting package has been verified for high-quality forecasting performance, there are a few challenges for its deployment in the wind forecasting service market as:

- Maintenance and support: Stability is always great to have when running software. The developed wind power forecasting package also requires maintenance to modify and update the application to fix bugs and improve system performance. However, it is costly. During the demonstration at WEICan in 2021, the UNB team had very limited resources (HQP, time, etc.) to respond/debug the issues that occurred during the installation and operation. This forecasting service requires 24/7 support to make sure it is involved in the grid operation. In addition, the package is also difficult to maintain compatibility with constantly changing external environments like operating systems, databases, and Java SDK tools.
- Customer engagement: The current package asks end-users to provide consistent power

measurement as an input of the forecasting models. However, it may be challenging for the customers either in the beginning of the configuration setup or during the daily operation.

- Privacy and security concerns: Either the wind generation data or the wind farm operation data is highly private, thus requiring high-level data security protection. This presents a real challenge for toolkit development. Furthermore, the package has shown more issues like an unstable connection to the EC HRDPS database when running in a server with a high level of computer and network security.

3.3 Conclusions

A desktop wind forecast package has been developed by the UNB Team which includes the functions of the day-ahead/ hours-ahead wind power production forecasting, ramp event forecasting and performance assessment for historical data. The demonstration staged at UNB and WEICan using the data collected from six wind farms for a period from January 2019 to August 2021 reveals that the UNB wind power forecasting package is capable of providing consistent high-quality services of the day-ahead wind speed/power production forecast, the hours-ahead wind speed/power production forecast and the day-ahead wind power ramp forecast for utilities, system operators, wind farm owners and operators, and other sector players. Compared with one of the existing high-reputation commercial wind forecasting service vendors, a noticeable degree of improvement of the forecasting performance can be found in the UNB wind power forecasting package [33].

Even though the performance of this comprehensive wind power forecasting tool has been verified, the deployment is still challenging due to the limited maintenance support, high requirement for customer engagement, privacy and data security concerns, etc., thus requiring more R&D efforts in the future.

4 Future Work

Wind power capacity in Canada continued to experience strong growth at a pace closer to 1000MW per year and is expected to reach a cumulative installed capacity of 23.4 GW by the end of 2040 [35]. All of this imposes the new requirement on the service market of wind forecasting to integrate the advanced wind power forecasting technologies into the real-time power system operation, thus reducing the operating cost and maintaining the power system reliability. This project funded by NRCan has focused on the development and validation of innovative wind forecasting technologies, aiming for applications in utilities, system operators, wind farm operators, etc. The tasks proposed by the project proponent (University of New Brunswick - UNB) in partnership with TechnoCentre éolien (TCE) and Wind Energy Institute of Canada (WEICan) and associated with the deliverables have been successfully completed and delivered during the project period from 2016 to 2022 detailed in the previous progress reports, which include:

- Task 1: Data collection and acquisition
- Task 2: Assessment of EC wind forecasting model
- Task 3: Assessment of wind power production based on EC wind forecast model
- Task 4: Development of icing forecasting model
- Task 5: Development of wind power ramp forecasting method
- Task 6: Study of bulk energy storage for wind plant operation
- Task 7: Interim report
- Task 8: Development of an integrated wind power forecasting package
- Task 9: Expanded assessment and validation of the integrated wind forecasting package
- Task 10: Extended assessment and evaluation of short-term wind power production forecasting and wind power ramp forecasting methods
- Task 11: Dissemination of results (i.e., this white paper)

Beyond the scope of this project there are several areas with emerging technologies recommended for future work:

a. Improvement on model robustness

The current wind power forecasting models developed in this project are highly dependent on both the input of weather forecast from the EC HRDPS model and a larger amount of historical data. When the EC HRDPS model changes (e.g., its recent update in November 2021) or the training data is very limited, the accuracy of the existing forecasting models after training may vary and be unpredictable, or even fail. In these cases, advanced online machine learning or transfer learning techniques may be necessary to ensure forecasting performance against the variations of external parameters and factors.

b. Wind forecasting services using cloud-based solutions

Although a standalone desktop-based application of wind forecasting tools hosted locally, saves the data in a private environment securely on the customers' server configurations. However, it can be costly as customers may need to have a support specialist on-site to install the software and make updates from time to time. On the other hand, a cloud-based tool package may provide a more cost-effective solution, leaving cloud platforms for data protection, backup, maintenance, and customized interface for the grid and wind farm operation. In addition, a cloud-based wind forecasting tool can have more calculating power of the server to support more complicated models for better forecasting performance.

c. Potential of (aggregated) distributed wind generation forecast

The proliferation of renewable distributed energy resources (DERs) on the grid will introduce heightened levels of complexity and present new opportunities and challenges for grid operation. With increased penetration of distributed wind generation, the utility cost of mis-forecasting behind-the-meter can be not trivial. Utilities and system operators thereby require forecasts of distributed wind generation not only to reduce the risk of distributed wind energy integration but also to assist DER planning benefit to both power system reliability and end-users' electricity costs. Due to the characteristics of distributed wind generation, dynamic or decentralized modelling approaches may be required for the development of the forecasting methods for distributed wind energy.

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