A Hybrid Intelligent Model for Deterministic and Quantile Regression Approach for Probabilistic Wind Power Forecasting

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***Abstract*—With rapid increase in wind power penetration into the power grid, wind power forecasting is becoming increasingly important to power system operators and electricity market participants. The majority of the wind forecasting tools available in the literature provide deterministic prediction, but given the variability and uncertainty of wind, such predictions limit the use of the existing tools for decision-making under uncertain conditions. As a result, probabilistic forecasting, which provides information on uncertainty associated with wind power forecasting, is gaining increased attention. This paper presents a novel hybrid intelligent algorithm for deterministic wind power forecasting that utilizes a combination of wavelet transform (WT) and fuzzy ARTMAP (FA) network, which is optimized by using firefly (FF) optimization algorithm. In addition, support vector machine (SVM) classifier is used to minimize the wind power forecast error obtained from WT+FA+FF. The paper also presents a probabilistic wind power forecasting algorithm using quantile regression method. It uses the wind power forecast results obtained from the proposed hybrid deterministic WT+FA+FF+SVM model to evaluate the probabilistic forecasting performance. The performance of the proposed forecasting model is assessed utilizing wind power data from the Cedar Creek wind farm in Colorado.**

***Index Terms*—Deterministic and probabilistic wind power forecasting, firefly, fuzzy ARTMAP, support vector machine classifier, wavelet transform.**

NOMENCLATURE

ANFIS	Adaptive Neuro-fuzzy Inference System
ARIMA	Autoregressive Integrated Moving Average
ART	Adaptive Resonance Theory
BPNN	Backpropagation Neural Network
FA	Fuzzy ARTMAP
FF	Firefly
GA	Genetic Algorithm
GS	Grid Search
KNN	k-Nearest Neighbor
MAPE	Mean Absolute Percentage Error
NMAE	Normalized Mean Absolute Error
NN	Neural Network
NRMSE	Normalized Root Mean Square Error
NWP	Numerical Weather Prediction
PI	Prediction Interval
PS	Plasticity-Stability
PSO	Particle Swarm Optimization
QR	Quantile Regression
RBFNN	Radial Basis Function Neural Network
SCM	Soft Computing Model
SVM	Support Vector Machine
WP	Wind Power
WPF	Wind Power Forecasting
WS	Wind Speed
WT	Wavelet Transform

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I. INTRODUCTION

THE U.S. Department of Energy has projected that wind power penetration in the U.S. electric grid will exceed 20% by 2030, anticipating the U.S. wind power capacity would exceed 300 gigawatts [1]. Given the variability and unpredictability of wind generated power, the high penetration of the energy source into the power grid poses a fundamental problem for power system operators, which can result in economic uncertainty and reduced system reliability [2]. On the other hand, accurate wind power forecasting (WPF) is beneficial for wind plant operators, utility operators as well as utility customers.

Traditionally, the output power of wind power plants is predicted by deterministic forecasts. However, in general, deterministic forecasts provide information regarding historical performance of the method, but these methods cannot estimate the uncertainty associated to a given prediction. Uncertainty is expressed in the form of probabilistic forecasts that are associated to deterministic wind power forecasts. The application of probabilistic wind power forecasts on energy bidding in a day-ahead electricity market can lead to higher economic benefits than those obtained by only using deterministic forecasts [3].

Several methods such as the persistence method, physical modeling approach, statistical models, and soft computing models (SCMs) are reported in the literature for short-term deterministic WPF. The persistence method, also known as a "Naive Predictor", is used as a benchmark for comparing other tools for short-term WPF [4]. Any developed forecast method is first tested against the persistence method in order to baseline its performance [5], [6]. Numerical weather prediction (NWP) is a physical modeling approach used in wind forecasting that utilizes various weather data and operates by solving complex mathematical models [7]. The statistical models such as autoregressive moving average, exponential techniques, and grey predictors use historical data to tune the model parameters and error minimization occurs when the patterns match the historical ones within a certain bound [5], [8], [9]. SCMs, such as backpropagation neural network (BPNN), probabilistic NN, radial basis function NN (RBFNN), cascade correlation NN, fuzzy ARTMAP (FA) [10], support vector machines (SVMs) [11], Gaussian process [12], and fuzzy logic are widely used in WPF. Some evolutionary optimization techniques, such as genetic algorithm (GA) and particle swarm optimization (PSO) are used for optimizing the NN [13]–[16]. In addition, hybrid intelligent algorithms for WPF are getting popular, namely neuro-fuzzy methods [17]. Adaptive neuro-fuzzy inference system (ANFIS) is a hybrid model using fuzzy logic and NN models, and its application to wind forecasting has been discussed in [2], [17], [18].

An excellent overview of probabilistic WPF methods is provided in [19] and optimal coordination of hydro-generation and wind energy production is investigated using a probabilistic prediction model in [20]. Probabilistic wind power prediction models use meteorological ensembles that are obtained by a traditional wind power and NWP time-series [21]. These models apply a statistical method to estimate the predictive distributions in the form of quantiles or intervals. For example, as presented in [22], a local linear quantile regression (QR) is applied to estimate ten different quantiles for wind power forecasts. In [23], a spline basis function is used with QR to estimate quantiles of the forecast error of the WPF model. Wind power prediction errors always exhibit some skewness, and confidence intervals of prediction point are asymmetric. QR method can handle uncertainty analysis of wind power prediction having without hypothesizing the distribution of wind power prediction error. A method to provide the continuous predictive probability density function of wind power is proposed in [24] and [25] based on kernel density estimators and time-adaptive kernels. In addition, prediction intervals (PIs) can be estimated by adaptive resampling using the uncertainty information of an appropriate risk index obtained from consecutive weather forecasts [26]. A new framework is proposed for synthesizing PIs generated using an ensemble of NN models in the lower upper bound estimation method for wind power generation [27]. Two NN-based methods (lower upper bound estimation and bootstrap method) are presented for direct and rapid construction of PIs for short-term forecasting of power generation [28]. A novel approach is shown to directly formulate the prediction intervals of wind power generation based on extreme learning machine and PSO, where prediction intervals are generated through direct optimization of both the coverage probability and sharpness, without the prior knowledge of forecasting errors [29], [30]. In [31], a probability distribution model named "versatile distribution" is formulated and developed along with its properties and applications. This model can well represent forecast errors for all forecast timescales and magnitudes. Recently, Qadrdan *et al.* [32] utilized three operational planning methods: deterministic, two-stage stochastic programming and multistage stochastic programming, in order to investigate the operation of a Great Britain integrated gas and electricity networking considering wind forecasts uncertainty and it is reported that the operational strategies determined by the stochastic programming methods produced reduction in operation cost by 1% compared to the solution using the deterministic method.

This paper presents a novel hybrid intelligent algorithm for deterministic wind power forecasts, the results of which are further evaluated by performing probabilistic forecasts using QR method. The innovative contribution of this paper is to develop an accurate, efficient, and robust deterministic WPF model using a combination of a data filtering approach based on wavelet transform (WT) and a soft computing model based on FA network, which is optimized using an optimization technique called firefly (FF) algorithm. The SVM classifier is also applied to minimize the WPF error. Hereinafter, the proposed hybrid deterministic model will be termed as WT+FA+FF+SVM in this paper. Then, the QR method proposed in [23], is used for probabilistic forecasting. Finally, the forecasting performance of the proposed deterministic hybrid model is compared with that of other soft computing and hybrid models (i.e., BPNN, FA, WT+BPNN, WT+FA, WT+BPNN+SVM, WT+FA+SVM, and the benchmark "persistence" method) using wind power data from the Cedar Creek wind farm in Colorado. The comparison demonstrates a significant improvement in daily and weekly mean absolute percentage error (MAPE). The average MAPEs improvement by the proposed model over the other forecasting models for daily and weekly forecasts are around 53% and 38%, respectively. Furthermore, to evaluate the forecasting performance of the proposed hybrid intelligent WT+FA+FF+SVM deterministic model, it is also tested using wind power data from the Kent Hill wind farm in New Brunswick, Canada. The proposed model reduced the MAPEs by around 27.5%, when compared with the deterministic approach proposed in [33]. The test results of probabilistic forecasting also demonstrate the effectiveness of the proposed hybrid deterministic model.

The rest of this paper is organized as follows. Section II describes WT, FA, FF and SVM classifier, followed by the probabilistic WPF in Section III. Section IV presents deterministic WPF steps of the proposed model. The numerical results and discussion are presented in Section V. Section VI outlines the conclusions.

II. Proposed Hybrid Approach for Deterministic Wind Power Forecasting

The detailed description of BPNN is available in [34] and is not repeated here. A brief description of WT, FA, FF, and the SVM classifier algorithm and suggested references for further reading are given below.

A. Wavelet Transform

WT is a mathematical tool, which has been used in various signal processing applications to parameterize signals with complex time-frequency structures. A wind power data series

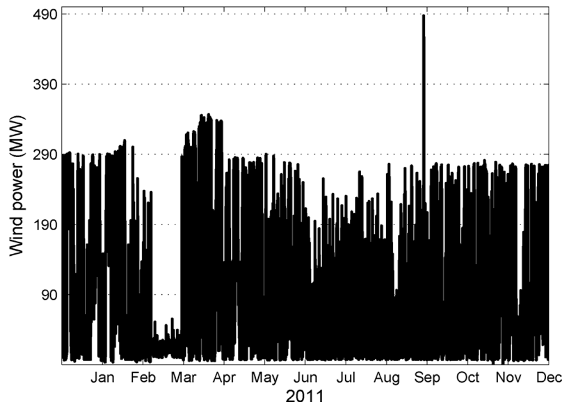

Fig. 1. Hourly wind power output of Cedar Creek wind farm in 2011.

contains various fluctuations, spikes, and different types of non-stationarity (see Fig. 1). Due to the filtering effect, the decomposed time-series of WT has a better behavior, in terms of data variance and outliers, than the original time-series [33]. Therefore, WPF will have better error improvement [18]. In this study, three levels of discrete WT decomposition have been chosen, and consequently three details and one approximation signal are obtained from the original wind power time-series signal. As decomposition involves high-pass and low-pass filtering and downsampling, the wavelet reconstruction involves three steps of upsampling and filtering. A 4th order Daubechies wavelet function is used in this study as the mother wavelet. The detailed description of the WT decomposition, reconstruction and equations are available in the previous work done by the authors [33], [35].

B. Fuzzy ARTMAP Network

The FA network is a self-organizing, supervised learning NN model based on fuzzy adaptive resonance theory (ART), which is able to carry out learning without forgetting the previously learned inputs. Most NNs face the plasticity-stability (PS) dilemma during the learning phase. The PS dilemma is used to make the system adaptive in response to significant input data changes, while remaining stable in response to irrelevant data [36]. The FA network differs from other NNs such that a generic NN has difficulties in preserving the previously learned knowledge in memory while continuing to learn new concepts. However, the FA network addresses this dilemma by incorporating a feedback mechanism between the competitive and input layers to allow new information to be learned without eliminating the previously obtained knowledge. This results in a more stable learning environment and a faster convergence capability [37]. This attribute improves WPF performance. The detailed architecture of the FA network is available in the previous work done by the authors [10], [35], [38].

C. Firefly Optimization Algorithm

FF algorithm is a metaheuristic, nature-inspired, optimization algorithm, which is based on the flashing behavior of fireflies. It was applied to optimize FA network in day-ahead electricity price forecasting in [35] and found satisfactory performance. In this study, FF algorithm is applied to enhance the WPF performance by tuning vigilance parameter ρ of the FA network. The FF algorithm utilizes three idealized rules based on some of the characteristics of real fireflies [35], [39]: 1) all fireflies are unisex, and they move towards the more attractive and brighter ones regardless of their gender; 2) attractiveness is proportional to their brightness, which decreases as the distance from the other fireflies increase. If there is not a brighter or more attractive firefly in the search space, then that firefly moves randomly; and 3) the brightness of a firefly is determined by the value of an objective function of a given problem.

D. Support Vector Machine Classifier

SVM is an excellent tool for classification and regression problems of good generalization ability, which is developed from statistical learning theory [40]. In this study, SVM classifier is employed to minimize the forecasting error obtained from the WT+FA+FF forecasting output. The basic idea of SVM applied to regression classifier is described below [41], [42].

Suppose there is an observation sample set $\{x_i, y_i\}_{i=1}^N$ where each $x_i \in \mathbb{R}^n$ denotes the input space of the sample and has a corresponding target value $y_i \in \mathbb{R}$ for $i = 1, \ldots, N$ with N corresponding to the size of the data points. The SVM's basic idea is to find a nonlinear map from the input space to output space and map the input data to a higher dimensional feature space. Then the following estimate function is used to make linear regression in the feature space [43]:

$$f(x) = \langle w^T, \phi(x) \rangle + b \tag{1}$$

where $\phi(x)$ denotes the high-dimensional feature space, which is nonlinearly mapped from the input space, w contains the coefficients that have to be estimated from the data, and b is a real constant. The objective is to minimize the following risk function [44]:

$$\min_{w,b,\xi_i,\xi_i^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{2}$$

$$\text{subject to } \begin{cases} y_i - \langle w^T, \phi(x_i) \rangle + b \le \varepsilon + \xi_i^* \\ \langle w^T, \phi(x_i) \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{3}$$

where x_i is mapped to a higher dimensional space by the function Φ, and ξ_i^* is slack variables of the upper training error (ξ_i is the lower) subject to the ε-insensitive tube $\langle w^T, \phi(x_i) \rangle + b - y_i \le \varepsilon$. The parameters that control regression quality are the cost of error C, the width of the tube ε, and the mapping function Φ. The inner products $\phi(x_i)$ in the high-dimensional space can be replaced by some kernel functions $K(x, x_i)$. In this paper, radial basis function (RBF) is used as a kernel:

$$K(x, x_i) = \exp(-\gamma\|x - x_i\|^2) \tag{4}$$

where γ is the kernel parameter.

III. Probabilistic Wind Power Forecasting Using Quantile Regression

The probabilistic WPF model is built to analyze forecasting performance obtained from the proposed deterministic hybrid WT+FA+FF+SVM model. In this study, QR probabilistic forecasting model is used. The conventional way to estimate forecasting uncertainty directly from the deterministic forecasting models is to make some assumptions about the distribution of the forecasting errors. Since wind power does not represent any

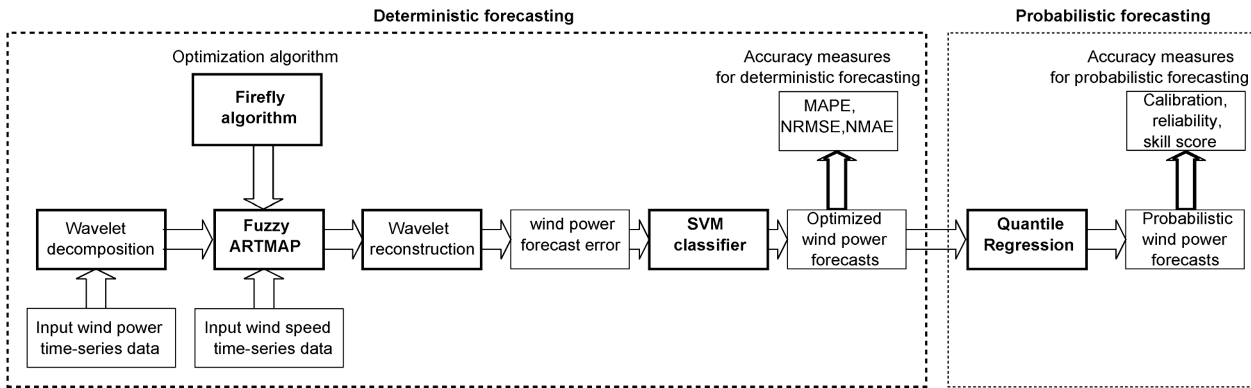

Fig. 2. Schematic diagram of wind power forecast process.

specific distribution, it can be beneficial to model the uncertainty without assuming any distribution properties. One method for doing such modeling is QR, which is based on a linear model [23]:

$$y = x^T\hat{\beta} + r = \hat{Q}(\tau;x) + r \tag{5}$$

where τ-quantile $\hat{Q}(\tau;x)$ is modeled as

$$\hat{Q}(\tau;x) = \beta_0(\tau) + \beta_1(\tau)x_1 + \cdots + \beta_p(\tau)x_p \tag{6}$$

where x are the p known regressors, also called explanatory variables, and $\beta(\tau)$ are unknown coefficients depending on τ, to be determined from observation $(x_1,\ldots,x_p)$. The estimate of $\beta \in \mathbb{R}$ given N observations is [45]:

$$\hat{\beta}(\tau) = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \rho_\tau[y_i - (\beta_0(\tau) + \beta_1(\tau)x_1 + \cdots + \beta_p(\tau)x_p)] \tag{7}$$

where

$$\rho_\tau(r) = \begin{cases} \tau r, & \text{if } r \geq 0 \\ (\tau - 1)r, & r < 0 \end{cases} \tag{8}$$

is an asymmetrical and piecewise linear loss function.

The objective of utilizing QR is to estimate the WPF uncertainty in terms of a set of forecast quantiles. Each quantile is modeled as a sum of nonlinear smooth functions of the forecasted wind power generation. Spline bases are used to approximate each of the smooth functions as a linear combination of basis functions [46], [47]. This study employs a linear QR model, which considers the formulation of the basis functions as cubic B-splines, in order to obtain the quantile with a proportion of the forecast errors [46]

$$\begin{aligned} Q(\tau; f_e) &= \beta_{0,t}(\tau) + f_t(f_p,\tau) \\ &= \beta_{0,t}(\tau) + \sum_{j=1}^{K-1} b_j(f_p)\beta_{j,t}(\tau) \end{aligned} \tag{9}$$

where b_j's are natural cubic B-spline basis function, K is the number of knots used for the spline basis functions, f_p and f_e are forecasted power and forecasting error obtained from the deterministic model, respectively. The probabilistic forecast is represented through a set of quantiles ranging from 5% to 95% (in 5% increments). The detailed description of QR forecast is available in [22], [23], [46], and [48]. In this work, the authors present deterministic and probabilistic WPF techniques. The strategy for deterministic forecasting uses a novel hybrid intelligent WT+FA+FF+SVM model, the results of which are further tested using the QR method in order to assess the performance of probabilistic forecasting.

IV. Proposed Hybrid Intelligent Algorithm for Deterministic Wind Power Forecasting

Fig. 2 depicts the schematic diagram of the proposed forecasting engine that includes deterministic as well as probabilistic WPF. The steps below describe the deterministic WPF procedure:

A. Step-1

The input parameters of the hybrid forecasting model are historical wind power (WP) time-series and wind speed (WS) data. The effect of WP and WS data of previous hour is also considered in the proposed model in order to enhance the forecasting capability. In other words, the input parameters of the FA network are the data of WP and WS for the current hour t and the previous hour $(t-1)$, i.e., $WP_t, WP_{t-1}, WS_t, WS_{t-1}$. Only the WP data series is passed through the WT; the WS data is passed directly to the FA network. The WP data series is decomposed into four components by WT: the low frequency approximation signal and three high frequency details coefficients, which are obtained by downsampling with a low-pass and a high-pass filter, respectively.

B. Step-2

The individual decomposed signal is then fed into the FA network. For the sake of training the FA network, the input data of the past 60 days ($60 \times 24 = 1440$ hourly sample data) before the forecast day are employed. As stated earlier, the FF algorithm is used to optimize ρ in the FA network. The initial (starting) value of ρ is chosen by trial-and-error [49]; in this study, 0.75 was used. Once the training phase is completed, the forecasting error is then calculated. The reciprocal of mean square error is chosen as the fitness function of the FA in the training stage, which is defined as

$$f_i = \frac{N}{\sum_{i=0}^{N}(WP_i^a - WP_i^f)^2} \tag{10}$$

where WP_i^a is the actual wind power, WP_i^f is the forecasted wind power, and N is the total number of data points. The input parameters of the FF algorithm are the vigilance parameter vector set $\rho = [0.1, 0.15, \ldots, 1]^T$ and the fitness function.

C. Step-3

The individual forecast value of decomposed approximation and detail signals are then obtained from the FA network. The desired wind power forecasts are obtained after the wavelet reconstruction.

D. Step-4

After getting the wind power forecast error from Step-3, the forecasting error vector is passed through the SVM classfier. The SVM classifier is denoted as

$$SVR_e = \{x_i, f(e)\} \in [0,1]^n \times \{-1, 0, 1\} \tag{11}$$

where e is the forecasting error and

$$f(e) = \begin{cases} -1 & e \leq -\varepsilon \\ 0 & -\epsilon \leq e \leq \varepsilon \\ 1 & e \geq \varepsilon \end{cases}$$

where ε is an threshold. In this study, ε is chosen as standard deviation of the normalized error vector set. The ε provides the forecasting error obtained from the WT+FA+FF model into three classifications, i.e., positive big error, error near zero, and negative big error; $w \in \{-1, 0, 1\}$. The forecasting errors are estimated using IF-THEN rules

$$\begin{cases} \text{IF} \quad w = 1 \quad \text{THEN} \ e_o = \varepsilon \\ \text{IF} \quad w = 0 \quad \text{THEN} \ e_o = 0 \\ \text{IF} \quad w = -1 \quad \text{THEN} \ e_o = -\varepsilon \end{cases}$$

where w is the output of the SVM classifier and e_o is the estimated forecasting error.

The final deterministic forecasting output is optimized as follows:

$$\widehat{WP}_{final} = WP_{WT+FA+FF} - e_o \tag{12}$$

where $WP_{WT+FA+FF}$ is the wind power forecast from the WT+FA+FF forecasting model and e_o is the estimated forecasting error using the SVM classifier, thus forming the proposed hybrid WT+FA+FF+SVM intelligent model. Deterministic WPFs are then tested using the QR model to evaluate the performance of probabilistic forecasting. Flowchart for the developed hybrid WT+FA+FF+SVM deterministic forecasting model is presented in Fig. 3.

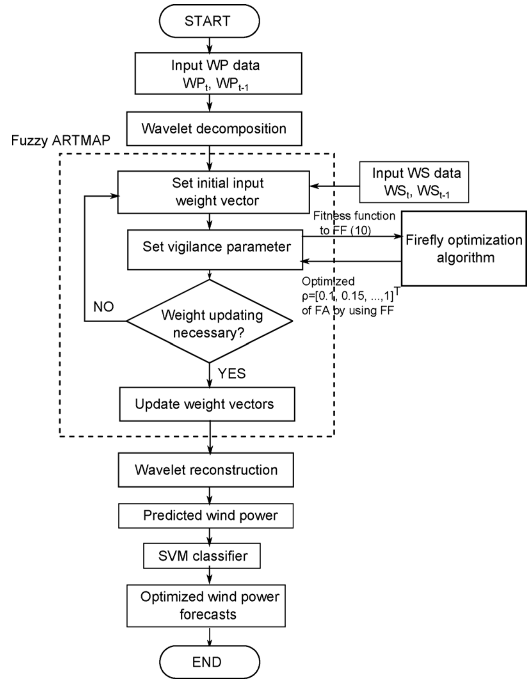

Fig. 3. Flowchart for the developed WT+FA+FF+SVM deterministic model framework.

V. Numerical Results and Discussions

This paper presents a new hybrid intelligent deterministic forecasting algorithm based on WT, FA, FF, and SVM classifier which takes into account the interactions of wind power and wind speed. The proposed hybrid model is tested by using real data from Cedar Creek wind plant in Colorado, USA. Data sets of WP and WS are recorded in 10-min interval for the year 2011 in the Cedar Creek wind plant. The measured data of the six 10-min interval over an hour are averaged to obtain hourly data used in this paper. The test data set is chosen for four days (one day from each season) for daily wind power forecasting and four weeks (one week from each season) for weekly wind power forecasting. Also, each month of the year 2011 is chosen as test case. To evaluate the effectiveness and performance of the proposed WT+FA+FF+SVM forecasting model, the results are compared with persistence and other SCMs such as BPNN and FA, and also with the combination of WT, SVM and these SCMs.

The principal statistics used to evaluate the performance of the proposed deterministic WPF model is measured by using MAPE, defined as [18]

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{|WP_i^a - WP_i^f|}{\overline{WP_i}^{a,N}} \times 100\% \tag{13}$$

where N is the total number of data points, WP_i^a is the actual wind power in hour i, WP_i^f is the forecasted wind power for that hour, and $\overline{WP_i}^{a,N}$ is the average true wind power for the Nth hour:

$$\overline{WP_i}^{a,N} = \frac{1}{N}\sum_{i=1}^{N} WP_i^a. \tag{14}$$

In addition, normalized root mean square error (NRMSE) is also calculated as [16]

$$NRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{WP_i^a - WP_i^f}{WP_N}\right)^2} \times 100\% \tag{15}$$

where WP_N is the nameplate capacity of wind farm. It is noted that the nameplate capacity of Cedar Creek wind farm is 551.3 MW.

Furthermore, the normalized mean absolute error (NMAE) criterion, which provides an indication of error range is calculated as follows in order to assess the prediction capacity of the proposed hybrid model [16]:

$$NMAE = \frac{1}{N}\sum_{i=1}^{N} \frac{|WP_i^a - WP_i^f|}{WP_N} \times 100\%. \tag{16}$$

A detailed framework to evaluate probabilistic WPF is available in [50]. For the evaluation purpose, this study considers three metrics for probabilistic forecasting performance: calibration (reliability), sharpness, and skill score. Calibration is a measure of how well the forecasted quantiles match the observed values. In other words, observed proportions should be equal to the preassigned probability exactly in an infinite set of probabilistic forecasts. The difference between observed and nominal probabilities is the bias of the probabilistic forecasting methods. Sharpness is the tendency of probability forecasts towards discrete forecasts, measured by the mean size of the forecast intervals. For sharpness evaluation, quantiles are gathered by pairs in order to obtain intervals with different nominal coverage rates [25]. The skill score is defined as [25]

$$S_c = \sum_{i=1}^{n} (I_k^{\alpha_i} - \alpha_i)(p_{t+k} - \hat{q}_{t+k}^{\alpha_i}) \tag{17}$$

where p_{t+k} is the forecasted wind power, α_i is the quantile proportion, n is the number of quantile and $I_k^{\alpha_i}$ is an indicator variable for a quantile forecast $\hat{q}_{t+k}^{\alpha_i}$, which is denoted by

$$I_k^{\alpha_i} = \begin{cases} 1 & \text{if } p_{t+k} \leq \hat{q}_{t+k}^{\alpha_i} \\ 0 & \text{otherwise.} \end{cases}$$

A. Deterministic Daily Wind Power Forecast Results

Table I presents the results obtained from the proposed hybrid deterministic forecasting WT+FA+FF+SVM model, and the results are compared with the persistence method and other models. It can be seen from Table I that the MAPE values obtained from the persistence method are very large (21.07%, 25.70%, 31.52%, and 33.28%) compared to those obtained from the proposed hybrid method (9.95%, 12.19%, 12.07%, and 13.44%) for the seasonal days under consideration. The predicting performances of the models are found to be inconsistent with varying MAPEs for the multiple seasons. Hence, average of MAPEs of the four seasons is considered to have better comparison among all the models. The test results indicate that in most of the cases, SCMs and the proposed hybrid model outperform the persistence method. The forecasting capability of the proposed hybrid model is not only superior to the persistence method but also it outperforms all the considered SCMs with or without combination of WT and SVM. Table I also presents NRMSE and NMAE results obtained for daily wind power forecast, respectively. As it can be seen from Table I that the average NRMSE (5.76%) obtained from the proposed WT+FA+FF+SVM model shows the best prediction capability over other models. Table II presents MAPE comparison of the proposed hybrid deterministic WT+FA+FF+SVM model with other evolutionary algorithms (e.g., GA and PSO) hybrid forecasting model. Also, for comparison purpose, a simple grid search (GS) algorithm is tested instead of optimization algorithm (FF) to tune FA network's vigilance parameter. A simple k-nearest neighbor (KNN) classifier is compared with SVM classifier to observe how both classifiers perform to minimize the WPF error from the WT+FA+FF forecasting model. In addition, a traditional time-series linear model, i.e., autoregressive integrated moving average (ARIMA) is also compared with proposed deterministic model. In all cases, the proposed hybrid WT+FA+FF+SVM model outperforms other models. It is well known that the for the case of soft computing models, performance significantly changes from one simulation to another. To make the results credible, simulations are repeated 20 times for each case study. Fig. 4 presents the statistics of the assessment measures of multi simulations of various forecasting models reported in the form of box plots.

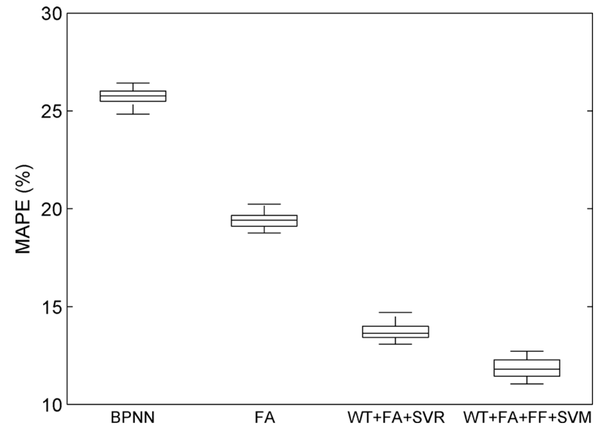

Fig. 4. Box plot of several simulations of the forecasting models.

TABLE I
MAPE, NRMSE, NMAE COMPARISON FOR DAILY WIND POWER FORECASTS

Season	Error	Model							
		Pers.	BPNN	FA	f_1	f_2	f_3	f_4	$\boldsymbol{f_p^*}$
Winter	MAPE	21.07	24.37	17.58	20.43	14.62	16.43	11.07	**9.95**
	NRMSE	7.07	7.85	6.72	7.02	6.38	6.22	5.79	**5.16**
	NMAE	5.53	5.48	5.21	5.35	5.19	5.10	5.02	**4.81**
Spring	MAPE	25.70	26.81	19.22	24.10	17.31	20.37	14.63	**12.19**
	NRMSE	7.72	7.79	7.17	7.42	6.93	7.11	6.58	**5.98**
	NMAE	4.61	4.69	4.27	4.51	4.29	4.43	4.18	**4.03**
Summer	MAPE	31.52	23.63	18.92	21.74	17.83	18.16	14.33	**12.07**
	NRMSE	7.96	7.46	6.93	7.40	6.64	6.59	5.86	**5.69**
	NMAE	5.49	5.36	5.11	5.10	4.98	4.87	4.76	**4.38**
Fall	MAPE	33.28	27.73	21.06	24.66	18.94	21.58	15.16	**13.44**
	NRMSE	8.08	7.93	7.65	7.77	7.25	7.42	6.88	**6.21**
	NMAE	5.47	5.23	5.18	5.20	5.05	4.99	4.79	**4.67**
Average	MAPE	27.89	25.67	19.20	22.73	17.18	19.14	13.80	**11.91**
	NRMSE	7.71	7.76	7.12	7.40	6.80	6.84	6.28	**5.76**
	NMAE	5.28	5.19	4.95	5.05	4.88	4.85	4.69	**4.47**

Pers.: persistence; f_1: WT+BPNN; f_2: WT+FA; f_3: WT+BPNN+SVM; f_4: WT+FA+SVM; f_p^*: proposed WT+FA+FF+SVM model

B. Deterministic Weekly Wind Power Forecast Results

The predicting performance of the proposed model is further validated by carrying out hour-ahead forecasting considering the forecasting look-ahead time up to a week. The seasonal weekly forecasts as presented in Table III show MAPE, NRMSE, and NMAE of the developed deterministic forecasting models. It can be seen from the Table III that the seasonal average MAPEs, MRMSEs, NMAEs obtained from the proposed WT+FF+FA+SVM method are consistently lower than those obtained from the other models. In particular, the proposed model outperforms the benchmark (hour-ahead) persistence method. As stated earlier, the wind power data series contains various fluctuations, spikes, and different types of nonstationarity, and WT is used for filtering those spikes. The effectiveness of using WT is demonstrated in Table III where it can be seen that the average weekly MAPEs obtained from the BPNN and FA are 25.02% and 19.67%, respectively. However, when these individual SCMs are combined with WT,

TABLE II
MAPE Comparison of the Proposed Deterministic WT+FA+FF+SVM Model With Other Hybrid Models and Time-Series Model (ARIMA) for Daily Wind Power Forecasts

Model	Season			
	Winter	Spring	Summer	Fall
ARIMA	15.53	18.73	19.21	19.86
WT+FA+GS	14.60	17.28	17.82	18.76
WT+FA+GA	14.62	17.30	17.79	18.90
WT+FA+PSO	13.97	17.02	17.11	18.23
WT+FA+FF	13.81	16.26	16.54	17.75
WT+FA+GS+KNN	13.24	16.20	16.96	17.75
WT+FA+GA+KNN	14.01	16.54	17.14	17.26
WT+FA+PSO+KNN	11.92	16.33	15.82	16.94
WT+FA+FF+KNN	11.05	13.28	12.75	14.44
WT+FA+GS+SVM	13.44	16.29	16.93	16.71
WT+FA+GA+SVM	12.83	16.41	16.88	16.89
WT+FA+PSO+SVM	11.86	15.65	14.16	16.47
WT+FA+FF+SVM (proposed)	**9.95**	**12.19**	**12.07**	**13.44**

TABLE III
MAPE, NRMSE, NMAE Comparison for Weekly Wind Power Forecasts

Season	Error	Model							
		Pers.	BPNN	FA	f_1	f_2	f_3	f_4	f_p^*
Winter	MAPE	17.78	19.51	15.33	17.06	14.73	15.55	14.23	**13.46**
	NRMSE	6.45	6.76	6.38	6.69	6.13	6.41	5.96	**5.90**
	NMAE	4.57	4.98	4.33	4.92	4.16	4.78	4.05	**3.95**
Spring	MAPE	23.14	26.98	19.77	24.20	17.86	21.30	17.05	**15.13**
	NRMSE	7.97	7.73	6.78	7.42	6.70	7.15	6.45	**6.31**
	NMAE	5.22	5.16	4.79	5.18	4.72	5.16	4.68	**4.56**
Summer	MAPE	35.52	25.41	18.72	22.37	16.74	19.81	14.83	**14.22**
	NRMSE	6.70	6.42	6.58	6.37	6.31	6.05	6.13	**5.88**
	NMAE	4.40	4.62	4.66	4.47	4.63	4.38	4.50	**4.39**
Fall	MAPE	25.32	28.19	24.87	27.16	22.39	24.67	20.09	**18.71**
	NRMSE	6.07	6.43	6.38	6.26	6.19	6.07	5.94	**5.98**
	NMAE	4.12	4.62	4.53	4.55	4.37	4.43	4.30	**4.22**
Average	MAPE	25.44	25.02	19.67	22.70	17.93	20.33	16.55	**15.38**
	NRMSE	6.80	6.84	6.53	6.69	6.33	6.42	6.12	**6.02**
	NMAE	4.58	4.85	4.58	4.78	4.47	4.69	4.38	**4.28**

Pers.: persistence; f_1: WT+BPNN; f_2: WT+FA; f_3: WT+BPNN+SVM; f_4: WT+FA+SVM; f_p^*: proposed WT+FA+FF+SVM model

the MAPEs are reduced to 22.70%, 17.93%. These errors are further reduced to 20.33% and 16.55%, respectively, when SVM classifier is introduced. Moreover, FF algorithm optimizes the FA network efficiently and errors are further reduced to 15.38% by the proposed method.

The histograms in Figs. 5–7 show the daily and weekly MAPE, NRMSE, NMAE comparison of all the models used. It is clear from these figures that in all cases the proposed model outperforms the other models used. The selections of forecasting days and weeks have been done randomly in this paper, and the reported results are only representative. To further show the effectiveness of the proposed model, simulations were performed for several forecasting test days and weeks and similar results to those reported have been obtained.

Furthermore, the testing set is extended to 12 months in order to evaluate the prediction capability of the proposed hybrid intelligent algorithm. The monthly MAPEs obtained from the proposed model are compared with the persistence method and the

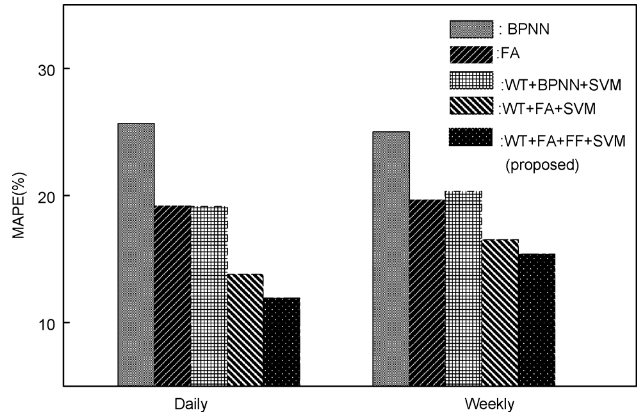

Fig. 5. Histogram showing daily and weekly MAPE comparison for wind power forecasts.

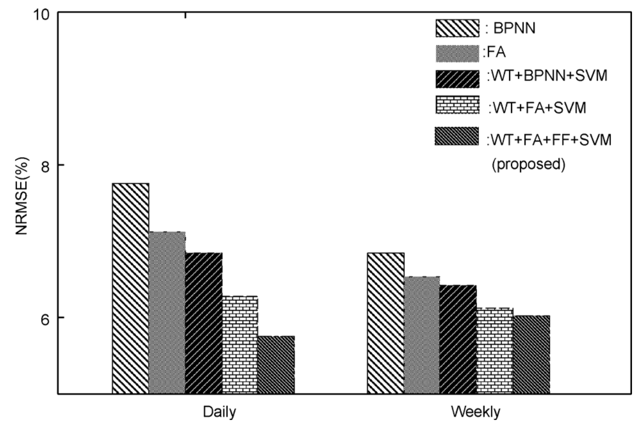

Fig. 6. Histogram showing daily and weekly NRMSE comparison for wind power forecasts.

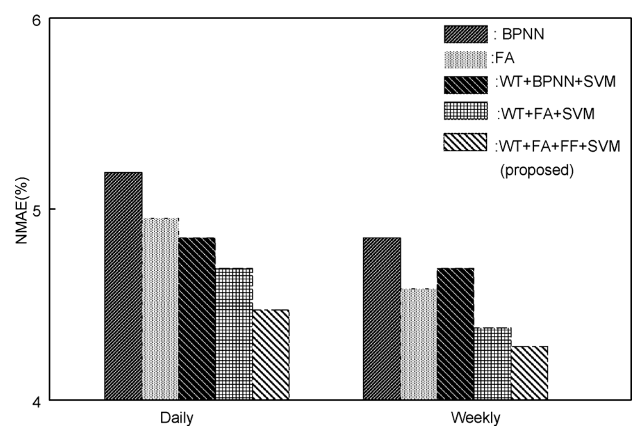

Fig. 7. Histogram showing daily and weekly NMAE comparison for wind power forecasts.

results are shown in Fig. 8. In all cases, the proposed model outperforms the persistence method. The monthly forecasts from the other models are not reported here.

We also generated deterministic wind power forecasts for the Kent Hill wind farm, Canada data [33] using the proposed model and compared the results with those reported in [33]. Fig. 9 shows NMAE and NRMSE comparison of the proposed deterministic forecasting WT+FA+FF+SVM model in terms of various forecasting horizon. It is seen from Fig. 9 that MAPE dete-

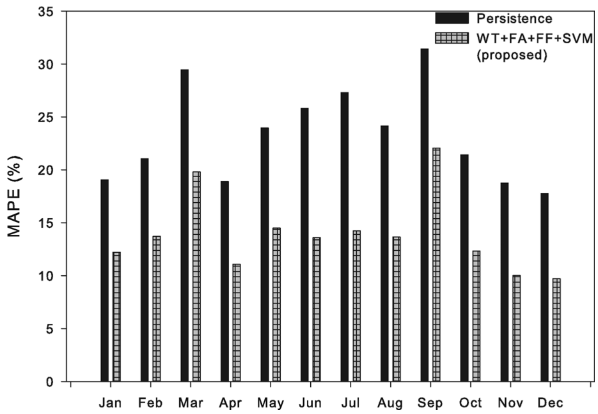

Fig. 8. Histogram showing monthly MAPE comparison for persistence method and the proposed hybrid model.

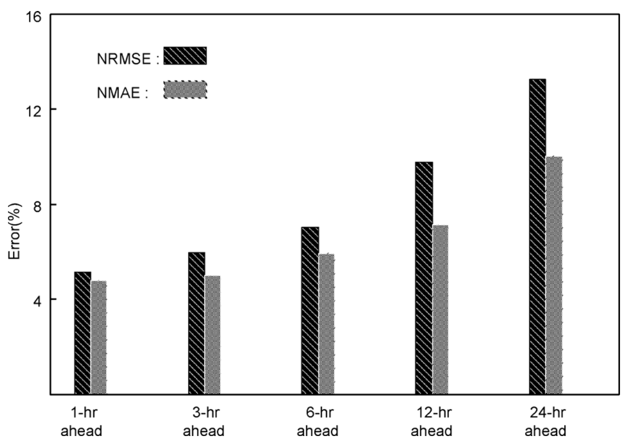

Fig. 9. NMAE and NRMSE comparison of the proposed WT+FA+FF+SVM model in terms of forecasting horizon.

TABLE IV
ERROR COMPARISON WITH THE PROPOSED MODEL OF [33]

Day	MAPE		MAPE	NRMSE		NMAE	
	f_c	f_p^*	Improvement	f_c	f_p^*	f_c	f_p^*
Winter	12.84	9.21	28.27	0.87	0.74	0.74	0.62
Spring	11.75	8.46	28.00	1.65	1.22	1.43	1.08
Summer	16.11	11.06	31.34	2.75	2.38	1.71	1.51
Fall	10.22	7.89	22.79	2.93	2.19	2.09	1.83

f_c: WT+FA [33]; f_p^*: proposed WT+FA+FF+SVM model

riorates as the hour-ahead increases and such trend is expected due to the time-series modeling. The comparison of the deterministic wind power forecast errors are presented in Table IV, where we can see a significant improvement in daily MAPEs through the application of our proposed model over the proposed model in [33]. In Table IV, NRMSEs and NMAEs of the proposed model are compared with those of the WT+FA model proposed in [33] for a random day in each season. It is clear from Table IV that the values obtained from the proposed deterministic forecasting model are significantly better than those of the model proposed in [33].

C. Probabilistic Wind Power Forecast Results

The objective in this section is to evaluate the effectiveness (reliability) of the proposed WT+FA+FF+SVM deterministic WPF model in a probabilistic sense. For this purpose, the probabilistic forecasting using spline QR [23] is used. The spline QR could be viewed as the most widely used tool for the representation of probabilistic wind power forecasts within the industry. Fig. 10 depicts the calibration diagram utilizing the spline QR model that considers average of seasonal deterministic daily wind power forecasts obtained from 1) BPNN and 2) the proposed WT+FA+FF+SVM model. The dotted horizontal line at zero deviation denotes "perfect calibration", i.e., perfect match between the nominal and observed probabilities. For most of the quantiles (except between 15%–25%), the QR estimator obtained from the proposed deterministic model shows a lower deviation than the QR estimator obtained from the BPNN, which shows the effectiveness of the proposed model in a probabilistic sense.

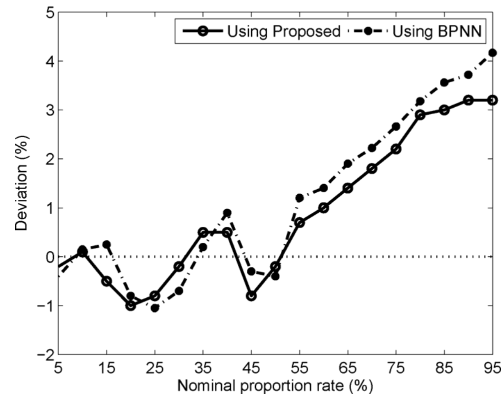

Fig. 10. Calibration diagram.

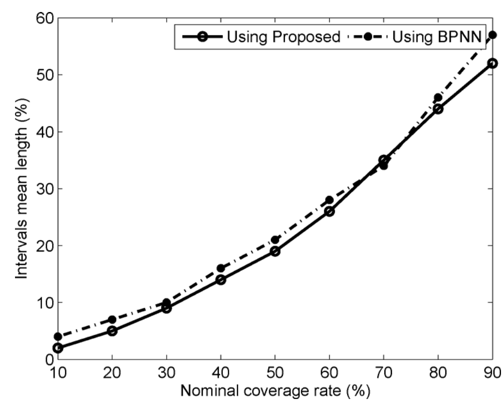

Fig. 11. Sharpness diagram.

Fig. 11 presents the sharpness diagram in which it is observed that the QR probabilistic forecast using the BPNN model is sharper than that using the proposed hybrid deterministic model. It is noted that there is a trade-off between reliability and sharpness, i.e., improving the reliability generally degrades the sharpness and vice-versa. However, reliability is a major indicator for an improved probabilistic forecasting model [25]. Fig. 12 depicts the skill score (17) computed for the nominal proportion rate. The performance of both approaches (QR output using BPNN and the proposed hybrid model) is quite similar. However, it can be confirmed from Fig. 12 that the performance of QR utilizing the proposed deterministic forecast model is comparatively better than BPNN, especially during the 5%–35% nominal proportion rate and also some part of other regions.

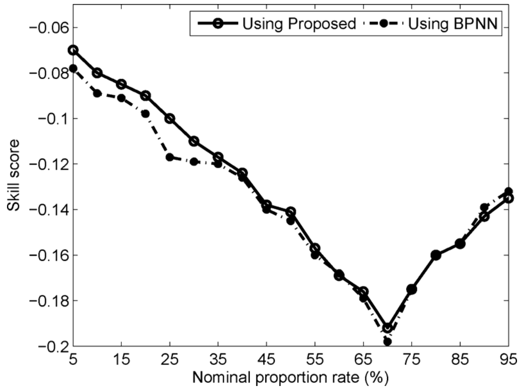

Fig. 12. Skill score diagram.

The three metrics: calibration, sharpness and skill score are normally used for evaluating probabilistic forecasting performance. These quantities are good indicators of the effectiveness of the forecast value. A calibration deviation may lead to situations of under or overestimation of the optimal quantile (in the expected value paradigm), and consequently a deviation from what is optimal in the economic sense. A lower sharpness performance may also lead to high amounts of recommend reserve, which means an increase in the cost of providing reserves. Calibration metric is the major requirement for the wind power bidding problem and also for the application to the problem of setting the operating reserve for a power system [25]. The simulation results confirm that the performance of the proposed hybrid model is highly efficient not only for deterministic forecasting but also for probabilistic forecasting.

Forecasting short-term wind power with a higher rate of accuracy is extremely important for the power system operators as they face challenges associated with fluctuating wind power production with the increasing installed wind power capacity. Based on the presented simulation results, the proposed forecasting framework demonstrates a significant improvement over the other tested alternatives compared with. For this work, MATLAB R2012a was used for developing the deterministic forecasting models and the freeware "R" version 2.15.2 was used for developing the probabilistic forecasting model (quantile regression). The average computation time required by the proposed hybrid WT+FA+FF+SVM model for short-term (hour-ahead) daily wind power forecasts is around 1–3 min using MATLAB on a PC with 4 GB of RAM and a 2.7-GHz-based processor.

VI. Conclusions

This paper presented a novel deterministic hybrid intelligent algorithm (WT+FA+FF+SVM) for short-term WPF. The developed deterministic hybrid WT+FA+FF+SVM model was rigorously compared with several other hybrid intelligent models and time-series model including the benchmark persistence method. The test results demonstrated that the forecasting performance of the proposed deterministic model is superior to all the tested alternatives. The proposed hybrid deterministic intelligent algorithm is more accurate and efficient, and produces a higher degree of accuracy in multiple seasons. After achieving deterministic forecasting output, a probabilistic forecasting model is developed based on the well known spline QR to show the effectiveness of a model in a probabilistic sense. Actual wind power data from Cedar Creek wind farm in Colorado and Kent Hill wind farm in New Brunswick, Canada were used in this study.

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