A Novel Hybrid Approach Based on Wavelet Transform and Fuzzy ARTMAP Network for Predicting Wind Farm Power Production

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***Abstract*—This paper presents a novel hybrid intelligent algorithm based on the wavelet transform (WT) and fuzzy ARTMAP (FA) network for forecasting the power output of a wind farm utilizing meteorological information such as wind speed, wind direction, and temperature. The prediction capability of the proposed hybrid WT+FA model is demonstrated by an extensive comparison with a benchmark persistence method, other soft computing models (SCMs) and hybrid models as well. The test results show a significant improvement in forecasting error through the application of a proposed hybrid WT+FA model. The proposed hybrid wind power forecasting strategy is applied to real life data from Kent Hill wind farm located in New Brunswick, Canada.**

***Index Terms*—Fuzzy ARTMAP, wind farm power forecast, soft computing models, wavelet transform**

I. Introduction

It is well known that wind power produced by wind turbines is intermittent in nature and this unpredictability poses a fundamental problem for power system operators. The fluctuation in the generated wind power causes a reduction in the operating economy and reliability for utilities with a large wind power penetration [1]. Accurate wind power forecasting is beneficial for wind plant operators, utility operators as well as utility customers. For meeting up the customers' demand, wind power forecasting facilitates scheduling the connectivity of wind turbines or conventional generators, thus improve the reliability of wind generated electricity.

Several methods are reported in literature for short-term wind power forecasting such as the persistence method, physical modeling approach, statistical models, and soft computing models (SCMs). The persistence method, also known as a 'Naive Predictor', is used as a benchmark for comparing other tools for short-term wind forecasting. This method simply uses the past hour wind power value as the forecast for the next hour. Any developed forecast method is first tested against the persistence method in order to baseline its performance [2]. Numerical weather prediction (NWP) is a physical modeling approach used in forecasting wind that utilizes various weather data and operates by solving complex mathematical models [3], [4]. NWP models generally perform well when the weather conditions are relatively stable [5]. The statistical model uses historical data to tune the model parameters and error minimization occurs when the patterns match historical ones within a certain bound. Some examples of statistical models are Autoregressive (AR), moving average (MA), ARMA, single exponential technique, double exponential, and grey predictors [2], [6]–[8].

Forecasting tools based on soft computing methods are well known for their capabilities in dealing with non-linear data and their popularity is gaining significant attention. Soft computing is an emerging field that consists of neural networks (NNs), fuzzy logic, evolutionary computation, machine learning, and probabilistic reasoning. The advantage of the SCM is that it has ability to handle non-linearity more effectively and to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques [9], [10]. Another advantage of SCMs is that they do not require explicitly mathematical expressions [11]. In simple terms, an NN model can be designed by identifying correct inputs, set up the network structure and then model a training algorithm, which gives the best prediction results. Among SCMs, NNs have been widely used in forecasting purposes. Different types of NNs are backpropagation NN (BPNN), probabilistic NN, radial basis function NN (RBFNN), self-organizing feature maps (SOFM), cascade correlation NN, extended Kalman filter (EKF)-based NN [12], [13], adaptive resonance theory NN [14], fuzzy ARTMAP (FA) [15], support vector machines (SVMs) [16].

Some other evolutionary optimization techniques, e.g., particle swarm optimization (PSO), genetic algorithm (GA) are used for updating the weight of a neuron while training the NN [17], [18]. Welch *et. al* used PSO to train the NNs, which are used in short-term wind forecasting [19]. Fuzzy theory has also been used for various forecasting applications [20], [21]. Approaches using a hybrid intelligent system for wind power forecasting are becoming more popular, namely neuro-fuzzy methods [22]–[24]. Xia *et. al* proposed an approach based on fuzzy logic and NNs for wind power forecasting [22]. 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 [1], [25]. Pinson and Kariniotakis developed an adaptive fuzzy-neural networks model for advanced wind forecasting that can be configured for short-term or long-term forecasting [23]. This method provides an online estimation of forecasting confidence intervals with an appropriate index for assessing risk due to NWP inaccuracy. Hervas-Martinez *et. al* proposed a hybrid evolutionary programming technique for wind speed forecasting [26]. Catalao *et. al* proposed a hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting [24]. Wind power is a complex process to model and predict as it is highly dependent on the weather and the output cannot be guaranteed at any particular time. It is emphasized that many wind farms are relatively new and their performance has to be adequately studied. Despite a number of techniques available for wind power forecasting as discussed here, there is still a great need of algorithm that provides high forecasting accuracy.

This paper proposes a novel hybrid intelligent algorithm for predicting wind farm power output. The innovative aspect of this paper lies on developing an accurate, efficient, and robust wind power forecast model using a hybrid approach based on wavelet transform (WT) and a SCM based on FA, i.e., WT+FA, which considers the interaction of wind power with wind speed, wind direction, and temperature in the forecast process. To the best knowledge of authors, a combination of WT and FA network has not been applied so far in order to forecast wind farm power output, thus making this approach novel. The hour-ahead test results obtained from the proposed hybrid WT+FA model demonstrate a significant improvement in daily (next 24-hour forecasts) and weekly (next 168-hour forecasts) mean absolute percentage error (MAPE) when compared with the benchmark persistence method, other individual SCMs (BPNN, RBFNN, ANFIS, and FA), and hybrid models (WT+BPNN, WT+RBFNN, and WT+ANFIS).

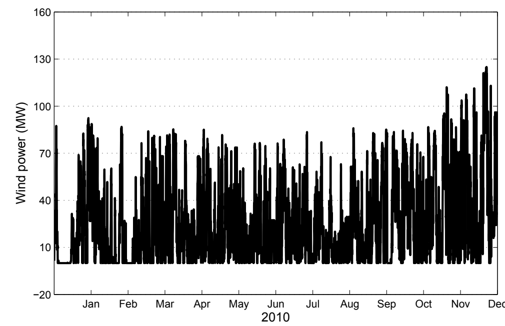

Fig. 1. Wind power profile of Kent Hill wind farm.

The major contributions of this paper utilizing a novel approach based on hybrid WT+FA model can be summarized as:

- Ability of modeling the interaction of wind power with meteorological information such as wind speed, wind direction, and temperature in the forecast process.
- Improvement in the average MAPEs over the persistence method by around 50% and 30% for the daily and weekly forecasts, respectively.
- Superior predicting performance over the individual SCMs and other hybrid models adopted in the paper.
- Effective forecasting performance for multiple seasons of the year with higher accuracy.

The rest of this paper is organized as follows. Section II describes WT and FA models followed by the forecasting procedure of the proposed hybrid intelligent algorithm in Section II-C. The numerical results and discussions are presented in Section III. Section IV includes the conclusions of the paper.

II. Description of Wavelet Transform and Fuzzy ARTMAP Network

A detailed description of BPNN, RBFNN, and ANFIS are available in references [14], [24]. A description of the WT and FA including the wind power forecasts procedure using the proposed hybrid WT+FA is given below.

A. Wavelet Transform

The wind power data series contain various fluctuations, spikes, and different types of nonstationarity. An example of wind power profile is shown in Fig. 1, which is characterized with random and chaotic changes. The WT can be considered as feature management tool to isolate these spikes. Therefore, wind power forecasting using the WT can be used to improve wind power forecast error. The WT can be divided into two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT is defined as [27]:

$$CWT_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} \Psi^*(t)x(t)dt,\ a > 0 \quad (1)$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right),\ \ a > 0 \text{ and } -\infty < b < +\infty \quad (2)$$

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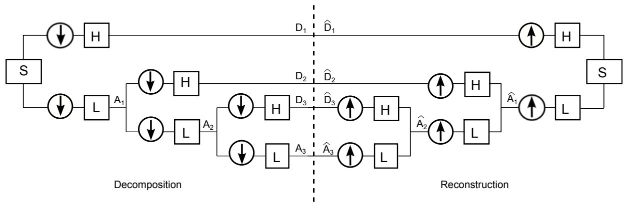

Fig. 2. Wavelet decomposition and reconstruction.

where $x(t)$ is the signal to be analyzed, $\Psi_{a,b}(t)$ is the mother wavelet scaled by a factor a and shifted by a translated parameter b, and $*$ denotes complex conjugate. Low frequencies (large scale) expand the signal and provide non-detailed information regarding the signal, whereas high frequencies (low scales) compress the signal and provide detailed information about the signal. As the CWT is obtained by continuously scaling and translating the mother wavelet, substantial redundant information is generated [28]. Therefore, the mother wavelet can be scaled and translated using certain scales and positions known as discrete wavelet transform (DWT). The DWT uses scale and position values based on power of two, called dyadic dilation and translations, which are obtained by discretized the scaling and translation parameters, denoted as [27]:

$$DWT_x(m,n) = 2^{-(m/2)} \sum_{t=0}^{T-1} x(t)\Psi\left(\frac{t-n.2^m}{2^m}\right), \quad (3)$$

where T is the length of the signal $x(t)$. The scaling and translation parameters are functions of the integer variables m and n, where, $a = 2^m$ and $b = n2^m$, t is the discrete time index.

To implement DWT using filters, Mallat developed an approach called Mallat algorithm or Mallat's multi-resolution analysis (MRA) [27], [29]. This algorithm has two stages: decomposition and reconstruction. In this paper, three level decompositions have been chosen; consequently three detail (D) and one approximate (A) signals are obtained from the original wind power signal as shown in Fig. 2. As decomposition involves filtering (high pass and low pass filter) and downsampling, the wavelet reconstruction involves three steps of upsampling and filtering, which is also shown in Fig. 2. In this paper, a wavelet function of type Daubechies of order 4 (db4), which is selected from [27], is used as the mother wavelet.

B. Fuzzy ARTMAP

The FA network is a supervised learning method based on fuzzy adaptive resonance theory (ART). It is a promising method since FA is able to carry out learning without forgetting previously learned input. It can store previously learned categories (adaptive to changes in the environment) and is self-organizing [30]. The FA network is a relatively new concept for forecasting applications including wind forecasting [15]. There are some significant advantages of FA network over the traditional SCMs. These can be described as follow:

1) Most NNs during the learning phase in forecasting application face the plasticity-stability dilemma. The plasticity-stability dilemma asks how a learning system can be designed to remain plastic, or adaptive, in response to significant input data changes, yet also remain stable in response to irrelevant data [31], [32]. In this sense, a generic NN has difficulties in preserving previously learned knowledge in memory while continuing to learn new concepts. The FA technique addresses this dilemma by incorporating a feedback mechanism between the competitive and input layers to allow new information to be learned without eliminating previously obtained knowledge. This results in a more stable learning environment and a faster convergence capability [33].

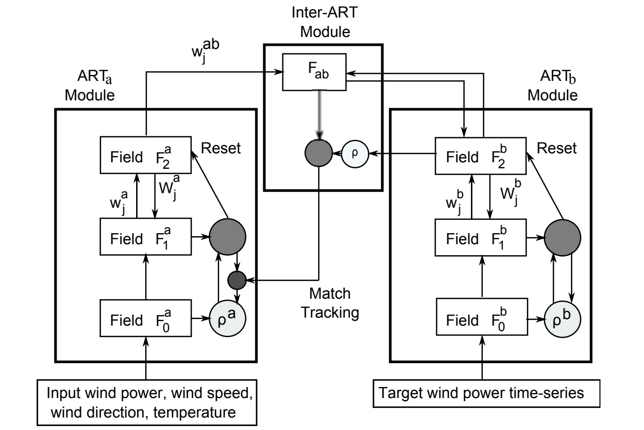

Fig. 3. Architecture of the Fuzzy ARTMAP network for wind power production forecasts.

2) In the case of BPNN, there is a tendency towards catastrophic forgetting, whereby earlier memories are eased by subsequent training data. Unlike BPNN, the FA network dynamically increases the category neurons when the input data does not have a minimum allowed similarity to any of the previously presented learning input. Therefore, catastrophic forgetting of previously trained patterns is avoided.

3) The FA model has the ability to carry out fast, stable learning, recognition, and prediction compare to the traditional SCMs.

Certainly, these attributes can improve wind power forecasting performance since the wind power data series is highly stochastic in nature as shown in Fig. 1.

In the architecture of the FA network as shown in Fig. 3, the preprocessing stages F_0^a, F_1^a take the input vector and produce complement coding, which avoids category proliferation, i.e., the creation of a relatively large number of categories to represent the training data [34]. A sequence of input vectors (wind power, wind speed, wind direction, and temperature) and a target vector (wind power) are introduced to the FA network in order to classify the input pattern correctly. The classified input patterns are then grouped into labels using membership functions. Seven membership functions, which are chosen in this work by trial-and-error basis, have been created within the range of minimum and maximum values of wind power time-series. The training stage is considered to be accomplished when the weights do not change significantly. The aforementioned training scenario is called *off-line learning*. In the off-line learning, the best matching category label during the classification is [31]:

$$J = arg \max_{0 \le j \le N} T_j(I_{tr}), \tag{4}$$

where

$$T_j(I_{tr}) = \begin{cases} \frac{|I_{tr} \wedge w_j|}{\alpha + |w_j|}, & \text{if } \frac{|I_{tr} \wedge w_j|}{|I_{tr}|} \ge \rho \\ 0, & \text{otherwise.} \end{cases}$$

The function T_j is referred to as the *choice function* and α is a positive real number called the *choice parameter*, and $\wedge$ is the fuzzy MIN operator defined by $(I_{tr} \wedge w_j) = \min(I_{tr}, w_j)$ [31]. The best matching F_2 node from the choice competition J satisfying the vigilance criterion:

$$\frac{|I_{tr} \wedge w_j|}{|I_{tr}|} \ge \rho, \tag{5}$$

where ρ is the vigilance parameter. Resonance occurs when match function of the selected category meets the vigilance criterion in (5). During the training stage, the vigilance criterion varies from an initial value called the baseline vigilance $\bar{\rho}$. If the vigilance test is passed, the category J becomes the representative membership function for the input wind power time-series I_{tr}. The weight vector of the winning category w_j is updated by applying the following equation:

$$w_j^{(new)} = \beta(I_{tr} \wedge w_j^{(old)}) + (1 - \beta) w_j^{(old)}, \tag{6}$$

where β is the learning rate. Otherwise, category J is deactivated for the current input I_{tr} by setting T_j equal zero [35]. The search procedure continues until the chosen category, J, satisfies the vigilance test in (5). In case, current cells in F_2 layer do not satisfy the vigilance test, a new cell is added to the field F_2 layer. In this paper, the chosen values of the network parameters, i.e., α, β, $\bar{\rho}$, ρ, and ε are 0.005, 1, 0, 0.75, and 0.00001, respectively. If ART_b does not predict the correct output for ART_a, then ρ is increased. This process is called *match tracking*. Match tracking increases ρ slightly and the new value of ρ becomes:

$$\rho = \frac{|I_{tr} \wedge w_j|}{|I_{tr}|} + \varepsilon, \tag{7}$$

where ε is a learning precision. As the new patterns are presented to the FA network, the network's weights are updated during the training phase until they reach the state of convergence, which is achieved by repeating the value of w_j^{new} in (6) after performing a few iterations through the training data.

Once the training stage is completed, the FA network is used as a classifier of the input data presented to ART_a. ART_b is not used during the classifying process and the learning network capability is deactivated (β=0) [36]. In this stage, we get predicted classified labels in the map field output. These classified labels are de-fuzzified for getting the forecasted wind power.

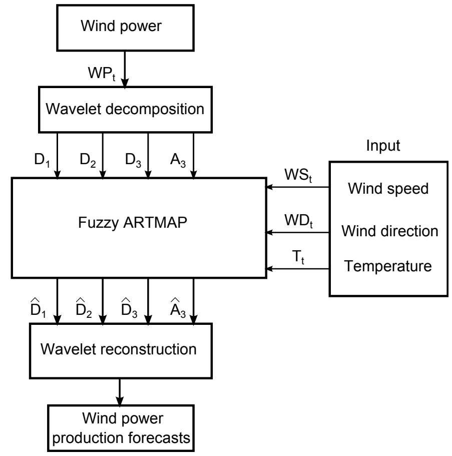

Fig. 4. Schematic diagram of the proposed hybrid WT+FA model for wind power forecasting.

C. *Proposed Hybrid Method for Wind Power Forecasting*

Fig. 4 shows schematic diagram of the proposed hybrid method for hour-ahead wind power forecasting based on the FA network combined with the WT. The forecasting procedure is explained as follows:

Step-1: Input variables considered in the proposed hybrid forecasting model are hourly data of wind power (WP), wind speed (WS), wind direction (WD), and temperature (T). To be precise, WP, WS, WD, T at current hour (t) are taken into consideration in order to have better forecast process. The authors attempted to incorporate various input lagging, e.g., WP_{t-1}, WP_{t-2}, WS_{t-1}, ..., WD_{t-2}, ..., T_{t-2} etc., however, the sensitivity analysis showed that WP_t, WS_t, WD_t, and T_t are the best possible combination to be considered as input parameters for the proposed model (Fig. 4). Note that only the WP data series is passed through WT; WS, WD, and T data are not passed through WT. The WP data series is decomposed into four components by WT. The decomposed approximation signal, A_3 (low frequency component) and detail coefficients, D_1, D_2, D_3 (high frequency components) are obtained by downsampling with low pass filter (L) and high pass filter (H), respectively.

Step-2: The individual decomposed wind power signals (A_3, D_1, D_2, and D_3) along with WS, WD, and T data are then fed into FA network. The training process of approximation signal (A_3) in the FA network is described in the previous section. Other detail coefficient signals (D_1, D_2, and D_3), which are high frequency components follow the similar training procedure. The FA network is an incremental learning NN that is capable of self-organizing information and network configuration on presentation of input data–WP_t, WS_t, WD_t, and T_t. For training the FA network, input data of past 25 days before the forecast day are considered.

Step-3: The output components of the FA network are the individual forecast of decomposed approximation ($\hat{A}_3$) and detail signals ($\hat{D}_1$, $\hat{D}_2$, and $\hat{D}_3$), which follow the process of wavelet reconstruction as shown in Fig. 2 in order to produce the final wind power forecasts.

III. Numerical Results and Discussions

This paper presents a new hybrid intelligent algorithm based on WT and FA, which takes into account the interactions of wind direction, wind speed, temperature and wind power. The proposed hybrid model is tested by using the real data from Kent Hill wind farm in New Brunswick, Canada. To evaluate the effectiveness and forecasting performance of the proposed WT+FA model, the results are compared with other SCMs such as BPNN, RBFNN, ANFIS and FA, and also with the combination of wavelet and these SCMs. Considering t as current time, WP_t, WS_t, WD_t, and T_t are selected as input parameters for all the wind power forecasting models implemented in this paper.

The principal statistics used to evaluate the performance of the proposed model is mainly measured by using MAPE [24]:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|WP_t^{true} - WP_t^{forecast}|}{\overline{WP_t}^{true,N}} \times 100\%, \quad (8)$$

where N=24 for daily wind power forecasts, N=168 for the weekly wind power forecasts, WP_t^{true} is the actual wind power in hour t, $WP_t^{forecast}$ is the predicted wind power for that hour, and $\overline{WP_t}^{true,N}$ is the average true wind power for the Nth hour:

$$\overline{WP_t}^{true,N} = \frac{1}{N}\sum_{t=1}^{N} WP_t^{true} \quad (9)$$

In addition, normalized root mean square error (NRMSE) is also calculated as [18]:

$$NRMSE(\%) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\frac{WP_t^{true} - WP_t^{forecast}}{WP_N}\right)^2} \times 100, \quad (10)$$

where WP_N is the nameplate capacity of wind farm. Note that the nameplate capacity of Kent Hill wind farm is 150MW.

Furthermore, the normalized mean absolute error (NMAE) criterion, which provides an indication of error range is calculated in order to assess the prediction capacity of the proposed hybrid model [18]:

$$NMAE(\%) = \frac{1}{N}\sum_{t=1}^{N}\frac{|WP_t^{true} - WP_t^{forecast}|}{WP_N} \times 100 \quad (11)$$

A. Daily Wind Power Forecast Results

Table I presents the results obtained from the proposed hybrid WT+FA model, and the results are compared with the persistence method and other models. Utilizing the MAPE definition as defined in (8), it can be seen from Table I that the MAPE values obtained from the persistence method are very large (30.48%, 26.37%, 36.79%, and 21.74%) compared to those obtained from the proposed hybrid method (12.84%, 11.75%, 16.11%, and 10.22%) for the seasonal days under consideration. Note that December 10 (Friday), May 25 (Tuesday), July 23 (Friday) and October 15 (Friday) of the year 2010 have been chosen from the seasons–winter, spring, summer and fall, respectively. The predicting performances of the models are found to be inconsistent with varying MAPEs for the multiple seasons. Hence, average of MAPEs of 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. Particularly in fall, the MAPEs obtained from the RBFNN (23.05%) and ANFIS (22.31%) models show comparatively worse performance than the persistence method. This observation depicts that the performances of the considered SCMs method are seasonal sensitive and their forecasting performances are inconsistent. However, the forecasting capability of our proposed hybrid model is not only superior than the persistence method but also it outperforms all the considered SCMs with or without combination of WT. Tables II and III present NRMSE and NMAE results

TABLE I
MAPE Comparison for Daily Wind Power Forecasts

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	30.48	26.37	36.79	21.74	28.85
BPNN	27.64	19.64	24.55	18.21	22.51
RBFNN	26.39	18.14	27.78	23.05	23.84
ANFIS	31.08	19.27	22.71	22.31	23.84
FA	19.11	14.46	19.16	13.52	16.56
WT+BPNN	23.51	15.97	22.44	17.80	19.93
WT+RBFNN	22.43	15.30	23.97	19.39	20.27
WT+ANFIS	22.34	14.65	19.64	18.55	18.80
WT+FA	**12.84**	**11.75**	**16.11**	**10.22**	**12.73**

TABLE II
NRMSE Comparison for Daily Wind Power Forecasts

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	3.13	4.34	3.13	6.67	4.32
BPNN	2.85	3.63	3.64	5.28	3.85
RBFNN	2.64	3.77	4.26	5.75	4.11
ANFIS	3.07	3.58	3.79	5.11	3.89
FA	1.66	2.92	3.44	3.66	2.92
WT+BPNN	1.94	3.11	3.18	4.23	3.12
WT+RBFNN	1.81	3.27	3.44	4.41	3.23
WT+ANFIS	1.75	2.76	3.12	3.83	2.87
WT+FA	**0.87**	**1.65**	**2.75**	**2.93**	**2.05**

TABLE III
NMAE Comparison for Daily Wind Power Forecasts

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	1.76	3.19	2.53	4.57	3.01
BPNN	1.60	2.85	2.96	4.16	2.89
RBFNN	1.53	2.97	3.07	4.24	2.95
ANFIS	1.71	3.01	2.73	3.84	2.82
FA	1.06	2.66	2.42	2.94	2.27
WT+BPNN	1.22	2.94	2.91	3.26	2.58
WT+RBFNN	1.18	2.73	3.03	3.44	2.60
WT+ANFIS	1.21	1.92	2.02	2.97	2.03
WT+FA	**0.74**	**1.43**	**1.71**	**2.09**	**1.52**

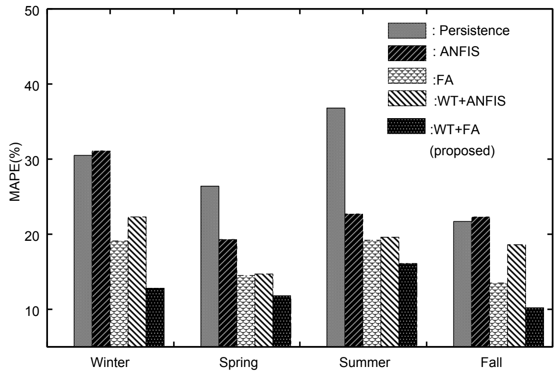

Fig. 5. Histogram showing daily MAPE comparison for wind power forecasts.

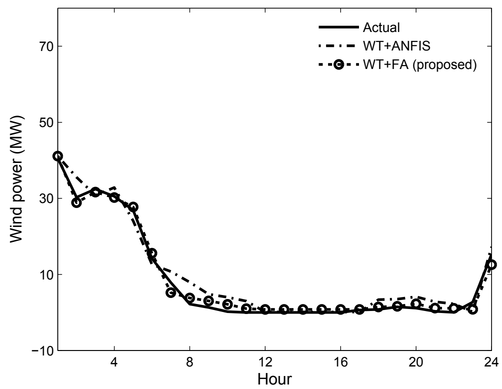

Fig. 6. Daily wind power forecasts in a winter day.

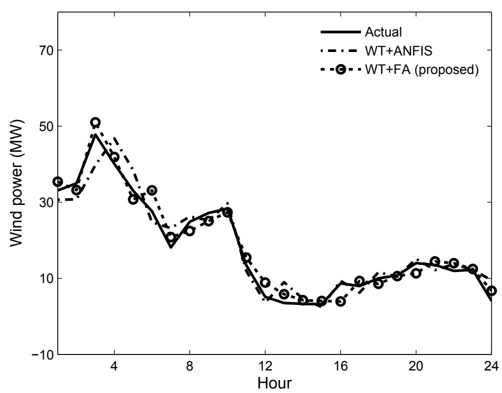

Fig. 7. Daily wind power forecasts in a spring day.

obtained for daily wind power forecast, respectively. As it can be seen from Table II that the average NRMSE (2.05%) of the proposed WT+FA shows the best prediction capability over other models. With the application of WT+SCM, the NMAEs are greatly improved as it can be observed in Table III that when WT is combined with FA, the average NMAE value is found to be lower (1.52%) than that of single use of FA (2.27%).

Comparison of MAPEs obtained from the persistence, ANFIS, FA, WT+ANFIS and proposed WT+FA are further presented in the form of histogram as shown in Fig. 5 where we can observe the highly efficient and robust performance of the proposed hybrid WT+FA model.

Figs. 6 and 7 show the actual and forecast curves for winter and spring, respectively. For the better clarity of the figure, this paper presents only forecasted curves obtained from the proposed WT+FA and WT+ANFIS. Note that the proposed new hybrid approach based forecasted wind power output curves are quite close to the true ones.

TABLE IV
MAPE COMPARISON FOR WEEKLY WIND POWER FORECASTS

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	26.52	24.92	23.24	15.84	22.63
BPNN	28.17	22.34	27.92	19.47	24.48
RBFNN	25.77	23.19	25.66	18.24	23.22
ANFIS	24.39	20.28	21.72	16.32	20.68
FA	18.46	18.66	19.31	13.25	17.42
WT+BPNN	25.00	20.45	22.33	16.38	21.04
WT+RBFNN	23.81	21.43	21.52	15.20	20.49
WT+ANFIS	20.63	18.26	19.26	12.25	17.60
WT+FA	**14.89**	**17.37**	**18.05**	**12.93**	**15.81**

TABLE V
NRMSE COMPARISON FOR WEEKLY WIND POWER FORECASTS

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	7.96	4.76	4.25	4.80	5.44
BPNN	8.22	4.12	4.58	5.09	5.50
RBFNN	7.65	4.33	4.62	4.73	5.33
ANFIS	7.09	3.77	4.15	4.34	4.84
FA	5.33	3.16	3.46	4.10	4.01
WT+BPNN	6.42	3.65	3.83	4.52	4.61
WT+RBFNN	6.74	3.72	3.60	4.30	4.59
WT+ANFIS	5.63	3.07	3.51	3.92	4.03
WT+FA	**3.72**	**2.86**	**3.32**	**3.87**	**3.44**

TABLE VI
NMAE COMPARISON FOR WEEKLY WIND POWER FORECASTS

Model	Season				Average
	Winter	Spring	Summer	Fall	
Persistence	4.87	3.07	2.84	3.18	3.49
BPNN	5.06	2.54	2.77	3.46	3.46
RBFNN	4.74	2.72	3.14	3.19	3.45
ANFIS	4.63	2.26	2.54	2.86	3.07
FA	3.99	1.97	2.33	2.94	2.81
WT+BPNN	4.83	2.28	2.18	3.13	3.11
WT+RBFNN	4.91	2.11	2.75	2.76	3.13
WT+ANFIS	4.41	2.03	2.40	2.57	2.85
WT+FA	**2.94**	**1.76**	**2.07**	**2.62**	**2.35**

B. 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 Tables IV–VI, are for the weeks of December 10–16 (winter), May 12–18 (spring), July 1–7 (summer), and October 22–28 (fall). Utilizing the MAPE definition as mentioned in (8), the seasonal average MAPEs obtained from the persistence method is around 22.63%, whereas this value is comparatively lower (15.81%) using the

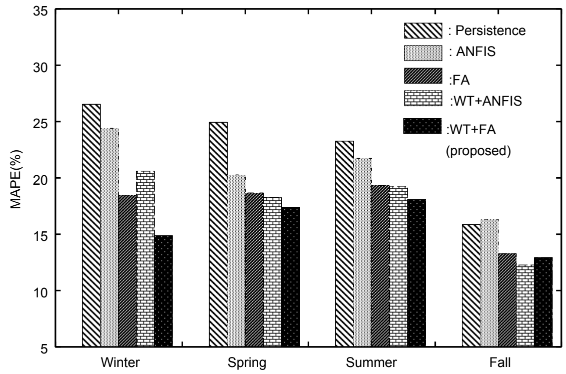

Fig. 8. Histogram showing weekly MAPE comparison for wind power forecasts.

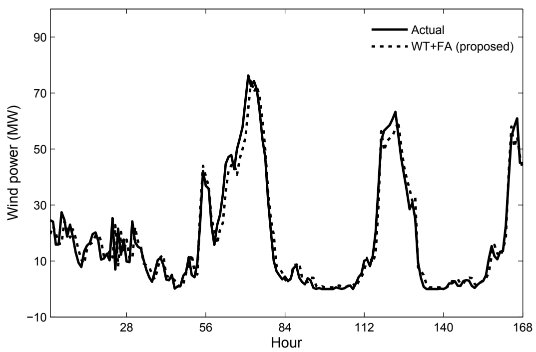

Fig. 9. Weekly wind power forecasts in a summer week.

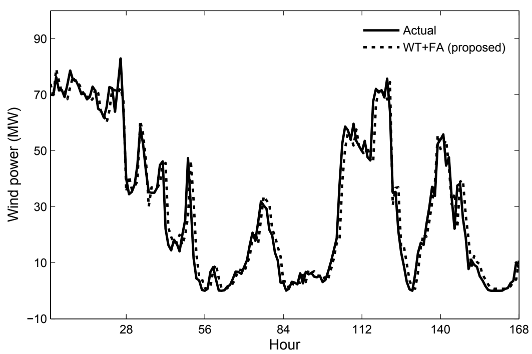

Fig. 10. Weekly wind power forecasts in a fall week.

proposed WT+FA method. In other words, the benchmark persistence method is also outperformed by our proposed model in weekly forecasts as well. As stated earlier, the wind power data series contain a various fluctuations, spikes, and different types of nonstationarity, and the WT is used as filtering those spikes. The effectiveness of using WT is demonstrated in Table IV where we can see that the average weekly MAPEs obtained from the BPNN, RBFNN, ANFIS, and FA are 24.48%, 23.22%, 20.68%, and 17.42%, respectively. However, when these individual SCMs are combined with WT, the MAPEs are reduced by around 14%, 11%, 14%, and 9%, respectively. The forecasting performances of these models are further compared by calculating NRMSE and NMAE as shown in Tables V and VI. Note that in all the simulated cases as shown in Tables IV–VI, the test results demonstrate the superior predicting performance of the proposed WT+FA model over the persistence method, individual SCMs, and WT+SCMs.

TABLE VII
MAPE MONTHLY WIND POWER FORECASTS

Model	Month										
	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
Persis.	18.31	22.45	17.21	20.38	24.81	20.38	23.54	19.10	14.59	16.91	16.32
WT+FA	11.17	12.31	9.87	11.35	12.66	11.74	12.13	10.83	9.67	10.29	11.44

Persis.: persistence

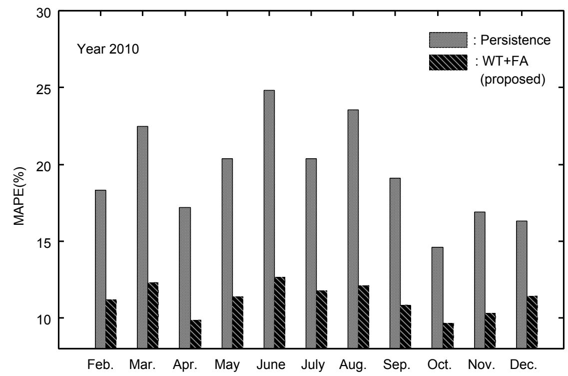

Fig. 11. Histogram showing monthly MAPE comparison for persistence method and the proposed hybrid model.

Furthermore, the histogram in Fig. 8 shows the MAPEs comparison of the persistence, ANFIS, FA, WT+ANFIS and the proposed WT+FA in all the seasons. The actual wind power production curves are compared with forecasted curves as shown in Figs. 9 and 10 where we can observe that the proposed WT+FA based projected curves are close to the true ones. It is emphasized that selections of forecasting days and weeks have been done randomly in this paper, and the reported results are only representative. Note that several forecasting test days and weeks are simulated, which have not been included in this paper due to space limitation.

Furthermore, the testing set is extended to 11 months in order to evaluate the effectiveness of the proposed hybrid intelligent algorithm to the several atmospheric processes. The monthly MAPEs obtained from the proposed WT+FA are compared with the persistence method as shown in Table VII and Fig. 11, which demonstrate the better functioning of our proposed model over the persistence method. The forecast for the month of January is not included in this paper due to the lack of training data length. Note that the monthly forecasts from other models are not reported here.

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 other tested alternatives.

IV. CONCLUSIONS

A novel hybrid approach was proposed in this paper for short-term wind power forecasting. The proposed approach is based on the combination of WT and FA. The spike and chaotic changes in wind power time-series are filtered through the application of WT. On the other hand, the FA network captures the non-linear wind power fluctuation in a significant way for its stability-plasticity dilemma. These attributes make the proposed hybrid algorithm adequate and highly efficient. The average MAPE, NRMSE, and NMAE results obtained from the proposed hybrid model outperform the other presented models such as persistence, BPNN, RBFNN, ANFIS, FA, WT+BPNN, WT+RBFNN, WT+ANFIS. The presented work contributed to alleviate an important problem of wind power production forecasting as the test results obtained through the simulation demonstrate that the proposed hybrid intelligent algorithm is significantly accurate, efficient, robust and performs well in multiple seasons. The future work would be interesting to carry out uncertainty associated with wind power forecasting.

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