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Long Term Wind Power Forecast Using Adaptive Wavelet Neural Network

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***Abstract*—With the growing uncertainty due to high wind power penetration, an accurate wind power forecast tool is very much essential for economic and stable operation of the electricity markets. It helps the system operators, to include wind generation into economic scheduling, unit commitment and reserve allocation problems. It also assists the wind power producers to minimize their losses through strategic bidding in the day ahead electricity markets. In this paper the problem of long-term wind power forecast is addressed, considering the numerical weather prediction (NWP) system wind speed and wind direction forecasts as inputs. An adaptive wavelet neural network is proposed for mapping the NWP's wind speed and wind direction forecasts to wind power forecasts. Wind direction inheritantly being a circular variable, for better training and function approximation, a transformed version of wind direction variables are used as inputs. Further, a closest set of patterns based on euclidean distance are chosen for training patterns and block wise training and forecast strategy is employed for carrying wind power forecast. The results show that the significant improvement over persistence method is achieved.**

***Index Terms*—Wind power forecast, extended Kalman filter, recurrent neural network, adaptive wavelet neural network.**

I. Introduction

GLOBAL warming concerns, scarcity, and high predicted fossil fuel cost, has led to a significant growth in renewable energy conversion systems in the last few decades. Particularly, wind power generation has its major contribution, possibly due to, large size wind turbine manufacturing, equipped with controllable capabilities similar to that of conventional synchronous machines. The stability and operation of electric power system is mainly governed by demand and supply balance. However, due to intermittent nature of wind power generation, its integration into the conventional power system imposes many operational and economic challenges to system operators. The usual practice was to accept it, as and when is available. However, with high level wind power penetration this strategy is not feasible as it can hamper the day to day operation of the power system. Many grid codes have come in to enforcement which strategically says how the incoming wind power generation has to fulfil the reactive power support and voltage control at point of common coupling (PCC) [1].

The wind power forecast tools can help in integrating wind power generation into conventional power system and satisfy the grid code. A long term wind power forecast tool enables the system operators to include wind power generation into economical scheduling and unit commitment problems, maintaining system frequency and operating reserve. It also helps wind power producers to bid in day-ahead electricity markets. It plays critical role in minimizing the imbalance costs in balancing markets [2]. A more elaborate review on economical benefits of wind forecasting tools can be found in [3]–[5].

Wind power forecast methods are broadly classified into physical and statistical models. Physical models are based on weather modeling similar to that of NWPs and are used for long term wind power forecast. Where as statistical models are further divided into two types based on whether they use NWP inputs or not. The forecast models using NWP inputs are long-term models having forecast range upto 72 h and above are useful in planning problems. The statistical models based on purely historical data are called short-term models having range upto 6 h and are useful in dealing operation problems. In general for long term forecast, the NWP forecasts are prime inputs to the forecast models and are highly influential on the final wind power forecast errors.

Statistical systems are simple to build and require no mathematical modelling. They try to map the underlying non-linear relation between the wind speed forecast from NWPs to wind power output through statistical and/or artificial intelligence based techniques. However, the accuracy of these statistical models lies in, how close the numerical grid point is located from the wind farm and also how best the NWPs wind speed forecasts are correlated with the wind power output. Wind Power Prediction Tool (WPPT), a time series based statistical model, Wind Power Management System (WPMS) and Advanced Wind Power Prediction System (AWPPS) are artificial intelligence and fuzzy based models are some of the examples of statistical prototype wind power forecast models which take NWP wind forecasts as inputs [6], [7]. Barbounis *et al.* [8] proposed Recurrent Neural Networks (RNN) to forecast wind speed and power up to 72 hours ahead. The networks are trained for one step ahead prediction considering NWP forecast of wind speed, wind direction and measured wind power as inputs. In carrying the forecast upto 72 h the past wind power forecast are taken as inputs. An average improvement of 50% over persistence for look-ahead times longer than 20 hours is achieved. In [9], Sideratos *et al.* proposed

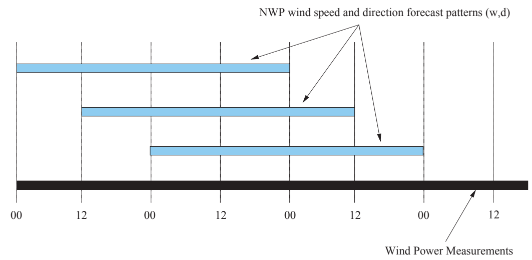


Fig. 1. NWP forecast patterns and wind power series

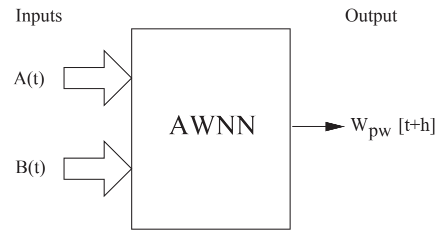


Fig. 2. Multi-input single output network training.

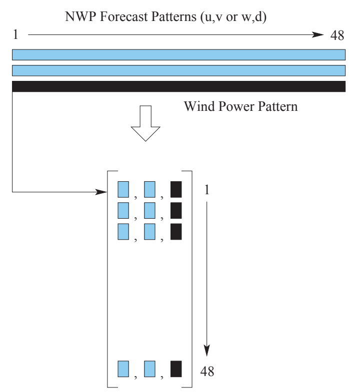


Fig. 3. Transformation of input-output patterns for network training in multi-input single output fashion.

an artificial intelligence and fuzzy logic based approach for wind power prediction up to 48 hours ahead. Wind speeds values are divided in to three categories low, medium and high and these data sets are used for training three radial basis function neural networks. Networks are trained for one step ahead prediction and results show that an improvement of 40% over persistence. In [10], Shu Fan *et al.* proposed a Bayesian clustering by dynamics for clustering the NWP wind speed forecast patterns and support vector machines (SVMs) are used for training these clusters.

In this research work, an Adaptive Wavelet Neural Network (AWNN) is used for long term wind power forecast. A new approach is suggested for selecting the network input features and training samples for carrying the long term wind power forecast and the results show that the proposed model showed a considerable improvement over the benchmark forecast models.

II. Problem Formulation

The NWP meteorological outputs are formulated as records comprising predictions of wind speed and wind direction as $(\hat{\mathbf{w}}_k, \hat{\mathbf{d}}_k)$ where $\hat{\mathbf{w}}_k = \{\hat{w}[t_k + h] \mid h = 1, \ldots, 48\}$ and $\hat{\mathbf{d}}_k = \{\hat{d}[t_k + h] \mid h = 1, \ldots, 48\}$, where $k = 1, \ldots, N$ and N denotes the number of such records, as shown in Figure 1. The wind power output measurements recorded hourly for the whole year is denoted by $W_{pw}[t]$.

Wind power forecast is carried in hourly basis, i.e., the forecast of wind power at a particular hour is mapped through the featured inputs selected from current and past values of NWP wind speed and direction forecast. The networks are trained in Multi-Input Single-Output (MISO) approach, as shown in Figure 2. The corresponding input-output training patterns are formulated, by re-organizing the NWP forecast and wind power output records, as shown in Figure 3. After network training, when new/unseen NWP forecasts are available, the network is ready to forecast the corresponding wind power output in hourly basis. The network model can be described by

$$\hat{W}_{pw}[t_k + h] = f(\hat{\mathbf{A}}(t), \hat{\mathbf{B}}(t), \Theta), \quad h = 1, \ldots, 48 \tag{1}$$

where $\hat{\mathbf{A}}(t)$ and $\hat{\mathbf{B}}(t)$ are given as

$$\hat{\mathbf{A}}(t) = \quad \{\hat{w}[t_k + h], \hat{w}[t_k + (h-1)], \ldots\} \tag{2}$$

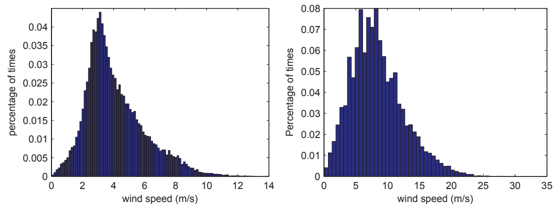
$$\hat{\mathbf{B}}(t) = \quad \{\hat{d}[t_k + h], \hat{d}[t_k + (h-1)], \ldots\} \tag{3}$$

III. Data Description

In this work, the data sets from two wind farms with different characteristics have been taken for evaluating the forecast model. The first data sets are taken from Global Energy Forecasting Competition 2012 - Wind Forecasting [11] (WF1). The data sets consists of NWP wind speed and direction forecasts and the wind power output (normalized) series for the period 01 July 2009 to 31 Dec. 2010. The NWP forecast outputs are available twice daily at 00 hrs and 12 hrs and has forecast horizon of 48 hours with hourly resolution. The second data sets are from the Klim wind farm located at north-west part of Jutland, Aalborg [12] (WF2). The wind farm has a total capacity of 21 MW with 35 wind turbines each of 600 kW rating. The wind farm output power measurements cover the period from 1st Jan., 2001 to 31 Dec., 2002. The NWP data from the Danish HIRLAM model.

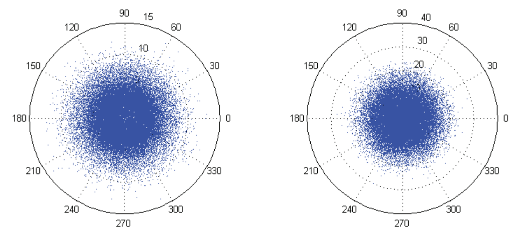
Figure 4 shows the probability distribution function of wind speeds in both wind farms WF1 and WF2. In the case of WF1, the mean and maximum wind speed around 3.5 and 12 m/s whereas in the case of WF2, the mean and maximum wind speeds are around 8 and 25 m/s. Figure 5 illustrates the wind rose of both wind farms. It is clearly understood that wind blown is uniform in all directions in both the cases.

Figure. 6 illustrates the relation between wind speed and wind power output of wind farms WF1 and WF2. Wind farm WF1 has wide variation in output power over a given speed ranging almost entire spectrum of wind speed. In the case of wind farm WF2, a narrow variation in wind power output for a given speed is observed. The annual capacity factor of the



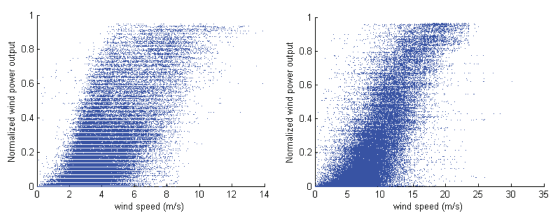
(a) (b)

Fig. 4. Wind speed density function of wind farms (a) WF1 (b)WF2.



(a) (b)

Fig. 5. Wind rose of wind farms (a) WF1 (b)WF2.



(a) (b)

Fig. 6. Relation between wind speed and wind power output in the case of WF1 and WF2.

wind farms WF1 and WF2 are found to be 0.2420 and 0.2226, respectively.

IV. Forecast Methodology

In literature majority power forecast models used only wind speed forecasts as inputs, whereas the wind directions are not considered. Although wind power output is highly correlated with wind speed, a fine tuning of the model happens only when the wind direction are used as input feature. In this research work long term wind power forecast is carried using MISO training method. Wherein forecasting is carried in hourly basis. The input features, NWP wind speed and direction forecasts, are selected for mapping on to wind power output forecast.

A. Wind Direction Feature Selection

Fig. 6 shows the scatter plots of wind speed and normalized wind power output for both the wind farms. Wide variation in wind power output from zero value to the rated capacity can be seen at a particular wind speed. This is mainly due to change in wind direction and hence it plays an important role in wind power forecast.

The ability of any network for better approximation lies in selecting proper input features. In case of wind power forecast, although the NWP's wind direction forecasts are available, it cannot be selected as input feature as it is. This is mainly due to fact that wind direction is a circular variable. Usual practice is to transform the circular variable in to two signal of $cos(\cdot)$ and $sin(\cdot)$. However this increases the number input variables and it is noticed that straight forward using the wind direction signal does not improve the forecast model accuracy.

In this research work a transformation on wind direction signal is carried and the new transformed signals are used in wind power forecast. Fig. 7(a) shows the NWP wind speed forecasts and the corresponding wind power outputs and Fig. 7(b) shows the wind direction forecasts. From the NWP's wind direction forecasts the wind direction differences forecast values are calculated as

$$\widehat{dd}[t_k+h] = \begin{cases} \hat{d}[t_k+h] - \hat{d}[t_k+(h-1)] \\ \qquad\qquad \forall h = 2, \ldots, 48 \\ \hat{d}[t_k+h] - \hat{d}[t_{k-1}+(h+12)] \\ \qquad\qquad \text{for } h = 1 \end{cases} \tag{4}$$

From the Fig. 7(c) it is clear that the wind direction difference signal are correlated with wind power output when compared to simple wind direction signal. As it is clear that for steady wind flows or with minimal wind direction differences (from 40 to 48 hours) the wind power output is higher than the wind power outputs corresponding to high wind speeds with large wind direction differences (from 0 to 10 hours).

In the second step, for the sake of uniformity in normalization of all input signals, the wind direction differences are converted to absolute values. However, the positive and negative side wind direction differences after first step indicates that reversal of wind movement from clockwise to anticlockwise direction or vice-versa. It should be noticed that though the value of wind direction difference at 26h is very small, it is the point of reversal in the wind movement, causing low wind power output production as shown in Fig. 7(a).

To address this issue in the third step, blocks of positive and negative wind direction differences are formed and the intermediate wind direction differences between the maximum value in positive block to the maximum value in negative block are raised to the value such that it touches the interpolating line joining the two adjacent peak values. Finally, a moving average of three values are taken. The final version of the transformed wind direction differences are shown in Fig. 7(d).

B. Over all Forecast Methodology

Wind power forecast is carried in hourly basis, i.e., the forecast of wind power at a particular look-ahead hour is mapped through the corresponding look-ahead hour and past hour values of NWPs forecasts as given in (1). Here the input variables are NWPs wind speed and the transformed wind direction differences. Once the new NWP wind speed forecast (for 48 h) pattern is available, the closest set of patterns selected based on simple euclidean norm, from the transformed records comprising the wind speed forecasts and wind direction differences $(\hat{\mathbf{w}}_k, \widehat{\mathbf{dd}}_k)$ are used for network

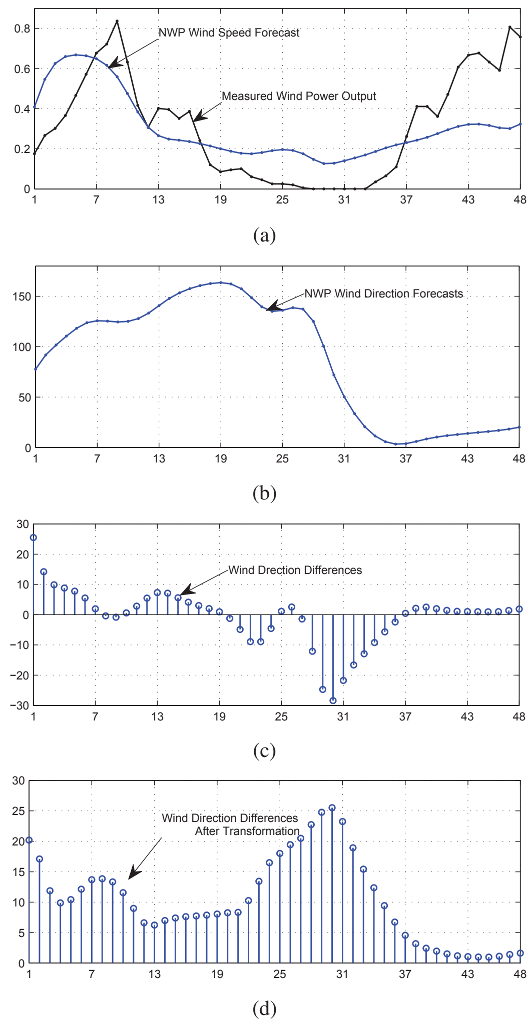


Fig. 7. Sample patterns denoting a) NWP wind speed forecast and measured wind power output b) NWP wind direction forecasts c) wind direction difference pattern d) the final version of modified wind direction difference pattern.

training. However, clustering based techniques [10] can be applied for wind power forecast. Wherein in NWP forecast patterns are formed in to clusters and network training is carried accordingly. The main drawback with this method is choosing the number of clusters. Due to varied nature of wind speed patterns from one wind farm to the other a predefined number of clusters may not represent a general feature of the forecast model.

After selecting the closest set of wind speed forecast patterns, and the corresponding transformed wind direction difference patterns, the hourly basis input-output patterns are formulated for training the network as shown in Fig. 3. Single forecast model can be trained using these input-output patterns and when new/unseen NWP forecasts are available the trained network is able to forecast all the look-ahead hours. A block wise training/forecast is carried dividing the hourly basis input-output patterns in two batches. One from 1 to 24 h and other from 25 to 48 h of all NWPs forecast wind power patterns as shown in Fig. 8. These two batches of hourly input-

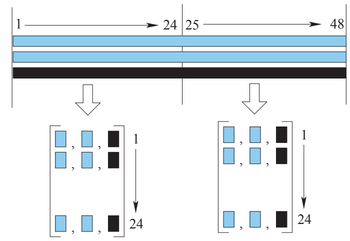


Fig. 8. Transformation of input-output patterns for network training in multi-input single output fashion.

output patterns are then used for training the two separate networks to forecast the wind power corresponding to those look-ahead hours.

In this research work a wavelet neural network (WNN) is used as a wind power forecast model. Due to time and localization properties of wavelets, and the concept of adapting the wavelet shape according to training data set instead of adapting the parameters of the fixed shape basis function, WNNs are having better generalization property [13]. The WNNs have been successfully applied in the field of function learning, nonlinear system identification, and time series prediction. Pindoriya et al. [14] used Adaptive WNN (AWNN) for energy price forecasting. WNNs, structure wise resemble similar to feed forward neural network (FFNN), except the linear connections between the input output nodes and the wavelons instead of sigmoidal activation functions in the hidden layer. Authors have successfully applied AWNN for short term wind power forecast without using NWP forecast inputs [15].

V. Results and Discussion

The performance of the AWNN forecast model is compared with, our earlier work on long term wind power forecast using a Node Decoupled Extended Kalman Filter (NDEKF) trained Recurrent Neural Network (RNN) [16] and with the benchmark persistence model. The measure of error used to evaluate the forecast models are BIAS, MAE, and RMSE and are defined in [15].

In this work, AWNN architecture consisting of two input, two hidden and one output nodes are considered. NWP wind speed forecast $\mathbf{A}(t) = \hat{w}[t_k + h]$ and transformed direction forecast $\mathbf{B}(t) = \widehat{dd}[t_k + h]$ are taken as two inputs for predicting the corresponding hour wind power output $W_{pw}[t_k + h]$. The AWNN input-output training patterns are formulated from the NWP records as shown in Figure 3. In doing so, the closest 50 NWP patterns to the current NWP pattern which need to be converted to wind power forecast are used in generating the input-output patterns. In training process the following system parameters are employed. The initial learning rate and momentum parameters are set to 0.1 and 0.1, respectively. As a stopping criterion the mean square error E is set to 0.0001 and maximum iteration to 3000. In case of validation as an early stopping criterion, the maximum fails are set to 300.

A. Case-I: WF1

The forecast models performance evaluation using MAE and RMSE computed for whole range of prediction horizon is illustrated in Figure 9. It is noticed that consistent reduction in forecast errors MAE and RMSE for all look-ahead hours can be seen in AWNN model as compared to NDEKF_RNN model. Table I shows the forecast errors averaged over 48 h look ahead range for all the forecast models. AWNN forecast model has an average MAE and RMSE, over entire forecast horizon, of 11.72% and 15.31% respectively and it is noticed that 1.08% and 1.59% reduction in MAE and RMSE is obtained with the AWNN forecast model over the NDEKF_RNN model.

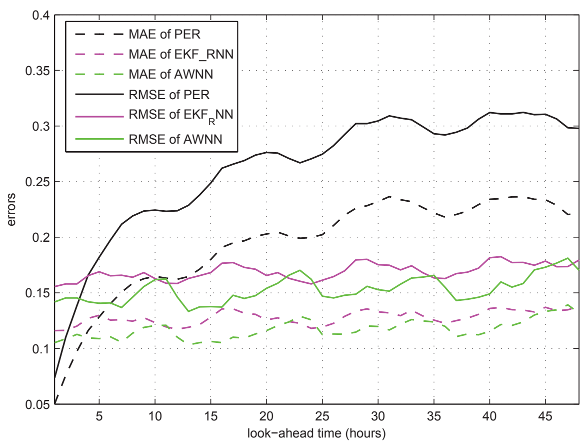


Fig. 9. Forecast errors MAE and RMSE of AWNN, NDEKF_RNN and Persistence model for WF1.

Figure 10 shows the percentage error reduction of both the forecast models against benchmark persistence model. Long term forecast models using NWP forecast inputs although has ability to forecast longer time horizon, their forecast accuracy for first few hours could not beat persistence benchmark model. The same is also found here, that the forecast errors of NDEKF_RNN and AWNN models upto 3 h ahead are greater than persistence model errors. Normally day-ahead electricity markets gate closure takes place some where in the noon. Which implies market participant should have wind power forecasts for the following delivery day atleast 12 h ahead. More specifically, at the time of gate closure wind power forecast pertaining to 12 and above forecast horizon are more important for day-ahead bidding process. In that sense, the average improvement in MAE, over persistence model for the 13-36 h forecast horizon, 38.14% and 43.80% improvement is obtained by NDEKF_RNN and AWNN models. Similarly, in the case of RMSE, an improvement of 39.26% and 45.40% is obtained by the NDEKF_RNN and AWNN. In both cases AWNN model has 5% more improvement over NDEKF_RNN model.

B. Case-II: WF2

The forecast models performance evaluation using MAE and RMSE computed for whole range of prediction horizon is illustrated in Figure 11. The average errors over 48 h forecast horizon are tabulated in Table II. AWNN forecast model has an average MAE and RMSE, over entire forecast horizon, of 10.29% and 14.35% respectively. It is found that 0.56% and 0.75% reduction in MAE and RMSE is obtained with the AWNN forecast model over the NDEKF_RNN model for this wind farm. Figure 12 shows the percentage error reduction of both the forecast models against benchmark persistence model. It is found that, in bath cases MAE and RMSE, the average improvement over persistence model for the 13-36 h forecast horizon, a 53% and 56% improvement is obtained by NDEKF_RNN and AWNN forecast models. In both cases

TABLE I
FORECAST MODEL ERRORS MAE AND RMSE AVERAGE OVER 13 TO 36 H IN THE CASE OF WF1.

Forecast Model	Average over 48 h	
	MAE (%)	RMSE (%)
Persistence	19.41	29.19
NDEKF_RNN	12.80	16.90
AWNN	11.72	15.31

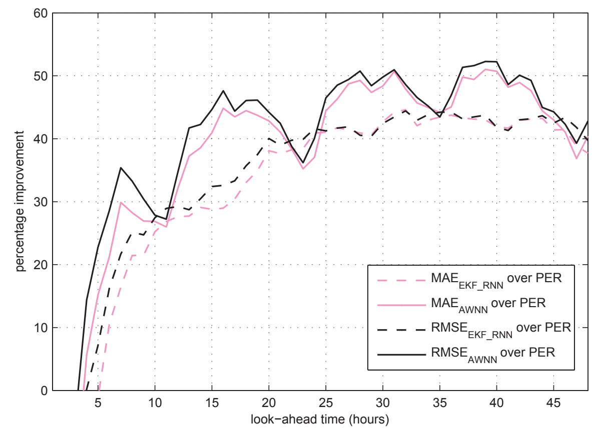


Fig. 10. Improvement of forecast models AWNN and NDEKF_RNN over Persistence model in the case of WF1.

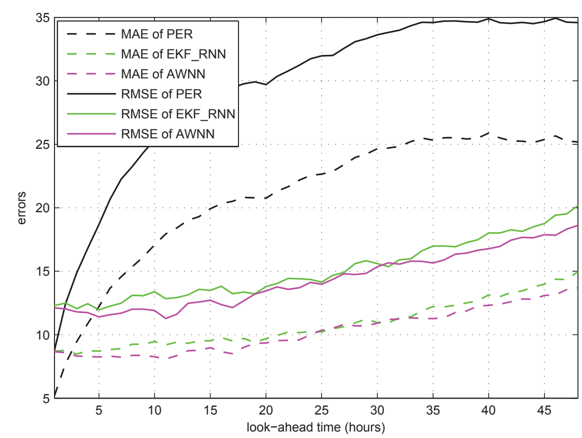


Fig. 11. Forecast errors MAE and RMSE of AWNN, NDEKF_RNN and Persistence model for WF2.

TABLE II
FORECAST MODEL ERRORS MAE AND RMSE AVERAGE OVER 13 TO 36 H IN THE CASE OF WF2.

Forecast Model	Average over 48 h	
	MAE (%)	RMSE (%)
Persistence	20.9474	29.4958
NDEKF_RNN	10.8533	15.1073
AWNN	10.2923	14.3516

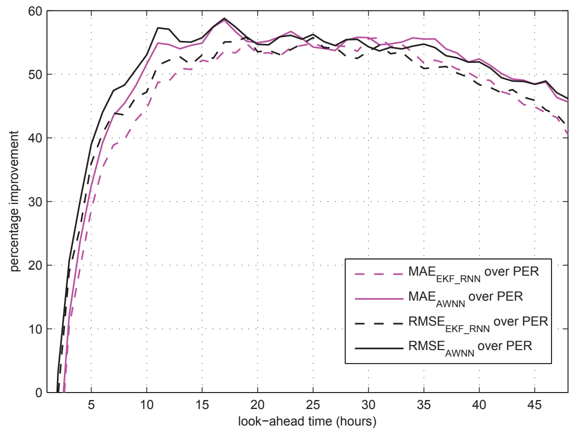


Fig. 12. Improvement of forecast models AWNN and NDEKF_RNN over Persistence model in the case of WF2.

AWNN model has 3% more improvement over NDEKF_RNN model.

Due to wide scattered relation between wind speed and wind power output of WF1 as compared to that of WF2, the average errors MAE and RMSE of both the forecast models NDEKF_RNN and AWNN are higher in the case of WF1 as compared to the errors obtained in the case of WF2. However, AWNN forecast model outperformed the NDEKF_RNN model in both the cases and showed 5% improvement in case of WF1 and 3% improvement in case of WF2 over NDEKF_RNN model. As the mean wind speed of WF1 is 3.5 m/s, which is lower as compared to that of WF2 (8 m/s), the change in wind direction could be the major cause for scattered relation between wind speed and wind power output. And it is noticed that, in the case of WF1, the AWNN forecast model showed better improvement due to consideration of direction feature in the input.

VI. CONCLUSIONS

In this research work long term wind power forecast using Adaptive Wavelet Neural Network is carried. Both NWP wind speed and direction forecasts are considered for network training. For better network training and nonlinear approximation, the circular variable wind direction input is transformed in to a direction difference inputs. Further the new strategy is employed for selecting the training samples for forecasting the wind power output. The data sets from two wind farms having different scatter relationship between wind speed and wind power are considered for evaluation of the forecast models. It is found that wind direction information with proper transformation helps in reducing the forecast errors. The AWNN model taking both wind speed and direction information, better performance than the NDEKF_RNN and persistence model in both the cases.

VII. ACKNOWLEDGMENT

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