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Application of Ensemble Neural Networks for Different Time Scale Wind Speed Prediction

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ABSTRACT: In the past decades, numerous researchers suggested various approaches for wind speed prediction model, but still an exact wind speed prediction is of high thrust field. This paper introduces novel Ensemble neural networks for different time scale wind speed prediction, which is developed by means of the accumulation of absolute neural networks such as improved back propagation networks (IBPN), radial basis function networks (RBFN), multi-layer perceptron networks and ELMAN networks. Prediction accuracy, correctness and effectiveness of the proposed Ensemble neural networks is rigorously confirmed based on K-fold cross validation. Experimentation was conducted on MATLAB simulation, based on the lowest training and testing mean square error appropriate Ensemble neural network framework is identified. Experimental results prove the validity of different time scale wind speed prediction using Ensemble neural networks in term of enhanced global generalization ability, stability and lower minimal training and testing errors.

KEYWORDS: Ensemble Neural Networks; K-Fold Cross Validation; Prediction; Time Scale; Wind Speed.

I. INTRODUCTION

Wind Energy is the leading renewable energy generation approach; most important explanatory variable for wind power generation is wind speed. Hence, exact wind speed prediction plays key role in the wind power estimation, operation control of wind turbine in wind farms, planning, scheduling and economic dispatch. Wind speed prediction can be classified as very short-term, short-term, medium-term, long-term based on the time scale. Very short-term prediction predicts the wind speed from a few seconds to 30 minutes ahead time scale range. Short-term prediction predicts the wind speed from 30 minutes to 6 hours ahead time scale range. Medium-term prediction predicts the wind speed from 6 hours to 1 day ahead time scale range. Long-term prediction predicts the wind speed from 1 day to 1 week or more ahead time scale range.

In [1] wind speed forecasting carried out based on improved back propagation networks and novel criterion is proposed for hidden neurons selection. Wind speed prediction using radial basis function networks performed in [2]. One-hour ahead wind speed forecasting based on three artificial neural networks such as back propagation, adaptive linear element and radial basis function analyzed in [3]. Multilayer perceptron network based wind speed prediction by means of meteorological data developed in [4]. 72hours a head wind speed prediction based on recurrent neural network model implemented in [5]. Characteristics of learning with larger and smaller ensembles are studied in [6].

The artificial neural network is one of the important computational intelligence techniques which mimic the function of the human brain. An Ensemble neural network is a new trend of artificial neural networks, which is developed by means of the collaboration of independently trained neural networks. Hence, the independent neural network diversity is avoided and significantly improves the generalization ability and stability. This paper proposed the novel ensemble neural networks for different time scale wind speed prediction and the effectiveness of the proposed prediction approach is confirmed by means of the k-fold cross validation.

II. DETAILED DESCRIPTION AND IMPLEMENTATION OF ENSEMBLE NEURAL NETWORKS

The ensemble neural network is a learning structure, where a collection of finite number of artificial neural networks is trained for the same task and put together taking the average of their prediction. The proposed Ensemble

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neural networks described as all individually trained neural networks (IBPN, MLPN, RBF and ELMAN) of whose predicted output is averaged to achieve the best predicted wind speed, improve the stability and generalization ability by avoiding the large variance of the individual network model. Therefore, generalization ability is improved. Neural network designing process plays a vital role in the network performance.

Proposed Ensemble neural networks based wind speed prediction model input layer is developed based on the six input neurons and output layer has a single output neuron. The architecture of the proposed Ensemble neural networks for different time scale wind speed prediction is shown in Fig. 1.

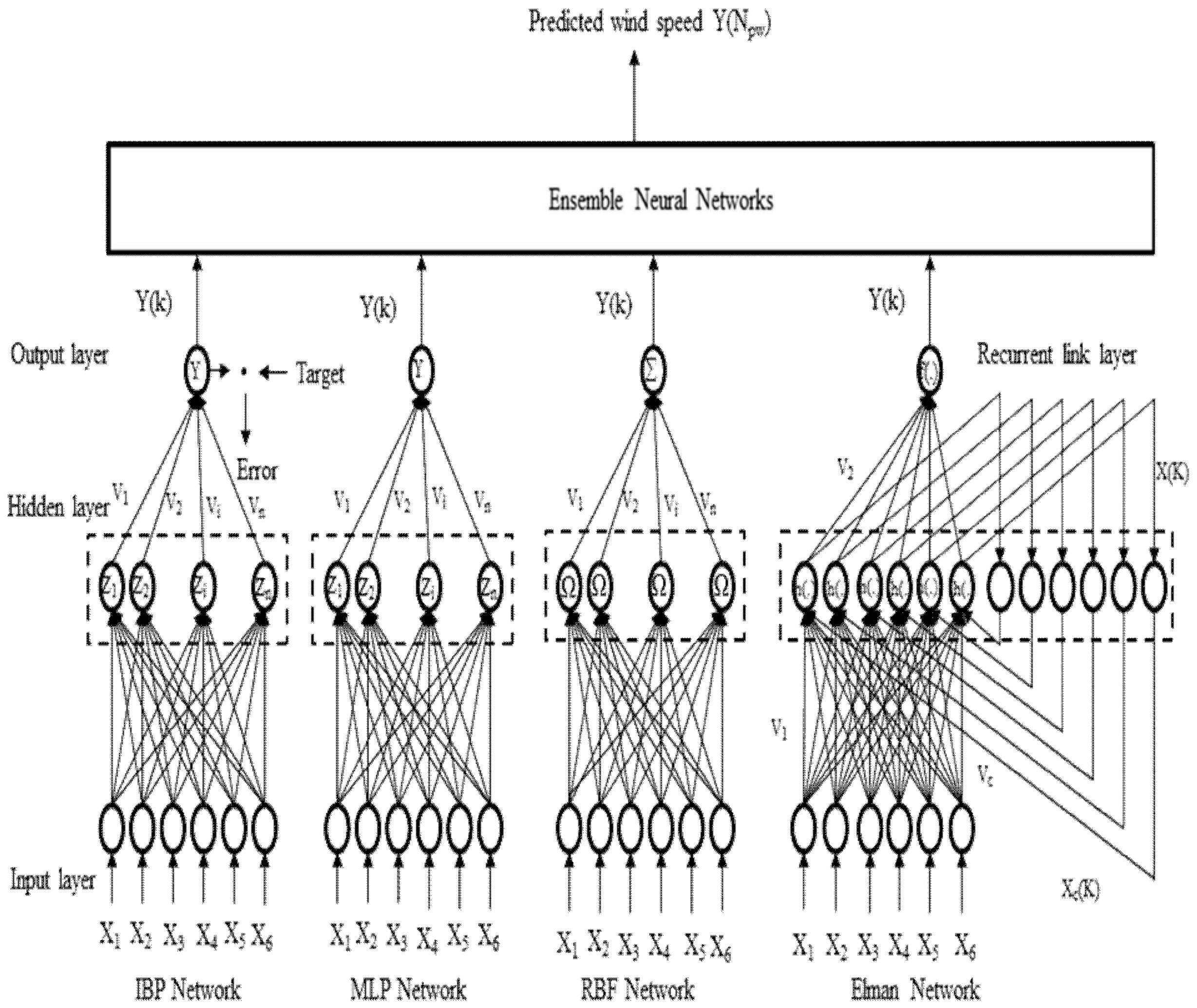

Fig. 1. Ensemble neural networks architecture

The Fig. 1 inferred input and the output target vector pair are defined as follows:

Input vectors,

$$X = [WD_w, N_w, T_w, AP_w, RH_w, PW_w] \quad \text{eq. (1)}$$

Output vector, $Y = [N_{pw}]$ eq. (2)

$(X_1, X_2, X_3, X_4, X_5, X_6 : Y)$ = (Wind direction, Wind speed, Temperature, Air Pressure, Relative Humidity and Precipitation of water content: Predicted wind speed).

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$$(X_1, X_2, X_3, X_4, X_5, X_6 : Y) = (WD_w, N_w, T_w, AP_w, RH_w, PW_w : N_{pw}) \quad \text{eq. (3)}$$

Where, N_{pw} is the predicted wind speed.

The Fig. 1 inferred that incorporated all absolute neural networks each and every layer performs the independent computations on received data and the computed results are passed to the next layer and lastly neural network output determined.

A. *Steps Involved in Proposed Ensemble Neural Networks:*

The proposed Ensemble neural networks involved the following steps

Step 1: Input data samples gathering & scaling

The Suzlon Energy Pvt. Ltd provides Coimbatore site real-time observation from January 2011 to April 2015. The input neurons to the independently designed neural networks are Wind direction (Degree), Wind speed (m/s), Temperature ($^{\circ}C$), Air Pressure ($mbar$), Relative Humidity (%) and Precipitation of water content (%). Min-Max scaling method is used to scale the observed real-time data samples within the range of zero to one. Scaling formula is given as below:

Scaled Data input,

$$X_r' = \left(\frac{X_r - X_{input\min}}{X_{input\max} - X_{input\min}} \right) \left(X'_{t\arg et\max} - X'_{t\arg et\min} \right) + X'_{t\arg et\min} \quad \text{eq. (4)}$$

Where, X_r is real input data, $X_{input\min}$ is minimum input data, $X_{input\max}$ is maximum input data, $X'_{t\arg et\min}$ is minimum target value, $X'_{t\arg et\max}$ is maximum target value.

Step 2: Parameter Selection

The proposed Ensemble neural networks designed parameters includes dimensions and epochs shown in Table. 1. The dimensions such as input neurons, hidden neuron numbers, output neuron are defined in the network design. Presented neural network design has six input neurons (Wind direction, Wind speed, Temperature, Air Pressure, Relative Humidity and Precipitation of water content), one hidden layer, one output neuron (predicted wind speed) and the hidden neuron numbers in the hidden layer is selected from 1 to 10 based on the lowest minimal error.

Table. 1. Parameters for Ensemble neural networks

IBPN	**MLPN**	**RBFN**	**ELMAN Network**
Input neurons = 6	Input neurons = 6	Input neurons = 6	Input neurons = 6
Hidden layer = 1	Hidden layer = 1	Hidden layer = 1	Hidden layer = 1
Output neuron = 1	Output neuron = 1	Output neuron = 1	Output neuron = 1
Epochs = 2000	Epochs = 2000	Epochs = 2000	Epochs = 2000
Threshold = 1	Threshold = 1	Spread = 2.5	Threshold = 1
Learning Rate = 0.1	Learning Rate = 0.1	-	-
Momentum Factor =0.8	-	-	-

Step 3: Neural Network Design

The proposed Ensemble neural networks are developed based on combination of IBPN, MLP, RBF and Elman network which is developed by 1,00,000 numbers of samples. Considered improved Back Propagation (IBP) network inputs are transferred to hidden layer that multiplies weight W using hyperbolic tangent sigmoid activation function and output from the hidden layer is transferred to the output layer that multiplies with weight V using tangent sigmoid activation function. IBPN network achieves faster convergence by means of the momentum factor (η). Multilayer Perceptron (MLP) network inputs are transferred to hidden layer that multiplies weight W using hyperbolic tangent sigmoid activation function and output from the hidden layer is connected to the output layer that multiplies with weight V using purelin activation function. Radial Basis Function (RBF) network input layer and hidden layer are connected by means of hypothetical connection. The hidden layer has Gaussian function. The hidden layer and output

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layer are connected by means of weighted connection. The output layer has linear function. Elman networks the input are linked to hidden layer that multiplies weight V_1using hyperbolic tangent sigmoid activation function and output from the hidden layer is transferred to the output layer that multiplies with weight V_2 using purelin activation function. As a result of training, the previous information is reflected to the Elman network. Incorporated, all absolute neural networks (IBPN, MLP, RBF and Elman) training learns from the normalized data. Error coming to a very negligible value is the stopping condition for test. The proposed Ensemble neural network is designed based on the aggregation of four absolute neural networks (IBPN, MLP, RBF and Elman networks). The sum total of the incorporated four absolute neural network output is the Ensemble neural network final output (i.e.) predicted wind speed.

Step 4: Training & Testing

The observed $1{,}00{,}000$ real-time data samples are divided into training and testing. Training set contains 70% $(70{,}000)$ observed data samples and testing set contains 30% $(30{,}000)$ observed data samples. The proposed Ensemble neural network learns based on the training set, while the performance is evaluated based on the testing set. Input the training and testing set for considered four absolute neural networks, train and test the designed individual neural networks obtain the individual output.

$$Y^{net}(K) = \left\{h_1^{IBPN}(s), h_2^{MLPN}(s), h_3^{RBFN}(s), h_4^{Elman}(s)\right\} \quad \text{eq. (5)}$$

Where, $Y^{net}(K)$ is individual neural network output, $h^{net}(s)$ is individual neural network.

Ensemble neural network final predicted wind speed computed as

$$Y_{pw}^{Ensemble} = \frac{1}{n}\sum_{i=1}^{n} Y_i^{net}(K) \text{ for } i = 1,2,3,\ldots,n \quad \text{eq. (6)}$$

Where, n is the number of individual neural network, $net = IBPN, MLPN, RBFN \;\&\; Elman\, Networks$.

$$N_{pw}^{Ensemble} = \left(N_{pw}^{IBPN} + N_{pw}^{MLPN} + N_{pw}^{RBNF} + N_{pw}^{Elman}\right)/4 \quad \text{eq. (7)}$$

Error computed as

$$MSE^{Ensemble} = \frac{1}{n}\sum_{i=1}^{n} MSE_i^{net} \quad \text{eq. (8)}$$

Select suitable hidden neuron numbers by means of the minimum error performance.

Step 5: Performance Criterion

The mean square error is used as a performance criterion to verify the accuracy and effectiveness, the error criterion formula is given as below:

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(Y_r^{'} - Y_p)^2 \quad \text{eq. (9)}$$

Where, n is the number of samples, $Y_r^{'}$ is real output, Y_p is predicted output.

The proposed Ensemble neural network makes the best predicted wind speed by means of four absolute neural networks (IBPN, MLP, RBF and Elman) sum total. The individual neural network has had uncertainties due to the imperfection initialization, parameterization. Therefore, the Ensemble neural network is minimized uncertainties by aggregation of individual neural network outputs.

III. K-Fold Cross Validation

The performance of the Ensemble neural networks on unseen real-time data set is evaluated based on the K-fold cross validation. K-fold cross validation is one of the important and famous re-sampling method, K-fold validation with 10 folds obtain the best result. The collected real-time observation divided into K-fold with same size, where K is taken as 10 for the proposed approach. In each of K turns, K-1 folds are used for ensemble neural networks, learning and the

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remaining one fold is utilized for the performance evaluation as depicted in Fig. 2. Training and testing mean square error (MSE) is evolved by means of the average of all K turns. Accuracy and quality of the proposed Ensemble neural networks are validated with K-fold cross validation.

1 **Testing**	2 Training	3 Training	4 Training	5 Training	6 Training	7 Training	8 Training	9 Training	10 Training

1 Training	2 **Testing**	3 Training	4 Training	5 Training	6 Training	7 Training	8 Training	9 Training	10 Training

1 Training	2 Training	3 **Testing**	4 Training	5 Training	6 Training	7 Training	8 Training	9 Training	10 Training

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1 Training	2 Training	3 Training	4 Training	5 Training	6 Training	7 Training	8 Training	9 Training	10 **Testing**

Fig. 2. K-fold Cross validation

IV. DISCUSSION OF RESULTS

The ensemble neural network is constructed with the amalgamation of improved back propagation network, radial basis function network, multi-layer perceptron network and ELMAN network. The Main aim of the proposed Ensemble neural networks is to make better wind speed prediction accuracy, reliability and generalization ability. Meanwhile, MATLAB simulation was performed using an Acer computer with dual core processor. Experimental results obtained from the proposed Ensemble neural network training and testing on real-time data samples are presented in Table. 2. Based on the Table. 2, it can be observed that the proposed Ensemble neural network (6-1-5) with 6 input neurons, 1 hidden layer and 5 hidden neuron numbers architecture had the best prediction accuracy with lower training and testing MSE.

Due to clarity results, only a part of the experimental results are presented. Real wind speed vs. predicted wind speed for training with 7000 data samples is shown in Fig. 3 and data samples vs. error for the training are noticed from Fig. 4. Fig. 5 depict the real wind speed vs. predicted wind speed for testing with 3000 data samples and data samples vs. error for testing are noted from Fig. 6. The Fig. 3 and Fig. 5 confirmed that the proposed Ensemble neural networks based wind speed prediction model predicted wind speed is highly match closely with the real wind speed of evolution on training and testing data samples respectively. Therefore, obtained prediction error is very low it can be clearly inferred from Fig. 4 and Fig. 6. Hence, Ensemble neural network (6-1-5) may be used for various time scales such as very short-term, short-term, medium-term and long-term wind speed prediction with MSE as the evaluation criterion. Proposed Ensemble neural networks, honest assessment of the true accuracy is provided by means of the K-fold cross validation. The K-fold cross validation training and testing results are shown in Table. 3. Different time scale wind speed prediction based on the proposed Ensemble neural networks is established in the Table. 4.

Proposed Ensemble neural networks outperform for different time scale wind speed prediction with lower training and testing mean square error, it can be observed from the Table. 4. Experimental results and K-fold cross validation demonstrate that the proposed Ensemble neural network not only provides accurate wind speed prediction, but also achieve better generalization ability, stability and reliability.

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Table. 2. Ensemble Neural Networks Computed Error

Ensemble Neural Networks	Computed MSE for Training	Computed MSE for Testing
6-1-1	0.1542	0.1925
6-1-2	0.3058	0.3374
6-1-3	0.0085	0.0089
6-1-4	0.0393	0.0395
6-1-5	**6.3334e-04**	**6.5591e-04**
6-1-6	0.0055	0.0067
6-1-7	0.1503	0.1606
6-1-8	0.0030	0.0041
6-1-9	0.0071	0.0081
6-1-10	0.2019	0.2135

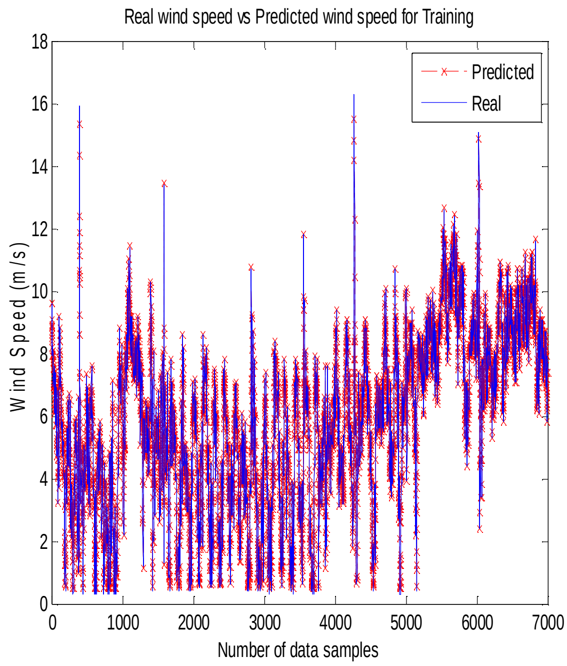

Fig. 3. Real wind speed vs. predicted wind speed for training

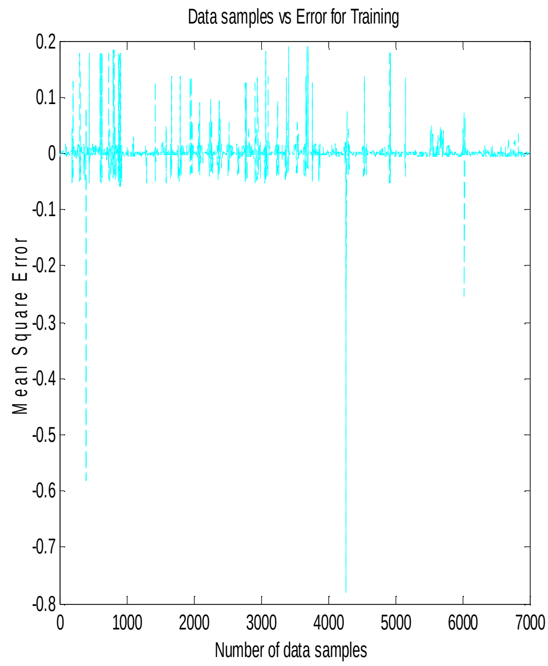

Fig. 4. Data samples vs. error for training

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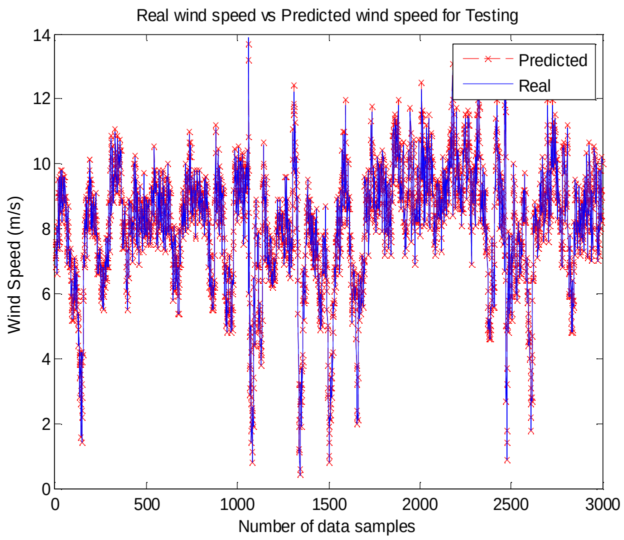

Fig. 5. Real wind speed vs. predicted wind speed for testing

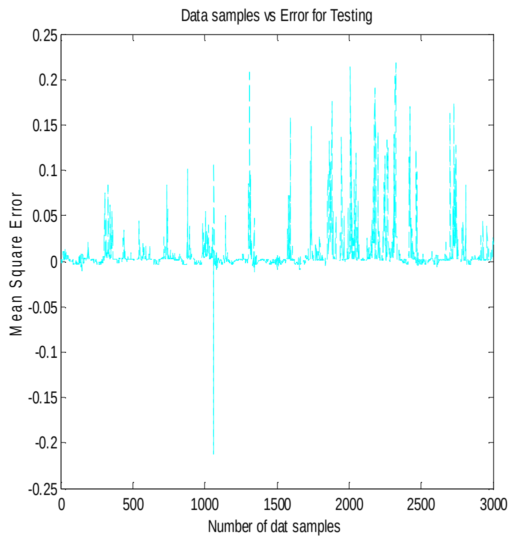

Fig. 6. Data samples vs. error for testing

Table. 3. K-Fold Cross Validation of Ensemble Neural Networks

K	MSE for Training	MSE for Testing
1	5.9138e-04	6.3669e-04
2	6.3276e-04	6.5155e-04
3	6.2168e-04	6.4395e-04
4	6.1582e-04	6.5812e-04
5	6.4131e-04	6.4494e-04
6	7.0080e-04	7.1380e-04
7	6.6211e-04	7.1615e-04
8	5.9436e-04	6.1496e-04
9	6.7400e-04	6.9750e-04
10	6.3812e-04	6.9898e-04
Average MSE	**6.3723e-04**	**6.6766e-04**

Table. 4. Different Time Scale Wind Speed Prediction using Ensemble Neural Networks

Different Time Scale Wind Speed Prediction uses Ensemble Neural Networks	Computed MSE for Training	Computed MSE for Testing
Very Short-Term Prediction	1.2358e-04	1.3582e-04
Short-term Prediction	3.9341e-04	4.1452e-04
Medium-term Prediction	5.4391e-04	5.6021e-04
Long-term Prediction	6.3334e-04	6.5591e-04

V. CONCLUSION

The proposed Ensemble neural networks have been successfully applied to different time scale wind speed prediction with an improved training and testing accuracy in order to aid planning, scheduling and dispatch of wind farm and power system. Presented Ensemble neural network effectiveness, reliability and generalization ability are confirmed based on K-fold cross validation. Simulation results prove the validity of Ensemble neural networks in terms of lower minimal error (MSE) and efficient wind speed prediction accuracy of different time scale predictions.

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BIOGRAPHY

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