

Application of sliding window technique for prediction of wind velocity time series

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Abstract The uncertainty caused by the discontinuous nature of wind energy affects the power grid. Hence, forecasting the behavior of this renewable resource is important for energy managers and electricity traders to overcome the risk of unpredictability and to provide reliability for the grid. The objective of this paper is to employ and compare the potential of various artificial neural network structures of multi-layer perceptron (MLP) and radial basis function for prediction of the wind velocity time series in Tehran, Iran. Structure analysis and performance evaluations of the established networks indicate that the MLP network with a 4-7-13-1 architecture is superior to others. The best networks were deployed to unseen data and were capable of predicting the velocity time series via using the sliding window technique successfully. Applying the statistical indices with the predicted and the actual test data resulted in acceptable RMSE, MSE and R^2 values with 1.19, 1.43 and 0.85, respectively, for the best network.

Keywords Wind energy · ANN · Time series prediction · Sliding window · Multi-layer perceptron · Radial basis function · Tehran

Introduction

Environmental effects of fossil resources combined with energy demand growth are important reasons for humanity's recent desire for harnessing clean energy [1, 2]. High potential, sustainability and availability are factors supporting solar and wind energy, as potentially the most applicable renewable energy sources around the world [3, 4]. In this regard, Fig. 1 presents an illustrative comparison of the global average annual growth rate of renewable energy utilization in 2010 and 2005–2010 [5].

To cover the uncertainty caused by the discontinuous nature of wind resources, a reliable energy system is required [6, 7]. Hence, forecasting the behavior of the wind resource can be a crucial role for energy managers, policy makers and electricity traders, to overcome the risk of unpredictability, and to provide energy security, for energy planning and handling energy storage policies including economic dispatch. Furthermore, such forecasting gives perspectives regarding time of operation, repair and replacement of wind generators and conversion lines and could help to shift towards optimum electrical networks.

Various approaches to forecast wind velocity and power have been reported. Examples include autoregressive integrated moving average (ARIMA) [8–10], nearest neighbor search, polynomial regression, Bayesian structural break [11], support vector machines (SVM) [12], Taylor Kriging [9], fuzzy logic and artificial neural network (ANN) [13, 14], ARIMA–Kalman [15], ARIMA–ANN [16] and wavelet derivatives such as wavelet-GP, wavelet-ANFIS, wavelet-ANN and wavelet packet [17–20]. These approaches are among the most utilized methods to predict wind resource components. The ANNs have resulted in acceptable performance compared to conventional methods due to their robustness and capability to address unpredictable complexities.

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Fig. 1 Average annual growth rate of renewable energy capacity [5]

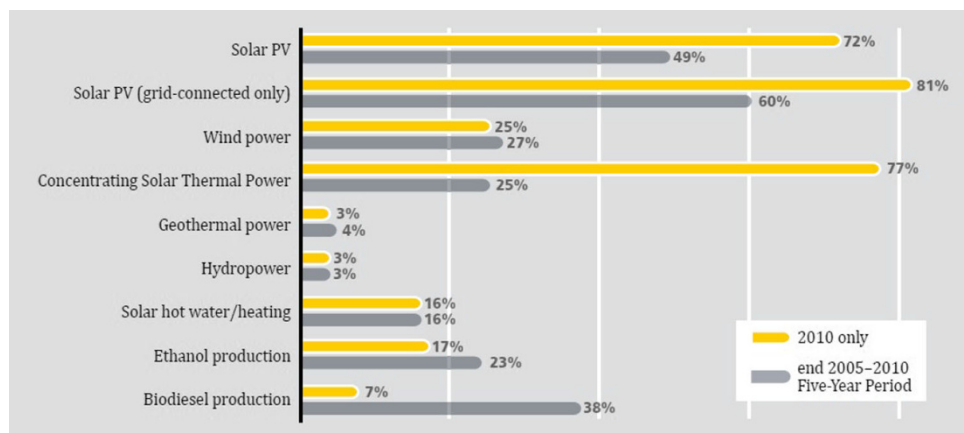


Table 1 Comparison of size of predicted data

Study	Prediction size (h)
Ref. [20]	50
Ref. [21]	50
Ref. [16]	45
Present study	1,314

The objective of this paper is to utilize various ANN approaches to forecast the behavior of wind velocity time series in Tehran, Iran. For this purpose, measured wind velocity data of the region (at an altitude of 10 m) for 1 year (8,760 h) at 1-h intervals (averaged values of every 10 min) are provided by a meteorological ground station of the Iran National Meteorological Organization, to predict 1,314 test data points after training multiple networks. Regarding the sufficiency of the prediction size to be used for evaluation of the proposed networks, Table 1 compares the size of the predicted data of the present study to the data size related to prediction goals of recent similar studies. To check the accuracy of predictions, the output results are evaluated via applying common statistical error tests such as RMSE, MSE and R^2 using the predicted values and the actual data.

Sliding window technique, artificial neural networks

ANNs are of the most popular artificial intelligence techniques. They imitate the human brain systems and learn from examples. Applications of ANNs include but are not limited to clustering, regression analysis, estimating functions, fitness approximation, novelty detection, data processing as well as time series prediction. ANNs are capable of learning, memorizing and constructing relationships among data. An ANN consists of processing units, layers (input, output and hidden), neurons and transfer

(activation) functions. ANN units are connected by weighted links that pass information and store the required knowledge in hidden layers. An input (x_j) of the network travels through the connection and the link multiplies its strength by a weight (w_{ij}) to generate $x_j w_{ij}$ which is an argument of a transfer function (f). The transfer function produces an output as $y_i = f(x_j w_{ij})$, where i is an index of neurons in the hidden layer and j is an index of an input to the neural network [22]. During a training process, ANNs change weights to be trained for a minimum error and to achieve defined stopping criteria such as a considered error value, number of iterations, calculation time and validation limits. Multi-layer perceptron (MLP) networks are of the most common feed-forward estimator networks. These provide a robust architecture for learning nonlinear phenomenon. Feed-forward implies that neurons in continuous layers send their output (signals) forward and only forward connections exist [23]. MLP networks have been the most used architecture both in the renewable energy domain and in time series forecasting [24]. To predict values in MLP networks, a fixed number p of previous observed velocity values is considered as inputs of the network for each training process while the output is the forecasted values of the time series, which is the so-called the “sliding window technique” (see Fig. 2). The mathematical model for training the network can be expressed as:

$$y_t = w_0 + \sum_{j=1}^Q w_j f \left(w_{0j} + \sum_{i=1}^P w_{ij} \cdot y_{t-i} \right)$$

where P and Q are the number of inputs and hidden nodes, respectively, and f is the transfer function. Respectively, “ $w_j, j = 0, 1, \dots, Q$ ” and “ $w_{ij}, i = 1, 2, \dots, P \ \& \ j = 1, 2, \dots, Q$ ” are the weight vectors from the hidden layer to the output and the weights from the input to the hidden nodes. Also, w_{0j} is the weight for each output between the input and the hidden layer [25]. For network consistency and reducing calculation time, input data should be normalized.

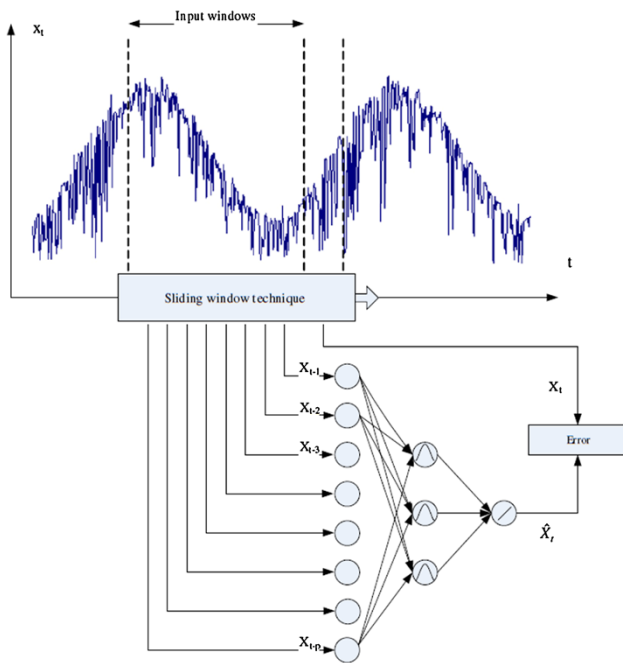


Fig. 2 Sliding window technique in ANN [22]

Table 2 Effective parameters considered in training of MLPs in preferred order

Effective parameter	Values/types
No. of input neurons	1–10
No. of hidden layers	1–2
No. of neurons in hidden layer	1–13
Transfer functions	Tansigmoid, Logsigmoid
Comparison function	MSE

Hence, the utilized data of the current study are normalized before processing. Normalization can be performed as follows:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

Network structures

The performance of trained networks depends on their architecture. The number of hidden layers, the number of neurons, the type of utilized transfer functions, the size of training and testing samples and the learning algorithms are effective training parameters in addition to the utilized stopping criteria. To find the best structure of the network in this study, various network structures are evaluated. Finding the best value/type for each network parameter involves finding a value/type for that parameter which minimizes the prediction error. In the same line, network parameters and their evaluated values/types in the study are given in Table 2. As noted earlier, a fixed number p of

Table 3 Statistical indices and their related expressions

Statistical index	Expression
RMSE	$\sqrt{\frac{1}{n} \sum_{i=1}^n (v_{i,m} - v_{i,f})^2}$
R^2	$\frac{\sum_{i=1}^n (v_{i,m} - v_{m,avg}) \times (v_{i,f} - v_{f,avg})}{\sqrt{[\sum_{i=1}^n (v_{i,m} - v_{m,avg})^2] \times [\sum_{i=1}^n (v_{i,f} - v_{f,avg})^2]}}$
MBE	$\frac{1}{n} \sum_{i=1}^n (v_{i,m} - v_{i,f})$

previous observed velocity values are considered as inputs to the network in each training process while the output is the forecasted velocity values of the time series. Data distribution for training, validation and test procedures is considered as 70, 15 and 15 % of the entire data set, respectively. The computation processes include training (via the Levenberg–Marquardt (LM) algorithm [26]) and evaluation of the results (via the statistical error indices), which are performed in the MATLAB® environment.

Also, the same data are provided to various radial basis function neural networks (RBFNNs) [27] for comparing their best outcome to the best performance yielded from the MLP networks trained by the LM algorithm. Regarding structure of the trained RBFNNs, a greater range of neuron numbers in the hidden layer is tested and compared to the MLP networks. To identify the best structure of the RBFNN, 0–25 neurons are examined in the hidden layer and the performances calculated for each structure are determined and compared in the results section.

Statistical indices for performance evaluation

The most common statistical indicators, including root mean square error (RMSE), absolute fraction of variance (R^2) and mean square error (MSE), are utilized with the forecasted data (v_f) and the actual measured data (v_m) to evaluate the performance of the proposed predictor systems. Table 3 shows the utilized statistical indicators accompanied by their relevant mathematical expressions.

Results and discussion

The results of training various networks with different structures are presented in this section.

For MLP networks, Table 4 shows a summary of trained structures with $p = 4$ input data and the related obtained errors (RMSE and MSE) and R^2 to find the best structure. Regarding the utilized statistical indices, RMSE provides information on the performance of the models, as it allows

Table 4 Performance summary of trained structures with all (train, validation and test) data using MLP

Transfer function	No. of neurons in hidden layers	MSE	RMSE	R^2
Logsig	4	1.5303	1.2371	0.8397
Logsig	5	1.4863	1.2191	0.8421
Logsig	7	1.4689	1.2120	0.8442
Logsig	10	1.4890	1.2203	0.8426
Logsig	13	1.4854	1.2188	0.8427
Tansig	4	1.4896	1.2206	0.8418
Tansig	5	1.4758	1.2148	0.8433
Tansig	7	1.4770	1.2153	0.8438
Tansig	10	1.4749	1.2145	0.8435
Tansig	13	1.4796	1.2164	0.8434
Tansig–Logsig	7–7	1.4742	1.2142	0.8436
Tansig–Logsig	7–13	1.4430	1.2012	0.8472
Tansig–Logsig	10–7	1.4586	1.2077	0.8454
Tansig–Logsig	10–13	1.4697	1.2123	0.8442
Logsig–Tansig	13–7	1.4544	1.206	0.8458
Logsig–Tansig	7–13	1.6862	1.2985	0.8221

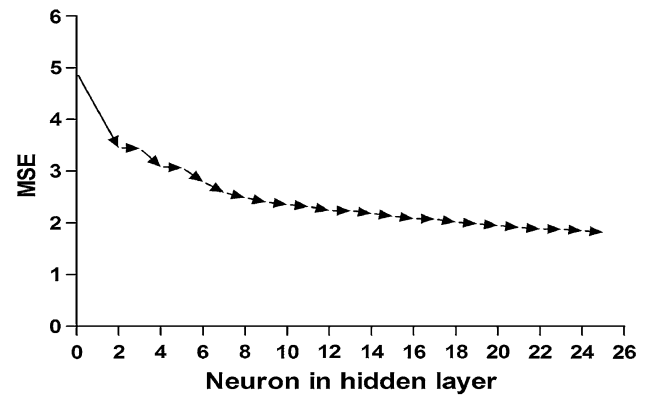
Bold row in table indicates the outperforming MLP network of the present study

a term by term comparison of the actual deviation between the calculated and the measured values. The commonly used parameter, R^2 , is a measure of the strength of the relationship between values. It is a function of RMSE and the standard deviation. Hence, to evaluate the performance of the established networks, low error values (nearer to 0) and high R^2 values (nearer to 1) are favorable for an efficient network.

According to the results, a network with 4-7-13-1 structure is chosen as the best MLP network of this study. This network utilizes 4 input data in the input layer with 7 and 13 neurons in its first and second hidden layers to predict the output. The activation functions of the first and the second relevant hidden layers of this network are Tansigmoid and Logsigmoid, respectively. The network utilizes a linear function in its output layer to transfer the data to the output.

Similarly, various RBFNN structures are examined to find the related outperforming architecture. The performances obtained for RBFNN structures with $p = 4$ input and 0–25 examined neurons in the hidden layer are summarized in Fig. 3.

To test the best structures of the trained RBF and MLP networks, the identified structure from each approach is separately deployed to the same unknown test data, which were not utilized in the training process. Table 5 shows the performance results related to the outperformed structures of MLP (4-7-13-1) and RBFNN (4-25-1), considering the same test data.

**Fig. 3** Performance summary of trained structures with all (train, validation and test) data using RBFNN**Table 5** Performance comparison of the best MLP and RBF trained structures

Network	Best structure	R^2	RMSE	MSE
MLP	4-7-13-1	0.85	1.19	1.43
RBF	4-25-1	0.83	1.36	1.84

Figure 4 illustrates the agreement of the actual target values and the predicted outputs for the outperformed structure of RBFNN (4-25-1) after de-normalization of the data. Along the same line, Fig. 5 illustrates the outperformed structure of MLP (4-7-13-1).

Evaluation of the statistical indices demonstrates acceptable predicted outputs and also the flexibility of both approaches when large changes occur. However, as shown in Table 5, the 4-7-13-1-MLP network performs better than the 4-25-1-RBFNN network, according to its higher R^2 value and lower MSE and RMSE values. Figure 6 illustrates a schematic structure of this selected network and its components.

For the outperformed structure of MLP network, applying the statistical indices with the predicted and the actual test data results in acceptable RMSE, MSE and R^2 values (considering similar previous studies, including Refs. [9, 14, 15]) of 1.19, 1.43 and 0.85, respectively. As can be seen in the error histogram of this network (Fig. 7), the largest error values range between -1 and 1 , which indicates acceptable overestimation and underestimation values. Also, the standard deviation of error is 1.1951 and the symmetric shape of the error histogram around the zero point (following a normal distribution pattern) ensures low error values (near zero) for the sum of overestimated (positive values) and underestimated (negative values) data, when the sum of predicted velocities in a given period is desired.

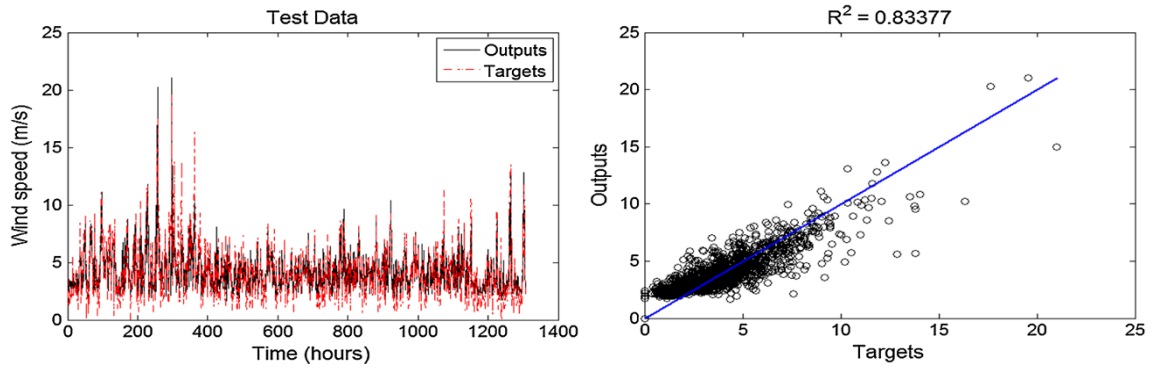


Fig. 4 Agreement of the actual and the predicted test outputs using RBF

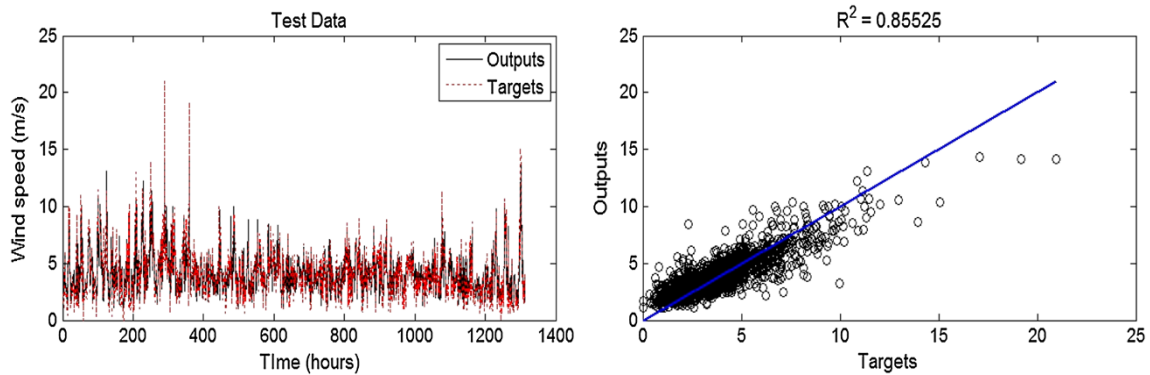
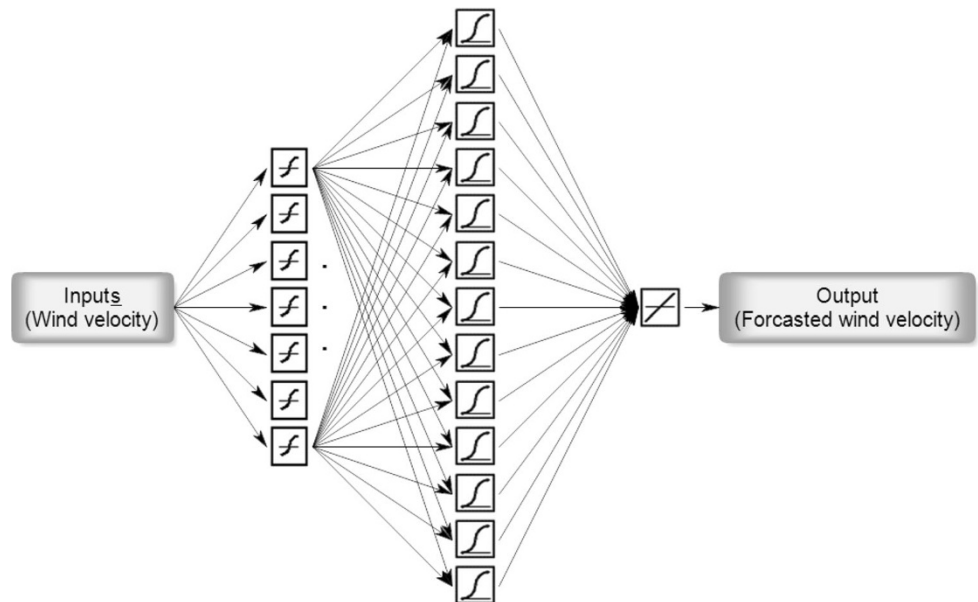


Fig. 5 Agreement of the actual and the predicted test outputs using MLP

Fig. 6 The best established network and its components



Conclusions

Forecasting the behavior of the wind resource can provide valuable information for energy managers, energy policy makers and electricity traders, as well as times of

operation, repair and replacement of wind generators and conversion lines. However, reliable power generation and effective integration of wind energy systems into the power distribution grid are affected by the intermittent and nonlinear nature of the wind resource. Accurate

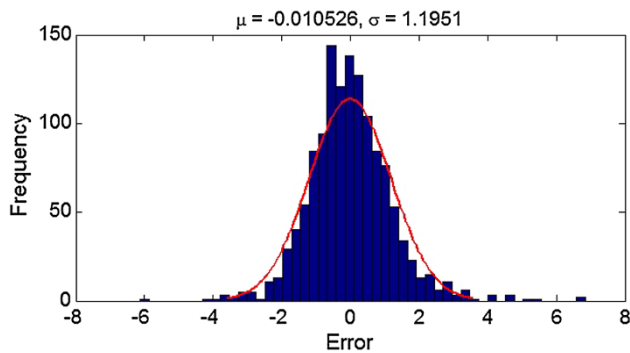


Fig. 7 Error histogram for predicted test data

forecasting of wind velocities not only can address the challenges such as adverse shocks in conventional power units caused by excessive wind speed but also can provide useful information regarding voltage and frequency instabilities resulting from variation in wind power. ANNs are robust tools with advantageous capabilities for addressing the unpredictable complexities of nonlinear phenomena such as the stochastic behavior of the wind resource, which cannot be handled by conventional methods accurately. In this paper, wind velocity data for 1 year at 1-h intervals are utilized to train various artificial neural network (ANN) architectures for prediction of wind velocity data of Tehran, Iran. Structure analysis and performance evaluations of the established networks determine that the MLP network with a 4-7-13-1 architecture is superior to others. The best network was deployed to the unseen data and found to be capable of predicting velocity data via the sliding window technique successfully. Applying the statistical evaluation indices with the predicted and the actual test data results in acceptable RMSE, MSE and R^2 values of 1.19, 1.43 and 0.85, respectively. Predictions of wind power density or wind energy density, which are related to wind velocity, as well as comparing the performance of the ANN with other forecasting approaches, merit further investigation as an extension of the present study.

Conflict of interest The authors declare that they have no competing interests

Authors' contributions MV, OR, and PA have participated in implementation of the methods, computation process, validation of the results, and giving the study ideas. MV has also drafted the manuscript. As supervisor Prof., MR and FF have checked the study procedure and commented for qualification of the manuscript structure. All authors read and approved the final manuscript.

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