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ORIGINAL ARTICLE

Wind speed forecasting in South Coasts of Iran: An Application of Artificial Neural Networks (ANNs) for Electricity Generation using Renewable Energy

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ABSTRACT
Prediction of wind speed is essential prerequisites in the sitting and sizing of wind power applications. In this study, monthly mean daily air temperature, relative humidity, vapor pressure and wind speed data monitored at 10 m above ground level for a period of 12 years (1994–2005) for eight ground stations, located in the south coasts of Iran, were used to create Artificial Neural Network (ANN) models to predict wind speed. To achieve this, month of the year, monthly mean daily air temperature, relative humidity and vapor pressure were used as input data, while the monthly mean daily wind speed was used as the output of the network. The measured data between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) used as testing dataset. Several configurations of ANNs were trained and finally, the optimum network was a three-layered ANN model with a Mean Absolute Percentage Error (MAPE) of 12.32 % and correlation coefficient (r) between the predicted and the measured wind speed values of 93.12%.
Keywords*: Artificial Neural Networks; Meteorology; Prediction; South Coasts of Iran.*

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INTRODUCTION

After the 1973-oil embargo, it becomes clear that the oil supplies would not remain for ever and so the other kinds of energy sources must be developed [1]. Nowadays, the power of wind, being economically competitive and environmentally friendly, has become the world's fastest growing green energy source of electricity generation. Accurate information of dynamic wind at the wind farm site is crucial for the operations and management of wind energy conversion systems. For instance, long-term wind speed prediction is vital for the sitting and sizing of wind power applications [2, 3], whereas short-term forecasting of wind speed is important for improving the efficiency of a wind power generation systems [4, 5] as well as for the integration of wind energy into the power system [6- 8]. However, due to the stochastic nature of wind speed from time to time and from site to site, prediction of wind speed at the intended site is of great importance.

Significant research efforts have been devoted to developing efficient forecasting methods for the prediction of wind speed. Commonly used techniques for average wind speed forecasting include Time Series and Artificial Neural Networks [9-13]. [14] presented a new linear prediction method for short-term wind speed forecasting. They used a linear prediction method in conjunction with filtering of the wind speed waveform to forecast wind speed based on the observation that filtering out less effective frequency components from a wind speed spectrum can increase the correlation between real and predicted winds. [15] suggested a method of exploiting the diversity in input data using banks of artificial neural networks for accurate short-term wind speed prediction, which yields better results compared to those obtained from a system using single neural networks. [1] introduced a support vector machines (SVM) algorithm for wind speed prediction and compared its performance with multilayer perceptron (MLP) neural networks. The results indicated that SVM compares favourably with the MLP model based on root mean square error testing between actual mean daily wind speed data from Madina city, Saudi Arabia and predicted data. [16] proposed a locally feedback dynamic fuzzy neural network (LF-DFNN) model using spatial wind speed information from remote measurement stations at wind farms to estimate multi-step ahead wind

speed from 15 min to 3 h ahead. Furthermore, they trained the LF-DFNN models using an optimal online learning scheme, the decoupled recursive prediction error algorithm (DRPE). It was shown that DRPE outperformed three gradient descent algorithms: the back propagation through time, real-time recurrent learning, and recursive back-propagation algorithms, in training of recurrent LF-DFNN forecast models. [17] proposed a new strategy in wind speed prediction based on fuzzy logic and artificial neural networks. They trained their new strategy on real wind data measured in Rostamabad in northern Iran from 2002 to 2005. The experimental results demonstrated that the proposed method not only provided significantly less rule base but also increased the estimated wind speed accuracy when compared to traditional fuzzy and neural methods.
In this paper, ANNs are applied to predict wind speed using measured monthly mean daily air temperature, relative humidity, vapor pressure data for south costs of Iran. The rest of this paper is organized as follows: Section 2 explains the proposed method in detail. The problem definition is presented in section 3.Simulation results are presented and discussed in Section 4. Finally, Section 5 highlights the findings and concludes the paper.

NEURAL NETWORKS

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing only simple computation [18]. Any how, the architecture of an artificial neuron is simpler than a biological neuron. NNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological system [19].
However, as an assembly of neurons, a neural network can learn to perform complex tasks including pattern recognition, system identification, trend prediction and process control [18].

Multi-layer Perceptron

MLPs are perhaps the most common type of feedforward networks. Figure 1 shows an MLP which has three layers: an input layer, an output layer and a hidden layer.

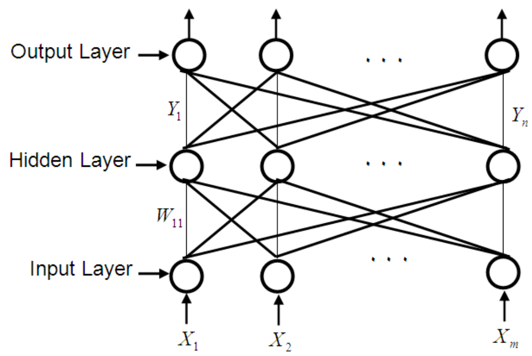

Figure 1.A multi-layer perceptron.

Neurons in input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neurons j (Fig. 2) in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum, viz.

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{1}$$

f can be a simple threshold function or a sigmoidal , hyperbolic tangent or redial basis function.

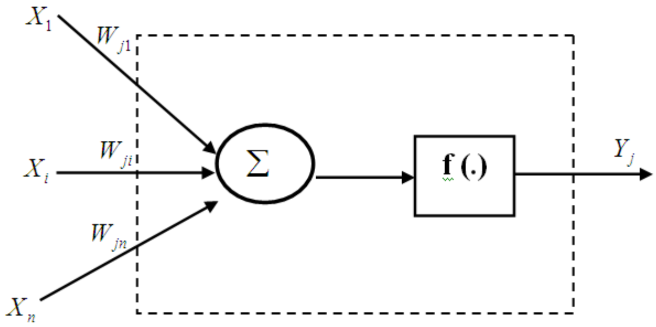

Figure 2.Details of a neuron

The output of neurons in the output layer is computed similarly the back propagation algorithm, a gradient the descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ji} the weight of a connection between neurons i and j as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \quad (2)$$

Where η is a parameter called the learning rate and δ_j is a factor depending on whether neuron j is an input neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\left(y_j^{(t)} - y_j\right) \quad (3)$$

And for hidden neurons,

$$\delta_j = \left(\frac{\partial f}{\partial net_j}\right)\sum_q w_{qj}\delta_q \quad (4)$$

In Eq.3, net_j is the total weighted sum of input signals to neurons j and $y_j^{(t)}$ is the target output for neuron j.

As there are no target outputs for hidden neurons, in Eq.4, the difference between the target and actual output of a hidden neurons j is replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output of j.

Thus, iteratively, beginning with the output layer, the δ term is computed for neurons in all layers and weight updates determined for all connections. The weight updating process can take place after the presentation of each training pattern (pattern-based training) or after the presentation of the whole set of training patterns (batch training). In either case, a training epoch is said to have been completed when all training patterns have been presented once to the MLP.

For all but the most trivial problems, several epochs are required for the MLP to be properly trained. A commonly adopted method to speed up the training is to add a (momentum) term to Eq.2 which effectively lets the previous weight change influence the new weight change, viz:

$$\Delta w_{ji}(k+1) = \eta \delta_j x_i + \mu \Delta w_{ji}(k) \quad (5)$$

Where $\Delta w_{ji}(k+1)$ and $\Delta w_{ji}(k)$ are weight changes in epochs $(k+1)$ and (k) respectively and μ is the momentum coefficient [20].

PROBLEM DEFINITION AND RESULTS

In this study, air temperature, relative humidity, vapor pressure and wind speed data, collected by Islamic Republic of Iran Meteorological Organization (IRIMO) between 1994 and 2005, are used for wind speed prediction using ANNs.

In order to create an efficient prediction model, the stations are divided to two categories:

Reference Stations: Kish, Siri, Jask, Bandarabass and Aboumosa are used as Reference Stations.

Target Stations: Dayer, Gheshm and Lengeh are used as Target Stations.

As it has described in the following section, the models are fixed for Reference Stations and generalized using Target Stations.

RESULTS AND DISCUSSION

Training and Testing the prediction models for Reference Stations

In order to create the prediction models for Reference Stations, the measured data between 1994 and 2003 for these stations (i.e Kish, Siri, Jask, Bandarabass and Aboumosa) are used to train MLP neural networks for wind speed prediction of south coast of Iran. Then, the measured data between 2004 and 2005 for same stations are used to test the trained networks. Month of the year, air temperature, relative humidity and vapor pressure data are used as inputs to the networks and wind speed data is used as output. In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. Eventually, logistic sigmoid transfer function (logsig) for both hidden layers, linear transfer function (purelin) for output layer and LM (Levenberg–Marquardt) train were found to perform reasonably well. Table 1 shows the performance of some trained networks for Reference Stations.

Table 1. Training and testing errors of some trained networks for Reference Stations.

#	Neuron in first hidden layer	Neurons in second hidden layer	Transfer function	Training		Testing	
				MAPE (%)	R^2 (%)	MAPE (%)	R^2 (%)
1	3	2	sigmoid	13.33	92.24	14.13	91.11
2	4	2	sigmoid	13.12	92.03	13.03	92.45
3	5	2	sigmoid	13.01	92.56	12.69	92.88
4	3	3	sigmoid	12.86	92.15	12.52	93.04
5	4	3	sigmoid	12.64	92.37	12.32	93.12
6	3	2	tanh	13.23	92.08	12.41	92.88
7	4	2	tanh	14.03	92.15	12.77	92.47
8	5	2	tanh	13.98	91.96	12.76	92.43
9	3	3	tanh	13.77	91.97	12.97	92.16
10	4	3	tanh	14.23	91.23	13.23	92.05

As it can be seen in this table, the optimum network is a three-layered ANN model with a Mean Absolute Percentage Error (MAPE) of 12.32 % and correlation coefficient (r) between the predicted and the measured wind speed values of 93.12% on testing period.

Figure 3 to 7 show the comparison between predicted wind speed values based on MLP and measured values on testing data (2004 and 2005) for all Reference Stations.

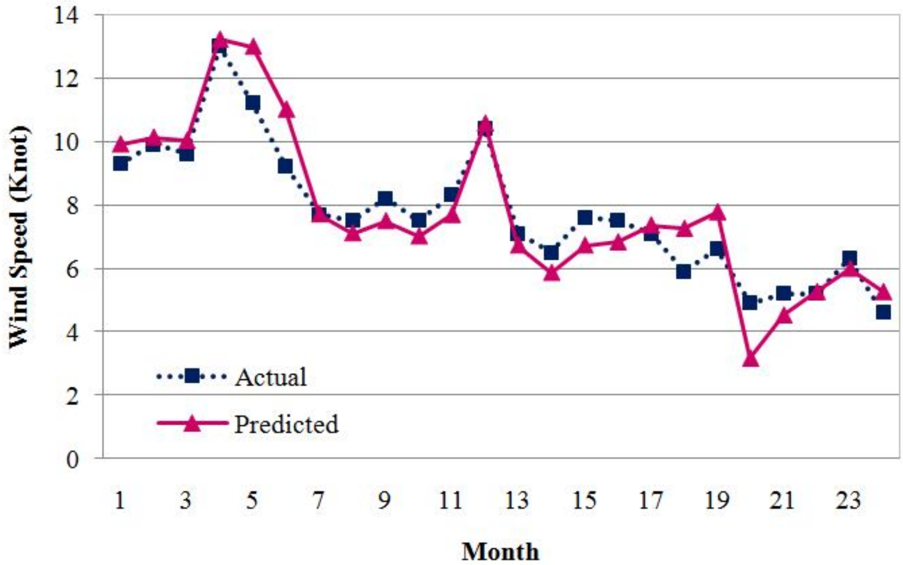

Figure 3. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Kish station.

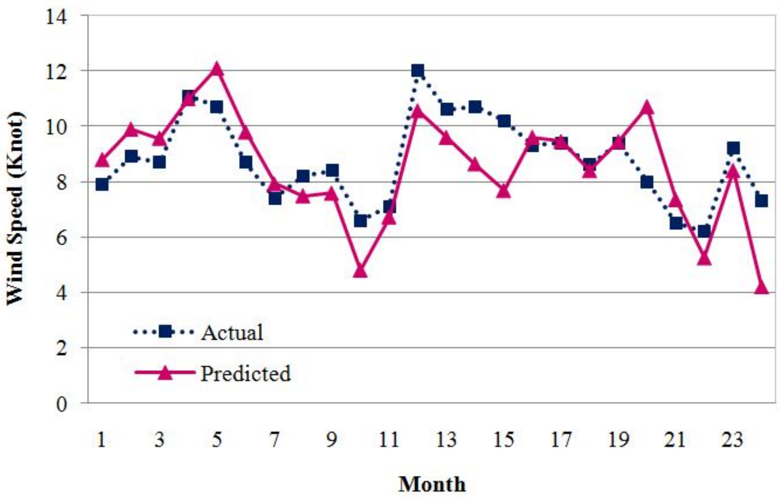

Figure 4. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Siri station.

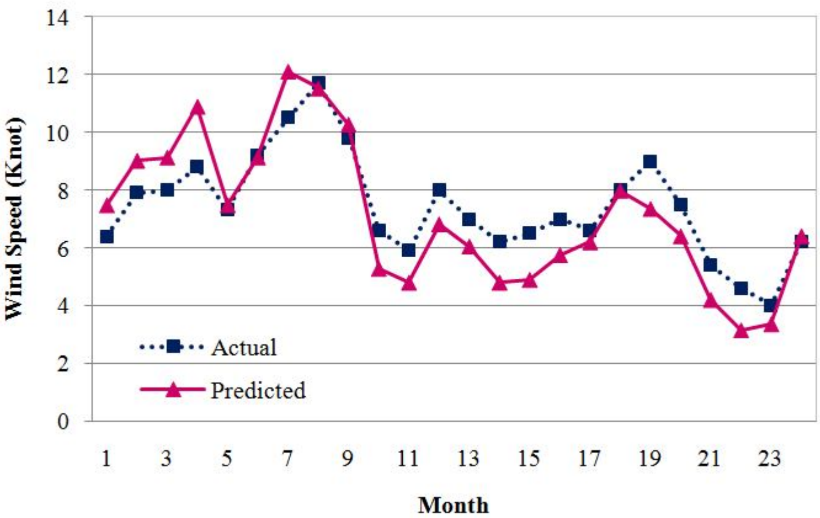

Figure 5. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Jask station.

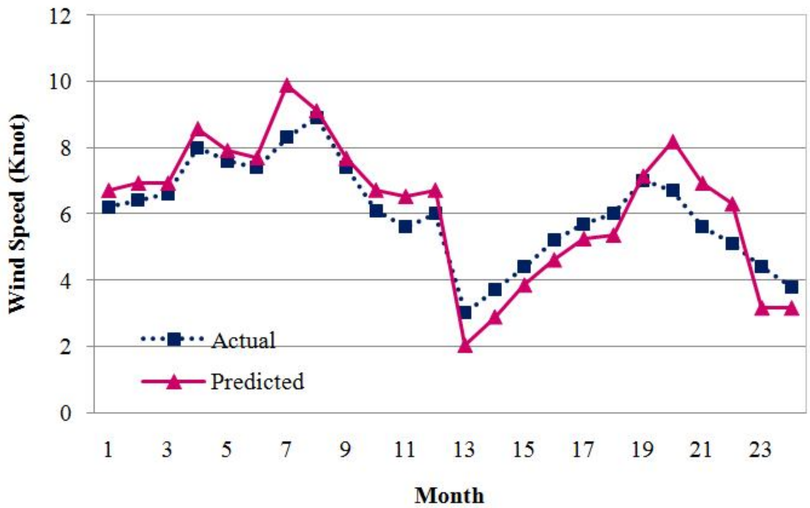

Figure 6. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Bandarabass station.

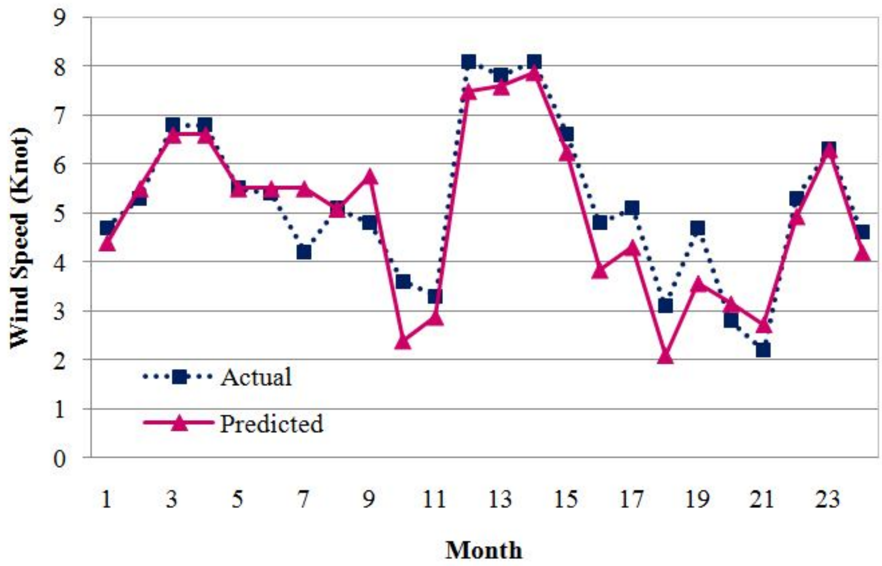

Figure 7. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Aboumosa station.

Validating the prediction models for Target stations

In order to show the applicability of a prediction model, the model should be able to predict wind speed values of unknown stations which no data for them are used to design the networks. To achieve this, the measured data for Target Stations (i.e. Dayer, Gheshm and Lengeh), between 2004 and 2005 are used to validate the designed models for Reference Stations. Table 2 shows the performance of best designed network of Reference Stations for Target Stations.

Table 2. Performance of the best trained network for Target Sta

Station	MAPE (%)	R^2 (%)
Dayer	13.78	92.03
Gheshm	12.23	92.98
Lengeh	14.08	91.90

Figure 8 to 10 show the comparison between predicted wind speed values based on the best designed network and measured values for Target Stations.

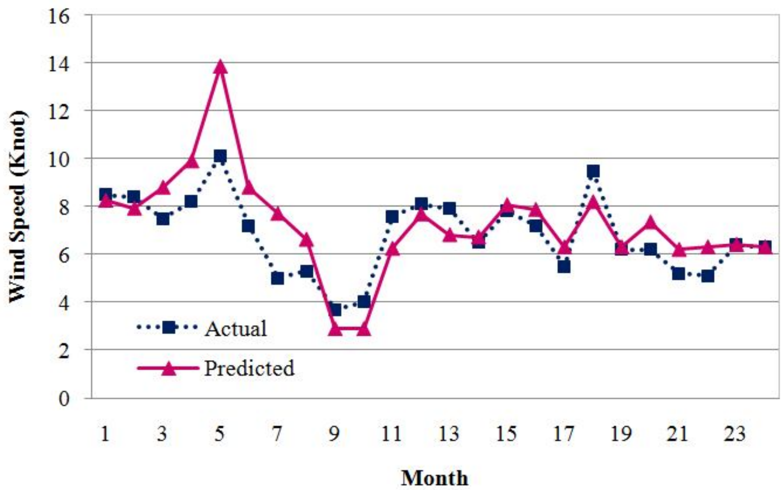

Figure 8. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Dayer station.

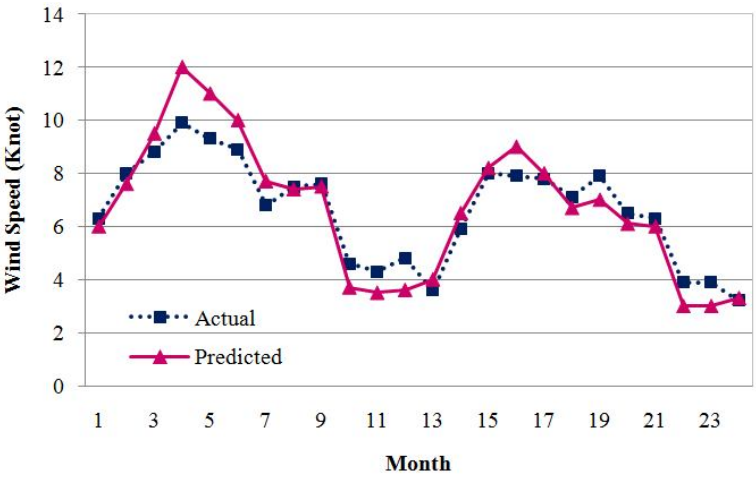

Figure 9. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Gheshm station.

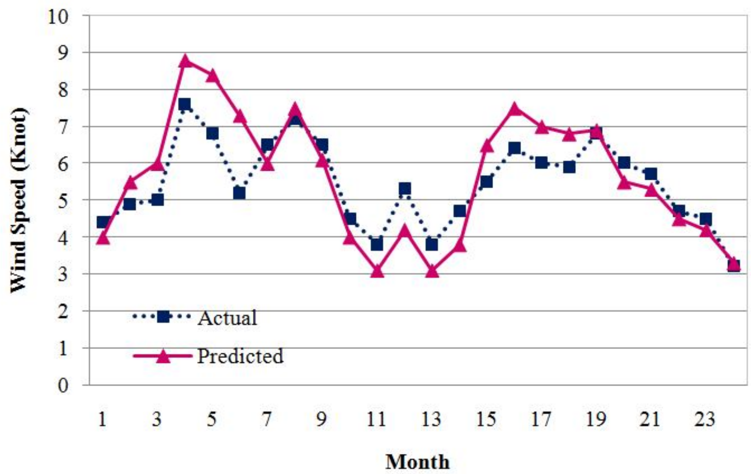

Figure 10. Comparison between predicted wind speed values based on best ANN model and measured values on testing data (2004 and 2005) for Lengeh station.

CONCLUSION

This study shows the results of an effort made to predict monthly wind speed according to measured values of air temperature, relative humidity, and vapor pressure. This is of great importance because above parameters are commonly accessible. In order to create an efficient prediction model, the stations are divided to two categories: Reference Stations and Target Stations. First, the measured data for Reference Stations between 1994 and 2003 were used as training and the remained data (i.e. 2004 and 2005) for same stations used as testing dataset. Several architectures of ANNs were trained and finally, the optimum network was a three-layered ANN model with a Mean Absolute Percentage Error (MAPE) of 12.32 % and correlation coefficient (r) between the predicted and the measured wind speed values of 93.12%. Then, the measured data for Target Stations, between 2004 and 2005 are used to validate the designed models for Reference Stations. The obtained results shows the applicability of the designed prediction models to predict wind speed values of unknown stations which no data for them are used to design the networks.Future work is focused on comparing the presented method with other available tools. Predicting of wind speed can also be investigated with intelligent optimization techniques like Bees Algorithm, Genetic Algorithm and etc. The results of the different techniques could be compared with available methods.

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REFERENCES

1. Mohandes, M.A., Halawani, T.O., Rehman, S., Hussain, A.A., 2004. Support vector machines for wind speed prediction, Renewable Energy 29 939–947.
2. Xydis, G., Koroneos, C., Loizidou, M., 2009. Exergy analysis in a wind speed prognostic model as a wind farm sitting selection tool: a case study in Southern Greece. *Applied Energy* 86(11):2411–20.
3. Ucar, A., Balo, F., 2009. Investigation of wind characteristics and assessment of wind-generation potentiality in Uludag-Bursa, Turkey. *Applied Energy* 86(3): 333–9.
4. Monfared, M., Rastegar, H., Kojabadi, H., 2009. A new strategy for wind speed forecasting using artificial intelligent methods. *Renewable Energy* 34(3): 845–8.
5. Pinson, P., Nielsen, H.A., Madsen, H., Kariniotakis, G., 2009. Skill forecasting from ensemble predictions of wind power. *Applied Energy* 86(7–8): 1326–34.
6. Lei, M., Shiyan, L., Chuanwen, J., Hongling, L., Yan, Z., 2009. A review on the forecasting of wind speed and generated power. Renewable and Sustainable Energy Reviews 13(4): 915–20.
7. Luickx, P.J., Delarue, E.D., Dhaeseleer, W.D., 2008. Considerations on the backup of wind power: operational backup. *Applied Energy* 85(9):787–99.
8. Sfetsos, A., 2000. A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renewable Energy 21(1):23–35.
9. Cai, K., Tan, L.N., Li, C.L., Tao, X.F., 2008. Short-term wind speed forecasting combing time series and neural network method, *Power System Technology* 32 (8) 82–85.
10. Du, Y., Lu, J.P., Li, Q., Deng, Y.L., 2008. Short-term wind speed forecasting of wind farm based on least square-support vector machine, Power System Technology 32 (15) 62–66.
11. Sun, C., Wang, Y., Li, X., 2008. Vector autoregression model of hourly wind speed and its applications in hourly wind speed forecasting, Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical Engineering 28 112–117.
12. Wu, X.H., Zhou, H., Huang, M., 2008. Wind speed and generated power forecasting based on pattern recognition in wind farm, Relay 36 (1) 27–32.
13. Yang, X., Xiao, Y., Chen, S., 2005. Wind speed and generated power forecasting in wind farm, Zhongguo Dianji Gongcheng Xuebao/Proceedings of the Chinese Society of Electrical Engineering 25 1–5.
14. Riahy, G.H., Abedi, M., 2008. Short term wind speed forecasting for wind turbine applications using linear prediction method, *Renewable Energy* 33 35–41.
15. Sancho, S.S., Angel, M.P.B., Emilio, G.O.G., Antonio, P.F., Luis, P., Francisco, C., 2009. Accurate short-term wind speed prediction by exploiting diversity in input data using banks of artificial neural networks, *Neurocomputin*g 72 1336–1341
16. Barbounis, T.G., Theocharis, J.B., 2007. A locally recurrent fuzzy neural network with application to the wind speed prediction using spatial correlation, Neurocomputing 70 1525–1542.
17. Mohammad, M., Hasan, R., Hossein, M.K. 2009. A new strategy for wind speed forecasting using artificial intelligent methods, Renewable Energy 34 845–848.
18. Pham, D.T., Koc, E., Ghanbarzadeh, A. and Otri, S. (2006a). Optimisation of the Weights of Multi-Layered Perceptrons Using the Bees Algorithm. in: Proceedings of 5th International Symposium on Intelligent Manufacturing Systems, Sakarya University, Department of Industrial Engineering, May 29-31, pp. 38-46 .
19. Yilmaz, A.S. and Ozer, Z., 2009. Pitch angle control in wind turbines above the rated wind speed by multi-layer percepteron and redial basis function neural networks, *Expert Systems with Applications* 36: 9767–9775.
20. Pham, D.T. and Liu, X., 1995. Neural Networks for identification, prediction and control, London: Springer verlag.

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