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EFFECT OF TIME HORIZON ON WIND SPEED PREDICTION WITH ANN

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ABSTRACT

Proper utilization of renewable energy sources in electricity production is inevitable due to the environmental concerns and global warming fight. Therefore, predictability of renewable electricity is a very significant issue for a long time. Main aim of this study, different from the literature, is to investigate the change of wind speed prediction errors for different time horizons. Different prediction time horizons (10, 30, 60, 90 and 120 minutes) were used, and the results were compared through the error measures and the regression values. The mean squared errors and the regression values vary between 0.819 and 5.570, and between 77.8% and 97.1%, respectively. The prediction error changes almost logarithmically, and the rate of change decreases with the increasing time horizon. A new analysis approach was proposed to see the change of the prediction error with time horizon. The equation, $y = 1.5413ln(x) - 2.7428$, representing the change of the mean squared error with time horizon was obtained.

Keywords: *Wind Energy, Wind Speed Prediction, Artificial Neural Network, Time Horizon*

INTRODUCTION

Global temperature has been increasing continuingly for years due to global warming [1]. Using of fossil fuels is an important cause of global warming [2-4]. Utilization of renewable energy sources in electricity production is a promising way of decreasing fossil fuel usage.

Availability and reliability of the power plants in the grid are the most significant subjects for the electric utilities. The increasing level of wind power penetration to the grid is an important consideration in energy planning. For the existing wind farms, the authorities should have the ability of predicting the amount of electricity production.

In wind energy applications, the most important parameters are wind speed and direction. However, due to the intermittent nature of wind, it has some problems to think it as a classical energy supply method [5-9]. Additionally, wind speed is a non-storable renewable energy resource [10-12]. Technical challenges associated with the integration of wind power into power systems are represented by Georgilakis [13]. The increase of the wind electricity penetration to the grid makes planners to think it in depth due to the discontinuity. Therefore, the integration of wind power to the grid is an important issue nowadays.

Integration of wind power to the grid depends on its predictability and availability. The availability of wind power is out of the scope of this study. The predictability is the key factor for the economic integration of wind power to the grid. Statistical methods can be used to predict wind speed at wind farms to estimate the electricity production of wind farms or to predict wind power production directly. There are various studies that focus on statistical approaches and artificial intelligence techniques to forecast wind speed or wind power [10-31]. Additionally, the artificial intelligence is used in many other research areas [32-33].

As an alternative to classical prediction methods, the neural network (NN) approach can be used to model relationship between random input data and output data. The NN has many superior features than the classical methods over capability, speed, high amount of data, etc. [34-35]. In wind speed prediction, the artificial neural network (ANN) technology is a promising one [36-37]. As expectedly, short term predictions give better results. Effectiveness of short term wind speed prediction is mentioned in many studies such as [10, 39-40]. Li and Shi studied the performance of different ANN based models for 1 hour ahead prediction of wind speed [37]. Grassi and Vecchio used neural network approach to predict monthly wind energy output of three wind farms [36]. Alexiadis et al. proposed ANN predictor which is 10% better than persistence model [28]. Song used ANN technology to forecast wind speed, which works well when data does not fluctuate much [41]. Akyuz et al.

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proposed a new approach to predict hourly wind speed characteristics [30]. Akinci and Nogay proposed a wind speed estimation method which uses data of neighboring measurement station [31].

Time horizon is a significant issue in wind speed predictions as studied by others. In study of Foley et al., effect of length of the time horizon on wind speed and wind power predictions was presented [42]. It was mentioned that wind speed prediction error increases with the increasing length of the time horizon. Wang et al. studied on ANN approach to predict wind speed [43]. They achieved to get better results in predicting wind speed at different time horizons. It is noted that larger prediction periods reduce the accuracy.

Advances in applied mathematics offer some other methods like MARS, CMARS, RCMARS, GPLM, etc. for real life problems on prediction [44-46]. In the near future, these methods will make it easier and accurate.

About wind speed prediction, most of the studies in the literature aim to predict wind speed better than the previous attempts. Main aim of this study is to evaluate the prediction performance of the ANN approach at different time horizons but not to develop the best ANN model to predict wind speed. Therefore, different from the studies in the literature, the present study focuses on the change of the prediction error with time horizon. The evaluated time horizons in the analyses are 10, 30, 60, 90 and 120 minutes. The results were compared through the error measures and the regression values. Results of this study may be used to understand accuracy and sensitivity of the wind speed predictions.

PRESENTATION OF THE DATA

The data used in this study is from a measurement station located in the Aegean region, Turkey. At 30 m measurement height, average wind speed, maximum wind speed, minimum wind speed and standard deviation were stored in ten minutes time interval. The data from 2002 to 2005 were used in the analyses.

Monthly mean wind speed changes were presented in Figure 1 for each year. The highest wind speed values occur in summer months. Maximum monthly mean wind speed is 9.21 m/s (July 2004). As can be seen from the figure, monthly mean wind speed values change significantly. This high variability makes wind speed prediction difficult.

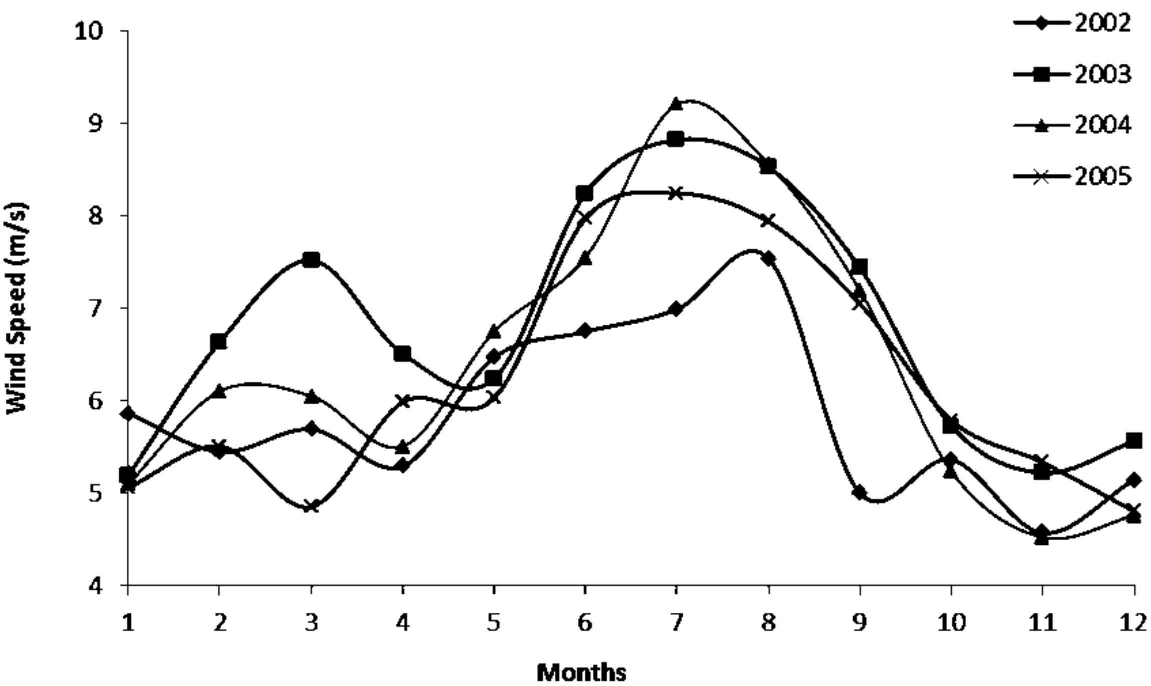

Figure 1. Monthly mean wind speed for each year

ARTIFICIAL NEURAL NETWORK APPROACH

Today, the ANNs are being used in many different studies and applications. The ANN based methods are usually used to forecast the short term data. In the present study, same configuration of the ANN was used to evaluate the performance of the ANN on short term wind speed predictions at different time horizons.

Figure 2 shows the ANN structure used in this study. As input parameters average wind speed, maximum wind speed, minimum wind speed and standard deviation were used in the present study. The wind data used in the analyses were 10 minutes measured data. Additionally, values of year, month, day, hour and minute were used as input parameters in the ANN model. Therefore, the number of input parameters is nine. The neural network used in this study is a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons. As a training algorithm, Levenberg-Marquardt back-propagation algorithm is used. Number of hidden neurons is selected as 40.

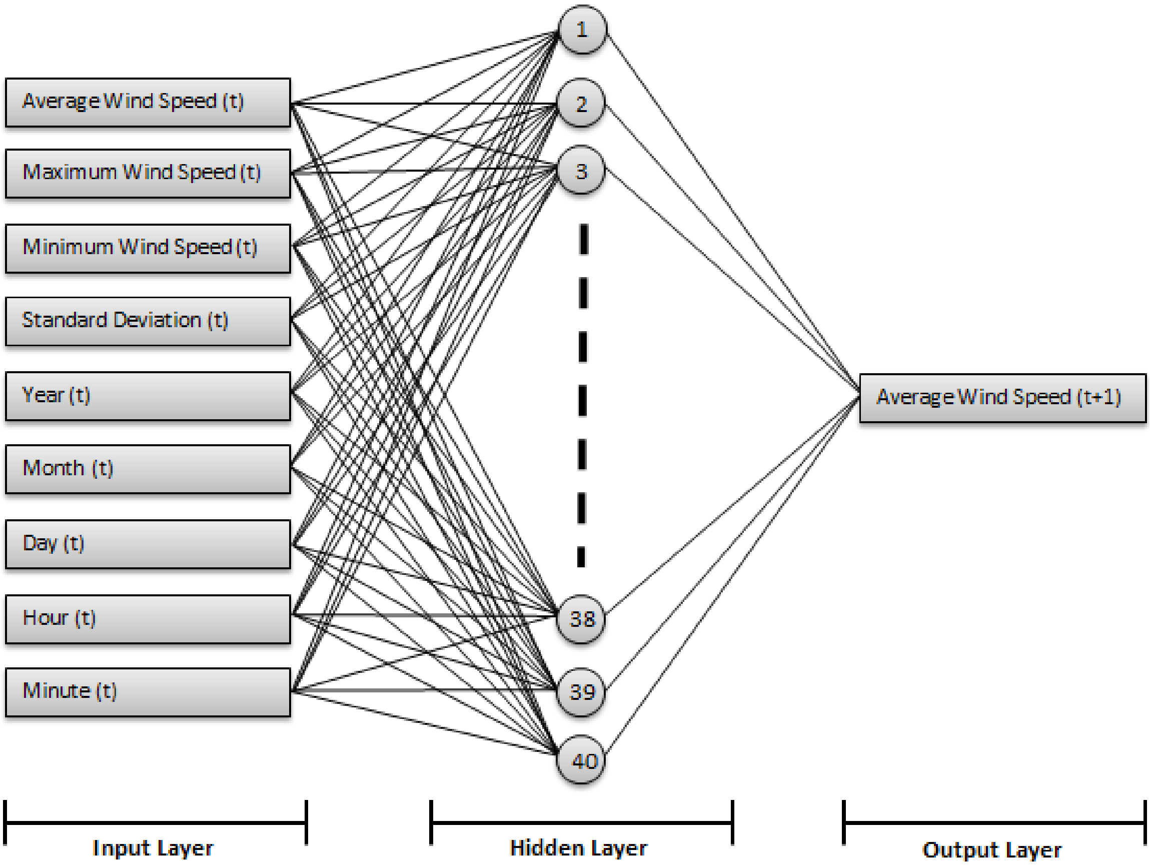

Figure 2. The ANN structure

The data of the first three years were used for training, validation and testing issues in the ANN method. 70% of the data was used in the training stage, 15% of the data was used in the validation stage, and 15% of the data was used in the testing stage. The data were divided up randomly for the stages.

Additionally, the random data from the last year were used in the additional tests to see the efficiency of the ANN. While evaluating the results of the ANNs, two different approaches were employed as the mean squared error (MSE) and the regression value (R value).

RESULTS AND DISCUSSION

The results of the ANN method were given in this section. Firstly, the initial results were given for the training, validation and testing stages. Secondly, the results of the additional tests were presented.

The initial results of the MSE and the regression analyses were presented in Table 1 for each time horizon. The MSE values vary between 0.819 and 5.570, and the regression values vary between 77.8% and 97.1%. The increasing length of the time horizon increases the MSE and decreases the R value. The increase of the MSE decreases with the increasing prediction period.

Table 1. Initial results of the ANN model

Time Horizon (min)	MSE			R value			
	Training	Validation	Testing	Training	Validation	Testing	All
10	0.820	0.819	0.828	0.971	0.971	0.970	0.970
30	2.175	2.132	2.178	0.920	0.922	0.920	0.920
60	3.656	3.571	3.618	0.861	0.863	0.864	0.861
90	4.634	4.618	4.642	0.819	0.821	0.819	0.819
120	5.570	5.529	5.449	0.778	0.780	0.781	0.779

In Figure 3, scattering of the predicted and the actual wind speed values were presented. The scatter can be understood by the R value. The lower R value means more the scatter. Therefore, the scatter becomes more as the prediction horizon increases. The highest overall R value was calculated for 10 minutes time horizon as 0.970.

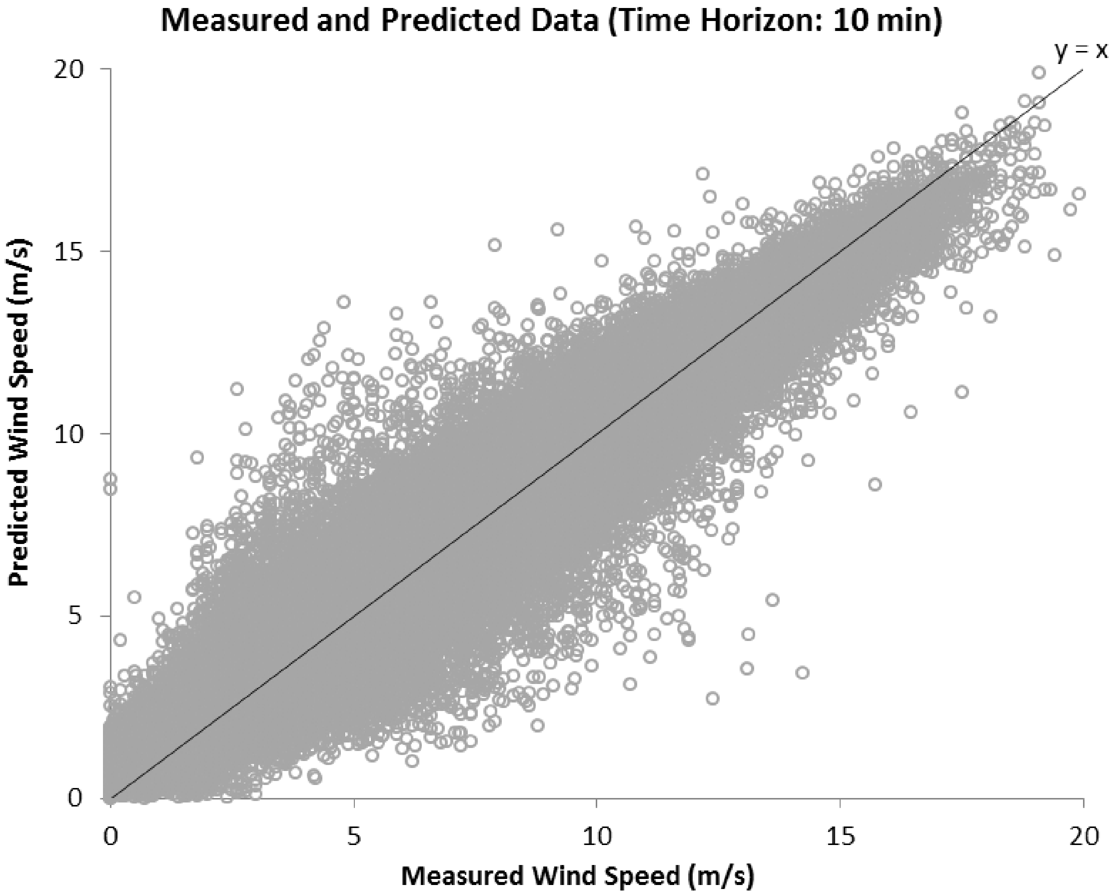

Figure 3. Relationship between the measured and the predicted wind speed values for 10 minutes ahead

The additional test results were given in Table 2. The additional tests were performed by using the data from the last year. 106 data were taken randomly, and the prediction tests were done for the same time horizons (10, 30, 60, 90 and 120 minutes). The MSE values for 60, 90 and 120 minutes time horizons decreased comparing to the initial results.

Table 2. Additional test results of the ANN

Time Horizon (min)	MSE
10	0.906
30	2.418
60	3.459
90	3.987
120	4.933

The predicted and the measured wind speed values and the prediction errors can be seen in Figures 4-8 for each time horizon. The predictions get worse with the increasing time horizon as in the initial works. The MSE error was under 1 only for 10 minutes ahead prediction. As can be seen from the figures, the deviations increase for wind speed predictions with time horizon. For 10 minutes ahead prediction, wind speed prediction error occurs up to about 3 m/s while it occurs up to about 7 m/s for 120 minutes ahead prediction.

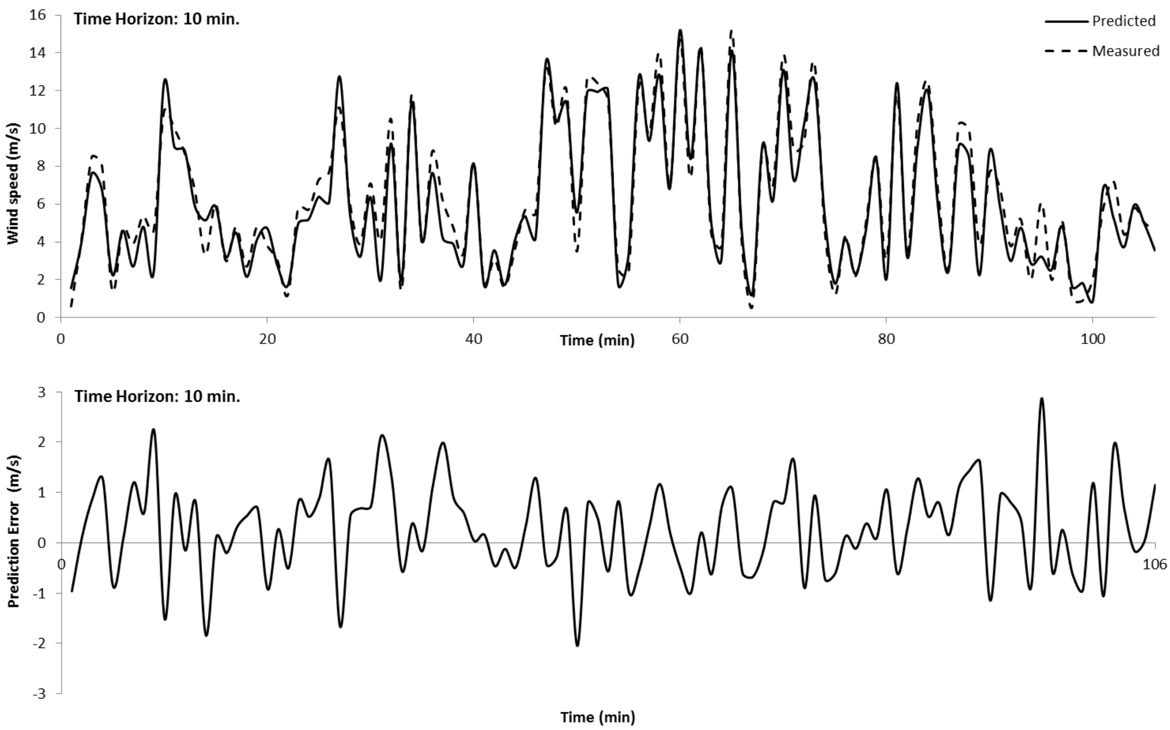

Figure 4. Measured and predicted wind speed values and prediction errors for the additional tests (10 min ahead)

In this part, some comparisons were done with other studies which have similar conditions. Sfetsos compared the performance of three forecasting models for two different locations to predict wind speed values of one hour ahead by using past hourly data [17]. The achieved root mean squared errors (RMSEs) for the ANN model were 1.200 m/s and 0.724 m/s (one hour ahead prediction) which are lower than the results presented at the additional tests (RMSE=1.860 m/s for one hour ahead) of this study.

Abdel-Aal et al. proposed using of abductive networks to forecast mean hourly wind speed at Dhahran, Saudi Arabia [22]. The R values achieved in the mentioned study were 0.826, 0.853 and 0.842 for different models. The R value (0.861) attained in this study (one hour ahead prediction) is better.

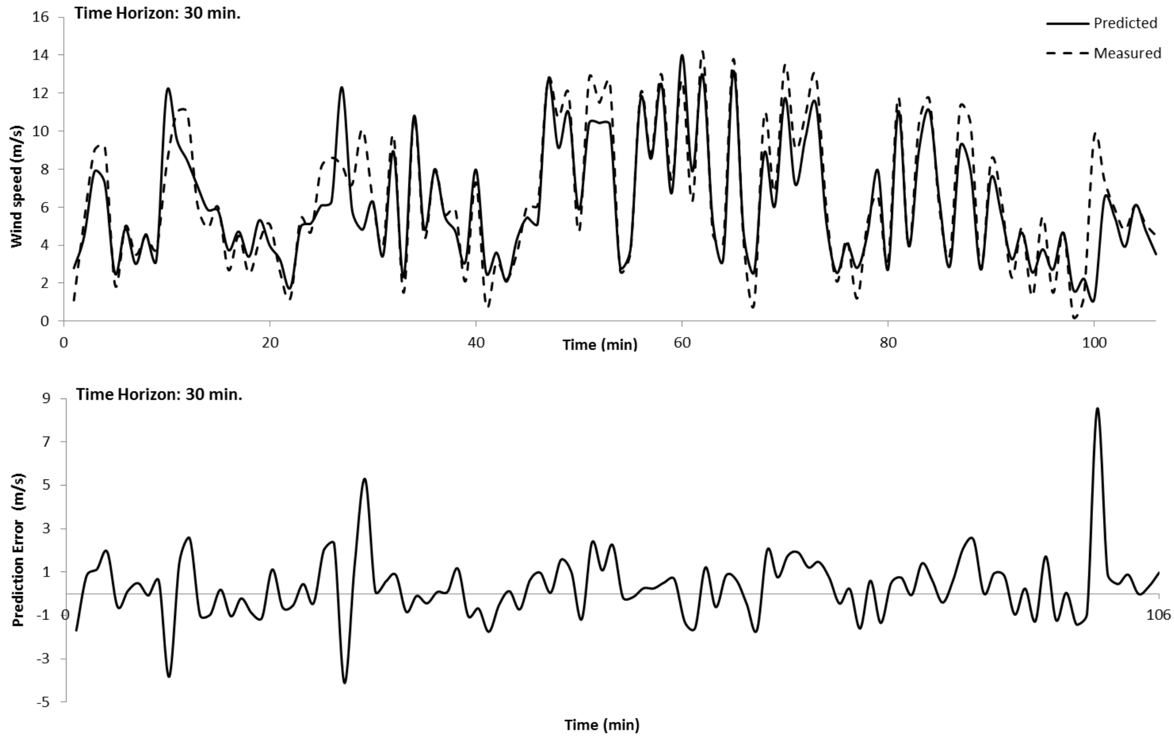

Figure 5. Measured and predicted wind speed values and prediction errors for the additional tests (30 min ahead)

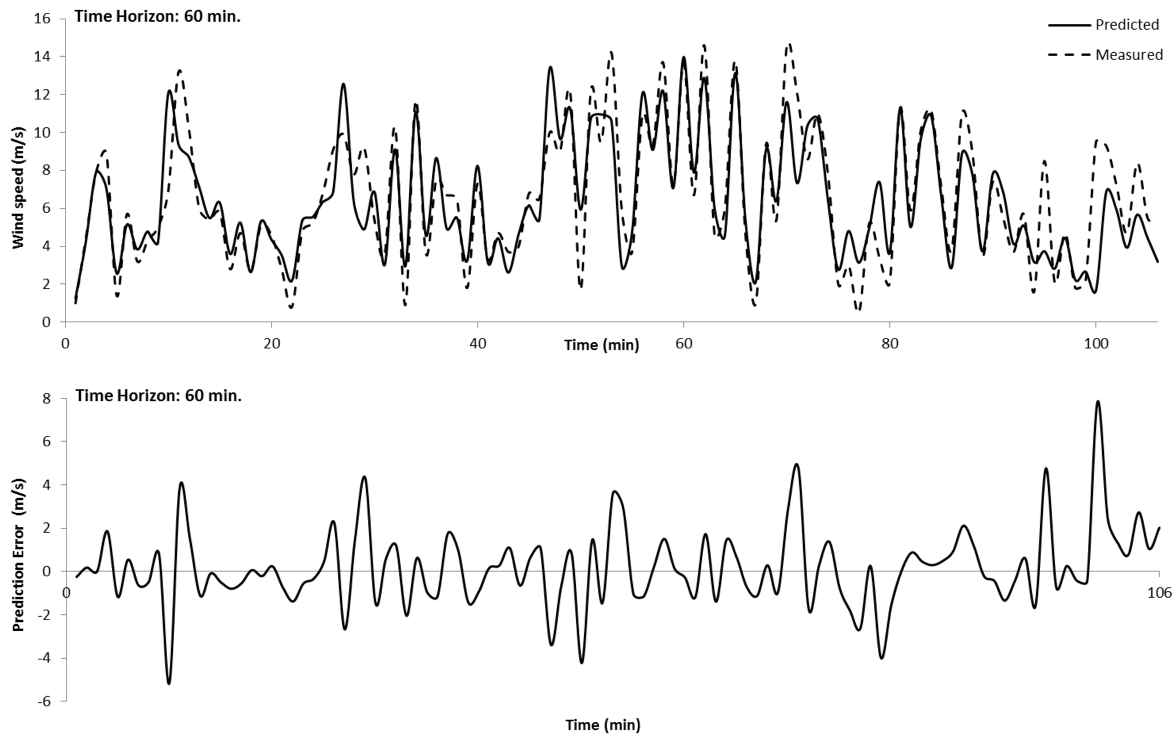

Figure 6. Measured and predicted wind speed values and prediction errors for the additional tests (60 min ahead)

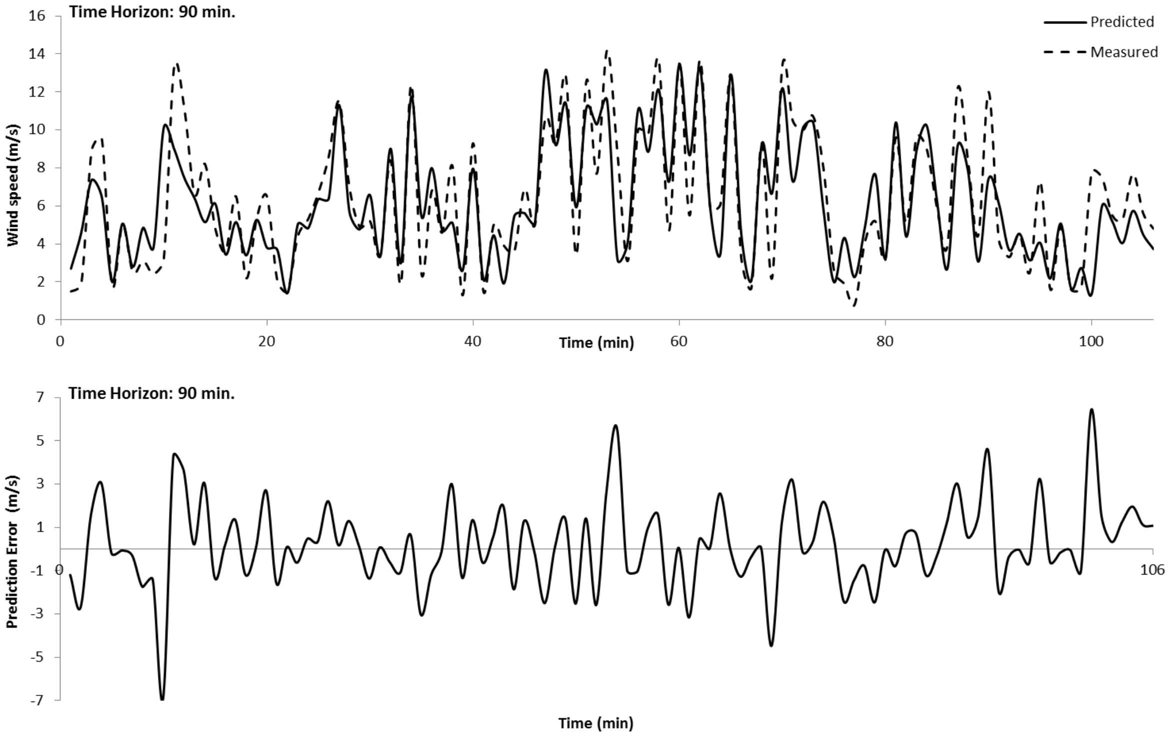

Figure 7. Measured and predicted wind speed values and prediction errors for the additional tests (90 min ahead)

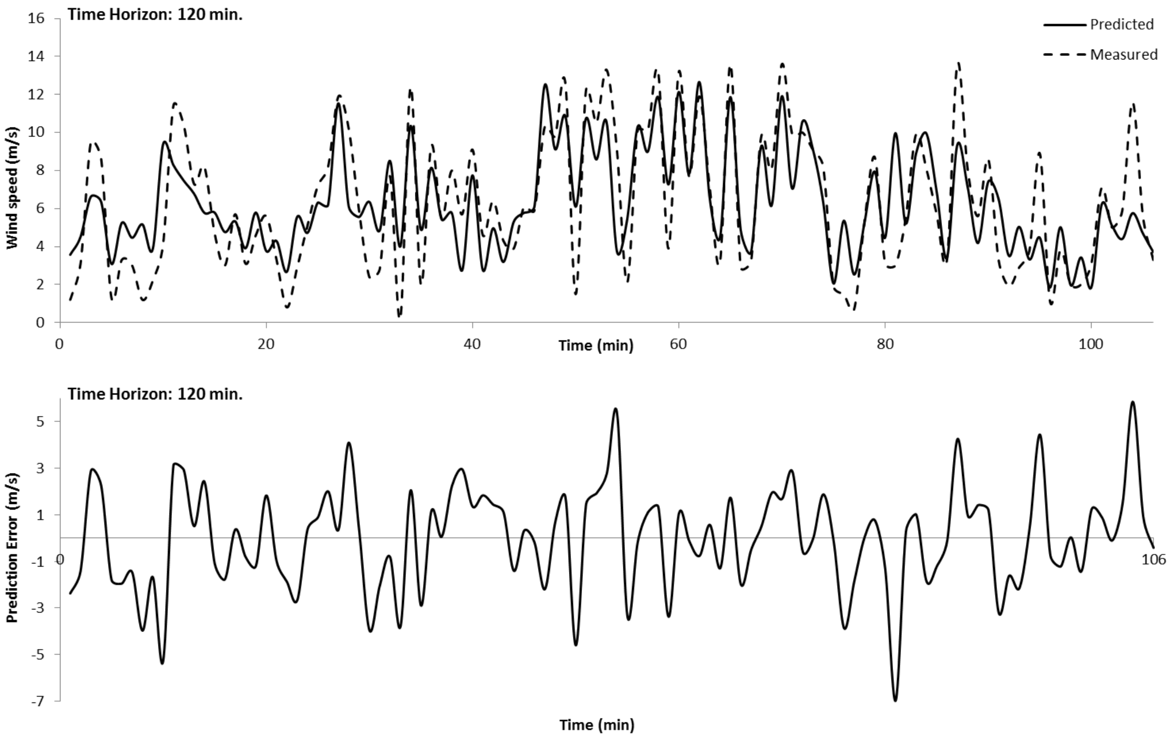

Figure 8. Measured and predicted wind speed values and prediction errors for the additional tests (120 min ahead)

The change of the MSEs at different time horizons was presented in Figure 9. The errors change almost logarithmically, and the rate of change decreases with the increasing time horizon. The equation fitted for the MSE eases to calculate the error for any time horizon. For instance, the MSE for 1440 min (24 hour) ahead forecast is 8.466. The representation of the change of the MSE with time horizon may be an important approach for the forecasting studies. However, in the literature, there is not much study using this approach.

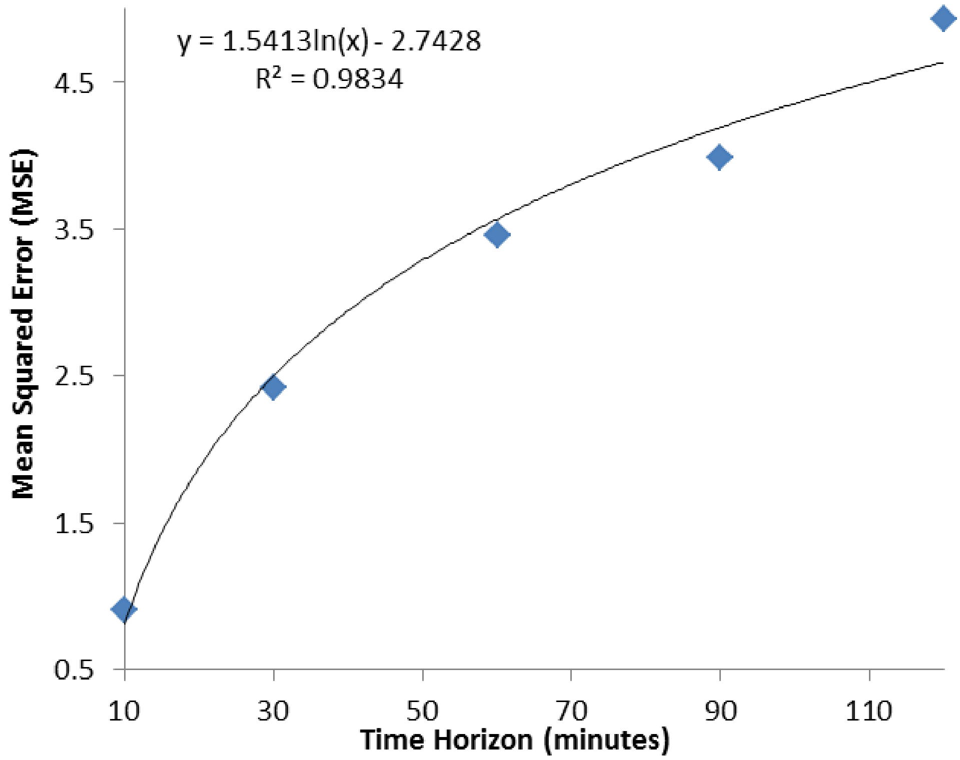

Figure 9. Change of the MSEs for different time horizons

CONCLUSION

In this paper, wind speed prediction study at different time horizons by the ANN approach was presented. Different from the literature, effect of time horizon on the performance of the ANN was evaluated. Additionally, a new approach, the representation of the change of the MSE with time horizon, was proposed.

The main results of this study are as following:

- The ANN model gives better results at very short time horizons (MSE_{10min}=0.906).
- The prediction error increases with the increasing length of time horizon (MSE_{60min}=3.459 and MSE_{120min}=4.933).
- The rate of change in the prediction errors decreases with the increasing time horizon.
- The equation, $y = 1.5413ln(x) - 2.7428$, representing the change of the MSE with time horizon was obtained.
- The proposed approach may be used to discover the accuracy and change of the estimations done by any method.
- Better wind speed predictions may provide more efficient wind farm operation.

As further studies, different prediction methods, such as ANFIS, Genetic Algorithm, MARS, CMARS, GPLM, CGPLM, etc., may be used to see the variation of prediction errors with time horizon.

NOMENCLATURE

NN	Neural network
ANN	Artificial neural network

MSE Mean squared error
R Value Regression value
RMSE Root mean squared error

REFERENCES

[1] Swift-Hook, D. T. (2013). The case for renewables apart from global warming. Renewable Energy, 49, 147–150.
[2] Pusat, S., & Akkoyunlu, M. T. (2018). Evaluation of wind energy potential in a university campus. International Journal of Global Warming, 14(1), 118-130.
[3] Tolga, T., & Demirci, O. K. (2014). Energy and Economic Analysis of the Wind Turbine Plant's Draft for the Aksaray City. Applied Ecology and Environmental Sciences, 2(3), 82-85.
[4] Pusat, S. (2017). Study to determine wind energy potential for Sakarya University. Pamukkale University Journal of Engineering Sciences, 23(4), 352-357 (in Turkish).
[5] Milligan, M., & Parsons, B. A. (1997). Comparison and Case Study of Capacity Credit Algorithms for Intermittent Generators. NREL.
[6] Roy, S. (2009). Economic Assessment of the Engineering Basis for Wind Power: Perspective of a Vertically Integrated Utility. Energy, 34(11), 1885–1897.
[7] Scorah, H., Sopinka, A., & van Kooten, G. C. (2012). The economics of storage, transmission and drought: integrating variable wind power into spatially separated electricity grids. Energy Economics, 34(2), 536-541.
[8] Sørensen, B. (2008). A sustainable energy future: Construction of demand and renewable energy supply scenarios. International Journal of Energy Research, 32, 436–470.
[9] Cai, Y. P., Huang, G. H., Yeh, S. C., Liu, L., & Li, G. C. (2012). A modeling approach for investigating climate change impacts on renewable energy utilization. International Journal of Energy Research, 36, 764–777.
[10] Potter, C., & Negnevitsky, M. (2006). Very short-term wind forecasting for Tasmanian power generation, IEEE Transactions on Power Systems, 21(2), 965–972.
[11] Gertmar, L. (2003). In: Power Electronics and Wind Power, 10th European Conference on Power Electronics and Applications, Toulouse.
[12] Outhred, H., & Thorncraft, S. (2010). In: Integrating Non-Storable Renewable Energy into the Australian Electricity Industry, Proceedings of the 43rd Hawaii International Conference on System Sciences.
[13] Georgilakis, S. P. (2008). Technical challenges associated with the integration of wind power into power systems. Renewable and Sustainable Energy Reviews, 12(3), 852–863.
[14] Mohandes, M. A., Rehman, S., Rahman, S. M. (2012). Spatial estimation of wind speed. International Journal of Energy Research, 36(4), 545–552.
[15] Alpay, S., Bilir, L., Ozdemir, S., & Ozerdem, B. (2006). Wind speed time series characterization by Hilbert transform. International Journal of Energy Research, 30(5), 359–364.
[16] Monfared, M., Rastegar, H., & Kojabadi, H. (2009). A new strategy for wind speed forecasting using artificial intelligent methods. Renewable Energy, 34(3), 845–848.
[17] Sfetsos, A. (2002). A novel approach for the forecasting of mean hourly wind speed time series. Renewable Energy, 27(2), 163–174.
[18] El-Fouly, T. H. M., El-Saadan, E. F., & Salama, M. M. A. (2006). Grey predictor for wind energy conversion systems output power prediction. IEEE Transactions on Power Systems, 21(3), 1450–1452.
[19] Bilgili, M., Sahin, B., & Yasar, A. (2007). Application of artificial neural networks for the wind speed prediction of target station using reference stations data. Renewable Energy, 32, 2350–2360.
[20] Damousis, I. G., & Dokopoulos, P. (2001). In: A fuzzy model expert system for the forecasting of wind speed and power generation in wind farms, Proceedings of the IEEE International Conference on Power Industry Computer Applications (PICA), 63-69.
[21] Ramírez-Rosado, I. J., & Fernández-Jiménez, L. A. (2004). An advanced model for short-term forecasting of mean wind speed and wind electric power. Control and Intelligent Systems, 31(1), 21–26.
[22] Abdel-Aal, R. E., Elhadidy, M. A., & Shaahid, S. M. (2009). Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks. Renewable Energy, 34(7), 1686–1699.
[23] Kariniotakis, G., Nogaret, E., & Stavrakakis, G. (1997). In: Advanced Short-Term Forecasting of Wind Power Production, Proceeding of the European Wind Energy Conference EWEC'97, Ireland, 751–754.
[24] Kamal, L., & Jafri, Y. Z. (1997). Time series models to simulate and forecast hourly average wind speed in Quetta. Solar Energy, 61(1), 23–32.
[25] Schlink, U., & Tetzlaff, G. (1998). Wind speed forecasting from 1 to 30 minutes. Theoretical and Applied Climatology, 60, 191–198.
[26] Torres, J. L., García, A., de Blas, M., and de Francisco, A. (2005). Forecast of hourly averages wind speed with ARMA models in Navarre. Solar Energy, 79(1), 65–77.

[27] Sfetsos, A. (2000). A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renewable Energy, 21(1), 23–35.
[28] Alexiadis, M. C., Dokopoulos, P. S., Sahsamanoglou, H. S., & Manousaridis, I. M. (1998). Short term forecasting of wind speed and related electric power. Solar Energy, 63(1), 61–68.
[29] Cadenas, E., & Rivera, W. (2009). Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks. Renewable Energy, 34(1), 274-278.
[30] Akyuz, E., Demiral, D., Coskun, C., & Oktay, Z. (2013). Estimation of the Monthly Based Hourly Wind Speed Characteristics and the Generated Power Characteristics for Developing Bidding Strategies in an Actual Wind Farm: A Case Study. Arabian Journal for Science and Engineering, 38(2), 263-275.
[31] Akinci, T. C., & Nogay, H. S. (2012). Wind Speed Correlation Between Neighboring Measuring Stations. Arabian Journal for Science and Engineering, 37(4), 1007-1019.
[32] Heidari, M., Heidari, A., & Homaei, H. (2014). Analysis of Pull-In Instability of Geometrically Nonlinear Microbeam Using Radial Basis Artificial Neural Network Based on Couple Stress Theory. Computational Intelligence and Neuroscience, Article ID 571632.
[33] Li, P., Li, Y., & Guo, X. (2014). A Red-Light Running Prevention System Based on Artificial Neural Network and Vehicle Trajectory Data. Computational Intelligence and Neuroscience, Article ID 892132.
[34] Pusat, S., Akkoyunlu, M. T., Pekel, E., Akkoyunlu, M. C., Özkan, C., & Kara, S. S. (2016). Estimation of coal moisture content in convective drying process using ANFIS. Fuel Processing Technology, 147, 12-17.
[35] Akkoyunlu, M. T., Akkoyunlu, M. C., Pusat, S., & Özkan, C. (2015). Prediction of Accurate Values for Outliers in Coal Drying Experiments. Arabian Journal For Science And Engineering, 40, 2721-2727.
[36] Lapedes, A., & Farber, R. (1987). Nonlinear signal processing using neural networks: prediction and system modeling. Tech. Rep., LA-UR-87-2662, Los Alamos National Laboratory, Los Alamaos, New Mexico 87545.
[37] Li, G., & Shi, J. (2010). On comparing three artificial neural networks for wind speed forecasting. Applied Energy, 87(7), 2313–2320.
[38] Grassi, G., & Vecchio, P. (2010). Wind energy prediction using a two-hidden layer neural network. Communications in Nonlinear Science and Numerical Simulation, 15(9), 2262-2266.
[39] Pinson, P., & Kariniotakis, G. (2004). On-line assessment of prediction risk for wind power production forecasts. Wind Energy, 7(2), 119–132.
[40] El-Fouly, T. H. M., El-Saadany, E. F., & Salama, M. M. A. (2006). In: One day ahead prediction of wind speed using annual trends, IEEE Power Engineering Society General Meeting.
[41] Song, Y. D. (2000). A new approach for wind speed prediction. Wind Engineering, 24(1), 35-47.
[42] Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2011). Current methods and advances in forecasting of wind power generation. Renewable Energy, July, 1–8.
[43] Wang, X., Sideratos, G., Hatziargyriou, N., & Tsoukalas, L. H. (2004). In: Wind speed forecasting for power system operational planning, Proceedings of the 8th International Conference on Probabilistic Methods Applied to Power System. Iowa State University, Ames, Iowa, September 12–16.
[44] Anaklı, Z. (2009). A Comparison of data mining methods for prediction and classification types of quality problems. MSc Thesis, The Graduate School of Natural and Applied Sciences, Department of Industrial Engineering, Middle East Technical University, Ankara, Turkey.
[45] Özmen, A., & Weber, G. W. (2014). RMARS: Robustification of multivariate adaptive regression spline under polyhedral uncertainty. Journal of Computational and Applied Mathematics, 259 (Part B), 914-924.
[46] Alp, Ö. S., Büyükbebeci, E., Çekiç, A. İ., Özkurt, F. Y., Taylan, P., & Weber, G. -W. (2011). CMARS and GAM & CQP—Modern optimization methods applied to international credit default prediction. Journal of Computational and Applied Mathematics, 235(16), 4639-4651.