*Corresponding Author' Email: hasanhcevik@selcuk.edu.tr
Proceedings of the International Conference on Academic Research in Science, Technology and Engineering, Vol. 1, Issue. 1, 2022, pp. 32-38
DOI: https://doi.org/10.33422/icarste.v1i1.42

ISSN: 2783-7742 online

Day-Ahead Wind Power Forecasting Using Numerical Weather Prediction

Hasan Hüseyin Çevik*, Mehmet Çunkaş
Selçuk University, Turkey

Abstract

New power plants are included in the grid continuously to meet the increasing need for electrical energy. More than half of the power plants that have been newly added to the grid since 2015 are renewable energy power plants. As of 2022, the total installed renewable energy power increased by 11% compared to the previous year and reached 3146 GW. This increase will likely accelerate with the widespread use of electric vehicles. Wind energy is one of the renewable energy types with the highest installed capacity among renewable energy sources. Due to the nature of the wind, fluctuations in production cause adverse effects on the management of the electricity grid. Therefore, the forecast of renewable energy generation is very important for managing the electricity grid. This paper presents a wind energy forecast for the next 24 hours using data from a wind farm in Turkey. The forecast model consists of two stages. In the first stage, numerical weather predictions (NWP) have improved by using Artificial Neural Networks (ANN) and Artificial Bee Colony (ABC) methods. In the second stage, estimation is carried out by the ANFIS method. Improving the NWP using past NWP data and actual wind speed data increases the power forecast accuracy. The forecast results are compared with the forecasts made by the wind power plant (WPP). The proposed model has forecasted wind power with NRMSE 16.73%, and it has given more successful results than the forecast made by the power plant.

Keywords: anfis, artificial bee colony, artificial neural networks, numerical weather prediction, short-term wind power forecast

1. Introduction

The global renewable energy sector experienced record growth in 2022 by adding a capacity of 314 GW to increase energy capacities, despite the supply problems and delays caused by the pandemic. While investments in renewable energy sources reached 366 billion dollars, for the first time in global production, more than 10% of electricity production in the world was met from wind and solar energy (REN21 Renewable Energy Policy, 2022). While the increase in energy prices and the use of energy as a political tool increase the interest in renewable energy, the expectation that the electric energy demands of electric vehicles will increase triggers this interest even more.

Wind energy has the largest share of renewable energy sources with solar energy. Due to the nature of renewable energy, fluctuations in electricity production cause uncertainties in the management of the electricity grid and higher energy costs. For this reason, forecasting renewable energy production provides convenience for managing the electricity grid and contributes to the continuity of electrical energy (Tascikaraoglu & Uzunoğlu, 2014).

Wind power forecasts are named as very short-term, short-term, mid-term, long-term forecasts according to forecast horizons. Very short-term forecasts are preferred for frequency control and to reduce fluctuations in power grids. Short-term forecasts are decisive for the power grid manager in setting plant work schedules. It also plays an important role in the energy market proposals for power plant owners. Mid-term forecasts are a factor that is considered when determining the wind farm's maintenance programs. Long-term estimations are used in the feasibility phases before the plant is established, while they are used for profitability calculations after the plant installation.

Wind energy forecasting is one of the fields of study that remains popular due to the development of new models and methods that increase forecast accuracy. Wind power forecasts are classified in the four group as physical, statistical, artificial intelligence methods and hybrid methods (Wang et al., 2019). In physical forecasts, meteorological forecasts are tried to improve by using techniques such as mesoscale model and multi-timescale model (Yamaguchi et al., 2007). Statistical methods such as Moving Average (Dong et al., 2022) and Kalman filters (Guo et al., 2016) try to establish the relationship between historical time series and forecasts. Time series-based forecasting methods give more successful results in forecasts from the next 10 minutes to the next 6 hours. Historical time series data were analyzed to predict wind power for the next 10 minutes - 1 hour for five wind farms in Michigan by using the Chaotic analysis and east-square support vector machine methods. The forecast result was obtained with an NRMSE between 5.86% and 9.55% (Ji et al., 2022).

Artificial intelligence methods are frequently applied with numerical weather prediction (NWP) in studies for the next 24-78 hours of wind power forecasting studies. Neural networks (Çevik et al., 2019, A), neuro-fuzzy (Xu et al., 2022), and support vector machines (Lian & He, 2022) are examples of artificial methods. A wind power forecast is made for the day-ahead power market. In the first stage, five weather types are determined by analyzing NWP. Secondly, Convolutional Neural Networks and Long Short-Term Memory methods are applied for the forecast. Lastly, the forecast results are combined. RMSE is obtained as 12.15% (He et al., 2022).

Hybrid methods are a hot topic in wind power forecast studies. In some studies, hybrid methods are used as the main estimation method, while in some studies, different methods are used for the process phase, main estimation phase, cluster phase, and post-processing phases. (Çevik et al., 2019, B). There are studies in which hybrid methods such as artificial neural networks (ANN), particle swarm optimization (PSO), and radial motion optimization (RMO) are used together (Kerem et al., 2022).

This paper presents a short-term wind power forecast for the next 24 hours using data from a wind farm in Turkey. Forecasting is a daily and mandatory process in wind power plants. Wind farms have to give hourly production forecasts for the next day every day to a system called the day-ahead market. Forecast accuracy is a very important factor in the profit of the power plant. The accuracy of the estimations reduces the monetary penalties arising from estimation errors while allowing the plant to bid at the most optimum price.

2. Wind Power Parameters

The formula for the power generated from the wind is theoretically as follows:

$$P = \frac{1}{2}\,\rho\,A\,C_p\,V^3 \tag{1}$$

Where P is generated power, ρ is the air density, A is swept area of blades, V is the wind speed. If we examine the variables in the formula respectively, air density is not always the same. This is a parameter that changes according to the amount of gases in the air, the amount of humidity, and the temperature. A is the swept area, which changes with the blade's radius. The Cp is a coefficient calculated by the turbine manufacturer and varies according to each turbine. In fact, a turbine does not only have a Cp value, but has wind power curve drawn according to different Cp values for each wind speed. Our last variable, wind speed, is the most important factor affecting the power produced. As seen in Equation (1), it is proportional to the cube of the wind speed. Therefore, wind speed is the most important parameter for wind power estimation. A small error in wind speed changes the generated power too much. If you forecast the actual wind speed with an error of 10%, the theoretical wind power to be produced changes by 33.1%.

NWP obtained by applying satellite image measurements and various fluid mechanics operations is used in wind power forecasting. In other words, the wind speed value we use as an input in the wind energy estimation is an estimate. Wind power forecast is a difficult process as it contains wind speed forecast errors as well as its own estimation errors. The fact that the accuracy of the estimation increases the gain obtained from the power plant is another factor that increases the importance of wind power estimation.

Wind direction is also an important parameter in installing the power plant and estimating the power. According to the measurements in the field before the power plant is installed, the positions of the turbines are determined so that weak loses are minimized. In the next stage, after the power plant installation, each turbine operates by turning to the direction of the wind, according to the information coming from the wind direction sensors on each turbine. Thus, the amount of weak loss changes according to the wind direction and affects the power produced. If the power plant area has a rough structure, topographic features such as valleys or slopes are another factor that makes the direction important.

Figure 1: Wind rose

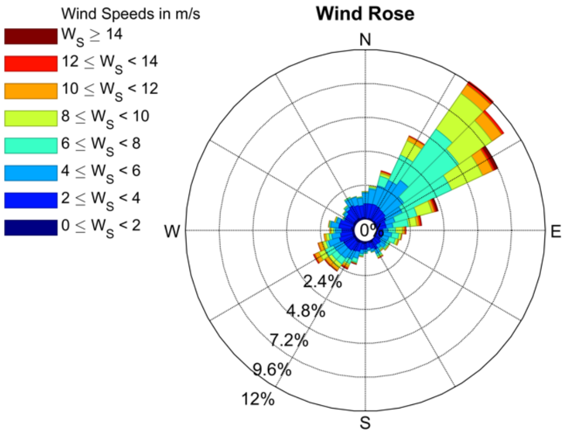

Table 1: Data Content

NWP	Measured data in WPP
Wind Speed Forecast	Measured wind speed for each turbine
Wind Direction Forecast	Measured wind direction for each turbine
Temperature Forecast	Generated power for each turbine
Air Pressure Forecast	Generated power for WPP

3. Data

The data used in this study belong to a power plant installed in Turkey. The data consists of two parts, NWP data and measurement data of the power plant. In NWP, there are wind speed forecasts, wind direction forecasts, temperature forecasts, and pressure forecasts for the next 24 hours for the power plant's location. The measurement values of the power plant are the wind speed measured from each turbine, the wind direction, the power produced, and the power produced by the power plant. These data are also given in Table 1. The wind rose formed by using the wind speed forecasts and wind direction forecasts is given in Figure 1. The dominant wind direction of the wind power plant is northeast. Wind speed in the range of 6-8m/s is the biggest share, according to the distribution of wind speed estimation.

4. Model

In this study, we proposed for next 24-hour wind power forecast. The general structure of the proposed model is given in Figure 2. Hybrid ABC-ANN and ANFIS methods are applied, respectively. The model consists of two stages. While the first step is the improvement of the wind speed forecast values, the second step is the forecast of the wind power values.

In the first stage, wind speed forecasted improved, NWP values are improved using historical wind speed predictions and measured wind speed values. Thus, NWP values have been converted into values that reflect the power plant area better. ANN and ABC methods are utilized for this stage. While ANN is selected to improve the NWP values, ABC optimizes some parameters. If there is a big difference in values between the input and output of the ANN, some problems are experienced. This can further distort the wind speed estimate when trying to improve it. The difference between ANN input and output must be limited to prevent this. The first parameter that the ABC method optimizes is this limit value. The second parameter is the value that should be added/subtracted when the limit value is exceeded. In case of exceeding the limit value, adding/removing the limit value directly is not considered. Instead, a value is specified to be added/subtracted when the limit is exceeded. This value is the second value that ABC optimizes. The last optimized value is the number of neurons in the hidden layer of the ANN. The optimized values of these three parameters obtained by the ABC method are given in Table 2.

Figure 2: General structure of the proposed model

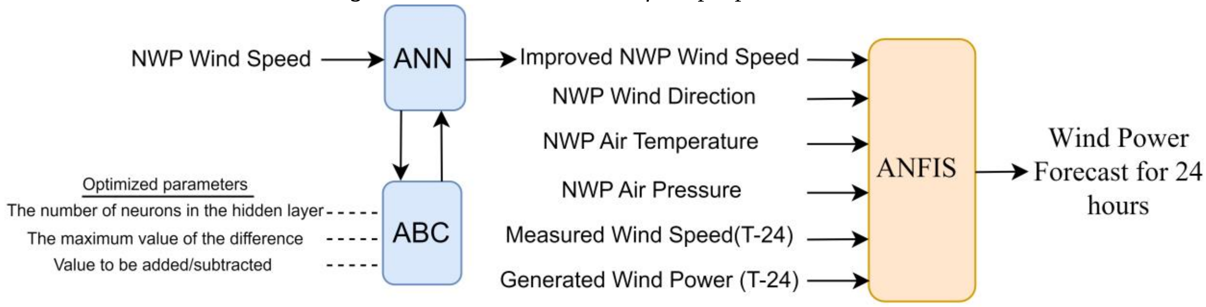

Table 2: Mean Absolute Error

	NWP - Measured Wind Speed	Improved NWP – Measured Wind Speed
Train	1.38	1.12
Test	1.39	1.21

The second stage is power forecasting. In this stage, improved NWP wind speed, NWP wind direction, NWP air temperature, NWP air pressure, measured wind speed(T-24), and generated wind power(T-24) are applied as inputs to power forecasting. As is known, NWP values are meteorological forecasts made for the power plant location 24 hours in advance. The use of NWP meteorological forecasts for power forecasting is a common approach to wind power forecasting. In addition to NWP, adding the measured wind speed and generated power values for T-24 hours as inputs reveals the relationship between the measurements the day before so that this relationship can be used in the next forecast. In the second stage, ANFIS is applied as the wind power forecast method.

5. Results

The data set is divided into three parts. 25% of the data is used to improve NWP values. The remaining part is reserved as 75% training and 25% testing for wind power estimation. The improved NWP and raw NWP values were compared with the measured wind speeds to see how the improvement of the NWP values affected, and the results are given in Table 3. In the test data, the MAE value between NWP-measured wind speed was found to be 1.39 m/s, while the MAE value between Improved NWP and measured wind speed was calculated as 1.21 m/s. As a result, the values given in Table 3 were obtained. It has been observed that the ANN method, some parameters optimized with ABC, improves the NWP value.

The results of wind power estimations by the ANFIS method are given in Figure 3 and Table 4. Here, the results of the power estimation are compared with the generated power value and the estimated values made by the wind farm. When the figure is examined, it is seen that the proposed method follows the estimated actual value more closely than the power plant's estimation. Especially in the 12-48 hours range, it gives better results than the estimation results of the proposed method. When the error values of all training and test data are examined, it is seen that the proposed method gives the best result with 16.73% NRMSE error value according to the estimation made with raw NWP and the estimation values made by the power plant.

Figure 3: Forecasted and generated wind power values for 72 hours

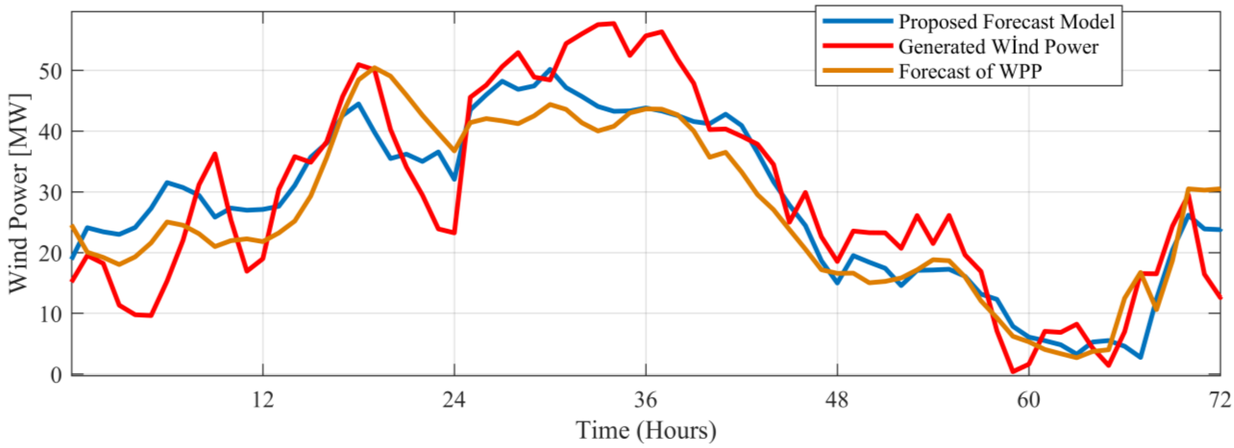

Table 3

	NWP Model	Improved NWP	Forecast of WPP
Train	15.74	13.59	**16.34**
Test	17.25	16.73	**17.23**

6. Conclusion

It is common to use NWP values for wind power estimates. By improving these values by using the wind speed values made in the past at the power plant site, NWPs can be developed by transforming them into values that can better express the power plant area. In this study, the NWP value was improved by ABC and ANN methods. The ANFIS method was used for wind power estimation. The results were compared with the power values made by the power plant. When the results are examined, it is seen that the proposed method gives successful results both according to the model using raw NWP and according to the estimation made by the power plant.

Acknowledgment

This study is supported by the Scientific Research Projects Unit of Selçuk University, Konya/Turkey.

References

Çevik H.H., Çunkaş M. and Özer O. (2019). Improving the next 24-hour wind power forecast using daily total wind energy forecast, *Proceedings of International Conference*, 27 Aralık, Dubai, BAE, pp. 36-40.

Çevik, H. H., Çunkaş, M. and Polat, K. (2019). A new multistage short-term wind power forecast model using decomposition and artificial intelligence methods, *Physica A: Statistical Mechanics and its Applications*, vol. 534, pp. 1-16.

Dong, Y., Ma, S., Zhang, H., and Yang, G. (2022). Wind Power Prediction Based on Multi-class Autoregressive Moving Average Model with Logistic Function, *Journal of Modern Power Systems and Clean Energy*, vol. 10(5), pp. 1184-1193.

Guo, J., Zhang, X. Y., Jang, W. and Wang, H. (2016). An improved wind power forecasting model based on eliminating outliers, *Wind Engineering*, vol. 40(1), pp. 50-58.

He, B., Ye, L., Pei, M., Lu, P., Dai, B., Li, Z. and Wang, K. (2022). A combined model for short-term wind power forecasting based on the analysis of numerical weather prediction data, *Energy Reports*, vol. 8, pp. 929-939.

Ji, T., Wang, J., Li, M. and Wu, Q. (2022). Short-term wind power forecast based on chaotic analysis and multivariate phase space reconstruction, *Energy Conversion and Management*, vol. 254, pp. 1-15.

Kerem, A., Saygin, A. and Rahmani, R. (2022). A green energy research: Forecasting of wind power for a cleaner environment using robust hybrid metaheuristic model, *Environmental Science and Pollution Research*, vol. 29(34), pp. 50998-51010.

Lian, L. and He, K. (2022). Wind power prediction based on wavelet denoising and improved slime mold algorithm optimized support vector machine, *Wind Engineering*, vol. 46(3), pp. 866-885.

REN21 Renewable Energy Policy. (2022). Renewables 2022-Global Status Report. Available: https://www.ren21.net/wp-content/uploads/2019/05/GSR2022_Full_Report.pdf

Tascikaraoglu, A. and Uzunoglu, M. (2014). A review of combined approaches for prediction of short-term wind speed and power, *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 243-254.

Wang, H., Lei, Z., Zhang, X., Zhou, B. and Peng, J. (2019). A review of deep learning for renewable energy forecasting, *Energy Conversion and Management*, vol. 198, pp. 1-16.

Xu, Y., Jia, L. and Yang, W. (2022). Correlation based neuro-fuzzy Wiener type wind power forecasting model by using special separate signals, *Energy Conversion and Management*, vol. 253, 1-19.

Yamaguchi, A., Ishihara, T., Sakai, K., Ogawa, T., and Fujino, Y. (2007). A physical-statistical approach for the regional wind power forecasting. *Proceedings of the European Wind Energy Conference EWEC*. Milan, Italy, pp. 1-4.