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Research Article

A New Artificial Neural Network Based Power Estimation Study for Wind Energy Systems

Bahtiyar Taşdemir[1], **Mustafa Yaz** [2]

[1]Yozgat Bozok University, Department of Electrical and Electronics Engineering, 66100 Yozgat, TÜRKİYE
[2]Yozgat Bozok University, Department of Electrical and Electronics Engineering, 66100 Yozgat, TÜRKİYE

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Abstract
Today, the demand for electrical energy is constantly increasing, primarily due to the advances in the industrial sector. This increase in demand has made wind energy a prominent option in the search for alternative energy sources due to its low investment costs and environmental friendliness. However, accurate forecasting methods are needed due to the variability of wind energy production affected by meteorological data. Including additional parameters besides the existing meteorological data could help improve the accuracy of these forecasts. This study explores the impact of the particulate matter (PM10) parameter on wind energy prediction through the employment of an artificial neural network (ANN) model. The comparison of prediction results based on Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) demonstrates that, when it comes to the daily wind power prediction of the PM10 parameter, the prediction model based on the artificial neural network (ANN) makes a significant contribution.

Keywords
Artificial neural network, forecasting, optimization, wind power generation, particulate matter, performance metrics

**** Corresponding Author:** bahtiyartasdemir1830@gmail.com*

1. Introduction

The escalating global demand for energy has given rise to a plethora of challenges, including the depletion of natural resources and the onset of climate change (Zhang et al., 2023). Among the plethora of promising renewable energy sources, wind energy has garnered significant attention due to its renewability, environmental friendliness, minimal environmental impact, and abundance of resources (Xiao et al., 2017; Zhao et al., 2019). According to the Global Wind Energy Council (GWEC), the worldwide installed capacity of wind energy is projected to reach 117 GW in 2023, and the aggregate capacity is anticipated to attain 1 TW. Furthermore, it is predicted that the global installed wind energy capacity will exceed 143 GW by 2030 (https://gWec.Net, 10.2.2025). However, it should be noted that the variability of wind energy is a consequence of various factors, including wind speed, wind direction, and geographical considerations. Additionally, the integration of wind energy into the grid poses significant challenges to the safe and stable operation of the grid (Farah et al., 2022). Consequently, the accurate forecasting of wind energy generation is imperative for effective planning of diverse energy resources and enhancing energy utilization (Li et al., 2023). Figure 1 shows the global trend in wind energy capacity installation between 2015 and 2023.

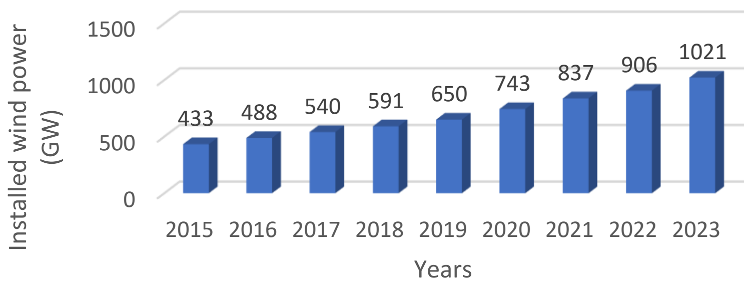

Figure 1. The installed capacity of global wind power plants

Concurrently with the augmentation of the global installed capacity of wind energy, Turkey has also experienced an escalation in the capacity of wind power plants (WPPs). According to the February 2024 report on installed capacity released by the Turkish Electricity Transmission Corporation (TEİAŞ), Turkey's total wind energy capacity stands at 11.9 GW (Teiaş, 2025). Figure 2 shows the evolution of wind energy's installed capacity in Turkey from 2015 to 2023.

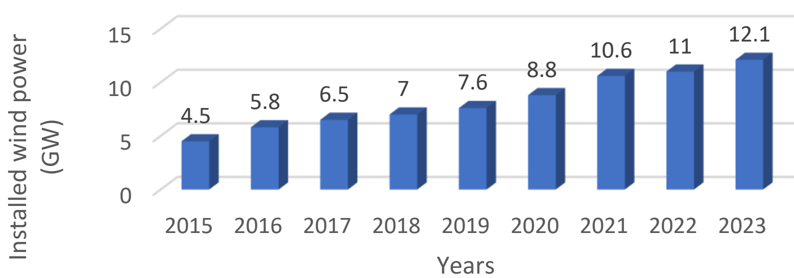

Figure 2. Installed capacity of wind power plants in Turkey

In reviewing similar studies in the literature, the input data, prediction intervals, validation and prediction models, and prediction results are compared for each forecast. Guo et al., an offshore wind farm in China with a nominal power of 202 MW is used. Hourly data is selected from 12 October 2017 to 31 January 2018, and the hourly output power of each wind turbine is recorded. Wind speed and wind direction are selected as inputs. The proposed prediction model uses the Wavelet Neural Network (WNN) model. As a result of the prediction, the mean absolute error (MAE), mean squared error (MSE), and RMSE values of 23.7%, 32.4%, and 23.2%, respectively, are obtained (Guo et al., 2022). Du et al., 10-minute data is taken from four wind farms in Galicia. Out of 1500 samples, 1200 are used as a training set, and 300 are used as a prediction set. The prediction model proposed in this study is the Empirical Mode Decomposition (CEEMD)-Multi-Objective Sine Cosine Algorithm (MOSCA)-WNN hybrid prediction model. This study has resulted in the emergence of a new hybrid forecasting model that employs the Multi-objective Moth Flame Optimization (MOMFO) algorithm for multi-step wind energy forecasting (Du et al., 2019).

Li et al., wind speed, temperature, humidity, pressure, and wind direction are used as input data. In this study, 15 minutes of data is collected. The proposed forecasting model is the Improved Aquila Optimization Algorithm (IAO) -Long Short Term Memory Algorithm (LSTM) hybrid model. In order to improve the prediction accuracy of the models, separate analyses are performed for the spring, summer, autumn, and winter seasons (Li et al., 2022). Abdoos., the following data is selected for use as the input data: wind speed, wind direction, and historical power data. The proposed prediction model is the Extreme Learning Machine Algorithm (ELM) prediction model. As a result of the comparison with ANN, Support Vector Machine Algorithm (SVM), and WNN prediction models on 22 January, 12 April, 18 August, and 27 November, the Normalized Root Mean Square Error (MMSE) and normalized Absolute Error (MAE) on 22 January is found to be 5.7053 and 3.9153, respectively. 5.7053 and 3.9153 on 22 January, 5.8785 and 4.0780 on 12 April, 3.2788 and 1.8947 on 18 August, 7.1851 and 4.4352 on 27 November. As a result of the 4-day comparison, the ELM forecast model has the best forecast accuracy compared to other forecast models (Abdoos, 2016).

Liao et al, historical power data, wind speed, wind direction, temperature, air density, and pressure are selected as input data. The data is recorded at 10-minute intervals between 28 July and 5 October 2019. The proposed prediction model is selected as Attention Network-LSTM. When the proposed prediction model is compared with other models, the coefficient of determination (R^2), RMSE, and MAE are 0.9898, 0.4184, and 0.2871, respectively. It is seen that the proposed prediction model has a better prediction effect on the temporal components (Liao et al., 2023). Wang et al., wind speed, wind turbine operating frequency, generator torque, generator current, and historical power data are taken as input parameters. The bidirectional LSTM-Autoregressive Integrated Moving Average Model (ARIMA) hybrid model is selected as the proposed forecasting model. As a result of comparing the proposed prediction models with other models, MSE, MAE, MAPE, and RMSE results of 12.332, 2.677, 1.74, and 3.511, respectively, are obtained (Wang et al., 2023).

Wang et al.,, a wind farm with an installed capacity of 337 MW in the northeast region of China is selected. Wind direction, wind speed, temperature, pressure, and air density between 2014 and 2018 are selected as input data. The data set is selected as a 60% training set, a 20% validation, and a 20% test set. The proposed prediction model is selected as the Multi-modal Multi-tasking Spatio-Temporal Attention Network (M2STAN). The proposed prediction model gave better results compared to other prediction models. Meng et al., historical power data, wind speed, and wind direction are selected as input data. It is validated with data with 10-minute sampling points between 1-15 January 2018. The first 10 days is selected as the training set and the last 5 days as the test set. The proposed forecasting model is an algorithm consisting of a Swarm Intelligence (SI), Particle Swarm Optimization (PSO), and Gated Recurrent Unit (GRU) hybrid forecasting model. Compared to other forecasting models, the proposed model validates its effectiveness in solving the learning problem for wind energy forecasting of newly constructed wind farms without sufficient data (Meng et al., 2022).

Ding et al.,, the proposed prediction model is selected as the CEEMD-Whale Optimization Algorithm (WOA)-Kernel Extreme Learning Machine (KELM) hybrid prediction model. When the proposed prediction model is compared with other models, the RMSE, MAE, and MAPE values are 0.4305, 0.2911, and 6.66, respectively (Ding et al., 2022). Jiang & Liu, the data sampling interval is 10 minutes, and 4199 data sets are used as the training set, and 1800 data sets are used as the test set. The proposed forecast model is a Batch Empirical Mode Decomposition (BEMD)-PSO-LSTM hybrid forecast model (Jiang & Liu, 2023).

Yamaçlı, LSTM-based time series forecasting algorithm adapted with different sampling and clustering options has been implemented to address the problem of forecasting the power generated from wind energy systems. Firstly, wind speed prediction is performed with the algorithm, and the results obtained are presented with different error metrics. In all case studies, the highest MSE was 0.3923 and the highest normalized RMSE was 0.6264. When all the results are analyzed, it can be seen that the effect of clustering decreases when the complexity of the inputs increases (Yamaçlı, 2025). Öztürk et al. analysed the wind potential and installed power plant power of the provinces of the Central Anatolia Region. The estimation of wind energy production in the Kırşehir region of Central Anatolia between 2024 and 2028 is the subject of this study. In the forecasting study, the artificial neural network (ANN) model, which is extensively utilised in the extant literature for wind power forecasting, was employed. In order to evaluate the performance of the proposed prediction model, the OMYH value was realised as 6.46% in the wind power forecast for 2023 (Öztürk et al., 2025).

Symbols and Abbreviations

ANN	Artificial Neural Network
PM10	Particulate Matter
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
GWEC	Global Wind Energy Council
WPPs	Wind Power Plants
TEİAŞ	Turkish Electricity Transmission Corporation
WNN	Wavelet Neural Network
MAE	Mean Absolute Error
MSE	Mean Squared Error
CEEMD	Complementary Ensemble Empirical Mode Decomposition
MOSCA	Multi-Objective Sine Cosine Algorithm
MOMFO	Multi-Objective Moth Flame Optimization
IAO	Improved Aquila Optimization Algorithm
LSTM	Long Short-Term Memory Algorithm
ELM	Extreme Learning Machine Algorithm
SVM	Support Vector Machine Algorithm
nRMSE	Normalised Root Mean Square Error

nMAE	Normalised Absolute Error
ARIMA	Autoregressive Integrated Moving Average Model
M2STAN	Multi-modal Multitasking Spatio-Temporal Attention Network
SI	Swarm Intelligence
PSO	Particle Swarm Optimization
GRU	Gated Recurrent Unit
WOA	Whale Optimization Algorithm
KELM	Kernel Extreme Learning Machine
BEMD	Batch Empirical Mode Decomposition
XOR	Exclusive OR
R^2	Coefficient of Determination

2. Material and Method

This chapter delineates the primary methodologies employed to accomplish the objective of this research, as outlined in the introduction. The prediction of wind power from wind turbines can be made using improved forecasting models to achieve higher accuracy and reliability, thus reducing the overall cost of the system. The artificial neural network forecasting method is utilized to ensure the acquisition of precise results and the power available to the electricity sector.

2.1. Artificial neural networks

Modern artificial intelligence did not formally emerge until 1956. Artificial intelligence is coined at a conference at Dartmouth College in Hanover, New Hampshire, in 1956. Shaping the existence of artificial intelligence is not so easy. Between 1974 and 1980, known as the "AI winter," many publications criticizing this process are published. After the publication, state support for artificial intelligence decreased. The decline in this field revived after the British state competed with the Japanese in 1980. In other words, according to Dr Robert Hecht-Nielsen, the first commercial developer of the artificial neural network, "an artificial neural network is a computing system consisting of simple interrelated elements that process information by generating a mobile response to external inputs (Caudill, 1987). According to Teuvo Kohonen, "Artificial neural networks are a progressive arrangement of a large number of basic elements connected in parallel, interacting with real-world objects in the same way as the biological nervous system (Kohonen, 1987).

The first studies on artificial intelligence ia conducted by McCulloch and Pitts, who studied the physiology of artificial neural networks and propositions using Turing's model. Functions only have "and" and "or" logical expressions, and it is stated that artificial neural cells would acquire the ability to learn with neuron logic. The work of scientists such as Hebb, Minsky, Edmonds, McCarthy, Shannon, and Rochester pioneered subsequent ANN research. Newell and Simon presented their work proving the first theory and their Physical Symbol Conjecture is the starting point for those working with human-independent intelligence systems (Saraç, 2004). Figure 3 shows the history of the development of ANNs. Change in the installed wind energy capacity in Turkey between 2015 and 2023.

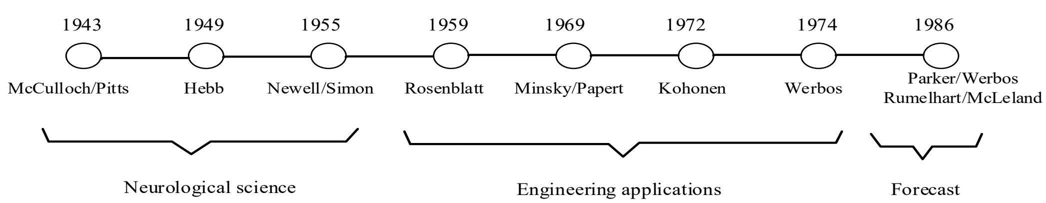

Figure 3. Development history of artificial neural networks

In their 1969 book "Perceptron," Papert and Minsky showed that single-layer artificial neural networks could not solve simple problems such as exclusive OR (XOR). This event led to the disruption of ANN's work. However, thanks to the research of scientists such as Hoppfield, Amari, Anderson, Arbib, Fukushima, Grossberg, Kohonen, Little, Malsburg, Broomhead, Lowe, Parker, and Werbos, ANN has developed and reached its current form. The Back Propagation Algorithm, developed by Rumelhart and McClelland for multilayer networks, is used by Parker and Werbos in 1986 to solve the XOR problem. Beginning in the 1990s, ANN research gained momentum. With the development of various fast-learning algorithms, it moved from theoretical and laboratory studies and started to be widely used in solving problems encountered in daily life. Just as there are nerve cells in biological neural networks, there are artificial neural cells in artificial neural networks. In engineering science, these artificial neural cells are also called process elements. In Figure 4, each process element has five essential components: inputs, weights, summation functions, activation functions, and outputs (Öztemel, 2006).

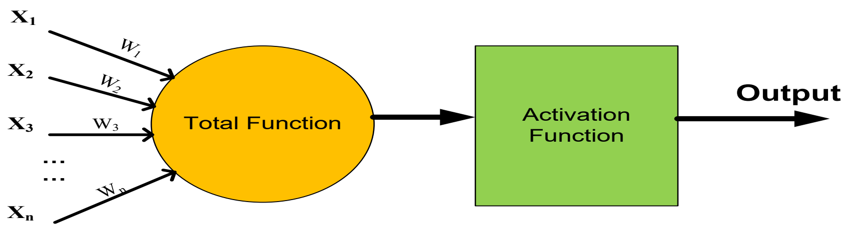

Figure 4. Artificial neural cell structure

Once the initial weight values are determined, each piece of information (x_i) coming from the cells in the input layer is multiplied by the weight value (w_i) of its respective connection and the total net input (s) value of each cell in the hidden layer is found with the help of the aggregate function. The aggregation function that generates the net input can be any aggregation operation, such as summing, averaging, or taking the largest or smallest input values multiplied by the weight values, depending on the network structure used. There is no formula for finding the most appropriate type of aggregation function for a problem. The combining function to be used is usually found by trial and error. A simple aggregation function that performs addition gives in Equation 1.

$$s = \sum x_i w_i \tag{1}$$

Artificial neural networks are systems created by connecting artificial neural cells in layers. The objective of such networks is to facilitate the resolution of intricate problems through emulation of the human brain's capacity for learning and rapid decision-making under diverse conditions, employing models that are simplified (Koç et al., 2004). The structural composition of an artificial neural network is as follows: it consists of three layers - input, hidden, and output. The input layer contains neurons that receive initial data from input factors. These neurons do not perform any processing on the input values; rather, they transmit them to the next layer. The output layer, in turn, consists of neurons that carry out the outputs or pass them on to another network (Anderson & McNeill, 1992). The intermediate layer, known as the 'hidden layer,' is positioned between the input and output layers. This is responsible for performing complex mathematical calculations and transferring data (Ray et al., 2023). In contrast to the input and output layers, which comprise a single layer, the hidden layer can comprise multiple layers. The neural network depicted in Figure 5 is comprised of one input layer, one hidden layer, and one output layer.

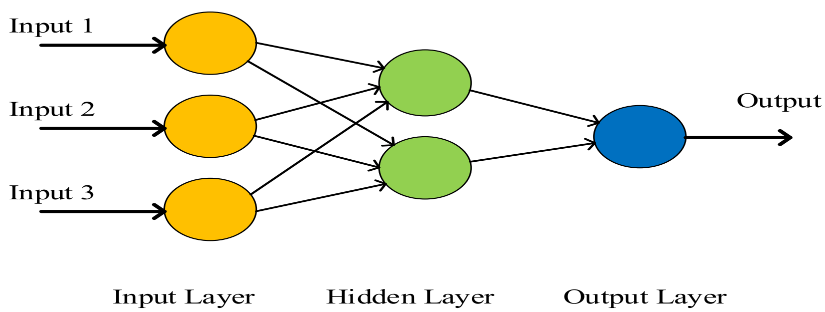

Figure 5. Artificial neural network

In this study, an ANN model with 4 input layers, one hidden layer, and one output layer is used for daily wind energy power forecasting. In the structure of ANN, a single hidden layer with 5 neurons and a sigmoid activation function is used because it is easy to calculate the derivative by compressing the inputs between 0 and 1. The trial-and-error method was adopted to determine the number of neurons in the hidden layer. The feed-forward neural network structure is favored in this research due to its ability to predict results and its effectiveness in tasks such as pattern recognition, visual recognition, and time series prediction. In the context of feed-forward neural networks, processing elements are generally arranged in layers. The transmission of signals occurs in a unidirectional manner from the input layer to the output layer through connections. In a feed-forward neural network, the cells are organized in layers, and the outputs of the cells in each layer are passed as input to the next layer with weights. The input layer conveys the information received from the external environment directly to the cells in the hidden layer without undergoing any modification. The information is processed in the hidden and output layers, and the final output of the network is obtained.

2.2. Description of the dataset

A real wind power plant dataset is used for forecasting using the artificial neural network method. The data set includes temperature, historical power data, wind direction, wind speed, and PM10 data as inputs from 01.06.2021 to 31.08.2021. Particulate matter with aerodynamic diameters less than 10 µm is called PM10. Aerodynamic diameter involves transporting and collecting particulate matter (Dubey & Pervez, 2008). PM10 Today, PM10 parameters can be detected with the help of fixed stations or portable measurement devices (Karakoç & Ekercin, 2024). The PM10 data used in the study is obtained from the air quality monitoring station of the Northern Central Anatolia Clean Air Center Directorate of the Ministry of Environment, Urbanization, and Climate Change.

In the data set utilized for the ANN prediction model, 80% of the data is allocated to the training set, 10% to the validation set, and 10% to the test set. The training set is responsible for training the proposed prediction model. The validation set, in turn, is employed to assess the efficacy of each parameter during the training period. The test set tests the parameters after the learning process is completed. The proportions chosen can be influenced by the dataset's size, the task's complexity, and the amount of training, validation, and test set data. To build an effective model, one must have enough training data, and to accurately evaluate performance, one must have enough validation and test data (Ağbulut et al., 2021).

2.3. Evaluation indexes

The root mean square error provides information about the short-term performance of forecasting models. It is imperative to note that the RMSE value is always positive, and it is therefore considered optimal for the value to be close to zero. RMSE is calculated using Equation 2 (Teke et al., 2015).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i - \bar{Q}_i)} \tag{2}$$

MAPE in percentage terms is a metric used to assess the accuracy of a model's predicted values by calculating the average distance between the predicted values and their true values. The presence of outliers, such as MAE, is not a concern in this context, as the absolute value is utilized in the calculation. As both MAE and RMSE have values ranging from zero to positive infinity, this method can analyze the model's performance by scaling the predicted values relative to the true value. MAPE is calculated using Equation 3 (Lever et al., 2016).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Q_i - \bar{Q}_i}{Q_i}\right| \tag{3}$$

In this study, Q_i denotes the actual wind power at time i, $\bar{Q}_i$ denotes the predicted wind power at time i, and n denotes the total number of predictions.

3. Simulation Results

In this study, two data sets is created for daily power forecasting. In Dataset-1, temperature, wind direction, historical power data, and PM10 are input parameters. In Dataset 2, wind speed, wind direction, historical power data, and temperature are input parameters. ANN-based prediction models are constructed for the training, testing and validation data sets for Data Sets 1 and 2. RMSE and MAPE are used as error evaluation indices to facilitate a comparison of the prediction results. The power output estimation results for the training set with Dataset-1 are shown in Figure 6. According to the simulation results, the error values for the training set, RMSE, and MAPE are 25.64 MW and 16.01%, respectively.

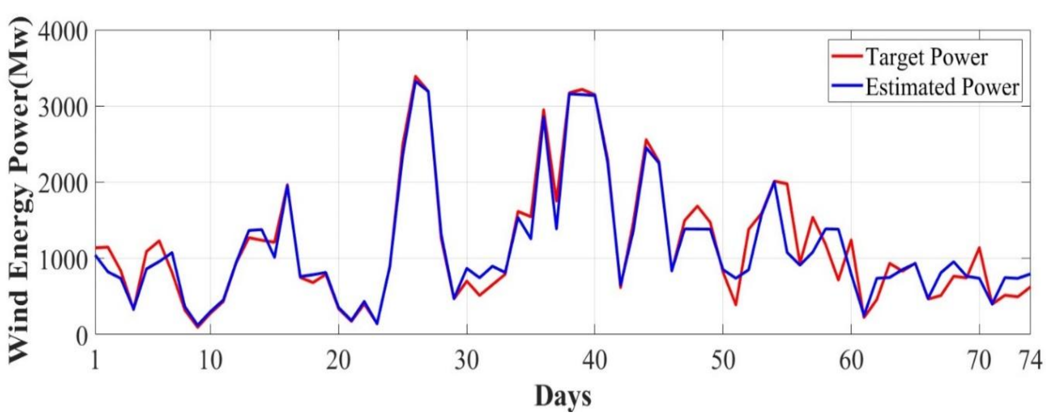

Figure 6. Power output estimation results for the training set of datasets 1

After the model training using dataset 1, the power output prediction results obtained on the validation set are visually presented in Figure 7. The prediction performance obtained is an important indicator to evaluate the overall performance of the model on the validation data. In this context, the error metrics calculated for the validation set are 34.27 MW and 13.59% for RMSE and MAPE, respectively.

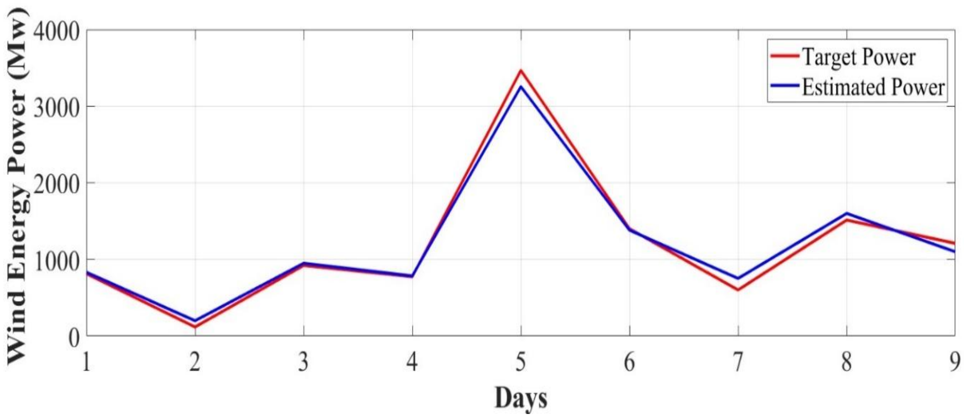

Figure 7. Power output estimation results for the validation set of datasets 1

The evaluation of the power output predictions obtained as a result of the model training using Dataset-1 on the test data is presented in Figure 8. According to the error metrics used to quantitatively evaluate the prediction performance, the RMSE calculated for the test set is 74.69 MW and the MAPE is 14.27%.

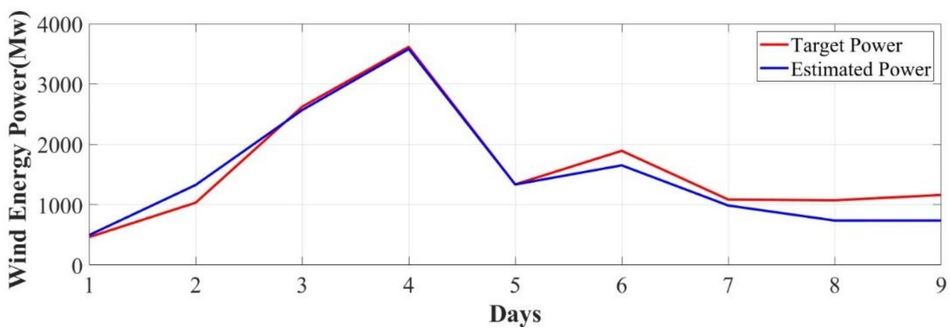

Figure 8. Power output estimation results for the test set of datasets 1

The power output estimation results for the training set with dataset 2 are shown in Figure 9. According to the estimation results, the error values for the training set RMSE and MAPE are 36.74 MW and 19.29%, respectively.

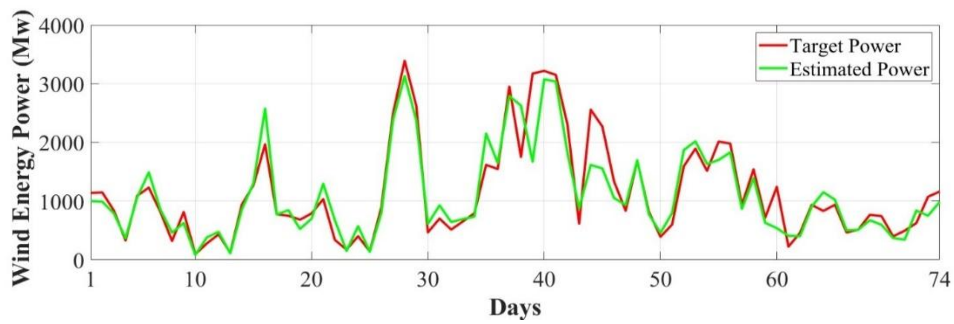

Figure 9. Power output estimation results for the training set of datasets 2

The power output prediction performance of the model developed using Dataset-2 on the validation set is visually presented in Figure 10. As can be seen from the figure, there is a certain correlation between the predicted power output values and the actual measurement data, but some deviations are observed. The predictive performance of the model on the validation data is quantitatively evaluated with commonly used error measures. In this context, the RMSE value was calculated as 90.43 MW and the MAPE value as 17.84%.

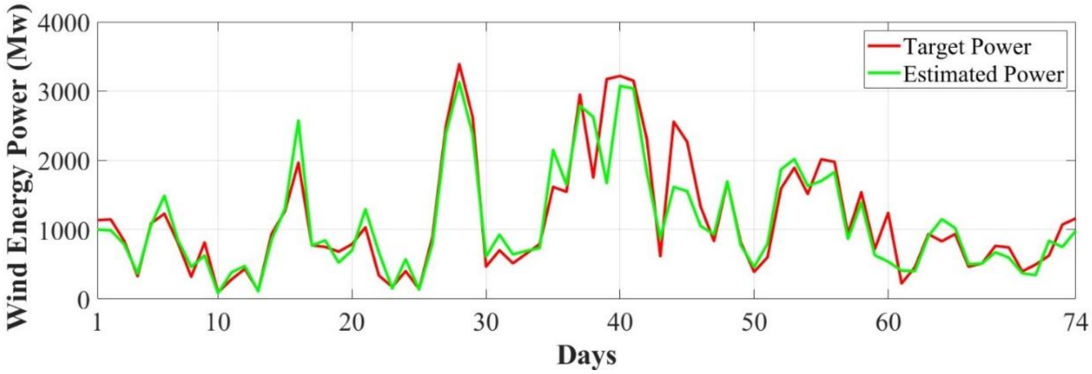

Figure 10. Power output estimation results for the validation set of datasets 2

The power output estimation results for the test set with dataset 2 are shown in Figure 11. According to the estimation results, the error values for the test set RMSE and MAPE are 142.89 MW and 20.36%, respectively.

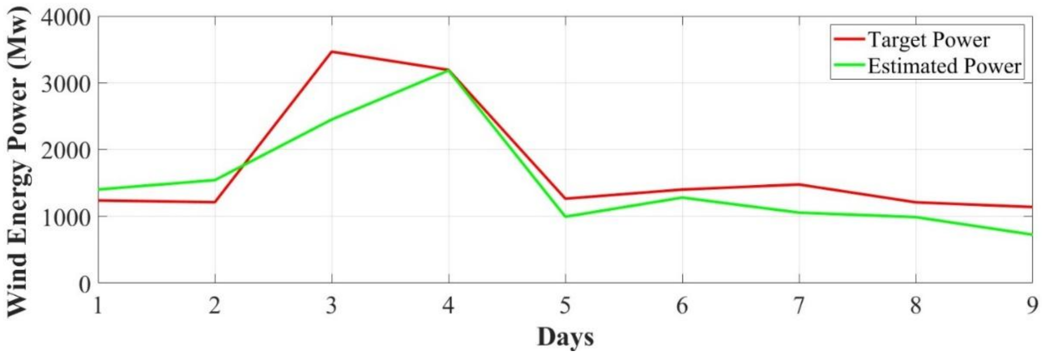

Figure 11. Power output estimation results for the training set of datasets 2

Actual and predicted RES output powers for all data sets are shown in Figure 12. According to the estimated power values in data set 1 RMSE and MAPE, the error values are 22.13 MW and 15.61%, respectively. In dataset 2, the error values according to the estimated power values RMSE and MAPE are 33.87 MW and 19.25%, respectively. In line with these results, the ANN-based prediction model developed using Dataset-1 gave better results than the prediction model developed using Dataset-2. It is concluded that the PM10 input parameter used in Dataset-1 increases the prediction accuracy of RES power output.

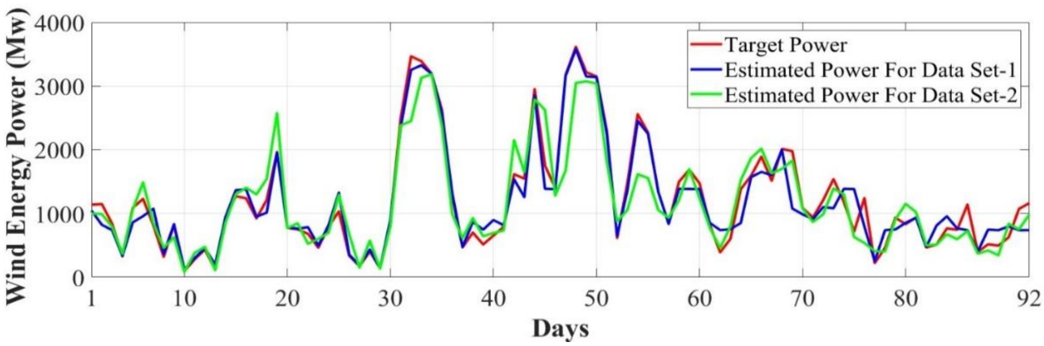

Figure 12. Actual and predicted RES output powers for all data

Table 1 gives the MAPE and RMSE values obtained from the ANN prediction model using datasets 1 and 2.

Table 1. MAPE and RMSE values for the datasets

Dataset/ Evaluation Index	Mape (%)	RMSE(MW)
Data set-1 training	16.01	25.64
Data set-2 training	19.29	36.74
Data set-1 validation	13.59	34.27
Data set-2 validation	17.84	90.43
Data set-1 test	14.27	74.69
Data set-2 test	20.36	142.89
Data set-1 all	15.61	22.13
Data set-2 all	19.25	33.87

4. Conclusion

Wind energy is an essential renewable energy source, but its sensitivity to meteorological factors poses a significant challenge for power systems. To address this inherent problem in wind power systems, accurate estimation of RES power is of great importance. This study performs a comprehensive analysis using two datasets covering meteorological parameters and WPP power generation. The primary objective of the present study is to undertake a comprehensive evaluation of the impact of the PM10 parameter on the forecasting of wind power. An artificial neural network model is applied using the generated datasets. As a result of this estimation, the Data Set 1 RMSE value was 22.13 MW and the MAPE value was 15.61%. For data set 2, the RMSE value was 33.87 MW and the MAPE value was 19.25%. It is observed that including the PM10 parameter in the ANN model significantly contributed to improving the prediction accuracy. Future research could investigate the impact of other air pollution parameters on RES power forecasting and seasonal variations of the particulate matter parameter in combination with the refined hybrid model.

References

Abdoos, A. A. (2016). A new intelligent method based on a combination of VMD and ELM for short-term wind power forecasting. Neurocomputing, 203, 111–120. https://doi.org/10.1016/j.neucom.2016.03.054

Ağbulut, Ü., Gürel, A. E., & Biçen, Y. (2021). Prediction of daily global solar radiation using different machine learning algorithms: Evaluation and comparison. Renewable and Sustainable Energy Reviews, 135, 110114. https://doi.org/10.1016/j.rser.2020.110114

Anderson, D., & McNeill, G. (1992). Artificial neural networks technology. Kaman Sciences Corporation.

Caudill, M. (1987). Neural network part 1. AI Expert, 2(12), 46–52.

Ding, Y., Chen, Z., Zhang, H., Wang, X., & Guo, Y. (2022). A short-term wind power prediction model based on CEEMD and WOA-KELM. Renewable Energy, 189, 188–198. https://doi.org/10.1016/j.renene.2022.02.108

Du, P., Wang, J., Yang, W., & Niu, T. (2019). A novel hybrid model for short-term wind power forecasting. Applied Soft Computing, 80, 93–106. https://doi.org/10.1016/j.asoc.2019.03.035

Dubey, N., & Pervez, S. (2008). Investigation of variation in ambient PM10 levels within an urban-industrial environment. Aerosol and Air Quality Research, 8(1), 54–64. https://doi.org/10.4209/aaqr.2007.07.0033

Farah, S., David, A. W., Humaira, N., Aneela, Z., & Steffen, E. (2022). Short-term multi-hour ahead country-wide wind power prediction for Germany using gated recurrent unit deep learning. Renewable and Sustainable Energy Reviews, 167, 112700. https://doi.org/10.1016/j.rser.2022.112700

Global Wind Energy Council. (2025). GWEC. https://gwec.net Date of acces: 10 February 2025

Guo, N.-Z., Shi, K.-Z., Li, B., Qi, L.-W., Wu, H.-H., Zhang, Z.-L., & Xu, J.-Z. (2022). A physics-inspired neural network model for short-term wind power prediction considering wake effects. Energy, 261, 125208. https://doi.org/10.1016/j.energy.2022.125208

Jiang, T., & Liu, Y. (2023). A short-term wind power prediction approach based on ensemble empirical mode decomposition and improved long short-term memory. Computers and Electrical Engineering, 110, 108830. https://doi.org/10.1016/j.compeleceng.2023.108830

Karakoç, O., & Ekercin, S. (2024). Generation of PM10 map with Sentinel-2 satellite images: The case of Çankırı Province. Afyon Kocatepe University Journal of Sciences and Engineering, 24(2), 350–359. https://doi.org/10.35414/akufemubid.1372761

Koç, M. L., Balas, C. E., & Arslan, A. (2004). Preliminary design of rock-filled breakwaters using artificial neural networks. Technical Journal, 15(74).

Kohonen, T. (1987, June 21). State of the art in neural computing. In IEEE First International Conference on Neural Networks.

Lever, J., Krzywinski, M., & Altman, N. (2016). Model selection and overfitting. Nature Methods, 13(9), 703–704. https://doi.org/10.1038/nmeth.3968

Li, Z., Luo, X., Liu, M., Cao, X., Du, S., & Sun, H. (2022). Short-term prediction of the power of a new wind turbine based on IAO-LSTM. Energy Reports, 8, 9025–9037. https://doi.org/10.1016/j.egyr.2022.07.030

Li, Z., Ye, L., Zhao, Y., Pei, M., Lu, P., Li, Y., & Dai, B. (2023). A spatiotemporal directed graph convolution network for ultra-short-term wind power prediction. IEEE Transactions on Sustainable Energy, 14(1), 39–54. https://doi.org/10.1109/TSTE.2022.3198816

Liao, X., Liu, Z., Zheng, X., Ping, Z., & He, X. (2023). Wind power prediction based on periodic characteristic decomposition and a multilayer attention network. Neurocomputing, 534, 119–132. https://doi.org/10.1016/j.neucom.2023.02.061

Meng, A., Chen, S., Ou, Z., Xiao, J., Zhang, J., Chen, S., Zhang, Z., Liang, R., Zhang, Z., Xian, Z., Wang, C., Yin, H., & Yan, B. (2022). A novel few-shot learning approach for wind power prediction applying secondary evolutionary generative adversarial network. Energy, 261, 125276. https://doi.org/10.1016/j.energy.2022.125276

Öztemel, E. (2006). Artificial neural networks (2nd ed.). Papatya Publishing.

Öztürk, M., Kayabaşı, R., & Taşdemir, O. (2025). Wind energy potential of kırşehir and power analysis of wind power plants in the central anatolia region. Kahramanmaraş Sütçü İmam University Journal of Engineering Sciences, 28(1), 189-201. https://doi.org/10.17780/ksujes.1533576

Ray, S. S., Verma, R. K., Singh, A., Ganesapillai, M., & Kwon, Y.-N. (2023). A holistic review of how artificial intelligence has redefined water treatment and seawater desalination processes. Desalination, 546, 116221. https://doi.org/10.1016/j.desal.2022.116221

Saraç, T. (2005). Estimating software project duration using artificial neural networks [Master's thesis, Gazi University Institute of Natural Sciences].

Teke, A., Yıldırım, H. B., & Çelik, Ö. (2015). Evaluation and performance comparison of different models for the estimation of solar radiation. Renewable and Sustainable Energy Reviews, 50, 1097–1107. https://doi.org/10.1016/j.rser.2015.05.049

Türkiye Elektrik İletim A.Ş. (2025). TEİAŞ. https://www.teias.gov.tr

Wang, J., Zhu, H., Cheng, F., Zhou, C., Zhang, Y., Xu, H., & Liu, M. (2023). A novel wind power prediction model improved with feature enhancement and autoregressive error compensation. Journal of Cleaner Production, 420, 138386. https://doi.org/10.1016/j.jclepro.2023.138386

Wang, L., & He, Y. (2022). M2STAN: Multi-modal multi-task spatiotemporal attention network for multi-location ultra-short-term wind power multi-step predictions. Applied Energy, 324, 119672. https://doi.org/10.1016/j.apenergy.2022.119672

Xiao, L., Qian, F., & Shao, W. (2017). Multi-step wind speed forecasting based on a hybrid forecasting architecture and an improved bat algorithm. Energy Conversion and Management, 143, 410–430. https://doi.org/10.1016/j.enconman.2017.04.012

Yamaçlı, V. (2025). Long-term and short-term memory in wind power forecasting: the effect of data sampling and clustering. Kahramanmaraş Sütçü İmam University Journal of Engineering Sciences, 28(1), 202-215. https://doi.org/10.17780/ksujes.1535461

Zhang, F., Li, N., Li, L., Wang, S., & Du, C. (2023). A local semi-supervised ensemble learning strategy for the data-driven soft sensor of the power prediction in wind power generation. Fuel, 333, 126435. https://doi.org/10.1016/j.fuel.2022.126435

Zhao, X., Wang, C., Su, J., & Wang, J. (2019). Research and application based on the swarm intelligence algorithms and artificial intelligence for wind farm decision systems. Renewable Energy, 134, 681–697. https://doi.org/10.1016/j.renene.2018.11.061