Research Article

RNN-Based Time Series Analysis for Wind Turbine Forecasting

Authors: Selahattin Barış ÇELEBİ Şehmus Fidan

To cite to this article: Çelebi, S. B. & Fidan, Ş. (2024). RNN-Based Time Series Analysis For Wind Turbine Forecasting, International Journal of Engineering and Innovative Research, 6(1), p 15-28.

DOI: 10.47933/ijeir.1387314

To link to this artice: https://dergipark.org.tr/tr/pub/ijeir/archive

International Journal of Engineering and Innovative Research

http://dergipark.gov.tr/ijeir

RNN-Based Time Series Analysis for Wind Turbine Energy Forecasting

Selahattin Barış Çelebi [1], Şehmus Fidan[2*],

[1]*Batman University, Department of Computer Technology, 72060, Batman, Türkiye
[2]Batman University, Department of Electronics and Automation, 72060, Batman, Türkiye

*Corresponding Author: sbariscelebi@gmail.com
(**Received:** 07.11.2023; **Accepted:** 23.11.2023)

https://doi.org/10.47933/ijeir.1387314

ABSTRACT: One significant source of renewable energy is wind power, which has the potential to generate sustainable energy. However, wind turbines have many challenges, such as high initial investment costs, the dynamic nature of wind speed, and the challenge of locating wind-efficient energy regions. Wind power prediction is crucial for effective planning of wind power generation, optimization of power generation, grid integration, and security of supply. Therefore, highly accurate forecasts ensure the efficient and sustainable operation of the wind energy sector and contribute to energy security, economic stability, and environmental sustainability. This study proposes a deep learning (DL) approach based on recurrent neural networks (RNNs) for long-term wind power forecasting utilizing climatic data. The input data that forms the basis of this study is obtained directly from a wind turbine system operating under real-world conditions. The proposed model in this study is based on a multilayer back-propagation neural network (RNN) architecture specifically designed to effectively handle complex data sets and time-dependent series. The architecture of the model is built on an RNN consisting of four separate layers, each with 50 hidden neurons, carefully structured to increase its capacity to capture complex features. To improve the robustness of the model and avoid overlearning, each RNN layer is followed by a dropout (regularizing) layer that randomly deactivates 20% of the neurons to enhance the generalization ability of the network. To finalize the prediction capability of the model, a linear function was chosen in the last layer to directly match the actual values. Evaluating the model performance metrics, the proposed architecture achieved a prediction accuracy of 91% R2 on the test dataset. The findings indicate that the proposed method based on multilayer RNN can successfully capture the relationships between the sequential data of the wind turbine.

Keywords: Recurrent Neural Networks, Machine learning, Wind power forecasting, Regression.

1. INTRODUCTION

The world is focusing on generating electricity using renewable energy and regulating energy demand [1, 2]. This method is crucial for creating an ecological and sustainable electricity system [3]. Wind energy stands out as a promising renewable resource for electricity generation. However, price fluctuations in energy use [4], changes in demand, and the instability of renewable energy production are foreseen as major problems in this field [5]. Therefore, it is critical to make highly accurate short- and long-term forecasts in the energy sector using historical meteorological data. For this, it is necessary to propose a model that helps make the right decisions. Such a model can increase stability by making energy projection more accurate [6, 7].

The use of wind energy is rising day by day. Many countries aim to reduce their carbon footprint and lower overall energy production costs by increasing green and renewable energy sources [8]. However, wind power generation is inherently variable and fluctuating. This is a factor that seriously affects the electricity grid [9]. In addition, it is necessary to ensure the balance between the amount of energy produced and consumption and to solve demand management problems [10]. In this study, a machine learning architecture is proposed to forecast the power generation of a wind power plant. In the proposed architecture, an RNN-based prediction model is trained with data from a real wind turbine. The performance results of the suggested architecture are analyzed using various metrics. In summary, the following objectives are aimed at in the study:

- Examining the performance of the suggested DL-based architecture for wind energy forecasting,
- Traditional machine learning-based methods may encounter difficulties due to performance degradation when faced with large datasets. Therefore, to improve prediction accuracy by developing a DL-based architecture,
- To clearly demonstrate the effectiveness of RNN-based architecture in power estimation with statistical performance indicators,

The rest of the paper has been structured into four sections. Section 2 summarizes the literature survey. Then, Section 3 presents the methodology applied to elaborate on the proposed RNN-based architecture. Then, the results are shown and discussed in Section 4. Section 5 concludes by summarizing the findings and conclusions of this study.

2. LITERATURE REVIEW

A successful forecasting model aims to perform the forecasting process with maximum accuracy [11, 12]. Forecasts for wind power contribute to better planning of energy systems and more efficient distribution of energy. Accurate forecasting of wind power is critical to avoiding technical and financial risks in advance [13]. Proposed models for actual power forecasting can be generally categorized into two main categories: machine learning-based or statistical methods [14]. In a study, four different models for power estimation were evaluated. There are two statistical and two machine-learning-based models. The findings demonstrated the improved prediction capabilities of machine learning algorithms [15]. Methods such as support vector machines (SVM) [16], decision trees [17], and artificial neural networks (ANNs) [18], which process data using predefined features and algorithms, are referred to as classical machine learning. In a study based on the SVM-based regression method, wind energy was successfully predicted. Shabbir et al. (2019) included variables such as wind speed and weather forecasts in their method. They compared the obtained results with convolutional time series analysis techniques. The simulation results indicated that the SVM-based model outperformed the other methods by approximately 30% [19].

ANNs are computer programs that mimic the learning and decision-making mechanisms of the human brain [20]. ANNs can be trained to learn the relationships between their inputs and outputs. They can also use this information to make predictions for new inputs [21, 22]. Mason et al. (2018) demonstrated that the ANN-based forecasting method demonstrated highly accurate forecasting performance by addressing output power differences due to wind speed differences between wind generators [23]. Similarly, in another study, ANN-based methods were used to predict wind power generation and electricity demand. It was observed that the proposed method was able to make successful forecasts up to approximately 2.5 hours in advance. However, the study concluded that the data set should be low-noise for the neural network-based model to be successful [24]. A new intelligent algorithm has been developed to predict wind energy power in each period using extreme learning machines [25] and self-adaptive evolutionary extreme learning machines (SAE-ELM). The results demonstrated the great efficacy of SAE-ELM-based models in this forecasting procedure [26].

These classical machine-learning-based methods have some problems. First, they lack advanced modeling methods to better understand the relationships between input data. Also, they may not provide the desired performance for large datasets [27, 28]. DL-based models can be used to solve these problems. DL is a sub-branch of machine learning that learns complex structures and patterns in large datasets using ANNs [29]. It has been effectively used in numerous fields, such as image recognition [30], energy prediction [31], healthcare [32], and construction [33]. DL consists of several sub-branches such as convolutional neural networks [34], recurrent neural networks (RNNs) [35], and transfer learning [36]. Time series data is a subset of sequential data [37]. Recurrent models such as RNNs adopt a sequential approach to processing the input values. Therefore, they can capture the temporal dependence between sequential data well [38, 39]. Research has demonstrated that recurrent models, as opposed to other well-liked machine learning methods like SVM and multilayer feed-forward neural networks, may predict sequential data more accurately [40]. RNN is known as an effective method for processing sequential data and time series analysis [41]. In another study, an RNN-based method is suggested to predict wind speed. In this way, long-term wind speed and power forecasts were obtained by using some meteorological data and RNN [42]. In another study, it was observed that the RNN-based model achieved a very small RMSE error value for turbine power output power prediction [43]. In this study, a multilayer RNN architecture is proposed to predict the actual power of the turbine.

When the results obtained from the above studies are evaluated, it can be deduced that machine learning techniques outperform statistical techniques in the prediction of energy. However, this success is closely related to the reliability of the data set. If sufficient and reliable data is available, machine learning-based algorithms can be quite successful in predicting energy output.

3. METHODS

3.1. Dataset Description

When using machine learning-based methods to predict turbine actual power, selecting the related features, which can be useful in solving problems, is a critical process. Therefore, it is necessary to carefully consider the factors affecting the turbine. The dataset used in this study belongs to a wind turbine in Turkey [44]. The proposed architecture uses data such as wind speed and wind direction as environmental factors as input. The dataset was recorded in 10-minute periods between 01.01.2018 and 31.12.2018. The dataset consists of 50530 records and five features. These attributes consist of wind speed (m/s), wind direction (°), theoretical power (kW), active power (kWh), and Date/Time.

The rated power of a turbine refers to the maximum amount of power that the turbine can produce at the ideal wind speed. This value is defined as the highest achievable power output (kW) at a given wind speed (8–12 m/s), which is specified in the design of the turbine. Figure 1 shows a graph of monthly wind power variation for one year. The red line on the graph shows the annual average power value (1492.18 kW).

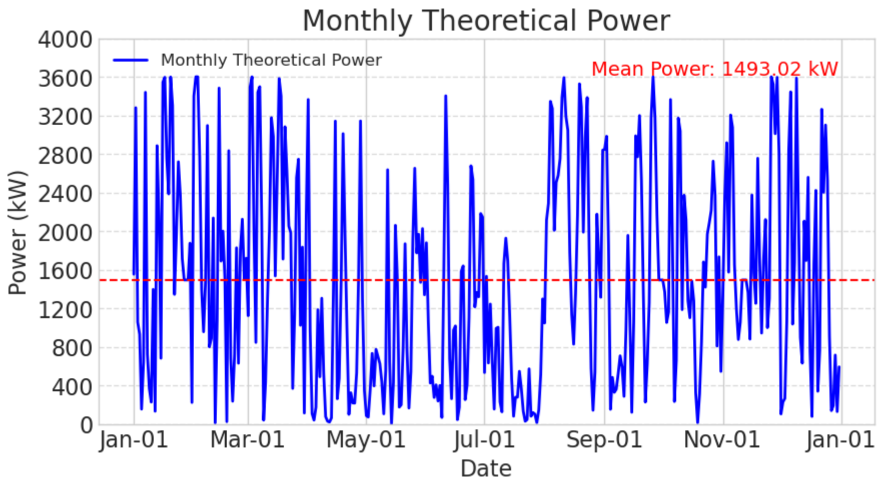

Figure 1. One-year theoretical power curve of the turbine

The actual power that can be obtained from a wind turbine is basically based on the principle that it is directly proportional to the kinetic energy of the wind, as shown in Eq. (1). Betz's law limits the maximum power that a wind turbine can extract from the wind, and this theoretical limit is defined as approximately 59.3% of the kinetic energy of the wind [9, 45].

$$P_w = \frac{1}{2}.\rho.A.C_p(\lambda,\beta)V^3 \tag{1}$$

In this equation, A stands for the turbine blade area (m^2), Cp represents the coefficient of performance, P_w signifies the turbine power, V denotes the wind speed (m/s), ρ represents the air density (1.225 kg/m³), β stands for the blade angle (°), and λ indicates the blade speed ratio. The blade area can be represented as in Eq. (2).

$$A = \pi R^2/4 \tag{2}$$

The coefficient of performance, which is another important parameter, varies depending on the blade speed ratio λ, wind speed V, angular rotational speed ω, and blade radius R. The blade speed ratio is shown in Eq. (3). The coefficient of performance can be determined using the equations in Eq. (4) and Eq. (5).

$$\lambda = \frac{R\omega}{V} \tag{3}$$

$$C_p(\lambda,\beta)=\mathrm{C}_1(\frac{C_2}{\lambda_i} - C_3 \cdot \beta - C_4)e^{-\frac{C_5}{\lambda_i}} + C_6\lambda \tag{4}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{5}$$

In Eq. (4), the coefficients are $C_1 = 0.5176$, $C_2 = 116$, $C_3 = 0.4$, $C_4 = 5$, $C_5 = 21$, and $C_6 = 0.0068$ [9]. However, this theoretical power calculation assumes the existence of a wind environment with an unlimited area coming from exactly the right direction to the wind blades. The efficiency of the turbine is reduced because of aerodynamic losses, mechanical friction, electrical losses, and other factors that reduce the actual power. Therefore, less than the theoretical power expected from a turbine is generated. The actual power is also expressed by the power coefficient (*Cp*) of the turbine, which is usually below the Betz limit (59.3%). Figure 2 shows the actual power curve obtained from the turbine for one year. When the graph is analyzed, it is seen that the average annual energy amount produced by the turbine is 1307.68 kW.

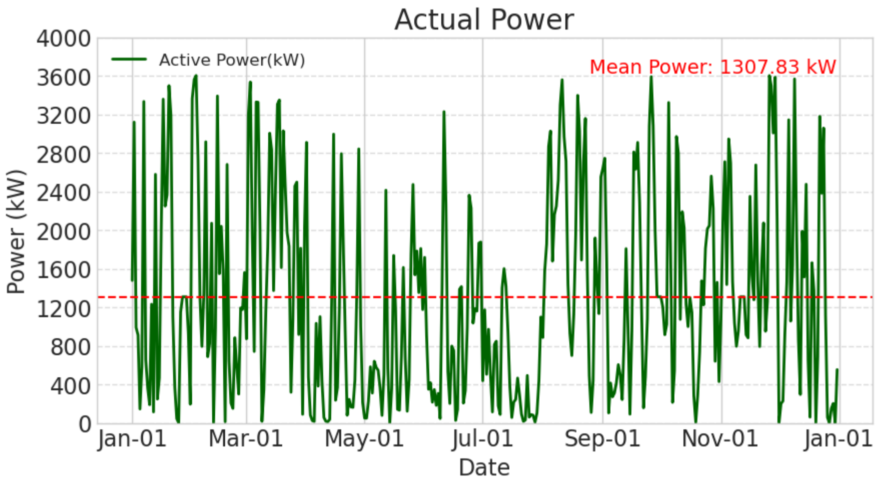

Figure 2. Actual power curve obtained from the turbine for one year

Considering the above information, an average annual power loss of approximately 185 kW occurs. In this case, more than 12% more power loss has occurred than the theoretically expected value. Figure 3 shows the theoretical (red) and actual power (blue) change curves against wind speed. When the graph is analyzed, it is seen that the actual power generated is variable and not compatible with the theoretical power from time to time.

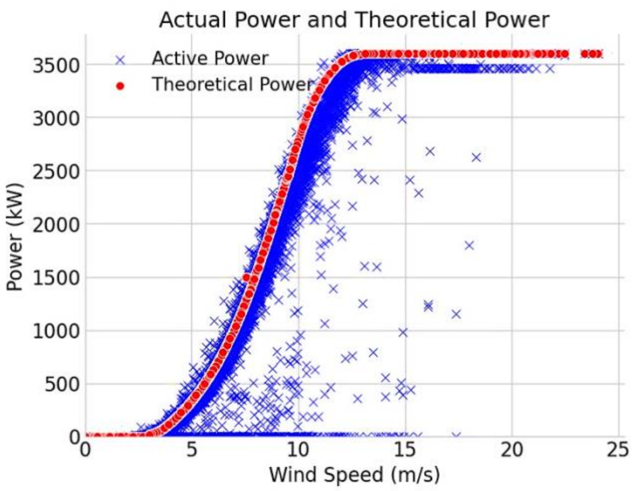

Figure 3. Theoretical & actual power curves against wind speed

3.2. Impact Factors Analysis

It is important to identify and quantify the impact of the characteristics in the dataset on actual wind energy production. Given the influence of various components on energy production, it is necessary to understand the relationships between these components. It may be useful to use a correlation matrix to examine these connections. The Pearson coefficient is a statistical term that measures the connection between two variables. This coefficient can determine the linear relationship between two variables and the strength of that relationship. It takes a value between -1 and +1 to explain the relationship between variables. As the coefficient value approaches 0, the relationship between the variables decreases. +1 represents a full positive relationship, while -1 represents a negative relationship. To measure the linear correlation between two continuous variables, the Pearson coefficient is defined as in Eq. (6) [46]:

$$r_{xy} = \frac{\sum(x_i - \bar{x})\sum(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}} \tag{6}$$

Where $\bar{x} = \frac{1}{n}\sum_{i=1}^{N} x_i$ points to the mean of x and $\bar{y} = \frac{1}{n}\sum_{i=1}^{N} y_i$ points to the mean of y and the r_{xy} is Pearson correlation coefficient. The correlation relationship between the variables can be analyzed on a heat map (Figure 4). There is a high and positive correlation between power generation and wind speed. The correlation coefficient is 0.91. However, there is a negative relationship between power and wind direction. In this case, the correlation coefficient between the two variables (-0.063) indicates a very weak negative relationship between the two variables.

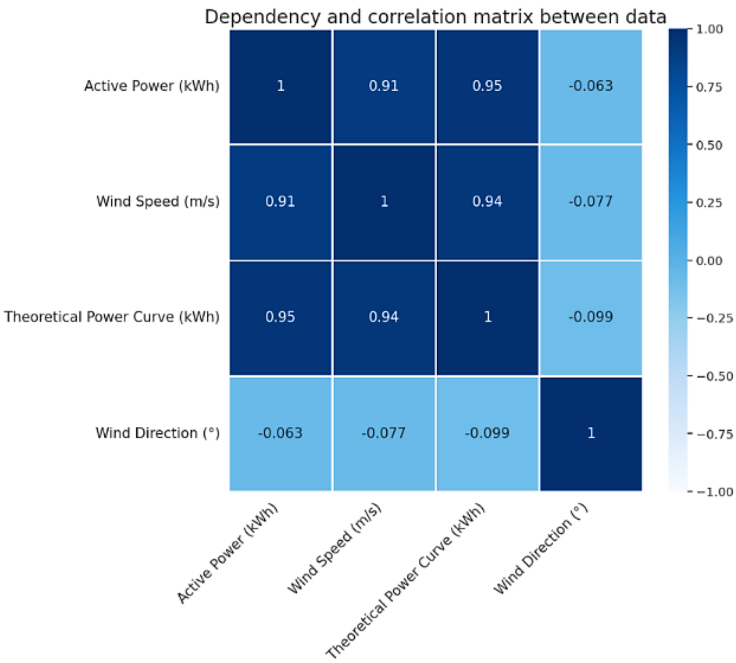

Figure 4. Actual power and impact factors

The parameters used for actual power estimation models can take different vector values. Therefore, standardizing these input vectors offers many advantages before entering the DL layers. For this purpose, the input features, or tensors, are scaled between 0 and 1 using a min-max scaler. The normalized value of an input value is calculated by Eq. (7). [47]:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{7}$$

Where x' represents the value to be normalized. x_{min} symbolizes the minimum value of the series, and x_{max} represents the maximum value in the series. The normalization process helps to evaluate different features on the same scale and allows the model to learn better.

3.3. Simple RNN

RNN is a machine learning technique that takes sequential data as input. Unlike other machine learning methods, it uses a recurrent connection architecture. This structure means that the current output of a cell is related to the input of the previous cell. In this way, the network could store information from previous outputs. Let $x= \{x_1, x_2,...,x_t\}$ be the input time series. And h_t the final state, y_t the predicted value to demonstrate the function of the RNN unit at time step t. Then, the hidden state h_t is expressed by Eq. (8) [48]:

$$h_t = f(h_{t-1}, x_t) \tag{8}$$

Where h_t is recalculated with the input x_t. This process involves adding the product of the weight matrix W_{xh} and the previous state h_{t-1}. Then, the sum of the weighted values is calculated by multiplying the weight W_{hh}. Finally, the sum is activated by a transfer function f. This equation can be calculated as shown in Eq. (9):

$$h_t = f(W_{hh} \cdot h_{t-1} + W_{xh} \cdot x_t) \tag{9}$$

The output y_t is calculated by multiplying the h_t by the output weight W_{hy}. This calculation can be shown as in Eq. (10).

$$y_t = f\left(W_{hy} \cdot h_t\right) \tag{10}$$

To obtain error information, the predicted output is compared to the target. After that, input is used to modify the weights in each layer until an acceptable error value is obtained. The RNN architecture is shown in Figure 5 [49].

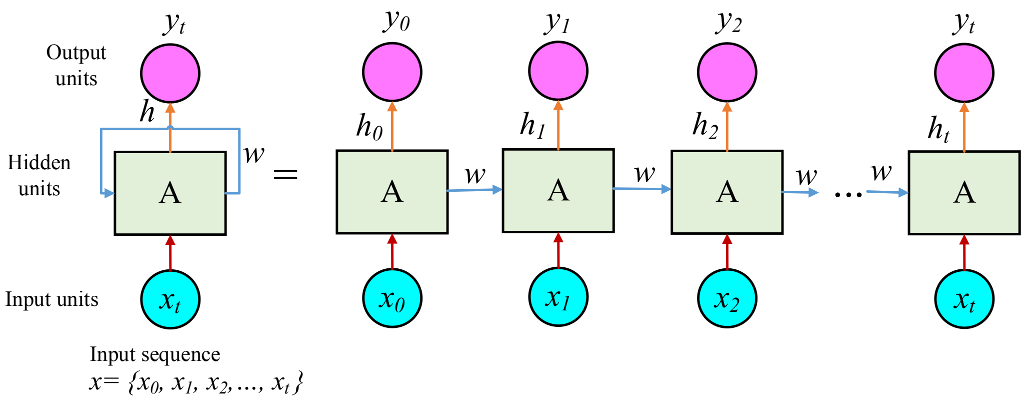

Figure 5. RNN cell architecture [49]

The approach suggested in this research consists of a four-layer RNN architecture. Each layer has 50 cells, and the "tanh" activation function is applied. To prevent overfitting, a 20% reduction is applied at the end of each layer. The last layer of the model is the dense layer, which produces a single prediction output. This layer uses the "linear" activation function (Table 1).

Table 1. RNN structure parameters

Layer	Output shape	Parameter
RNN	(,50,50)	2600
Dropout	(,50,50)	0
RNN	(,50,50)	5050
Dropout	(,50,50)	0

RNN	(,50,50)	5050
Dropout	(,50,50)	0
RNN	(, 50)	5050
Dropout	(, 50)	0
Dense	(,1)	21
Total Parameter		17801

3.4. Error Metrics

In this study, various statistical metrics are examined to evaluate the prediction results of the proposed DL-based architecture. These metrics include commonly used error measures such as RMSE (root mean square error), MSE (mean squared error), and MAE (mean absolute error). In addition, R^2 regression is used to determine the prediction accuracy of the model. In here:

- RMSE (Root Mean Square Error) computes the square root of the mean of the square root differences between the predicted and actual results.
- MAE calculates the mean results of the absolute differences between predicted and actual results.
- MSE calculates the mean square root of the squares of the prediction errors.
- R^2 measures the ability of the model to explain the observed outputs. The R^2 value ranges between 0 and 1. A higher R^2 value means that the data fits the regression line better.

The aim of the study is to demonstrate the successful prediction accuracy of the architecture by achieving lower MAE, MAPE, and RMSE values. In addition, the R^2 aims to measure the extent to which the independent variables explain the change in the dependent variables. Eq. (11–14) refers to R^2, RMSE, MSE, and MAE metrics, respectively [50, 51].

$$R^2 = \frac{\left(\sum_{i=1}^{N}(x_i^* - \overline{x_i^*})(x_i - \overline{x_i})\right)^2}{\sum_{i=1}^{N}(x_i^* - \overline{x_i^*})^2 \sum_{i=1}^{N}(x_i - \overline{x_i})^2} \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i^* - x_i)^2} \tag{12}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - x_i^*)^2 \tag{13}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - x_i^*| \tag{14}$$

Where x_i is the predicted, x_i^* is the true value, N is the sample size, $\overline{x_1}$ is the average estimated value, $\overline{x_1^*}$ is the average actual value.

4. RESULTS AND DISCUSSION

In this section, the performance findings of the proposed RNN-based energy prediction model are analyzed. The analysis of the results is important to evaluate how well the model works and how accurate the energy prediction is. This analysis will help us understand how effective the model is in real-world applications.

4.1. Experimental Settings

This study was carried out with the Python 3.10.12 programming language and the TensorFlow 2.12 library. The system has a 2199 MHz 4-core 64-bit processor and 32 GB of memory.

4.2. Hyperparameter and Optimization Techniques

The data set was subdivided into 20% tests, 20% validation, and 60% training. In this way, a total of 30318 samples were used for training, 10106 samples for validation, and 10106 samples for testing. Settings that have an effect on the performance results of the model are called hyperparameters. For the optimum determination of these settings, the model was evaluated with different parameters, and the best-performing values were selected. Firstly, the learning coefficient of the model was initialized as 1e-3. Adam Optimizer was used to improve the coefficient. The training was set to 200 epochs. The hyperparameters used in the proposed model are shown in Table 2.

Table 2. Training hyperparameters

Hyperparameter	Parameter
Learning rate	1e-3
Optimizer	Adam
Batch size	32
Loss function	MSE
Number of epochs	200
Re-scaling	MinMaxScale [0,1]

A linear regression plot visually illustrates the relationship between two variables. Figure 6 shows the linear regression plot of the proposed method. As can be seen from the figure, the proposed method accurately predicted the test data set. When the graph is analyzed, it is seen that the proposed DL-based method has achieved high accuracy performance with an R^2 value of 0.9168.

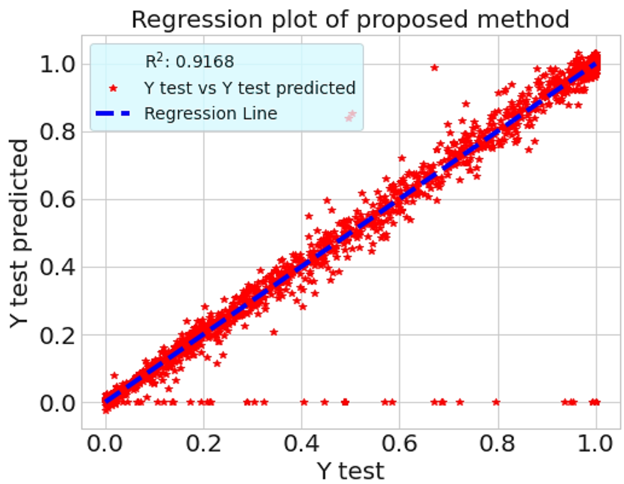

Figure 6. Regression plot of test and predicted data

Due to the large number of samples in the test data, it may be difficult to show the predicted values and our test set on the same graph in terms of graph readability. For this reason, a cross-section of test data and predicted values can be used to analyze the prediction outcomes of the model. Figure 7 shows the distribution of the test data and the values predicted by the proposed model for the date range of 18.10.2018–21.10.2018. When the graph is analyzed, it is seen that there is a harmonious relationship between the prediction and the test values.

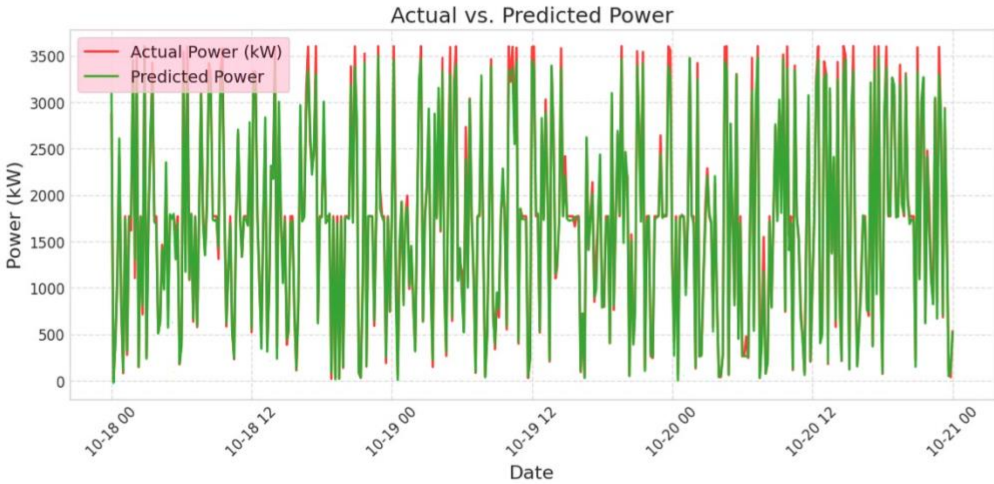

Figure 7. Comparison of test data and prediction results

Figure 8 shows the theoretical, actual, and predicted power values of the turbine in response to the wind speed. When the graph is analyzed, it is seen that the estimated power curve, the actual power curve, and the theoretical power curve have a similar distribution.

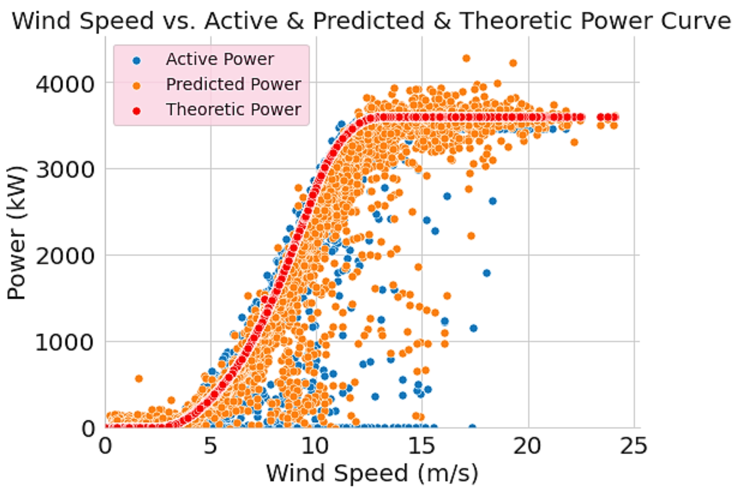

Figure 8. Graph of theoretical, actual, predicted power and wind speed

The results of a model should be analyzed in terms of statistical methods. According to the results presented in Table 3, the proposed method showed high performance with an R^2 value of 94.14% on the training dataset. In addition, MAE, MSE, and RMSE values of 0.0231, 0.0051, and 0.0716, respectively, have very low error rates. It also achieved an R^2 score of 91.63% on the test dataset, which demonstrates the model is able to represent the relationship between the newly encountered data well. The MAE, MSE, and RMSE values for the test dataset were 0.0276, 0.0074, and 0.0863, respectively. The statistical measurement results show that the proposed architecture produces high-accuracy predictions with low error metrics.

Table 3. Performance results of the propesed methos

	Training Dataset	Testing Dataset
MAE	0.0231	0.0276
MSE	0.0051	0.0074
RMSE	0.0716	0.0861
R^2	0.9414	0.9163
Training time (min.)	23.02 min.	

5. CONCLUSION

Wind energy is slowly being integrated into modern grids with the rise of low-cost turbines. As wind turbines become more widespread, various methods and approaches have been proposed in the literature to evaluate the potential contribution of artificial intelligence methods to wind turbine energy prediction. However, most techniques have considered short- or long-term forecasts separately and have not focused on real-time forecasts. However, real-time forecasts of turbine output energy are extremely important for turbine energy management and safety. Therefore, in this research, the proposed RNN-based architecture is trained based on real-time data. The results and performance metrics show that the model can achieve high success rates. RNN is superior to classical machine learning methods in analyzing sequential data with its ability to recall information from previous time steps. This feature enables meaningful use of data from previous time steps. It also helps to better capture the patterns in the time series. Thanks to this capability, the proposed DL-based method has achieved high prediction accuracy. In addition, this method offers the ability to make both real-time, short-term, and long-term forecasts of the output power of wind turbines with a single tool. This provides high forecasting performance without the need to use more than one technique. This study provides an effective approach to energy production and management by making significant progress in the wind energy sector. However, RNN-based machine-learning methods have some limitations. The gradients in RNN structures can shrink over time. This may make it difficult to appropriately convey information from previous time steps during training. This may limit the learning ability of the model. Therefore, in future studies, it is planned to use more advanced RNN variation methods such as LSTM (long short-term memory) and GRU (Gated recurrent unit) for analyzing sequential data.

REFERENCES

[1] BAYRAM, A. B., & YAKUT, K. (2022). RENEWABLE ENERGY SCENARIO IN ELECTRICITY SYSTEM FOR ISPARTA PROVINCE THE YEAR 2030. International Journal of Engineering and Innovative Research, 4(3), 163-177. https://doi.org/10.47933/ijeir.1144163

[2] Bektaş, Y., & Karaca, H. (2022). Red deer algorithm based selective harmonic elimination for renewable energy application with unequal DC sources. Energy Reports, 8, 588-596.

[3] Sevim, D., Fidan, Ş., POLAT, S., & OKTAY, H. (2017). Experimental and articial neural network based studies on thermal conductivity of lightweight building materials. European Journal of Technique (EJT), 7(1), 33-41. Retrieved from https://dergipark.org.tr/en/pub/ejt/issue/34033/376667

[4] Saglam, M., Spataru, C., & Karaman, O. A. (2022). Electricity Demand Forecasting with Use of Artificial Intelligence: The Case of Gokceada Island. Energies, 15(16), 5950. https://doi.org/10.3390/en15165950

[5] Karakaya, H., Fidan, Ş., Şen, İ. E., & Gündoğdu, A. (2017). Batman ili fotovoltaik güneş enerjisi potansiyelinin analiz ve değerlendirmesi. Retrieved from https://earsiv.batman.edu.tr/xmlui/handle/20.500.12402/3941

[6] De Giorgi, M. G., Congedo, P. M., & Malvoni, M. (2014). Photovoltaic power forecasting using statistical methods: impact of weather data. IET Science, Measurement & Technology, 8(3), 90-97. https://doi.org/10.1049/iet-smt.2013.0135

[7] SANCAR, M. R., & BAYRAM, A. B. (2023). Modeling and Economic Analysis of Greenhouse Top Solar Power Plant with Pvsyst Software. International Journal of Engineering and Innovative Research, 5(1), 48-59. https://doi.org/10.47933/ijeir.1209362

[8] Hassan, A., Rehman, A. U., Shabbir, N., Hassan, S. R., Sadiq, M. T., & Arshad, J. (2019, February). Impact of inertial response for the variable speed wind turbine. In 2019 International Conference on Engineering and Emerging Technologies (ICEET) (pp. 1-6). IEEE. https://doi.org/10.1109/CEET1.2019.8711826.

[9] Fidan, Ş., & Çimen, H. (2021). Rüzgâr türbinlerinde tork ve kanat eğim açısı kontrolü. Batman Üniversitesi Yaşam Bilimleri Dergisi, 11(1), 12-26. Retrieved from https://dergipark.org.tr/en/pub/buyasambid/issue/63446/880791

[10] Fidan, Ş. (2010). Değişken hızlı-değişken kanat açılı rüzgar türbinlerinin tork ve kanat açısı kontrolü (Master's thesis, Fen Bilimleri Enstitüsü).

[11] Mahmoud, T., Dong, Z. Y., & Ma, J. (2018). An advanced approach for optimal wind power generation prediction intervals by using self-adaptive evolutionary extreme learning machine. Renewable energy, 126, 254-269. https://doi.org/10.1016/j.renene.2018.03.035

[12] Süzen, A. A., Duman, B., & Şen, B. (2020, June). Benchmark analysis of jetson tx2, jetson nano and raspberry pi using deep-cnn. In 2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA) (pp. 1-5). IEEE. https://doi.org/10.1109/HORA49412.2020.9152915.

[13] Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. Renewable energy, 37(1), 1-8. https://doi.org/10.1016/j.renene.2011.05.033

[14] Zazoum, B. (2022). Solar photovoltaic power prediction using different machine learning methods. Energy Reports, 8, 19-25. https://doi.org/10.1016/j.egyr.2021.11.183

[15] Woon, W. L., Aung, Z., Kramer, O., & Madnick, S. (Eds.). (2017). Data Analytics for Renewable Energy Integration: Informing the Generation and Distribution of Renewable Energy: 5th ECML PKDD Workshop, DARE 2017, Skopje, Macedonia, September 22, 2017, Revised Selected Papers (Vol. 10691). Springer.

[16] Aydin, I., Celebi, S. B., Barmada, S., & Tucci, M. (2018). Fuzzy integral-based multi-sensor fusion for arc detection in the pantograph-catenary system. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 232(1), 159-170. https://doi.org/10.1177/0954409716662090

[17] Kingsford, C., & Salzberg, S. L. (2008). What are decision trees?. Nature biotechnology, 26(9), 1011-1013. https://doi.org/10.1038/nbt0908-1011

[18] POLAT, S., FİDAN, Ş., & OKTAY, H. (2020). Hafif Yapı Malzemelerinin Isıl İletkenlik Özelliklerinin Yapay Sinir Ağları Kullanılarak Tahmin Edilmesi. Batman Üniversitesi Yaşam Bilimleri Dergisi, 10(1), 28-41. Retrieved from https://dergipark.org.tr/en/pub/buyasambid/issue/55551/643721

[19] Shabbir, N., AhmadiAhangar, R., Kütt, L., Iqbal, M. N., & Rosin, A. (2019, October). Forecasting short term wind energy generation using machine learning. In 2019 IEEE 60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON) (pp. 1-4). IEEE. https://doi.org/10.1109/RTUCON48111.2019.8982365.

[20] Birecikli, B., Karaman, Ö. A., Çelebi, S. B., & Turgut, A. (2020). Failure load prediction of adhesively bonded GFRP composite joints using artificial neural networks. Journal of Mechanical Science and Technology, 34, 4631-4640. https://doi.org/10.1007/s12206-020-1021-7

[21] POLAT, S., FİDAN, Ş., & OKTAY, H. (2020). Hafif Yapı Malzemelerinin Isıl İletkenlik Özelliklerinin Yapay Sinir Ağları Kullanılarak Tahmin Edilmesi. Batman Üniversitesi Yaşam Bilimleri Dergisi, 10(1), 28-41. retrieved from https://dergipark.org.tr/en/pub/buyasambid/issue/55551/643721

[22] Kubilay, H. A. N., ÖZTÜRK, G., & ASLAN, A. (2023, June). Yapay Sinir Ağları Kullanarak Yüzey Pürüzlülüğü Tespiti. In International Conference on Pioneer and Innovative Studies (Vol. 1, pp. 487-492).

[23] Agarwal, K., & Vadhera, S. (2022, April). Short-term Wind Speed Prediction using ANN. In 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS) (pp. 496-501). IEEE. https://doi.org/10.1109/ICSCDS53736.2022.9760899.

[24] Mason, K., Duggan, J., & Howley, E. (2018). Forecasting energy demand, wind generation and carbon dioxide emissions in Ireland using evolutionary neural networks. Energy, 155, 705-720. https://doi.org/10.1016/j.energy.2018.04.192

[25] Fidan, Ş., Cebeci, M., & Gündoğdu, A. (2019). Extreme Learning Machine Based Control of Grid Side Inverter for Wind Turbines. Tehnički vjesnik, 26(5), 1492-1498. https://doi.org/10.17559/TV-20180730143757

[26] Mahmoud, T., Dong, Z. Y., & Ma, J. (2018). An advanced approach for optimal wind power generation prediction intervals by using self-adaptive evolutionary extreme learning machine. Renewable energy, 126, 254-269. https://doi.org/10.1016/j.renene.2018.03.035

[27] ÇELEBİ, S. B., & EMİROĞLU, B. G. (2023). Alzheimer Teşhisi için Derin Öğrenme Tabanlı Morfometrik Analiz. Journal of the Institute of Science and Technology, 13(3), 1454-1467. https://doi.org/10.21597/jist.1275669

[28] Süzen, A. A., & Şimşek, M. A. (2020). A novel approach to machine learning application to protection privacy data in healthcare: Federated learning. Namık Kemal Tıp Dergisi, 8(1), 22-30. https://doi.org/10.37696/nkmj.660762

[29] Çelebi, S. B., & Emiroğlu, B. G. (2023). Leveraging Deep Learning for Enhanced Detection of Alzheimer's Disease Through Morphometric Analysis of Brain Images. Traitement du Signal, 40(4). https://doi.org/10.18280/ts.400405

[30] ÇALIŞKAN, A. (2022). classification of tympanic membrane images based on VGG16 model. Kocaeli Journal of Science and Engineering, 5(1), 105-111. https://doi.org/10.34088/kojose.1081402

[31] KARAMAN, Ö. A., & BEKTAŞ, Y. (2023). Makine Öğrenmesi ve Optimizasyon Yöntemleri ile Uzun Dönem Elektrik Enerjisi Tahmini: Türkiye Örneği. Mühendislik Bilimleri ve Araştırmaları Dergisi, 5(2), 285-292. https://doi.org/10.46387/bjesr.1306577

[32] Yaman, O., & Tuncer, T. (2022). Exemplar pyramid deep feature extraction based cervical cancer image classification model using pap-smear images. Biomedical Signal Processing and Control, 73, 103428. https://doi.org/10.1016/j.bspc.2021.103428

[33] Çalışkan, A., Demirhan, S., & Tekin, R. (2022). Comparison of different machine learning methods for estimating compressive strength of mortars. Construction and Building Materials, 335, 127490. https://doi.org/10.1016/j.conbuildmat.2022.127490

[34] Çalışkan, A. (2023). Diagnosis of malaria disease by integrating chi-square feature selection algorithm with convolutional neural networks and autoencoder network. Transactions of the Institute of Measurement and Control, 45(5), 975-985. https://doi.org/10.1177/01423312221147335

[35] Medsker, L. R., & Jain, L. C. (2001). Recurrent neural networks. Design and Applications, 5(64-67), 2.

[36] Çelebi, S. B., & Emiroğlu, B. G. (2023). A novel deep dense block-based model for detecting Alzheimer's Disease. Applied Sciences, 13(15), 8686. https://doi.org/10.3390/app13158686

[37] Aydın, İ., Yaman, O., Karaköse, M., & Çelebi, S. B. (2014, June). Particle swarm based arc detection on time series in pantograph-catenary system. In 2014 IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA) Proceedings (pp. 344-349). IEEE. https://doi.org/10.1109/INISTA.2014.6873642

[38] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

[39] Süzen, A. A., & Çakıroğlu, M. A. (2019). Prediction of rebound in shotcrete using deep bi-directional LSTM. Computers and Concrete, An International Journal, 24(6), 555-560. https://doi.org/10.12989/cac.2019.24.6.555

[40] Rahman, A., Srikumar, V., & Smith, A. D. (2018). Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. Applied energy, 212, 372-385. https://doi.org/10.1016/j.apenergy.2017.12.051

[41] Wang, J., Li, X., Li, J., Sun, Q., & Wang, H. (2022). NGCU: A new RNN model for time-series data prediction. Big Data Research, 27, 100296. https://doi.org/10.1016/j.bdr.2021.100296

[42] Mahmoud, T., Dong, Z. Y., & Ma, J. (2018). An advanced approach for optimal wind power generation prediction intervals by using self-adaptive evolutionary extreme learning machine. Renewable energy, 126, 254-269. https://doi.org/10.1016/j.renene.2018.03.035

[43] Shabbir, N., Kütt, L., Jawad, M., Amadiahanger, R., Iqbal, M. N., & Rosin, A. (2019, November). Wind energy forecasting using recurrent neural networks. In 2019 Big Data, Knowledge and Control Systems Engineering (BdKCSE) (pp. 1-5). IEEE. https://doi.org/10.1109/BdKCSE48644.2019.9010593

[44] Kaggle.com. Online. Available: https://www.kaggle.com/datasets/berkerisen/wind-turbine-scada-dataset,. Accessed: 30-Oct-2023.

[45] Keyhani, A. (2016). Design of smart power grid renewable energy systems. John Wiley & Sons.

[46] Xu, H., & Deng, Y. (2017). Dependent evidence combination based on shearman coefficient and pearson coefficient. IEEE Access, 6, 11634-11640. https://doi.org/10.1109/ACCESS.2017.2783320

[47] Patro, S. G. O. P. A. L., & Sahu, K. K. (2015). Normalization: A preprocessing stage. arXiv preprint arXiv:1503.06462. https://doi.org/10.48550/arXiv.1503.06462

[48] Rahman, M. M., Shakeri, M., Tiong, S. K., Khatun, F., Amin, N., Pasupuleti, J., & Hasan, M. K. (2021). Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks. Sustainability, 13(4), 2393. https://doi.org/10.3390/su13042393

[49] Li, G., Wang, H., Zhang, S., Xin, J., & Liu, H. (2019). Recurrent neural networks based photovoltaic power forecasting approach. Energies, 12(13), 2538. https://doi.org/10.3390/en12132538

[50] Karaman, Ö. A. (2023). Prediction of Wind Power with Machine Learning Models. Applied Sciences, 13(20), 11455. https://doi.org/10.3390/app132011455

[51] Öztekin, A., & Erçelebi, E. (2016). An early split and skip algorithm for fast intra CU selection in HEVC. Journal of Real-Time Image Processing, 12, 273-283. https://doi.org/10.1007/s11554-015-0534-2