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Research Article

Average Wind Speed Prediction in Giresun-Kümbet Plateau Region with Artificial Neural Networks

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Abstract— **In order to estimate the electricity generation capacity and schedule the supply for vendor needs, wind speed prediction is crucial for wind power plant frameworks. Prior to the installation of the wind power plants, a reliable wind behavior model is necessary. To have such a model, wind data is recorded periodically. In this study, hourly recorded meteorological data of actual pressure, relative humidity, temperature, wind direction and average wind speed for the year 2023 were obtained from the General Directorate of Meteorology for the Kümbet plateau region of Giresun province. The data is used to accurately predict the future wind speed for the region. MATLAB Artificial Neural Networks (ANN) is utilized. Actual pressure, relative humidity, temperature and wind direction parameters are defined as inputs in the prediction process, while the average wind speed is the output parameter. 85% of the data set is used as training data and remaining 15% data set is used for testing data. An optimization process is applied to determine the number of hidden layers to have the prediction value with the smallest error. Bayesian Regularization training process was performed by seeing that the hidden layer has the lowest error at 90 neurons. Performance evaluations are performed with Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Pearson Correlation Coefficient (R) metrics. The values of the metrics for the test data are 26.7137, 5.1685, 3.5055 and 0.7457 respectively. The results show that, ANN based model is useful for the wind speed prediction over the region.**

Index Terms— **Wind speed. Artificial neural networks. Forecasting. Giresun.**

I. INTRODUCTION

WIND ENERGY has an key role in electricity markets as it is a environmentally safe energy source. According to the 2024 report of the Global Wind Energy Council (GWEC), installed wind power capacity worldwide reached approximately 1,021 GW by the end of 2023. 117 GW of new capacity was added in 2023, which means an increase of 50% compared to the previous year [1]. Turkey, with an installed capacity of 11,643 MW, ranks 10th in the world in annual electricity generation with China at the top and 5th in Europe with Germany at the top [2, 3].

In Figure 1, the Wind Energy Potential Atlas (REPA) prepared by the Ministry of Energy and Natural Resources shows the distribution of annual average wind speeds at a height of 100 meters in Turkey [4]. It can be seen that there is a significant wind energy potential in the coastal regions of Turkey. The regions with the highest wind capacity in Turkey are the Marmara, the Aegean and the Mediterranean coasts where the majority of wind power plants are installed. The Central Anatolian, the Black Sea, the Southeastern Anatolian and the Eastern Anatolian regions are the second most common regions for wind power plant installations [5].

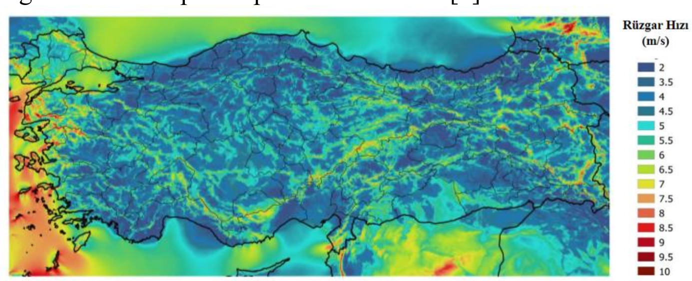

Fig.1. Turkey-wide annual average wind speed distribution at 100 meters [4]

Figure 2 shows the wind speed distributions in 100 meters for Giresun province. The average wind speed is 3.98 m/s throughout the province and reaches approximately 9 m/s in the central parts of the province.

The variability and unpredictability of wind speeds define difficulties in the stable supply of wind energy, therefore cause additional operating costs [6-8]. Thus, it is extremely important to develop effective wind speed forecasting methods to optimize the use of wind energy for electric power systems and minimize the waste of wind resources [9].

Accurate wind speed forecasting is crucial for predicting the energy production of wind turbines in the short, medium and long term. These forecasts can be used to calculate the profitability of power generation facilities and for investors to determine the feasibility of wind energy in a particular region

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[10]. In addition, accurate short-term and long-term wind power generation forecasts are very important for maintaining a balanced electricity generation between different sources. Wind speed forecasts can be categorized as short-term and long-term. The most commonly used approaches in the literature for short-term wind speed forecasting for the purpose of determining electricity energy exchange mainly include autoregressive methodologies, autoregressive moving average techniques and wavelet transform methodologies. These methods give better results, especially for a few hours [11]. In case of longer forecasting times, error rates increase and these methods cannot provide reliable results [12]. Long-term wind speed forecasting is used for maintenance planning, unit commitment decisions and optimal operating cost applications.

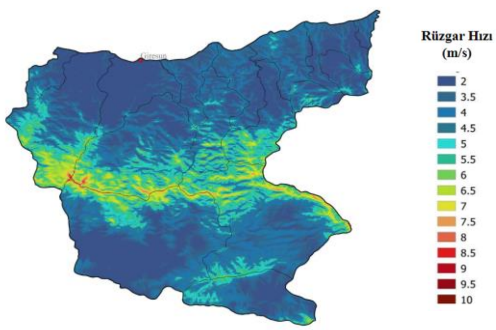

Fig.2. Annual average wind speed distribution at 100 meters in Giresun province [4]

Wind speed values were estimated based on ARIMA and artificial neural network methods using data from TÜBİTAK T60 Observatory meteorological station for the month of April 2016 [13]. In another study, specific to Konya province, 365 previous year data were used and wind speed values were estimated with ANN, based on temperature, pressure and humidity values [12]. Wind speed, humidity, pressure and temperature data of Bozcada district of Çanakkale province in 2014 were estimated by using Linear Regression and ANN. WEKA and MATLAB programming languages comparison was performed, and the correlation coefficient value for test data for ANN was found to be 0.63 [14]. Another study for Istanbul Avcılar region was performed. Nonlinear Autoregressive Exogenous (NARX) method was used for this particular study. The data collected for 10 minutes as wind speed, wind direction, temperature, relative humidity and pressure. The R value for the test data was found to be 0.98 [15]. Additional studies using various statistical and artificial neural network methods such as ARIMA, ANN, NARX, RNN, LSTM were performed for the regions of Tokat [16], Bilecik [17], Burdur [18] and Yalova [19] provinces.

Wind speed prediction studies for Turkey were performed mostly for western and southern part of Turkey. Although the coastal line of Black Sea region receive comparatively less wind, the situation is opposite for the highland parts of the region which can be seen from Figure 1. It is observed that, the average wind speed for Giresun province center at the coast of Black Sea is around 3.98 m/s. On the other hand, this value drastically changes to have an average value of 9 m/s in highland parts of the province. While existing studies focused on different provinces of Turkey, this study stands out by providing the first wind speed prediction for Giresun, an area previously overlooked in the literature. In contrast to other studies that typically rely on data from limited timeframes or specific meteorological stations, this study incorporates comprehensive, hourly recorded data for the entire year 2023.

In this study, wind speed was estimated by using hourly recorded actual pressure, relative humidity, temperature, wind direction and average wind speed data for the year 2023. The data is provided by General Directorate of Meteorology for Giresun province. The analyses are performed with ANN algorithm using MATLAB programming language. As a result of the prediction process in ANN trained with Bayesian regularization, performance evaluation is performed with MSE, RMSE, MAE and R metrics.

II. MATERIALS AND METHOD

A. Data Set and Preprocessing

In this study, the data obtained from Meteorological Station 17686 located at Kümbet Plateau (40°33'33.0 "N 38°26'23.0 "E) within the borders of Giresun Province are used. The location information of the station is given below.

Fig.3. Map image of the station used in the study

The data covering the period between 01.01.2023-31.12.2023 includes hourly actual pressure, relative humidity, temperature, wind direction and average wind speed data. In order for the data to be ready for analysis, it is necessary to go through some preprocess stages. As it is known, since the measurement stations are located in the plateau, there happens transportation and communication problems especially in winter months. Missing data occur as a result of power outage or sensor malfunction. Therefore, it is necessary to eliminate the missing data. The process of removing the missing data was carried out using the 'Data Clean' application in the MATLAB program. While the data for the wind direction parameter was determined according to the closest value, the missing data in other parameters were eliminated using the linear interpolation method.

The location of station 17686 has an altitude of 1724 meters. Since the location of the station is on the foothills of the mountain, and there are structures with trees around it, it was thought that the values of temperature, pressure and wind speed would not represent the location of the wind farm with sufficient accuracy. For this reason, the measured values were moved to a height of 200 meters. The following formulae were used for the transfer process [20].

$$T = 15.04 - 0.00649.h \tag{1}$$

$$p = p_0\left(1 - \frac{L.h}{T_0}\right)^{\frac{g.M}{R_0 L}} \tag{2}$$

$$\frac{V_2}{V_1} = \frac{\ln\left(\frac{h_2}{h_1}\right)}{\ln\left(\frac{h_1}{h_0}\right)} \tag{3}$$

In the equations: T is the temperature (°C), h is the altitude in meters, p is the actual pressure, V_1 and V_2 are the wind speeds at 1724 m and 1924 m altitude respectively, L is the temperature gradient, T_0 is the reference temperature at sea level, g is the gravitational acceleration, M is the mole mass and R_0 is the gas constant.

Table 1 shows the statistical properties of these parameters. Among these parameters, Actual Pressure and Wind Direction are generally distributed in a stable manner, while Relative Humidity has a wide distribution. Temperature shows a significant variability with a large standard deviation, while Mean Wind Speed shows a large variability with high minimum and maximum values. Pearson correlation analysis was performed to determine the relationship between these parameters.

TABLE I
STATISTICAL VALUES OF THE PARAMETERS IN THE DATA SET

Parameter name	Status	Mean	Standard Deviation	Minimum Value	Maximum Value	Median
Actual Pressure [mbar]	Input	0.81	0.01	0.79	0.82	0.81
Relative Humidity [%Rh]	Input	0.78	0.25	0.09	1.00	0.95
Temperature [°C]	Input	6.48	7.04	-14.80	28.80	6.90
Wind Direction	Input	0.47	0.29	0.00	0.94	0.50
Average Wind Speed [m/s]	Output	9.22	7.54	0.00	81.55	7.12

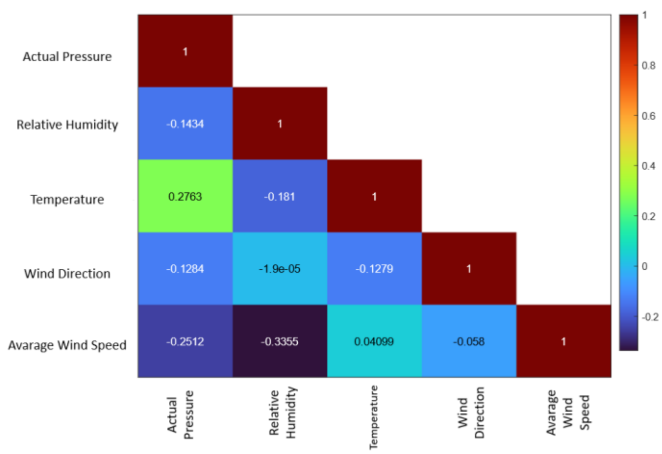

Fig.4. Correlation heat map of the variables in the data set

Figure 4 is a heat map showing the Pearson correlation coefficients between the meteorological parameters in the data set. The color scale represents the strength and direction of these correlations, with red indicating strong positive correlations, blue representing strong negative correlations, and lighter shades indicating weaker correlations. There is a positive correlation between Actual Pressure and Temperature, indicating that as the pressure increases, the temperature also increases (R = 0.2763, moderate correlation). While there are negative correlations between Actual Pressure and Relative Humidity (R = -0.1434), there are also negative correlations between Relative Humidity and Temperature (R = -0.181). There is no significant relationship between Wind Direction and other parameters. There are significant negative correlations between Wind Speed and Actual Pressure (R = -0.2512) and Relative Humidity (R = -0.3355), indicating that as wind speed increases, pressure and relative humidity decrease.

There is a weak positive correlation between Temperature and Mean Wind Speed (R = 0.04099), indicating that wind speed increases slightly as temperature increases. No significant relationship was observed between wind direction and mean wind speed (R = -0.058).

B. *Artificial Neural Networks*

Artificial neural networks are one of the supervised machine learning methods frequently used in regression problems. Inspired by the behavior of the brain and nerve cells, the algorithm includes data processing and decision-making processes. ANNs basically consist of input layer, hidden layer and output layer. The input layer contains neurons corresponding to the number of features in the data set. Each neuron represents one feature from the data set. The hidden layer(s) are the neurons that process the input data and transmit it to the output layer. The number of neurons in each hidden layer can vary depending on the complexity of the problem and the size of the data set. The output layer contains neurons that represent what the model is trying to predict [21, 22]. The ANN architecture used in the study is shown in Figure 5.

Each neuron in an Artificial Neural Network (ANN) performs information processing by weighting incoming signals and processing them through an activation function. The weights express the strength of synaptic connections and quantitatively determine the strength of the relationship between each input and the corresponding neuron. During the training of the network, these weights are iteratively adjusted to minimize the error rate using the backpropagation algorithm. The activation function is a generally non-linear function used to calculate the output of the neuron. This function determines the potential of the neuron and activates the neuron if it is above a certain threshold value. Various activation functions such as sigmoid, tanh, ReLU can be preferred according to different problems and network structures [23, 24].

$$y = \sum (w_i \times x_i) + b \tag{4}$$

Where y is the signal of the neuron, w_i is the weight of the *i*-th input, x_i is the *i*-th input value and b is the bias value.

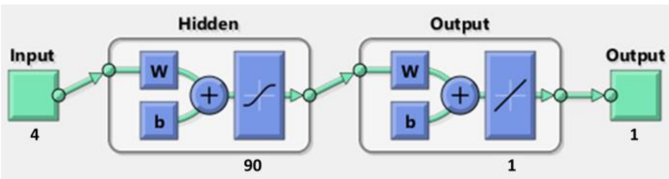

Fig.5. ANN architecture used in the study

In ANNs, two important techniques are the Lavenberg-Marquardt algorithm and Bayesian regularization, which strike a balance between the complexity of the model and the error function, preventing overlearning and increasing the generalization ability of the model. The Lavenberg-Marquardt algorithm uses a combination of steepest descent and Gauss-Newton methods to minimize the error function, while Bayesian regularization updates the weights of the model by adding an additional regularization term to the error term [25].

C. *Performance Evaluation*

In the study, Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Pearson Correlation Coefficient (R) metrics, which are frequently used in the literature, were used for performance evaluations as a result of prediction of wind speed values. The mathematical expressions of the performance metrics are as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

$$RMSE = \sqrt{\sum_{i=1}^{N}\frac{(y_i - \hat{y}_i)^2}{N}} \tag{7}$$

$$R = \frac{cov(y,\hat{y})}{\sigma_y \sigma_{\hat{y}}} \tag{8}$$

Where y is the actual value of wind speed, $\hat{y}$ is the estimated value of wind speed, σ is the standard deviation, cov is the covariance and N is the number of estimated data.

III. RESULTS

In this section, findings related to wind speed prediction results are presented. Wind speed was predicted by ANN using the values of Actual Pressure, Relative Humidity, Temperature and Wind direction and MSE, MAE, RMSE and R metric values were calculated as a result of the prediction. The analysis was carried out using MATLAB programming language and a computer system equipped with Intel Core i7-13700H 2.40 GHz Processor, 32 GB RAM and 8 GB RTX4070 Graphics Card.

In the training phase of the ANN, Levenberg-Marquardt and Bayesian regularization algorithms were tested. Bayesian regularization algorithm, which is superior to the Levenberg-Marquardt model, was used. The training was performed using the ***trainbr*** function in the MATLAB package program. The highest success rate was achieved by using the tangent sigmoid (tansig) function as the activation function.

Figure 6 shows the variation of MSE values of the training data according to the number of neurons in the hidden layer in the ANN architecture. It was determined that the number of neurons with the lowest error was 90 and the MSE value for this case was calculated as 21.2192.

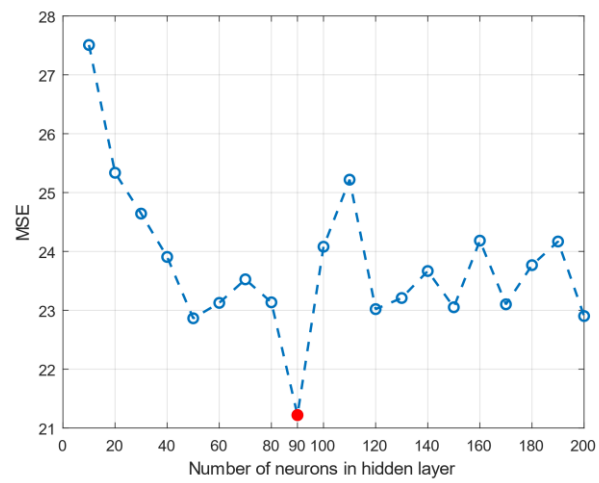

Fig.6. The relationship between the number of neurons in the hidden layer and error

Figure 7 shows the performance information of the network for training and test data during the training process. The X axis represents the number of iterations and the Y axis represents the MSE values calculated for each iteration in the graph. Training outputs are shown in blue and test outputs are shown in red. At epoch 1000, the best performance (MSE 21.2192) was obtained and the training process was finished.

Fig.7. MSE values of training and test data during the training process

Figure 8 shows the values of the parameters in iterations during the training process. X axis represents the number of iterations and Y axis represents the values of the parameters. During the analysis period, some conditions are defined that determine when the training process ends. In this study, the target values of iteration value 1000, ***gradien***t value 1x10^{-07}, ***mu*** value 1x10^{10}, ***gamk*** value 0 and Sum Squared Param (***ssX***) value 0 are the target values and the training process is terminated if any of the above conditions are met. The training process lasted 1 minute and 31 seconds and the training process was terminated because it reached 1000 iterations. In the finalized process, the ***gradient*** was 7.3295, ***mu*** 0.5, ***gamk*** 373.2331, ***ssX*** 1284.5032. Since the training process is done with the Bayesian Regularization method, there is no validation data and it shows zero values.

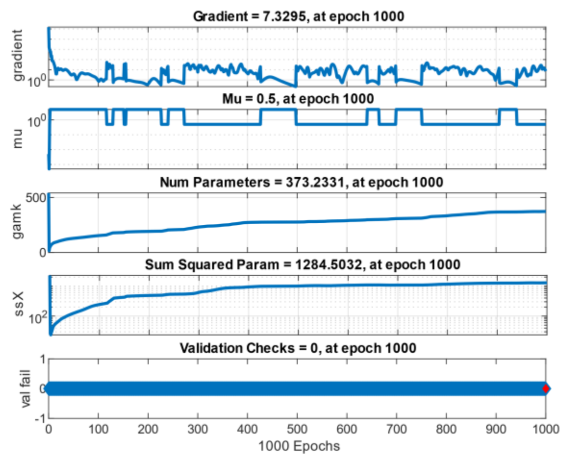

Fig.8. Parameter values in the training process

Figure 9 shows the error histogram showing the cumulative changes of the training and test errors. The vertical line in the graph shows the error at zero points. The majority of the errors are close to this vertical line, which means that the prediction values are consistent with the actual values.

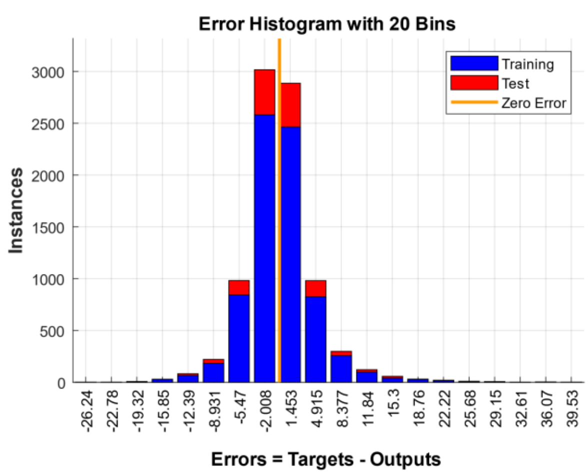

Fig.9. Error histogram at the end of the training process

The regression graphs of the training and test data between the input variables of actual pressure, relative humidity, temperature, and wind direction, and the target variable of wind speed are given in Figure 10. In these scatter plots, the solid lines represent the linear regression fits for the training and test datasets, while the R-values indicate the strength of the linear relationships between the predicted and actual wind speed values. The training data (R = 0.78993) demonstrates a strong correlation, suggesting that the model has learned the relationship between the input variables and wind speed quite effectively. The test data (R = 0.7457) also exhibits a strong correlation, although slightly weaker than the training data, indicating that the model performs consistently on unseen data. The "All" graph shows the combined performance (R = 0.78274), reinforcing the model's overall reliability in predicting wind speed based on the given meteorological factors.

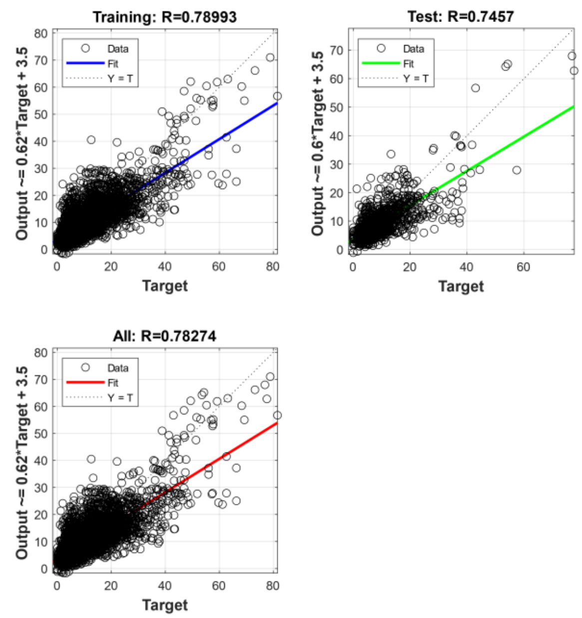

Fig.10. Regression plots for training, test and all data

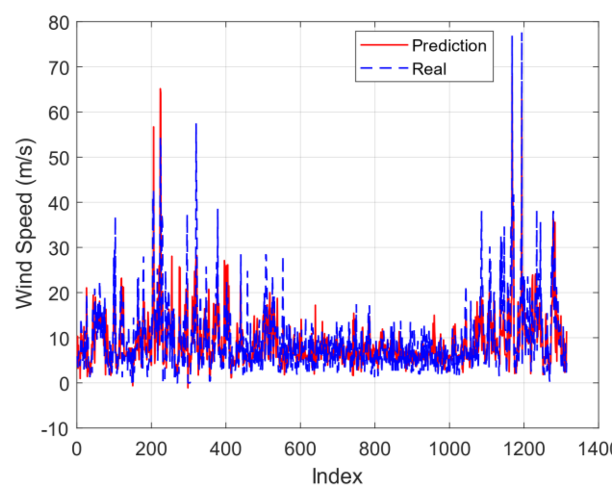

Fig.11. Comparison of test data with prediction values

Figure 11 shows the actual and predicted values of the test data. The red line represents the model's predicted wind speed, while the blue dashed line shows the actual wind speed values over the same period. The close alignment between the predicted and actual values suggests that the model captures the underlying patterns in the data well. Notable deviations, such as the peaks and troughs, occur in specific intervals, highlighting the challenges of accurately predicting extreme wind speed values. However, the overall trend suggests that the model is effective in tracking wind speed behavior, particularly in moderate conditions. The performance metric values between actual and predicted values for training and test data are given in Table 2.

TABLE II
PERFORMANCE METRIC VALUES FOR TRAINING AND TEST DATA

	Count	MSE	RMSE	MAE	R
Training	7446	21.2192	4.6064	3.1552	0.7899
Test	1314	26.7137	5.1685	3.5055	0.7457

When compared to other studies in the literature, our model's performance metrics, particularly the RMSE and R values, are within an acceptable range for wind speed forecasting in complex terrains. For instance, studies conducted in Bozcaada [14] and Istanbul Avcılar [15] report R values of 0.63 and 0.98, respectively, with varying levels of accuracy based on geographical and climatic conditions. In our case, the R value of 0.7457 for the test data, combined with an RMSE of 5.1685, suggests that the ANN model performs well for the highland conditions of the Kümbet Plateau. This further reinforces the viability of wind energy in this region, where wind speeds are higher compared to coastal areas.

Given these results and the favorable wind conditions in the Kümbet Plateau, the installation of wind power plants in this region is supported. The relatively high wind speeds, along with the model's demonstrated accuracy in predicting wind behavior, make the region a strong candidate for wind energy generation, contributing to the region's energy sustainability.

IV. Conclusion

In this study, the average wind speed values in the Kümbet Plateau region of Giresun province were estimated using hourly meteorological data for 2023. Meteorological data consist of five different parameters: actual pressure, relative humidity, temperature, wind direction and average wind speed. In the first stage; the values of the parameters were moved 200 m upwards and the missing data were completed by linear interpolation method.

In the other stage, the model was created and prediction process was carried out by using ANN. Mean wind speed values were predicted by using actual pressure, relative humidity, temperature and wind direction values and performance evaluation was performed by calculating MSE, RMSE, MAE and R values. ***MSE, RMSE, MAE*** and ***R*** values were found to be 21.2192, 4.6064, 3.1552 and 0.7899, respectively, for 7446 training data and 26.7137, 5.1685, 3.5055 and 0.7457, respectively, for 1314 test data. These performance metrics indicate that the model provides a reliable prediction of wind speed based on meteorological variables, with minor deviations between the predicted and actual values. In the light of the findings in Table 2, it is seen that there is no significant difference between meteorological values and predicted values. Therefore, it is predicted that the predicted results can be used instead of the actual values. The benefits of this study include the ability to forecast wind speed in regions with limited meteorological stations or incomplete data, allowing for better planning in areas such as renewable energy, agriculture, and construction

In future studies, a comprehensive study can be conducted by including various signal decomposition methods, machine learning and deep learning methods. This would further improve prediction accuracy and model generalization, broadening its applicability across different meteorological datasets and regions.

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BIOGRAPHIES

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