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Estimating Wind Speed with ANFIS: A Case Study in Karaman City

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Abstract

Wind energy, one of the renewable energy sources, plays an increasingly important role in our world as a clean and sustainable energy source. Since the electricity generation potential from wind energy has a variable structure, energy generation estimates to be made to minimize the adverse effects of this situation have an important place for both power plants and operators. Various estimation methods are used for wind energy sources. In this study, wind speed (m/s) is estimated using fuzzy logic, one of the 34902 data Adaptive-Network-Based Fuzzy Inference System (ANFIS) models consisting of hourly average temperature (°C), relative humidity (%), and actual pressure (hPa) parameters are taken at Karaman-17246 Meteorology Station in 2022. The Root Mean Square Error (RMSE) of the obtained results is examined, and it is seen that the method used approached the result with 0.97%. Thus, the technical information is presented for researchers to determine the wind energy potential for the Karaman region in Turkiye.

Key Words: Wind energy; estimation; wind speed; renewable energy, ANFIS

ANFIS ile Rüzgar Hızının Tahmini: Karaman Şehri Vaka Çalışması

Öz

Yenilenebilir enerji kaynaklarından biri olan rüzgar enerjisi, temiz ve sürdürülebilir bir enerji kaynağı olarak dünyamızda giderek daha önemli bir rol oynamaktadır. Rüzgar enerjisinden elektrik üretim potansiyeli değişken bir yapıya sahip olduğundan, bu durumun sebep olacağı olumsuz etkileri minimuma indirmek için yapılacak enerji üretim tahminleri hem santral hem de işletmeciler açısından önemli bir yere sahiptir. Rüzgar enerjisi kaynakları için çeşitli tahmin yöntemleri kullanılmaktadır. Bu çalışmada, 2022 yılında Karaman-17246 Meteoroloji İstasyonu'nda saatlik ortalama sıcaklık (°C), bağıl nem (%) ve gerçek basınç (hPa) parametrelerinden oluşan 34902 veriden oluşan Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS) modellerinden biri olan bulanık mantık kullanılarak rüzgar hızı (m/s) tahmini yapılmıştır. Elde edilen sonuçların Kök Ortalama Kare Hatası (RMSE) incelenmiş ve kullanılan yöntemin sonuca %0,97 ile yaklaştığı görülmüştür. Böylece araştırmacılara Türkiye'de Karaman bölgesi için rüzgar enerjisi potansiyelini belirlemede yardımcı olacak teknik bilgiler sunulmuştur.

Anahtar Kelimeler: Rüzgar enerjisi; tahmin; rüzgar hızı; yenilenebilir enerji, ANFIS

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1. INTRODUCTION

The rapidly increasing world population, significant technological advances, and accelerating industrialization significantly increase the energy demand. The widespread use of fossil fuels in energy production causes carbon emissions, environmental pollution, and global warming. The Kyoto Protocol (Doan et al. 2024), an international agreement adopted under the United Nations Framework Convention on Climate Change (UNFCCC) (Odeyemi 2020) and which imposes binding obligations on member countries, is taken into account in the increasing importance of renewable energy within the scope of sustainable and clean energy and in reducing greenhouse gas emissions that cause global warming and climate change. Following the end of the Kyoto Protocol in 2020, the Paris Agreement (Salman et al. 2022), which aims to regulate the climate change regime and strengthen socioeconomic resilience to climate change, has come into effect. The global increase in energy supply and the decrease in fossil energy sources and their adverse effects on nature are increasing the demand for environmentally friendly and sustainable renewable energy sources. On the other hand, wind energy stands out as a sustainable, clean, and scalable source with low operating costs compared to fossil energy sources.

According to the World Wind Energy Association 2024 Report (WWEA Annual Report 2023) in Fig. 1, global installed wind capacity has reached 1046.8 GW, meeting approximately 10% of global electricity demand and ranking second after solar energy. The share of wind energy in electricity production has exceeded 20% in more than ten countries worldwide. When these countries are examined, it is seen that Denmark leads with 56%, while Germany, the Netherlands, Portugal, the UK, and Uruguay are among the countries that produce one-third or more of their electricity from wind.

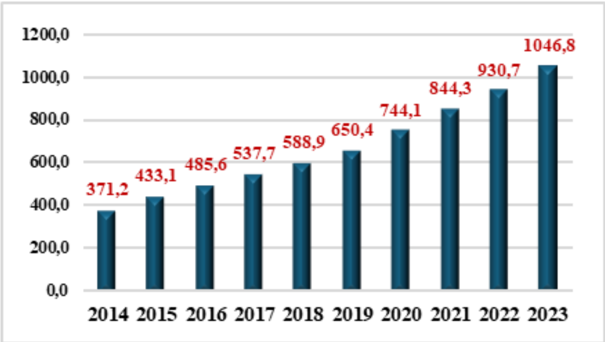

Figure 1. Total Cumulative Installed Capacity (World Wind Energy Association)

As of the end of June 2024, Turkiye's installed power reached 110,518 MW, and as seen in Fig. 2, 11.1% of this power is provided by wind energy.

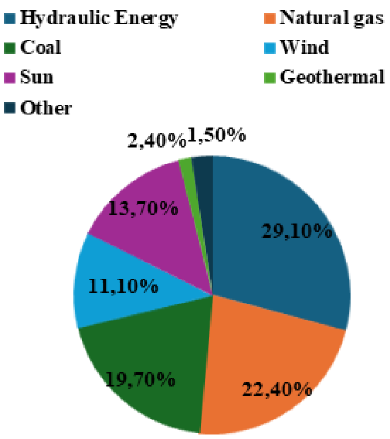

Figure 2. Turkey's Installed Power Distribution by Resources (Republic of Türkiye Ministry of Energy and Natural Resources)

With the increase in wind power plants, studies on production potential have become more important. Since the production potential in wind energy varies even during the day, especially with newly emerged artificial intelligence and optimization methods, estimation studies are applied in a way that will achieve minimum error. Accurate wind speed estimation allows for calculating the total energy capacity obtained from wind power plants, providing maximum benefit from wind energy, and monitoring daily changes. Therefore, in order to produce wind energy effectively, regional wind speed, depending on the location, must be known and estimated accurately. Different methods and techniques are used to estimate wind speed, and it comes to the fore as a studied subject.

Experimental data collected from three wind power plants in Southern Italy and the backpropagation learning algorithm have shown that a two-hidden-layer neural network can be useful for high-accuracy wind energy output prediction (Grassi and Vecchio 2010). Barbounis and Theocharis (2007) used the spatial correlation to estimate wind speed using locally recurrent neural networks. Cassola and Burlando (2012) investigated the Kalman filter to find the most suitable configuration for predicting wind speed and power. This method performed a retrospective test with wind speed data recorded by a Numerical Weather Prediction (NWP) model and two anemometer stations in eastern Liguria (Italy) over two years. It was shown that the methodology can provide significant forecast improvement over the direct output of the wind speed model, especially when used for short-term forecasts, by adjusting the Kalman filter's forecast period and time step. In Nouhitehrani et al (2024), a new reliable method for wind energy prediction was proposed using the Exponential Weighted Moving Average Algorithm, Johnson SU distribution mathematical techniques, and the Berstein Online Aggregation Method. The average error level is reduced by 28% with the proposed method. Short-term wind speed prediction for Bingöl province in Turkey was performed with a deep learning method using the Convolutional Neural Network (CNN) model (Kader 2024). Information is provided about the region's wind speed and power potential for wind energy investments to be made in the area. In Song et al (2023), where wind and wave energy are predicted using deep learning methods, and the prediction results of eight neural networks (LSM), Gated Recurrent Unit (GRU), and Bi-directional Long Short-Term Memory (BiLSTM) are compared. The proposed AT-BiLSTM performs better than other models regarding 11.25 W/m^2 and 0.1 kW/m mean absolute error, 22.947 W/m^2, and 0.3 kW/m root mean square error for wind and wave energy. Another case study is the wind speed forecast for Tokat province, which is made with a deep learning-based hybrid forecast model consisting of Gated Recurrent Unit (GRU) and Convolutional Neural Network (CNN) models (Findik 2022). The CNN-GRU hybrid model, which is used for the first time in wind speed forecasting, has been compared with different deep learning techniques (CNN-LSTM, CNN-RNN, LSTM-GRU, LSTM, GRU), and a significant success rate has been achieved as a result of the comparisons. In Tekin (2022), short-term artificial intelligence-based wind power forecasting has been made for the Çukurova Region.

The case study in Unes et al (2019) used meteorological measurement data from the Nevada Region of the United States of America. Wind forecasting was done using Fuzzy Logic Sugeno (S-BM) methods, Fuzzy Logic Mamdani

(M-BM), and Multiple Linear Regression (MLR) methods, and the results were compared.

In this study, hourly average temperature (°C), relative humidity (%), and actual pressure (hPa) parameters measured in the Karaman-17246 Meteorology Station region for the year 2022 were used as inputs in the Adaptive-Network Based Fuzzy Logic model to estimate wind speed (m/s). The method's performance was evaluated by considering the RMSE error results.

The contribution of this study to the literature can be summarized as follows:

- It was observed that the results obtained using ANFIS made an estimation with 0.97 RMSE error and are within the reliability limits.

- 34902 data analyses were performed for 2022. By accepting the base year, feasibility reports can be created by performing wind analysis and estimating this region for the following years.

2. MATERIAL AND METHOD

2.1. Adaptive-Network Based Fuzzy Inference Systems (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligence system that combines neural networks' learning capabilities with fuzzy logic's interpretability (Jang 1993). ANFIS is quite effective in modeling complex and nonlinear systems and is preferred in cases where traditional mathematical approaches are inadequate (Qureshi et al. 2023). This system provides learning and adaptation of fuzzy rules based on artificial neural networks, thus increasing the system's accuracy. ANFIS optimizes membership functions and fuzzy rules during training, usually using a combination of gradient descent and least squares methods (Chiu 1994). Fig. 3 shows the general working structure of ANFIS.

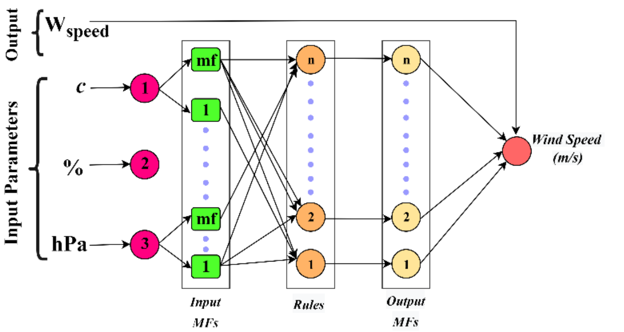

Figure 3. The working structure of the ANFIS

Sugeno fuzzy logic system plays an important role in ANFIS and is particularly effective in managing uncertainties with computational efficiency. Takagi and Sugeno developed the Sugeno model, which uses a linear combination of inputs as output, which provides advantages in optimization and control tasks. In ANFIS, the Sugeno model facilitates the creation of a fuzzy rule base that is adapted through training, thereby improving the accuracy of the system (Takagi et al. 1985). Integrating the Sugeno method with ANFIS solves various real-world problems in energy systems, such as estimation and control problems. It supports decision-making processes under uncertainty in these systems (Pérez-Pérez et al. 2022).

2.2. Case Study: Karaman Region (17246 Meteorology / Weather Station)

Wind energy is a low-cost and renewable resource compared to other energy sources. Cold air replaces rising heated air, creating pressure differences and triggering wind formation. This process provides circulation in the atmosphere and causes winds to move. Winds generally move from high pressure to low pressure. Therefore, the direction and speed of the wind are affected by the differences between different temperature and pressure areas. This movement varies according to the Earth's surface and between geographical regions.

Eq. 1 gives the power that the kinetic energy carried by the air mass called wind, with a mass of m, will transfer to a wind turbine with a power transfer factor of C_p due to its movement (Durak and Ozer 2008).

$$P = 0.5C_p\rho hAw^3 \tag{1}$$

where P, ρh, A, and w are respectively power (Watt), air density (1.225 kg/m^3), turbine rotor swept area (m^2), wind speed (m/s). As seen from Eq. (1), the power carried by the wind is directly proportional to the 3^{rd} power of the wind speed and the density of the air mass. This power carried by the wind is transferred to a wind turbine with a power transfer coefficient C_p in proportion to the area A swept by the turbine blades of radius r. This also indicates that wind speed is the most important factor affecting the potential of wind energy in a wind turbine.

The measurement area at the coordinates 37°11'37.2"N 33°13'16.2"E of the Karaman-17246 Meteorological Station located in the Central District of Karaman Province in Turkey was selected as the application area. We tried to estimate the wind speed using the annual hourly average values for 2022 received from the meteorological station. The obtained data was compared with the actual data. The reliability and accuracy of the method were also tested by calculating the RMSE errors of the obtained results with the formula given in Eq. 2. The general view of the Meteorological Station location is given in Fig. 4.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - y_{ii})^2}{n}} \tag{2}$$

Here, y_i, y_{ii}, and n are the estimated value, observed value, and a number of observations.

3. RESULTS AND DISCUSSION

In the analysis, Hourly Average Temperature (°C), Hourly Average Actual Pressure (hPa), and Hourly Average Relative Humidity (%) for 12 months of 2022 are the input parameters, and Hourly Average Wind Speed (m/s) is the output parameter. In the ANFIS method analysis, 23242 data from the first eight months are used as the training set, and 11660 data from the last four months are used as the test set. The training dataset includes 5832 data for each input parameter. The testing dataset includes 2926 data for each input parameter. The distribution chart for the ANFIS modeling of each epoch training dataset is given in Fig. 5.

Figure 4. Location of the Karaman 17246 Meteorology Station

The test set for the ANFIS Sugeno model is utilized to evaluate the model's accuracy and generalization ability following the training process (Kul et al. 2022). The test set has a similar structure to the dataset used for training, but it consists of data previously unseen by the model. This approach allows the model's performance to be assessed using new and unknown data. In this study, a total of 2928 data points for each pair, comprising Hourly Average Temperature (°C), Actual Pressure (hPa), and Relative Humidity (%) as input variables and Hourly Average Wind Speed (m/s) as the output variable for the last four months of 2022, were used as the test set for the ANFIS Sugeno Model, as seen in Fig. 6.

Figure 5. ANFIS modeling of training data pairs

Figure 6. ANFIS modeling of testing data pairs in the dataset

Fig. 7 presents the graph that compares the estimated data, and the data intended for testing. The estimation results obtained from the ANFIS test data demonstrate a good fit, thereby providing a successful case study for determining the average wind speed.

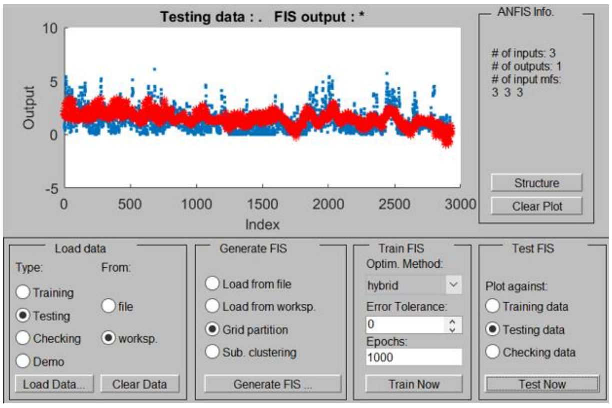

Figure 7. Comparison and analysis of the test results performance

Based on the results and distribution graphs, the probability of estimating the average wind speed value using three different input parameters trained with 250 epochs through sub-clustering is less than 1%. According to the results of the analysis, the error rate calculated using RMSE is 0.97%. In this context, the estimation of the average wind speed value based on the input parameters in the dataset and 27 Fuzzy Rule functions is presented in Fig. 8.

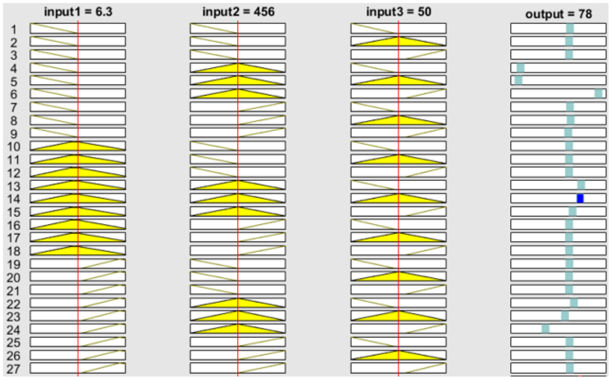

Figure 8. Testing ANFIS Model in Rule-based Viewer

The estimation results obtained from the ANFIS model for estimating the average wind speed based on the 2022 wind energy data for the Karaman region are summarized in Table 1, with input parameters categorized as annual, monthly, daily, and hourly. In this table, the error rates represented by RMSE indicate the accuracy level of the case study conducted.

4. CONCLUSION

This study conducted a case study to determine the wind energy potential using ANFIS based on wind data provided by the Karaman Meteorology Station. Hourly Temperature (°C), Hourly Average Actual Pressure (hPa), and Hourly Average Relative Humidity (%) were defined as input variables.

Table 1. Comparison of the dataset with ANFIS estimation values

Year/Months: 2022/12 Station Name/No: Karaman/17246	Day	Hour	Hourly Ambient Temperature (°C)	Hourly Average Actual Pressure (hPa)	Hourly Average Relative Humidity	Hourly Average Wind Speed (m/s)	Estimated Wind Speed (m/s)	RMSE
	1	0	20,0	897	44,0	0,7	1,81	1,22
	1	1	21,5	897	36,0	0,9	2,15	1,55
	1	2	21,8	897	34,0	1,5	2,24	0,54
	1	3	17,6	897	52,0	1,1	1,83	0,54
	1	4	16,8	897	51,0	0,6	1,86	1,59
	1	5	21,9	897	42,0	0,4	1,79	1,93
	1	6	21,8	897	43,0	0,7	1,76	1,12
	1	7	24,3	897	37,0	1,6	1,98	0,14
	1	8	29,5	897	27,0	1,7	2,46	0,58
	1	9	30,9	896	27,0	4,3	2,46	3,39
	1	10	31,2	896	24,0	5	2,65	5,50
	1	11	32,0	896	21,0	5,3	2,85	6,02
	1	12	32,5	896	20,0	5,4	2,93	6,12
	1	13	32,4	896	21,0	4,8	2,87	3,74
	31	13	9,1	910	47,0	1,3	0,26	1,08
	31	14	8,5	910	44,0	1,6	0,19	1,99
	31	15	6,3	911	52,0	1,2	0,16	1,08
	31	16	3,5	911	65,0	0,6	0,85	0,06
	31	17	2,3	911	72,0	0,2	0,85	0,42
	31	18	1,7	912	76,0	0,4	0,74	0,12
	31	19	0,7	912	80,0	0,1	0,61	0,26
	31	20	0,6	912	81,0	0,3	0,55	0,06
	31	21	-0,5	912	85,0	0,3	0,30	0,00
	31	22	-1,7	912	87,0	0,6	0,10	0,25
	31	23	-2,3	912	88,0	0,4	0,01	0,15
								0.97%

At the same time, hourly average wind speed (m/s) was used as the output variable for estimation analyses. For the dataset, 23,242 data points from the first eight months of 2022 were used as the training set, and 11,660 data points from the last four months were used as the test set.

The distribution graphs visually depict the training and test data. Additionally, a table summarizes the results obtained from the ANFIS model with input parameters categorized as annual, monthly, daily, and hourly. According to the estimation analyses, the error rate for the average wind speed output variable, calculated using RMSE, is 0.97%, indicating the accuracy of this case study.

This case study provides highly useful technical details for researchers aiming to assess the wind potential in the region using meteorological data. It has yielded successful results in determining average wind speed. Future research could explore the impact of wind potential estimation on the potential of electric power generation, potentially guiding artificial intelligence-based forecasting studies.

CONFLICT OF INTEREST

There is no conflict of interest between the authors.

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