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ARAŞTIRMA MAKALESİ **RESEARCH PAPER**

Monthly Average Wind Speed Forecasting in Giresun Province with Fuzzy Regression Functions Approach [*]

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Abstract: In recent years, fuzzy inference systems have been used as an effective method for forecasting problems instead of classical time series methods. Fuzzy inference systems are based on fuzzy sets and use membership values as well as the original data. The fuzzy regression functions approach, which is one of the popular fuzzy inference systems, has different importance from many fuzzy inference systems with its features that it does not have a rule base and is easier to apply, unlike many fuzzy inference systems in the literature. In this study, both the monthly average wind speed forecasting of Giresun Province is performed for the first time in the literature and the fuzzy regression functions approach method is used for the first time in the literature for wind speed forecasting. To evaluate the performance of the fuzzy regression functions approach used to forecast monthly average wind speed in Giresun Province, the results obtained from many methods suggested in the literature for forecasting problems are compared. As a result of the evaluations, it is concluded that the forecasts obtained by the fuzzy regression functions approach are superior to some other methods in the literature.

Keywords: Fuzzy inference systems, fuzzy regression functions approach, forecasting, Giresun province, wind speed.

Bulanık Regresyon Fonksiyonları Yaklaşımı ile Giresun İli Aylık Ortalama Rüzgâr Hızı Tahmini

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Öz: Son yıllarda öngörü problemleri için klasik zaman serisi yöntemleri yerine bulanık çıkarım sistemleri etkin bir yöntem olarak kullanılmaya başlanmıştır. Bulanık çıkarım sistemleri, bulanık kümelere dayalıdır ve orijinal verilerin yanı sıra üyelik değerlerini de kullanır. Popüler bulanık çıkarım sistemlerinden biri olan bulanık regresyon fonksiyonları yaklaşımı, literatürdeki birçok bulanık çıkarım sisteminden farklı olarak kural tabanına sahip olmaması ve uygulanmasının daha kolay olması özellikleriyle birçok bulanık çıkarım sisteminden farklı bir öneme sahiptir. Bu çalışmada hem literatürde ilk kez Giresun ilinin aylık ortalama rüzgâr hızı tahmini yapılmakta hem de rüzgâr hızı tahmini için literatürde ilk kez bulanık regresyon fonksiyonları yaklaşımı yöntemi kullanılmaktadır. Giresun ili aylık ortalama rüzgar hızını tahmin etmek için kullanılan bulanık regresyon fonksiyonları yaklaşımının performansını değerlendirmek için, öngörü problemleri için literatürde önerilen birçok yöntemden elde edilen sonuçlar karşılaştırılmıştır. Yapılan değerlendirmeler sonucunda, bulanık regresyon fonksiyonları yaklaşımı ile elde edilen tahminlerin literatürdeki diğer birçok yöntemden daha üstün olduğu sonucuna varılmıştır.

Anahtar kelimeler: Bulanık çıkarım sistemleri, bulanık regresyon fonksiyonları yaklaşımı, öngörü, Giresun İli, rüzgâr hızı.

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INTRODUCTION

The movement of air mass moving horizontally is called wind. For the wind to occur, there must be a pressure difference in two separate centers. Air currents are always from high pressure to low pressure. If the air temperature rises in one of the two adjacent regions on the earth, the air mass expands and rises. In this case, a low-pressure area is formed. In the region with less temperature, the air is cooled and compressed and collapses downwards by condensing. In this case, a high-pressure area is formed. This air, which is compressed in the high-pressure region, starts to flow towards the low-pressure region, and wind is formed.

Wind speed is the speed of movement of air, wind, and gases in the atmosphere. Factors affecting wind speed; pressure gradient, Rossby waves, jet steam, and local weather conditions. Wind speed is very important for monitoring and forecasting weather patterns and global climate.

Fuzzy inference systems are known as rule-based systems based on fuzzy sets and fuzzy logic. Fuzzy inference systems are based on fuzzy sets and use membership values alongside the original data, so a data augmentation mechanism is used in fuzzy inference systems.

Although the adaptive neuro-fuzzy inference system (ANFIS) proposed by Jang (1993) is the most well-known and frequently used fuzzy inference system in the literature, the fuzzy inference systems proposed by Takagi & Sugeno (1985) and Mamdani & Assilian (1975) are also important in the literature on fuzzy inference systems. The fact that these fuzzy inference systems have a rule base is a problem in the literature.

Turksen (2008) proposed the fuzzy regression functions approach (FRFA) to overcome such a problem. Unlike other fuzzy inference systems, FRFA does not depend on the rule base structure but uses fuzzy functions instead of rule base logic. FRFA, which is not based on a certain rule base, is an important fuzzy inference system method used in time series forecasting in recent years with this feature.

In FRFA, membership values and their nonlinear transformations are used together with the original input variables to improve the forecasting performance. More information is added to the system by using both the membership values and the non-linear transformations of the membership values and the original inputs in a single input set.

Although the FRFA has been used in many forecasting problems in the literature, it has not yet been used for wind speed forecasting. In this study, the monthly average wind speed of Giresun Province is firstly forecasted with fuzzy regression functions approach. The analysis results obtained with the fuzzy regression functions approach were compared with the forecasting methods based on both classical and artificial intelligence methods, and superior forecasting results were obtained. The rest of the paper is as follows. The literature review of the paper is given in Section 2. The fuzzy c means method and fuzzy regression functions approach are given in Sections 3 and 4 respectively. The application results of the paper are given in Section 5. The final section is for conclusion and discussion.

Literature Review: When the studies on time series forecasting in the literature are examined, it is known that these studies were carried out with classical time series, fuzzy inference systems, shallow and deep artificial neural networks, and many hybrid methods such as the studies of Zhang (2003), Chen & Hsu (2008), Chen & Wang (2010), Khashei & Bijari (2012), Chen et al. (2013), Rezaeianzadeh et al. (2014), Chen & Phuong (2016), Chen & Jian (2017), Jaramillo et al. (2017), Egrioglu et al. (2019), Bisht & Kumar (2019), Gupta & Kumar (2019), Qian et al. (2019) and Pant & Kumar (2021).

The studies in the literature on wind speed forecasting were examined, it is seen that many studies focus on the development of wind speed forecasting models. In this context, the methods used for wind speed forecasting in the literature can be divided into several categories.
These methods are traditional statistical forecasting models using models such as autoregressive model (AR), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA), artificial intelligence forecasting models using artificial neural networks, recurrent neural networks and long short-term memory, statistical machine learning models using models such as support vector machine (SVM) and fuzzy logic-based models using models such as ANFIS, and hybrid models using these models together.

If we refer to the studies made with traditional statistical forecasting models; Ewing et al. (2007) used the vector autoregression model to forecast the wind speed. Cadenas & Rivera (2007) compared ARIMA and artificial neural network (ANN) methods for wind speed forecasting on the South Coast of the Mexican state of Oaxaca. Erdem & Shi (2011) used four different methods based on the ARMA model for wind speed forecasting for the United States. Cadenas et al. (2016) forecasted the wind speed using multivariate nonlinear external input autoregressive network (NARX) and univariate ARIMA model.

If we refer to the studies made with artificial intelligence forecasting models; Alexiadis et al. (1998) used ANN for short-time wind speed forecasting. Sfetsos (2002) proposed an ANN method for forecasting average hourly wind speed data. Akıncı (2011) used ANN for short-time wind speed forecasting of Batman Province. Selcuk Nogay et al. (2012) used ANN for short-time wind speed forecasting of Mardin Province. Ren et al. (2014) proposed a method in which the parameter selection of the artificial neural network with backpropagation learning algorithm is made by particle swarm optimization (PSO), and the performance of the proposed method was compared to the daily average wind speed data of Jiuquan and the 6-hour wind speed data of Yumen in Gansu, China. Saberivahidaval & Hajjam (2015) evaluated the performance of different artificial neural network models for wind speed forecasting of Payam airport in Iran. Fazelpour et al. (2016) used four different artificial intelligence methods to forecast short-term wind speed for Tehran. Zucatelli et al. (2019) used ANN for short-term wind speed forecasting for Uruguay.

If we refer to the studies made with fuzzy logic-based models; Monfared et al. (2009) proposed a new strategy for wind speed forecasting based on fuzzy logic and artificial neural networks. Minaz (2011) used the ANFIS method for the wind speed estimation of Bilecik Province. Khosravi et al. (2018) forecasted the wind speed with feedforward neural networks, radial basis function, support vector machines, and ANFIS methods optimized with PSO. If we refer to the studies made with hybrid models; Cadenas & Rivera (2010) developed hybrid models consisting of ARIMA and ANN models for wind speed forecasting in three different regions in Mexico. Guo et al. (2011) proposed a hybrid method for wind speed forecasting in which the ANN model based on the backpropagation learning algorithm and the seasonal exponential smoothing method are used together. Shi et al. (2012) proposed hybrid methods using ARIMA, ANN, and SVM for wind speed forecasting. Wang et al. (2014) used a hybrid method in which empirical mode decomposition and Elman artificial neural network are used together for wind speed forecasting. Jiang et al. (2016) forecasted wind speed for China with a hybrid forecasting model based on a simulated annealing algorithm. Jiang et al. (2017) forecasted the wind speed with a hybrid approach in which the cuckoo search algorithm and SVM were used together.

MATERIAL AND METHOD

Fuzzy c Means Method: The fuzzy c-means method proposed by Bezdek (1981) performs clustering based on the minimization of the objective function and constraints given in the Equations (1-2). To apply the fuzzy c-means method, first of all, the number of clusters and the membership degrees of individuals to the cluster should be known. These values can be found randomly or by some developed techniques. The fuzzy c means method works based on iterative minimization of the following objective function and constraints. The objective function and restrictions used for the fuzzy c means method are given in Equations (1-2).

$$J(X,\mu,V)=\sum_{i=1}^{c}\sum_{k=1}^{n}u_{it}^{f}d^{2}(x_k,v_i) \tag{1}$$

$$\begin{gathered}0\le \mu_{ik}\le 1\\ \sum_{i=1}^{c}\mu_{ik}=1\\ 0<\sum_{k=1}^{n}\mu_{ik}\le n\end{gathered} \tag{2}$$

While f is the fuzziness index, $d(x_t,v_i)$ is a measure of similarity between the data and the cluster center. c , v_i $(i=1,2,\dots,c)$ and μ_{ik} ($i=1,2,\dots,c$; $k=1,2,\dots,n$) show the fuzzy cluster number, cluster centers and membership values, respectively. At each iteration, v_i $(i=1,2,\dots,c)$ and μ_{ik} $(i=1,2,\dots,c$; $k=1,2,\dots,n)$ are updated with Equations (3-4)

$$v_i=\frac{\sum_{k=1}^{n}(\mu_{ik})^{f}x_k}{\sum_{k=1}^{n}(\mu_{ik})^{f}}\ ,\ i=1,2,\dots,c \tag{3}$$

$$\mu_{ik}=\left[\sum_{j=1}^{c}\left(\frac{d(x_k,v_i)}{d(x_k,v_j)}\right)^{\frac{2}{f-1}}\right]^{-1},\ i=1,2,\dots,c\ ;\ k=1,2,\dots,n \tag{4}$$

Fuzzy Regression Functions Approach: The fuzzy regression functions approach proposed by Turksen (2008) has a system in which membership values obtained from the fuzzy c means method and observation values are used together. Celikyılmaz & Turksen (2009) used mathematical transformations of membership values and showed that exponential and various logarithmic transformations of membership values can increase the performance of the model. Thus, some transformations of membership values were added to the input set with the study of Celikyılmaz & Turksen (2009). Besides, there are some papers to contribute to the fuzzy regression functions approach. Tak et al. (2018) proposed a recurrent type fuzzy regression function. Tak (2018) proposed the meta fuzzy functions method. The algorithm for the fuzzy regression functions approach is given below step by step. Bas et al. (2019) proposed a fuzzy regression function based on ridge regression for forecasting. Tak (2020) proposed a novel forecasting method that combines the type-1 fuzzy functions with the autoregressive moving average model based on a grey wolf optimizer. Tak (2021) proposed a forecast combination with meta-possibilistic fuzzy functions for time series forecasting.

Step 1. First, a matrix of lagged time variables is created for the training set.

Step 2. Membership values are obtained by using the fuzzy c-means method.

Step 3. Create fuzzy regression functions.

The fuzzy regression functions for each fuzzy set can be expressed as given in Equation (5).

$$Y^{(i)}=X^{(i)}\beta^{(i)}+\varepsilon^{(i)}\ ;\ i=\ 1,2,\dots c \tag{5}$$

The inputs and outputs of the system are given in Equations (6-7), respectively.

$$\boldsymbol{X}^{(i)} = \begin{bmatrix} \mu_{i1} & \mu_{i1}^2 & exp(\mu_{i1}) & ln\big((1-\mu_{i1})/\mu_{i1}\big) & x_{11} & \cdot & \cdot & \cdot & x_{p1} \\ \mu_{i2} & \mu_{i2}^2 & exp(\mu_{i2}) & ln\big((1-\mu_{i2})/\mu_{i2}\big) & x_{12} & \cdot & \cdot & \cdot & x_{p2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mu_{in} & \mu_{in}^2 & exp(\mu_{in}) & ln\big((1-\mu_{in})/\mu_{in}\big) & x_{1n} & \cdot & \cdot & \cdot & x_{pm} \end{bmatrix} \quad (6)$$

$$\boldsymbol{Y}^{(i)} = \begin{bmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_n \end{bmatrix} \quad (7)$$

Step 4. Estimate fuzzy regression functions.

The fuzzy regression functions for each fuzzy set are estimated by Equations (8-9).

$$\hat{\beta}^{(i)} = (\boldsymbol{X}^{(i)\prime}\boldsymbol{X}^{(i)})^{-1}\boldsymbol{X}^{(i)\prime}\boldsymbol{Y}^{(i)} \quad (8)$$

$$\hat{\boldsymbol{Y}}^{(i)} = \boldsymbol{X}^{(i)}\hat{\beta}^{(i)}\ ;\ i = 1,2,\dots c \quad (9)$$

Step 5. Outputs of the system for the training set are obtained

The outputs of the system are obtained using Equation (10) with the help of membership values.

$$\hat{y}_k = \frac{\sum_{i=1}^{c}\hat{y}_{ik}\mu_{ik}}{\sum_{i=1}^{c}\mu_{ik}}\ , i = 1,2,\dots,c,\ k = 1,2,\dots,n \quad (10)$$

Step 6. To obtain the outputs for the test set, the $X^{(i)}$ and $Y^{(i)}$ matrices are updated with the test set in mind, and Steps 2-5 are repeated to obtain the outputs for the test set.

RESULTS

In this study, the performance of the fuzzy regression functions approach proposed by Turksen (2008) was evaluated by analyzing the monthly average wind speed time series of Giresun province between 2011 and 2018, which was obtained from the Giresun Meteorology Directorate. The graph of the time series consisting of all relevant years of the monthly average wind speed time series of Giresun province (GMAWS) between 2011-2018 is given in Figure 1.

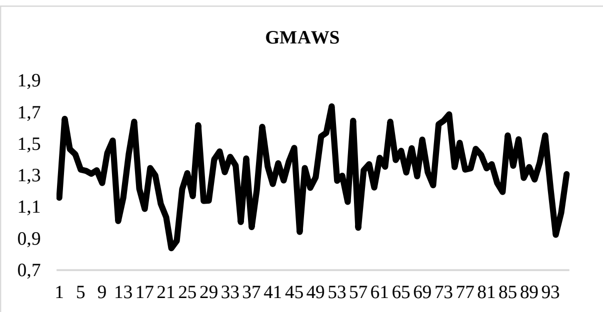

Figure 1. Giresun province monthly average wind speed time series between 2011-2018.

GMAWS time series data was analyzed with the ANFIS method proposed by Jang (1993), Pi-Sigma artificial neural networks based on artificial bee colony (PS-ANN-ABC), feed-forward artificial neural networks based on PSO (FF-ANN-PSO), linear and nonlinear ANN (L&NL-ANN) proposed by Yolcu et al. (2013), Naive method, Median-Pi ANN (MP-ANN) proposed by Egrioglu et al. (2019) and Chen (1996) methods apart from fuzzy regression functions approach (FRF). In the analysis of the GMAWS time series, the number of inputs of the model was changed between 1 and 12 and the number of fuzzy clusters between 2 and 5. The number of iterations was taken as 100 in all methods.

In the comparison of the related methods, the Root Mean Square Error (RMSE) criteria given by Equation (11) and the mean absolute percent error (MAPE) criteria given by Equation (12) were used. The analysis results obtained are given in Table 1.

$$RMSE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t-\hat{x}_t}{x_t}\right| \quad (11)$$

$$MAPE = \sqrt{\frac{\sum_{t=1}^{n}(X_t-\hat{X}_t)^2}{n}} \quad (12)$$

Table 1. Analysis results of GMAWS test data.

Method	RMSE	MAPE
Chen (1996)	0.2521	0.1744
Naive Method	0.1819	0.1128
ANFIS	0.1788	0.2579
PS-ANN-ABC	0.1719	0.1087
L&NL-ANN	0.1711	0.1064
FF-ANN-PSO	0.1670	0.1006
MP-ANN	0.1641	0.1052
FRF	0.1595	0.1046

From Table 1, it is seen that the FRF method has the lowest MAPE among all methods and when compared with other methods, FRF estimates the relevant time series with an error of 10.46%. The graph of the forecasts obtained by the FRF method and the GMAWS test set is given in Figure 2.

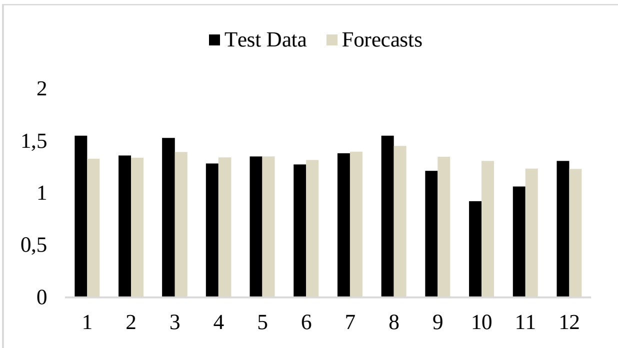

Figure 2. Graph of GMAWS time-series test set with predictions obtained by FRF method.

It is observed from Figure 2 that the predictions obtained by the FRF method and many months of the GMAWS test set are quite compatible with each other. It is seen that the predictions obtained by the FRF method are quite compatible with the test data of February, April, May, June, and July.

DISCUSSION AND CONCLUSION

In this study, the monthly average wind speed forecasting of Giresun Province was performed for the first time in the literature, and the fuzzy regression functions approach was used for the first time in wind speed forecasting. The forecasting performance of the fuzzy regression functions approach used in this study was compared with many well-known forecasting methods in the literature, and it was concluded that the fuzzy regression functions approach produced better prediction results than other methods.

In future studies, the fuzzy regression functions approach can be used to forecast wind speed in different provinces and different forecasting methods can be used for forecasting monthly average wind speed in Giresun Province.

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