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RESEARCH ARTICLE

MODELING OF CO_2 EMISSION STATISTICS in TURKEY BY FUZZY TIME SERIES ANALYSIS

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ABSTRACT

The process of determining the values which a time series will receive in the future is a very important concept. The fuzzy time series method has been widely used in recent years as it is more convenient to process data in small samples which are incomplete and/or ambiguous, and it does not contain any assumptions for time series. In this study, fuzzy time series analysis was used to predict CO_2 emission values for Turkey. For this purpose, time series (annual) for total greenhouse gas emissions by sectors (CO_2 equivalent) between 1990 and 2016 were analyzed. The main goal of this study is to model greenhouse gas emission statistics in Turkey with fuzzy time series analysis.

The RMSE value was taken into consideration to determine the most suitable model among the analysis performed.

Keywords: Time Series Analysis, Fuzzy Time Series Analysis, CO_2 emission, RMSE, Chen Models, Gustafson-Kessel clustering algorithm

1. INTRODUCTION

Global warming and climate change are among the most important problems in recent years. Global warming is caused the global economy, energy consumption, and by gases with greenhouse effect such as carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), Hydro flora carbon (HFC), Fluorocarbones (PFC), sulfur hexaflor (SF_6). Carbon dioxide (CO_2) is one of the most important greenhouse gases that cause climate change and global warming [1].

Greenhouse gases are released from both natural and human sources. The major greenhouse gases which exist in the atmosphere are water vapor (H_2O), carbon dioxide (CO_2), nitrogen oxide (N_2O), methane (CH_4), and ozone (O_3) gases. The most important greenhouse gases which are not naturally present in the atmosphere and which occur as a result of human activities are hydrofluorocarbones (HFCs), perfluorocarbones (PFCs), and sulfur hexafluoride (SF_6) gases. The amount of greenhouse gases has been increasing rapidly in recent years with economic activity and the use of fossil fuels. Consequently, this causes global warming [2]. With the atmosphere's heat retention feature, the seas and oceans do not freeze. This heating and heat retention feature of the atmosphere is called **the greenhouse effect**.

Emission factors are provided as carbon dioxide (CO_2) equivalent (CO_2). Emissions of greenhouse gases other than CO_2 (CH4, N_2O and CFC, HCFC) are calculated separately and converted into CO_2 equivalent. During this conversion, the release amounts of each greenhouse gas are multiplied by the global warming potential of that gas [3].

Carbon dioxide (CO_2): its share in greenhouse gases is 82%. CO_2, whose amount did not change in the atmosphere for millions of years, has increased by 31% since the start of the Industrial Revolution.

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According to the calculations, the annual increase of CO_2 gas in the atmosphere in the 20 years prior to 1990 was 0.4%, while the amount of increase in the following years ranged from 0.2% to 0.8%. The biggest source of CO_2 released into the atmosphere is fossil fuels, which are used a lot [4].

The Turkish Statistical Institute (TÜİK, 2018) announced that the total greenhouse gas emissions in Turkey in 2016 were 496.1 million tons of carbon dioxide equivalents. In this period, energy-derived emissions as CO_2 equivalent received the largest share of total emissions (72.8%). This was followed by industrial operations and crop use (12.6%), agricultural activities (11.4%), and waste (3.3%), respectively. Total greenhouse gas emissions as CO_2 equivalent increased by 135.4% compared to 1990. CO_2 equivalent emissions per capita were 3.8 tonnes per capita in 1990, while in 2016 it was 6.3 tonnes per capita [5].

2. LITERATURE REVIEW

2.1. Examining Classical ARIMA and CO_2 Studies

Abdullah and Pauzi (2015) examined the methods used to estimate CO_2 emissions. The articles published in international journals between 2003 and 2013 were analyzed to determine which methods should be applied and which factors have been regularly investigated [6].

Ozceylan (2018) estimated CO_2 emissions with the help of particle optimization (PSO) and artificial bee colony (ABC) techniques (models were used as linear, exponential, and quadratic) and by means of the socio-economic indicators in Turkey (energy consumption, population, GDP and number of motor vehicles). The data used are from 1980-2008 and the predictions have been made until 2030 [7].

Ayvaz et al. (2017) used different discrete grey models (DGM) to estimate energy-related CO_2 emissions in Turkey, Europe, and the Eurasian region. The data used covers the years between 1965 and 2014. With this data, CO2 emissions from 2015-2030 have been estimated [1].

Liu et al. (2017) handled the problem of carbon emission based on carbon emission time series data and chaos theory to make the relationships between the data clearer. The BP neural network model was used to estimate carbon emissions [8].

Appiah et al. (2018) exploited a two-layer forward feed neural network model with Tangent activation function that occurs with hidden neurons where neurons are used as linear output in their work. In the study, a nonlinear least squares algorithm such as LM (Levenberg-Marquardt) was applied to estimate emission for the selected emerging economies [9].

Garip and Oktay (2018) estimated Turkey's CO_2 emissions using random forest and support vector machines methods from popular machine learning methods. In the study, data from 1965-2003 were used for training, and estimates for 2004-2014 were obtained. According to the results of the study, the Support Vector Machine yielded more successful results than the random forest method [10].

Wang et al. (2019), in their study, used the metabolic grey model (MGM), adapted exponential curve model (MECM), autoregressive integrated moving average model (ARIMA), and neural network model Back Propagation (BP) to estimate the metabolic energy demand of Central Africa [11].

Sutthichaimethee et al. (2019) made use of a second-degree autoregressive structural equality model (second-degree autoregressive SEM) [12].

Dorogoi and Mokhtar (2019) implemented trend analysis and a double exponential smoothing method using the data between 1967 and 2014 to estimate energy consumption in some sectors (industry, agriculture, transport, and households - in general-commercial) which have a significant relationship with the greenhouse gas emissions in Iran [13].

Oyehan et al. (2017) applied trend analysis to CO_2 data for the years 1980-2008 for Persian Gulf Countries (Bahrain, Iran, Iraq, Qatar, Saudi Arabia, Kuwait, and the United Arab Emirates) [14].

Maleki et al. (2018) employed autoregressive integrated moving average (ARIMA) and Sini Network autoregressive (NNAR) techniques to the time series on water characteristics of water treatment plants. As a result of the study, it was determined that, compared to ARIMA, NNAR provided better predictive success for CO_2 in terms of R^2 [15].

2.2. On Reviewing the Studies Using Fuzzy ARIMA

In their study, Abd Rahman et al. (2013) envisioned a monthly air pollution index (API) for 10 years with data obtained from industrial and residential monitoring stations in Malaysia. In the study, ARIMA and Fuzzy Time Series (Chen's method and Yu's method) were used to predict API measurements. A comparison was made by obtaining RMSE values for the three proposed models. It was determined that the neural network model (ANN) provided better results [16].

Karaaslan and Gezen (2017) attempted to predict the total energy demand for Turkey and determine the amount of unused energy and the distribution of this demand among sectors. The study used annual data from 1990 to 2012 and estimated energy demand until 2023 using a fuzzy grey regression model [17].

Mahla et al. (2019) used the ARIMA model to predict emissions from biogas [18].

Atsalakis et al. (2015) examined hourly data (n=8760) for January 1, 2009-December 31-, 2009 period using an integrated neuro-fuzzy controller (PATSOS) technique. The prediction system is based on Adaptive Neural Fuzzy Systems (ANFIS) [19].

2.3. When Fuzzy and CO_2 Studies are Inspected

Tavan M (2019) introduced a new hybrid modelling to predict carbon dioxide emissions in order to make the correct decision to reduce air pollution in Iran. In the paper, CO_2 emissions in Iran in the period of 1980-2014 was predicted using three models of Auto-Regressive Distributed Lag (ARDL), Fuzzy Linear Regression (FLR), and hybrid model based on the combination of ARDL and FLR models, and then the prediction accuracy of the models is compared [20].

Examining the literature, it is observed that studies on greenhouse gas emissions and classical ARIMA, and studies on Fuzzy ARIMA and other application areas exist. However, the aim of this study is to model greenhouse gas emission statistics in Turkey with fuzzy time series analysis. For this purpose, greenhouse gas emission was modeled using four different Fuzzy ARIMA models, and their performances were evaluated.

This paper consists of four parts. The first section is the introductory section, and the second part contains fuzzy time series models. The third section is the application section. The fourth part is the concluding part.

3. FUZZY TIME SERIES

The fuzzy time series method has been widely used in recent years as it is more convenient to process data in small samples which are incomplete and/or ambiguous, and it does not contain any assumptions for time series. There is a fundamental difference between fuzzy time series and traditional time series.

The values in fuzzy time series are fuzzy clusters, whereas the values used in traditional time series are real numbers. A fuzzy set is a cluster with fuzzy boundaries.

The first definition of the fuzzy time series was proposed by Song and Chissom (1993a, 1993 b), and the method was developed by Chen (1996) [21-23]. Later, other studies were conducted on prediction problems using the fuzzy time series concept [21, 24-30].
Song and Chissom (1993a, 1993b, 1994) suggested the model of first order time-invariant fuzzy time series, and to predict an annual time series, they proposed first-order fuzzy time-varying time series [21, 22-24].

Sullivan and Woodall (1994) examined the first-order time-varying time series model proposed by Song and Chissom and the first-order time-invariant fuzzy time-series model. They compared the models to each other [30].

Song et al (1995) presented a new fuzzy time series model for a fuzzy number observation [28]. Chen (1996) developed a new prediction method using fuzzy time series [23]. Hwang et al (1998) proposed a method that eliminates the prediction problems with the use of fuzzy time series [26]. Chen and Hwang (2000) developed a method for temperature estimation using fuzzy time series [25].

Chen (2000) developed a new method for the prediction problem using high-order fuzzy time series [24].

3.1. Chen (1996) model: This method consists of 6 steps defined as follows.

Step 1: Determination of universal sets and subintervals.
In this step, the universal set is determined according to the smallest and largest values of the time series. The defined universal set is divided into a predetermined number of subintervals. If the smallest value of the time series is $Dmin$ and the largest value is $Dmax$, the universal set is defined as follows.

$$U=[Dmin-D_1,Dmax+D_2] \tag{1}$$

Here, D_1 and D_2 are two small randomly chosen numbers.

Step 2: Determination of fuzzy sets: fuzzy sets defined in peer (1) are determined**.**

Step 3: Observations are fuzzy

Subinterval for the observation of each classical time series is determined. The fuzzy set with the largest membership value of this subinterval gives the fuzzy value of the classical time series observation.

Step 4: Determination of fuzzy relations
Determination of the fuzzy logical relationships can be explained with an example. Let the elements of t, a fuzyy time series (FTS) with five observations, be as follows. $A1$, A1, $A2$, $A2$, $A3$.
In this case, fuzzy relations are defined as follows.
$A1\rightarrow A1$ $A1\rightarrow A2$ $A2\rightarrow A2$ $A2\rightarrow A3$
Fuzzy relations are grouped as follows.

$A1\rightarrow A1$,A2 $A2\rightarrow A2$, $A3$
Step 5: Predictions are obtained.
There are 3 different situations in the process of obtaining predictions.

Case 1, Aj is the predictive value for time t when there is only one fuzzy logical relationship as Ai → Aj in the fuzzy relations sequence.

Case 2, If Ai → Aj, s, Al, the predictive value is equal to Aj, As, Al.

Case 3, If Ai → $\emptyset$, the predictive value equals Ai.

Step 6: Obtained predictive values are defuzzified.
'Centralization-defuzzification method' is used to obtain the results. There are 3 different situations in defuzzification process.

Case 1, if the predictive value is equal to A_J, defuzzified predictive value is the cluster center cj of Aj fuzzy set.

Case 2, if the predictive value is Ajl, the defuzzified predictive value is calculated in the form of $(cj+cs+cl)3/$ as an arithmetic average of the cluster centers of the fuzzy sets Aj,As,Al.

Case 3, if Ai is equal to the empty set ($\emptyset$), then the defuzzified predictive value is cluster center ci of AI fuzzy set [31].

3.2. Chen (2002) Model: General Definitions
Let U=$\{u_1, u_2, u_3, \ldots, u_n\}$ be the universal cluster. The elements of U have intervals. These intervals are obtained by breaking down the universal set according to a previously determined fixed interval length. Fuzzy sets of U are defined as:

$$\text{s}A = f_A(u_1)/u_1 + f_A(u_2)/u_2 + \cdots + f_A(u_n)/u_n \quad (2)$$

f_A: is the membership function of A function. f_A : U→[0,1] and (u_i) denote the membership degree of the UI in A [32].

Definition 1:
Let X(t) be a real-valued subset with (t=..., 0,1,2,...). F(t) is the sum including the fuzzy set defined as f_i (t) (i = 1;2;...) and is defined as a fuzzy time series to F(t).

F(t) time series obtained after determining Ai fuzzy set corresponding to appropriate sub-intervals of the X time series and to the observation of each time series is called "**fuzzy time series".** F (t) is also a function of time. In other words, since the universal set can take different values at different times, F(t) can also take different values at different times.

In definition 1;
1. F(t) is a function of time.
2. F(t) can be thought of as a verbal variable, taking verbal values where all the values it will take can be represented by fuzzy sets.
3. $f_i(t)$ (i = 1,2,...) are possible verbal values of F(t). $f_i(t)$ (i = 1,2,...) is represented by fuzzy sets.

Definition 2: including F(T) fuzzy time series, for any time F(T)= F(T-1), and F(T) has only finite elements. Thus, F(t) is called time-invariant fuzzy time series.
Definition 3:

Let F (t) be a fuzzy time series. If F(t), F(t - 1), F (t - 2),... causes F(t - n), then the fuzzy logical relationship is expressed as follows.

$$F(t-n),...,F(t-2), F(t-1) \rightarrow F(t) \quad (3)$$

and it is called n-th order fuzzy time series predictive model.

Chen (2002) method consists of the following stages.

Step 1: Determination of universal sets and subintervals.
In this step, the universal set (U) is determined with the smallest (Dmin) and the largest value ($Dmax$) of the time series.

$$U=[Dmin-D_1, Dmax+D_2] \quad (4)$$

Here, D_1 and D_2 are two randomly chosen positive numbers.
A predetermined number of subintervals of u_i are defined so that this universal set is $U=\{u_1, u_2, u_3, ..., u_n\}$.

Step 2: Determination of fuzzy sets
The fuzzy A1, A2 , ..., Ak. sets are defined in the universal set of U.

$$A_1= a_{11} /u_1 + a_{12} /u_2+\ldots+a_{1m} /u_m$$
$$A_2= a_{21} /u_1 + a_{22} /u_2+\ldots+a_{2m} /u_m \quad (5)$$
.
.
.
$$A_k= a_k /u_1 + a_k /u_2+\ldots+a_{km} /u_m$$

Here, $a_{ij} \in [0,1]$ ve $1 \leq i \leq k$ $1 \leq j \leq m$. The values of a_{ij} in the A_i fuzzy set.

Step 3: Observations are defuzzified.
It is matched with the fuzzy set with the largest membership value for the subinterval set determined for each time series data. Thus, the time series is defuzzified.

Step 4: Determination of fuzzy relations
The determination of the fuzzy logical relationships can be explained with an example., let the elements of (t), a FTS with five observations, be as follows. $A1$,A1,$A2$,$A2$,$A3$. In this case, fuzzy relations are determined as follows. $A1 \rightarrow A1$ $A1 \rightarrow A2$ $A2 \rightarrow A2$ $A2 \rightarrow A3$ Fuzzy relations are grouped as follows. $A1 \rightarrow A1,2$ $A2 \rightarrow A2, A3$

Fuzzy predictions are obtained. Using the model obtained in the previous step, the outputs of the model are calculated. The calculated outputs are the numbers of fuzzy sets which the predictions belong to. Accordingly, fuzzy predictions are derived from the outputs of the model obtained in the previous step.

Step 5: Calculating predictions.
The following principles are taken into account at this stage.

Case 1: If fuzzified observations for year i.,,,,,from K(k≥2) k^{th} level are A_{ik},$A_{i(k-1)}$,..., and A_{il}, and there is a fuzzy logic present in k^{th} level fuzzy logic relations, then the groups are defined as follows.

$$A_{ik}, A_{i(k-1)}, ..., A_{il} \rightarrow A_j$$

A_{ik} , $A_{i(k-1)}$, ..., A_{il} ve A_j are fuzzy sets, and they are in m_j interval which is the midpoint of u_j and u_j, which is the largest membership of A_j, and predictive value for year i is m_j.

Case 2 If observations fuzzified from the kth level (k≥2) for the year are Aik, Ai (k-1), ..., and Ail, if there is a fuzzy logic relationship in the kth level fuzzy logic relations, the groups are defined as follows.

A_{ik} , $A_{i(k-1)}$, ..., A_{il} → A_{j1}
A_{ik} , $A_{i(k-1)}$, ..., A_{il} → A_{j2}
.
.
.
A_{ik} , $A_{i(k-1)}$, ..., A_{il} → A_{jp}
A_{ik}, $A_{i(k-1)}$,..., A_{il}, A_{j1}, A_{j2}, …, A_{jp} are fuzzy sets. It can be seen that there is an uncertainty to predict the record of year i (fuzzy observation for year i can be Aj1, Aj2 or Ajp). In this case, there should be high-order fuzzy observations for year i. Therefore, there will be no uncertainty for the prediction of the year i. To eliminate this uncertainty, suppose there is an integer value of m (m≥k). For the year i, the m^{th} degree fuzzified observation values are A_{im}, A_i (m-1), ...;, A_{i1} and the fuzzy logic relationships in m^{th} degree fuzzy logic relation groups are defined as follows:

A_{im}, $A_{i(m-1)}$, ..., A_{il} → A_j
A_{im}, $A_{i(m-1)}$, …, A_{il} and A_j are fuzzy sets.

The largest membership value of A_j is u_j, and it occurs in m_j interval which is the midpoint of u_2,…, u_j'. Consequently, the predictive value of year i is m_j.

Case 3: Let the observations fuzzified from k^{th} degree for year i be A_{ik},$A_{i(k-1)}$,..., and A_{il}. If the right side of the fuzzy logic relation is empty, the logical relation groups of k^{th} degree are defined as follows.
$A_{ik,}$ $A_{i(k-1)}$,… ,A_{il} → #
Here, $A_{ik,}$ $A_{i(k-1)}$,… and A_{il} are fuzzy sets, and the largest membership value of $A_{ik,}$ $A_{i(k-1)}$,… and A_{il} is u_{ik}, $u_{i(k-1)}$;...; and it occurs in m_{ik}, the midpoint of m_{ik}, $m_{i(k-1)}$,...i and m_{il} interval. Thus, the predicted value for year i is calculated as follows [31].

$$\frac{1*m_{ik}+2*m_{i(k-1)}+\cdots+k*m_{ik}}{1+2+\cdots+k} \tag{6}$$

Step 6. Defuzzification process for fuzzy predictions

The defuzzification process is applied to fuzzy predictions. During defuzzification, the centralization method is used. If fuzzy prevision is Aj, defuzzified prediction is the midpoint value of uj which is the interval with the highest membership value for this fuzzy set.

3.3. Fuzzy Time Series Models Based on Fuzzy Clustering

Gustafson ve Kessel (1979)

Gustafson and Kessel (1979) proposed an adapted version of the fuzzy clustering algorithm. This algorithm uses the Mahalanobis distance instead of the Euclidean distance. The distance of Mahalanobis forms ellipse-shaped clusters.
Mahalanobis distance ($d_{ikA_i}^2$), the distance norm of the GK algorithm, is defined as

$$d_{ikA_i}^2 = (Z_k - V_i)^T A_i (Z_k - V_i) \tag{7}$$

The purpose function of the GK clustering algorithm is expressed in equation (8).

$$J(X,U,V,A) = \sum_{i=1}^{N} \sum_{k=1}^{c} (u_{ik})^m d_{ikA_i}^2 \tag{8}$$

The steps of the Gustafson-Kessel clustering algorithm are as follows:

Step 1: Initial values, cluster number (c), fuzzification index (m), number of iterations (i), membership degrees matrix (u), cluster center values (v) and stop criteria (ε) are determined. Here, it is defined as (> 0), (1 <c <N), (m> 1).

Step 2: Fuzzy cluster centers are calculated.

$$v_k = \frac{\sum_{i=1}^{N} u_{ik}^{m} x_i}{\sum_{i=1}^{N} u_{ik}^{m}}, \quad 1 \leq k \leq c \tag{9}$$

Step 3: The Mahalanobis distance is calculated for each element.

Step 4: Fuzzy covariance matrices (F_i) are calculated for each set separately.

$$F_i = \frac{\sum_{k=1}^{N} (d_{ik})^m (Z_k - V_i)(Z_k - V_i)^T}{\sum_{k=1}^{N} (d_{ik})^m} \tag{10}$$

Step 5: The membership matrices are updated.

$$u_{ik} = \left[\sum_{j=1}^{c} \left({d_{ikA_k}}/{d_{ijA_k}} \right)^{2/(m-1)} \right]^{-1} \tag{11}$$

Step 6: The process is terminated when $\|V_t - V_{t-1}\| < \varepsilon$ condition is met. If not, return to step 2 [33-34].

4. ANALYSIS OF GREENHOUSE GAS EMISSION STATISTICS in TURKEY with FUZZY TIME SERIES ANALYSIS

Fuzzy logic applications, unlike statistical methods, may include methods that can be analyzed with a small number of data which do not require any assumptions. Fuzzy time series is also a method that can be applied in cases where the number of samples is small without requiring any assumption on the time series. The most important step in the implementation of the fuzzy time series models in the literature is that the fuzzy equivalent of the classical time series can be obtained, that is they can be fuzzified. The main purpose of the application is to model the greenhouse gas emission statistics in Turkey with fuzzy time series analysis. Expressing which model is the most appropriate in the analysis performed will be evaluated by considering the RMSE value.

In the implementation phase of the study, total greenhouse gas emissions (CO_2 equivalent) in Turkey between 1990 and 2016 will be evaluated using fuzzy time series analysis. For this purpose, data (Table 1) will be analyzed using Chen (1996) method, Chen (2002) method, and fuzzy time series models based on fuzzy clustering, which are fuzzy time series based on fuzzy C-Means (FCMFTS) and fuzzy time series based on Gustafson - Kessel clustering (GKFTS).

Table 1. Total greenhouse gas emissions by sector in Turkey (CO_2 equivalent)

Year	Greenhouse gas emission (million tons)	Year	Greenhouse gas emission (million tons)	Year	Greenhouse gas emission (million tons)
1990	210,7	1999	272,1	2008	387,9
1991	218,7	2000	293,5	2009	395,9
1992	224,7	2001	274,4	2010	402,6
1993	233,4	2002	280,8	2011	431,4
1994	227,6	2003	300,3	2012	445,6
1995	242,2	2004	311,2	2013	439,0
1996	261,2	2005	332,7	2014	451,8
1997	272,6	2006	356,8	2015	469,9
1998	274,5	2007	390,5	2016	496,1

(**Source**: Turkish Statistical Institue 13th 2018)

4.1. Chen 1996 Model Results

Implementing the prediction algorithm of Chen 1996 fuzzy time series model, fuzzy time series model prediction analysis was performed for CO2 emission value in Turkey. After the related analysis, RMSE value for CO_2 emissions of Chen (1996) model was obtained as 11.61.

Table 2. Chen (1996) Model Results

Year		Greenhouse gas emission (million tons)	Chen (1996)
Test Data	2012	445,6	445,6
	2013	439	439
	2014	451,8	451,8
	2015	469,9	469,9
	2016	496,1	496,1
		RMSE	11,61

4.2. Chen (2002) Model Results

Chen (2002) model, one of the fuzzy time series analysis methods, was applied for CO_2 emission value in Turkey. The Chen (2002) model is the high-order fuzzy time series model. Analyzing the Chen 2002 model for the related data, the values in Table 3 were obtained. In the analysis of time series, Chen (2002) model was tested from 2nd order to 12th order model by changing the number of fuzzy sets between 3 and 10.

The optimal model order and number of fuzzy sets were determined according to the RMSE criteria calculated for the validition by taking the time series training set between 1990 and 2006 and the observations validity set between 2007 and 2011. The performance of the method was observed using as a test set between 2012-2016 in the last 5 observations. The best results were obtained when the model rating was chosen as 2 and the number of fuzzy sets as 5. For CO_2 emissions in Turkey, the RMSE value obtained by Chen 2002 method was obtained as 24.86.

Table 3. Chen (2002) Model Results

Year		Greenhouse gas emission (million Tons)	Chen (2002) Order=2, number of cluster=5
Test Data	2012	445,6	410,4800
	2013	439	448,5333
	2014	451,8	429,5067
	2015	469,9	448,5333
	2016	496,1	467,5600
		RMSE	24,86

4.3. Fuzzy Time Series Model Based on Fuzzy Sets

Fuzzy time series analysis based on fuzzy clustering uses fuzzy cluster analysis methods in the step of converting into fuzzy time series. In this study, analysis was performed using fuzzy time series based on fuzzy c-means and fuzzy time series models based on Gustafson-Kessel clustering. In both methods, the number of clusters was taken as 5. As a result of the analysis, the RMSE value of the FCMFTS (Fuzzy-Cluster Means Time Series) method was obtained as 30.42, and the RMSE value of the GKFTS method was 25.85. The related results are given in Table 3.

Table 4: Fuzzy Time Series Model Based on Fuzzy Sets Results :

Year		Greenhouse gas emission (million tons)	FCMTS	GKFTS
Test Data	2012	445.6	417,4968	430,0034
	2013	439	417,4968	430,0034
	2014	451,8	417,4968	430,0034
	2015	469,9	417,4968	430,0034
	2016	496,1	417,4968	430,0034
		RMSE	30,42	25,85

5. CONCLUSIONS

In this study, fuzzy time series analysis was used to predict CO_2 emission values for Turkey. For this purpose, time series (annual) for total greenhouse gas emissions by sectors (CO_2 equivalent) between 1990 and 2016 were analyzed. In the data analysis section of this study, total greenhouse gas emissions (CO_2 equivalent) in Turkey between 1990 and 2016 will be evaluated using fuzzy time series analysis. For this purpose, data (Table 1) will be analyzed using Chen (1996) method, Chen (2002) method, and fuzzy time series models based on fuzzy clustering, which are fuzzy time series based on fuzzy C-Means (FCMFTS) and fuzzy time series based on Gustafson - Kessel clustering (GKFTS) and the performances of the models were evaluated.

Expressing which model is the most appropriate in the analyses performed was put forward considering the RMSE value. As a result, modeling the greenhouse gas emission statistics with fuzzy time series analysis as the main goal of the study was achieved, and the applicability of four different fuzzy time series models proposed to the related data set was revealed. Comparing RMSE values, it was seen that Chen 1996 model had the smallest value. In this study, it was tried to estimate the CO_2 emission value for Turkey by using Chen (1996), Chen (2002) and Gustafson and Kessel (1979) techniques. Since such a comparison is made, the study is original.

The techniques used in the study can be used for other time series. As there is no other study using four different fuzzy time series as in this study, the study has originality as it is.

CONFLICT OF INTEREST

The author stated that there are no conflicts of interest regarding the publication of this article.

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