International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2017, 7(1), 67-77.

Forecasting of Turkey's Sectoral Energy Demand by Using Fuzzy Grey Regression Model

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ABSTRACT

Population growth, technological developments, economical growth and efforts to achieve a high standard of living increase the demand for energy. Satisfying this increasing demand without interruption is of vital importance for countries to ensure security of supply. Safely forecasting the energy demand of Turkey, which is about 3-4 times the world average, is important for sustainable development and improving standards of living in the country. This study seeks to forecast Turkey's total energy demand and determine the distribution of this demand among sectors and the amount of unutilized energy. In the study, the energy demand projection until 2023 was revealed with fuzzy grey regression model using the data between years 1990 and 2012.

Keywords: Fuzzy Grey Prediction, Sectorial Energy Demand in Turkey, Fuzzy Grey Regression Model
JEL Classifications: C610, L690

1. INTRODUCTION

Industrial growth in conjunction with development, rapid urbanization and population growth increase sectorial energy demand. Uninterrupted supply of this increasing demand in the future is a national and international problem. In order to overcome this problem, an important step in countries' energy policies is to forecast reliably the future energy demand. Reliable forecasting has, in this context, a vital importance for sustainable future, the drawing up of proper policies and regulations and development of energy strategies. Energy demand forecasting is an attempt for constructing energy policies required by the uncertainties in the complicated global energy equation (GIF, 2013). Decision makers should endeavor to reduce these uncertainties in the energy sector as much as possible and to create flexible structures to benefit from this. The global energy demand increases about 2% a year and in Turkey which is a developing country with an energy need 3-4 times the world average, this increase is between 6% and 8%. These scores necessitate Turkey to pursue more aggressive energy strategies compared to other countries and for sustainability of development, to make medium- and long-term energy investments.

2. LITERATURE REVIEW

In the international literature, there are many energy demand forecast studies performed using various methods. Those that come into prominence are artificial neural network (ANN) model (Geem and Roper, 2009; Limanond et al., 2011; Xiao et al., 2015), genetic algorithm (GA) (Forouzanfar et al., 2012; Ghanbari et al., 2013; Yu and Zhu, 2012; Yu et al., 2015), Grey model (Bianco et al., 2010; Chen and Wang, 2012; Lu et al., 2008; Pao et al., 2012; Shen and Lu, 2014; Wang et al., 2013; Xie et al., 2015), group method of data handling neural network (Srinivasan, 2008), a new method based on a physical-statistical approach (Lü et al., 2015), support vector regression (SVR) analysis (Jain et al., 2014). In Turkey, under energy planning operations, energy demand forecast is done using model of analysis of the energy demand since 1984 by the Ministry of Energy and Natural Resources (MENR). In addition to these studies, there are other studies in literature, performed for Turkey using different forecasting methods (Table 1). These studies forecasted Turkey's demand for various types of energy using ANN method (Hamzaçebi, 2007; Murat and Ceylan, 2006; Sözen et al., 2004), autoregressive integrated moving average model method (Ediger and Akar, 2007; Ediger et al., 2006; Erdogdu, 2007), ant colony optimization (ACO) algorithm (Toksarı, 2007; 2009), GA (Canyurt and Ozturk, 2008; Ersel Canyurt et al., 2004; Haldenbilen and Ceylan, 2005), SVR method (Kavaklioglu, 2011), fuzzy logic methodology (Kucukali and Baris, 2010), grey predict method (Yılmaz and Yılmaz, 2013) and optimized grey modeling (OGM (1, 1)) technique (Hamzacebi and Es, 2014). In addition to these methods, hybrid studies in recent years draw attention for improving the reliability of results. Some of these studies are grey prediction with rolling mechanism (Akay and Atak, 2007), ANN and GA methods (Cinar et al., 2010); ANFIS and ARMA methods (Demirel et al., 2010); practical swarm optimization and ACO (Kıran et al., 2012).

In addition to literature fuzzy grey regression model (FGRM) is utilized in our study, which is a method that hasn't been used in Turkey for energy demand forecasting. FGRM forecasts demand amounts as an interval consisting of lower and upper bounds, instead of a definite value. This method is also an effective technique for improving the reliability of the forecast for exponential and chaotic data like energy demand. This makes it possible to obtain more reliable results compared to other methods. The FGRM analysis forecasted the amount of energy demanded by industrial, transportation, residence and other sectors, the amount of unutilized energy and the amount of total energy demand, considering the demand amount for each sector between 1990 and 2012.

3. GREY FORECASTING MODEL AND FUZZY THEORY

In order to evaluate the fuzzy relationship between dependent and independent variables, and to obtain results with more safety; the fuzzy set theory and the grey model GM (1, 1) have been hybridized in this paper (Tsaur, 2008).

3.1. Grey Forecasting Model

Grey model can be characterized as a system with one unknown. Even in cases of insufficient data, it's a method which can make effective estimations (Chen and Chang, 2000). The original time series set f^0 to be defined as follows:

$$f^{0} = \{f_t^{0} | t \in 1,2,\ldots,n\} \tag{1}$$

Where t denotes the number of data observed in period t (Tsaur, 2008). Due to internal and external peripheral variables, the system development is generally irregular. Therefore, Deng (1989) proposed the technique of accumulation generating operation (AGO) in order to bring out hidden regular pattern (Lin et al., 2012). The f_t^1 AGO value of the original time series of f_t^0 is obtained as follows:

$$f_t^{1} = \left(\sum_{k=1}^{t} f_k^{0}\right) \quad t=1,2.,n \tag{2}$$

The grey model GM (k, N) is defined as:

$$\frac{d^k F_t^1}{dt^k} + a_1 \frac{d^{k-1} F_t^1}{dt^{k-1}} + \ldots + a_{k-1} \frac{dF_t^1}{dt} + a_k F_t^1 = b_1 X_1^1(t) + b_2 X_2^1(t) + \ldots b_{N-1} X_{N-1}^1(t) \tag{3}$$

Where k stands for the k^{th}-order derivative of the dependent variables f_t^1, and N stands for N variables (i.e. one dependent variable f_t^1 and N−1 independent variables.

$X_1^1(t), X_2^1(t), \ldots, X_{N-1}^1(t)$. If k=1 and N=1, then the grey model GM (1, 1) with first-order differential equation and one dependent variable model can be constructed as:

$$\frac{dF_t^1}{dt} + aF_t^1 = b,\ t = 1,2,\ldots,n \tag{4}$$

The parameters of the Model A and B to be estimated are a unknown developed parameter and B unknown grey controlled parameter (Wu and Chen, 2005). F_t^1 is the dependent variable with AGO input value f_t^1. For solving Model (4), the derivative $\frac{dF_t^1}{dt}$ for the dependent variable is represented as (Tsaur, 2008).

$$\frac{dF_t^1}{dt} = \lim_{h\to 0} \frac{F_{t+h}^1}{h},\quad \forall t \geq 1 \tag{5}$$

Because the collected data is a set of time-series, we assume the sampling time interval between period t and t+1 to be one unit. Then, the derivative $\frac{dF_t^1}{dt}$ can be approximated to be the difference between two successive periods of F_t^1 and F_{t+1}^1, defined as an inverse AGO (IAGO) variable F_{t+1}^0 as (Zeng et al., 2014).

$$\frac{dF_t^1}{dt} \approx \frac{F_{t+1}^1 - F_t^1}{1} = F_{t+1}^1 - F_t^1 = F_{t+1}^0,\quad \forall t \geq 1 \tag{6}$$

For the original (t+1)-th time series data f_{t+1}^0, ∀t≥1. In order to have a more steady value for the dependent variable F_t^1, ∀t≥1, the second part of Model (4) is suggested as the average of two successive periods of F_t^1 and F_{t+1}^1, ∀t≥1. Then, we can rewrite Model (4) as (Tsaur, 2008).

$$F_{t+1}^0 = a\left[-\frac{1}{2}\left(F_{t+1}^1 + F_t^1\right)\right] + b,\quad \forall t \geq 1 \tag{7}$$

Then (7) can be rewritten into matrix from as,

$$\begin{bmatrix} F_2^0 \\ F_3^0 \\ \ldots \\ F_n^0 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left(F_2^1 + F_1^1\right) & 1 \\ -\frac{1}{2}\left(F_3^1 + F_2^1\right) & 1 \\ \ldots & \\ -\frac{1}{2}\left(F_n^1 + F_{n-1}^1\right) & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \tag{8}$$

When the GM (1, 1) is considered as a conventional regression practice, the equivalence for both parameters defined in 8 can be estimated through the least-squares method. Let $\hat{\beta}$ be an estimated parameter vector for all a and b, then the least-squares estimate for $\hat{\beta}$ is expressed as in Equation (9) (Chen and Chang, 2000).

$$\hat{\beta} = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T F^0 \tag{9}$$

Where matricies;

$$F^0 = \begin{bmatrix} f_2^0 \\ f_3^0 \\ \dots \\ f_n^0 \end{bmatrix}, \quad B = \begin{bmatrix} -\frac{1}{2}\left(f_2^1 + f_1^1\right) & 1 \\ -\frac{1}{2}\left(f_3^1 + f_2^1\right) & 1 \\ \dots & \\ -\frac{1}{2}\left(f_n^1 + f_{n-1}^1\right) & 1 \end{bmatrix}$$

The solutions include two part. The first, differential equation of Model (4) can be solved to obtain the estimated value $\hat{f}_{t+1}^1$ for dependent variable F_t^1, ∀t≥1 as,

$$\hat{f}_{t+1}^1 = \left(f_1^0 - \left(b/a\right)\right)e^{-at} + \left(b/a\right), \quad \forall t \geq 1 \tag{10}$$

The second, Equation (6) is used as a manipulation basis to perform IAGO by which the result, $\hat{f}_{t+1}^1$ yield in Equtıon (11).

$$\hat{f}_{t+1}^0 = \hat{f}_{t+1}^1 - \hat{f}_t^1, \ \forall t=1,2,\dots,n \tag{11}$$

Therefore, by inputting the series $f_1^0, f_2^0, \dots, f_n^0$ into the grey model GM (1, 1), it can obtain the extrapolaritive value of $\hat{f}_2^0, \hat{f}_3^0, \dots, \hat{f}_n^0, and\ \hat{f}_{n+1}^0$.

3.2. The Fuzzy Regression Model

The fuzzy regression was first introduced by Tanaka in 1982. According to this method, the regression coefficients are fuzzy numbers which can be expressed as interval numbers with membership values. As regression coefficients are fuzzy numbers themselves, the estimated dependent variable will also be a fuzzy number (Chang and Ayyub, 2001). The basic model presumes a fuzzy regression equation as seen below:

$$\widehat{Y_i} = \hat{A}_0 + \hat{A}_1 X_{i1} + \dots + \hat{A}_N X_{iN} = \hat{A} X_i \tag{12}$$

Where $\hat{A}_O$ is a fuzzy intercept coefficient, and is $\hat{A}$ a fuzzy slope coefficient. Each fuzzy parameter $\hat{A}_j = \left(m_j, c_j\right)$ is expressed as symmetrical triangular membership function, which consists of fuzzy center m_j and fuzzy half-width c_j (Chang and Ayyub, 2001).

$$\mu_{\hat{A}_j}\left(a_j\right) = \begin{cases} 1 - \dfrac{\left|m_j - a_j\right|}{c_j}, & m_j - c_j \leq a_j \leq m_j + c_j \\ & \forall j = 0,1,\dots,N \\ 0 \quad , & otherwise \end{cases} \tag{13}$$

The derived membership function of fuzzy number $\widehat{Y_i}$ is shown as (14),

$$u\left(Y_i\right) = \begin{cases} 1 - \dfrac{\left|Y_i - X_i m\right|}{c^T \left|X_i\right|}, & X_i \neq 0 \\ 1, & X_i = 0, Y_i \neq 0 \\ 0, & X_i = 0, Y_i = 0 \end{cases} \tag{14}$$

The purpose of the fuzzy regression model is to find the narrowest fuzzy regression interval in accordance with the equivalence defined in 15. By requiring that the membership degree of each observation Y_i is at least equal to the value h as shown (16) below,

$$MIN \sum_{j=0}^{N} \left[c_j \sum_{i=1}^{M} \left|X_{ij}\right| \right] \tag{15}$$

$$1 - \frac{\left|Y_i - X_i^T m\right|}{c^T \left|X_i\right|} \geq h, \ \forall i=1,2,\dots,M \tag{16}$$

Thereby, the linear programming model seen below can be obtained in order to solve the fuzzy regression equation (Tsaur, 2008).

$$MIN \sum_{j=0}^{N} \left[c_j \sum_{i=1}^{M} \left|X_{ij}\right| \right]$$

$$\sum_{j=0}^{N} m_j X_{ij} + (1-h) \sum_{j=0}^{N} m_j \left|X_{ij}\right| \geq Y_i, \ \forall i=1,2,\dots,M$$

$$\sum_{j=0}^{N} m_j X_{ij} - (1-h) \sum_{j=0}^{N} m_j \left|X_{ij}\right| \leq Y_i, \ \forall i=1,2,\dots,M$$

$$c \geq 0,\ X_{i0}=1,\ 0 \leq h \leq 1;\ \forall i=1,2,\dots,M \tag{17}$$

Then Formula (12) can be rewritten as,

$$\widehat{Y_i} = \left(m_0, c_0\right) + \left(m_1, c_1\right) X_{i1} + \dots + \left(m_N, c_N\right) X_{iN} \tag{18}$$

Each value of the dependent variable can be estimated as a fuzzy number $\widehat{Y_i} = \left(Y_i^L, Y_i^{h=1}, Y_i^U\right)$, i=1,2.,M where the lower bound of $\widehat{Y_i}$ is $Y_i^L = (m-c)^T X_i$; the center value of $\widehat{Y_i}$ is $Y_i^{h=1} = m^T X_i$; the upper of $\widehat{Y_i}$ is $Y_i^U = (m+c)^T X_i$ and $c^T=(c_0, c_1, \dots, c_N)$, $m^T=(m_0, m_1, \dots, m_N)$.

The degree of fitness of the estimated fuzzy regression equation $\widehat{Y_i} = \hat{A}_0 + \hat{A}_1 X_{i1} + \dots + \hat{A}_N X_{iN} = \hat{A} X_i$ to the given data Y_i is measured by indeks h with $Y_i^h = \left\{Y_i \left| u_{\widehat{Y_i}}(Y_i) \geq h\right.\right\}$.

The value of h is a membership degree which requires it to be in the fuzzy regression interval derived from the smallest h degree. Moskowitz and Kim (1993) proposed that if the data is obtained with safety, a smaller h value is optable, if not a higher h value is preferred. Besides, Moskowitze and Kim also suggested that "ıf the solution for a fuzzy regression model is obtained as $\hat{A}_{j,h_1} = \left(m_j^*, c_j^*\right)$, than the solution is changed into $\hat{A}_{j,h_2} = \left(m_j^*, \frac{1-h_1}{1-h_2} c_j^*\right)$ when the confidence value h is adjusted from h_1 to h_2" (Tsaur, 2008).

3.3. FGRM with Crisp-input and Fuzzy-output Model

For a limited time series set $f^0 = \left\{f_t^0 | t \in 1,2,\ldots,n\right\}$, an AGO time series set $f^1 = \left\{f_t^1 | t \in 1,2,\ldots,n\right\}$ is obtained as $f_t^1 = \sum_{k=1}^{t} f_k^0$. In order to safely estimate with limited time series data in this study, the fuzzy set theory and the grey model GM (1, 1) have initially been hybridized, then the fuzzy regression model with crisp-input and fuzzy-output value. In the equivalence 7, the fuzzification of the grey model GM (1,1) is as follows:

$$\widehat{F}_{t+1}^{0} = \hat{A}_0 + \hat{A}_1 F_t^1, \forall t \geq 1 \tag{19}$$

Where,

$\hat{A}_0 = (a_0, c_0) ve\, \hat{A}_1 = (a_1, c_1)$ center values are fuzzy values defined as a_0, a_1 and spread values c_0, c_1, respectively. Besides, the piecewise/partial membership function of the fuzzy output value $\hat{F}_{t+1}^0$ is as shown in (20).

$$\mu\left(f_{t+1}^0\right) = \begin{cases} 1 - \dfrac{\left|f_{t+1}^0 - \left(a_0 + a_1 f_t^1\right)\right|}{c_0 + c_1 f_t^1}, & \left(a_0 + a_1 f_t^1\right) - \left(c_0 + c_1 f_t^1\right) \leq f_{t+1}^0 \leq \left(a_0 + a_1 f_t^1\right) + \left(c_0 + c_1 f_t^1\right) \\ 0, & o.w \end{cases} \tag{20}$$

Finding the closest regression interval with FGRM requires the membership degree of each observation value f_{t+1}^0 to be greater than or equal to one h value.

$$1 - \frac{\left|f_{t+1}^0 - \left(a_0 + a_1 f_t^1\right)\right|}{c_0 + c_1 f_t^1} \geq h, \quad \forall t = 1,2,\ldots,n-1 \quad, 0 \leq hh, \tag{21}$$

Finally, in order to obtain the minimum fuzzy relation in the FGRM, it is necessary to require the spread values of the fuzzy output value $\hat{F}_{t+1}^0, \forall t = 1,2,\ldots,n-1$ to be as small as possible. Based on this objective, we can obtain the following linear programming model.

$$min \sum_{t=1}^{n-1} (c_0 + c_1 f_t^1)$$

$$f_{t+1}^0 \geq a_0 - (1-h) c_0 + \left(a_1 - (1-h) c_1\right) * \left(f_t^1\right)$$

$$f_{t+1}^0 \leq a_0 + (1-h) c_0 + \left(a_1 + (1-h) c_1\right) * \left(f_t^1\right)$$

a_0, $a_1 \in R$, c_0, $c_1 \geq 0$, $0 \leq h < 1$,

$$\forall t = 1,2,\ldots,n-1 \tag{22}$$

By solving the linear programming model (22), the fuzzy parameters $\hat{A}_0 = (a_0, c_0) ve\, \hat{A}_1 = (a_1, c_1)$ can be solved. The equation of the FGRM is obtained as $\hat{F}_{t+1}^0 = (a_0, c_0) + (a_1, c_1) F_t^1$, $t = 1,2,\ldots,n$. This equation of the FGRM is obtained as,

$$\hat{F}_{t+1}^0 = \left(F_{t+1}^{0,L}, F_{t+1}^{0,h=1}, F_{t+1}^{0,U}\right), \ t = 1,2,\ldots,n$$

Where,

$F_{t+1}^{0,L} = (a_0 - c_0) + (a_1 - c_1) * \left(f_t^1\right)$ is the lower bound of $\hat{F}_{t+1}^0$;

$F_{t+1}^{0,h=1} = a_0 + a_1 * f_t^1$ is the center value of $\hat{F}_{t+1}^0$

$F_{t+1}^{0,U} = (a_0 + c_0) + (a_1 + c_1) * f_t^1$ is the upper bound of $\hat{F}_{t+1}^0$.

Therefore, by the crisp-input values $(f_1^0, f_2^0, \ldots f_n^0)$, the extrapolative fuzzy-output values $\widetilde{F}_2^0, \widetilde{F}_3^0, \ldots, \widetilde{F}_n^0$, and $\widetilde{F}_{n+1}^0$ can be obtained to granulate a concept into a set with membership function. Figure 1 summarizes the methodology used in the study.

4. ANALYSIS AND RESULTS

Turkey is a country that is heavily dependent on outside sources for petroleum and natural gas and consumes mainly fossil fuel even though it has sufficient amount of domestic coal resource for itself. It is neighbor with strategic petroleum and natural gas countries and is an important petroleum transit country and a potential natural gas transit country with increasing importance (GIF Working Group Report, 2013). This sensitizes Turkey's economy and hence its energy market to domestic and foreign policies, economic and market developments in the short term. For example, in parallel with economic fluctuations caused by the economic crises in 2001, 2005 and 2008, energy demand had also fluctuated in Figure 2. Industry, residence and transport sectors are the main energy consuming sectors in Turkey. Examining the shares of the sectors in total energy demand in Figure 3 and Table 3, it is seen that, in between 1990 and 2012, the largest share belongs to residence sector followed by industrial and transportation sectors. In general, the shares of residence and industrial sectors in total demand experience a downward trend. Demand shares of residence and transportation sectors decrease to 24% and 19% in 2012 from 36% and 23% in 1990, respectively. While the share of industrial sector in total demand in 1990 is 27% on average, it increased to 33%, the highest share, on average in between years 2000 and 2010 with a major development and then declined 29% after 2000 but will conserved its place with the highest share. It is seen in Figure 3 that the sectors with a share in energy demand that has ever increased are the sector which we define as other, including agriculture/forestry, fishing, non-specified, etc. and commercial and public service sector. The share of commercial and

Figure 1: The flowchart for the construction of a fuzzy grey regression model model

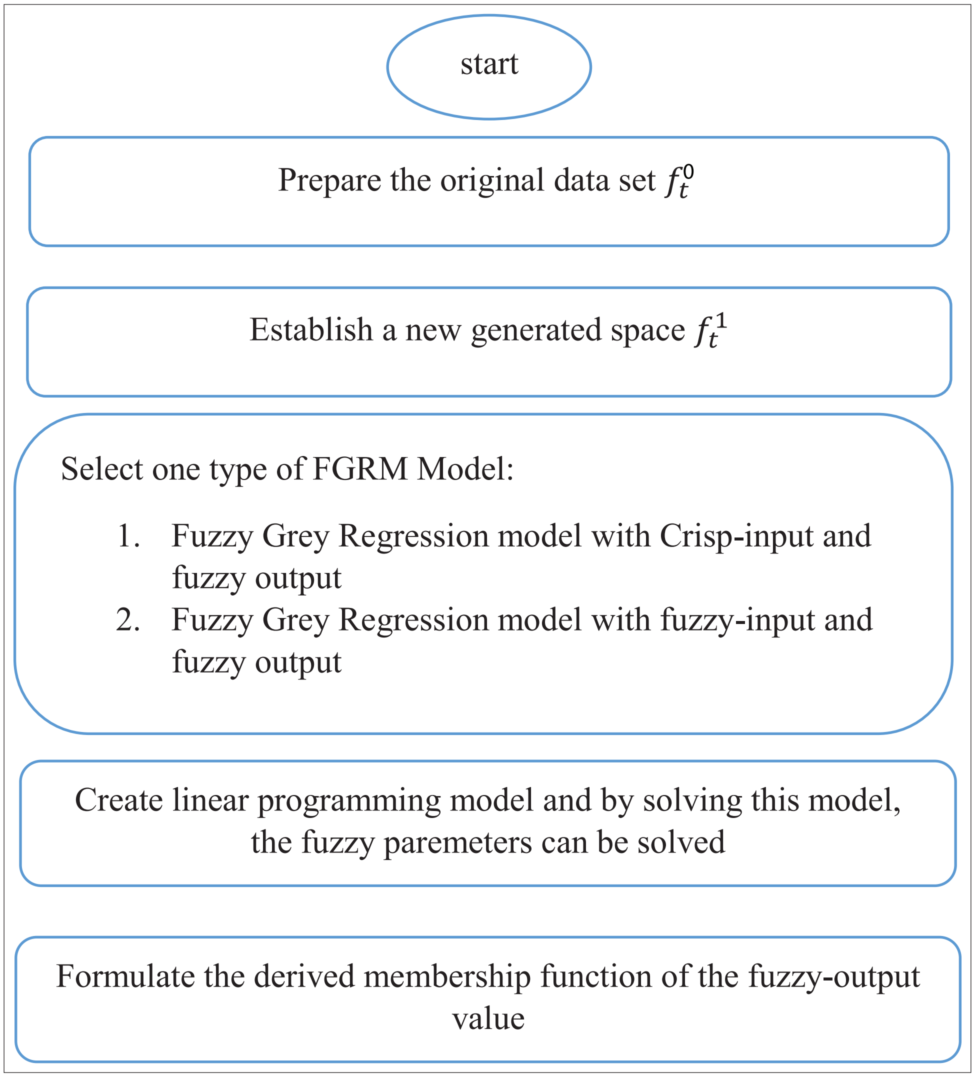
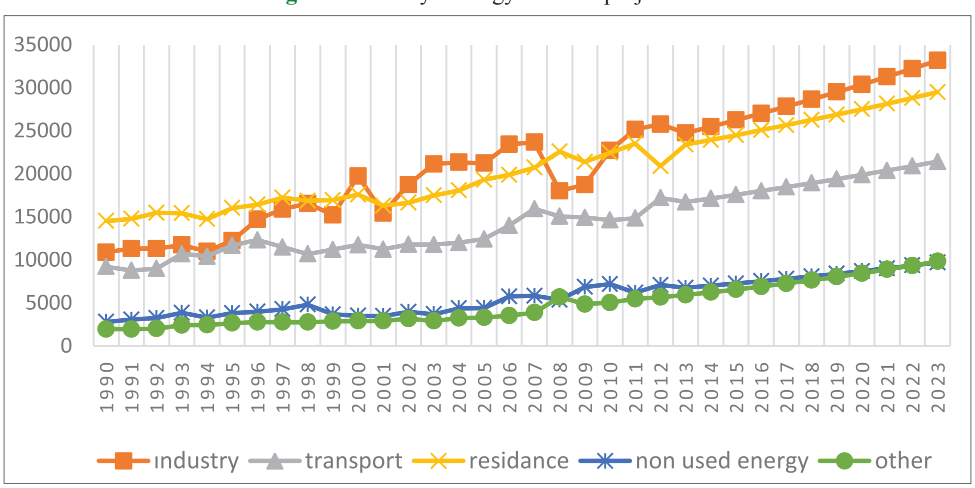


Figure 2: Turkey's energy demand projections



public service sector in total demand was 1 % in 1990, increasing to 12% in 2012. The shares of other sectors were 5 % in 1990 and continuously increased and reached to 6 % in 2012.

In Figure 2, it is seen that raw data f_t^0, the amount of energy demand used for FGRM, are distributed irregularly. Therefore, instead of analyzing the data of the grey systems directly, the grey systems theory exploits the AGO technique to outline the systems behaviors because the external and latent behaviors will become more apparent due to decrease of the random intensity after the AGO practice (Chen and Chang 2000). 'FGRM with Crisp-input and fuzzy output' shown in eq. 19 is formed using data f_t^1 obtained through EGO. The linear programming model in equation 22 is solved for various values of the variable h and the smallest values possible for fuzzy output $\hat{F}^{0}_{t+1}$ are obtained this way. Examining Figures 4-6, it is observed that as h value decreases, forecast interval gives results that are closer to actual values. Therefore, it would be more reliable to perform the analysis for h=0.

The analysis is performed separately for each sector and the amount of energy that may be required by industrial, transportation and residence sectors, the amount of energy unutilized and the amount of energy that may be demanded by other sectors are forecasted with a reliability of average 91% (Table 2) for the years 2013 to 2023 in Turkey (Figures 7-12).

Figure 3: The shares of the sectors in total energy demand (%)

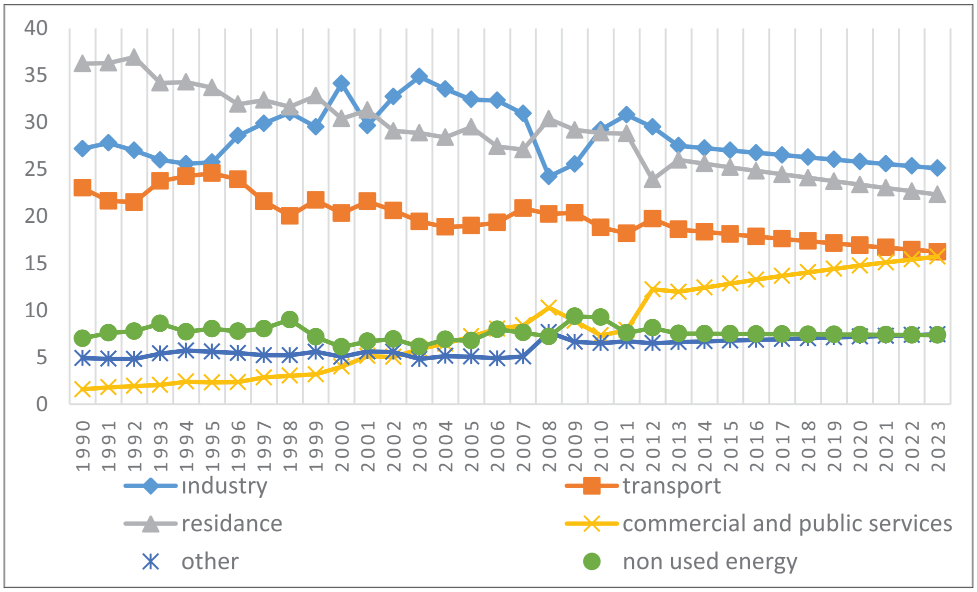


Figure 4: Total energy demand prediction interval estimated for h=0,8

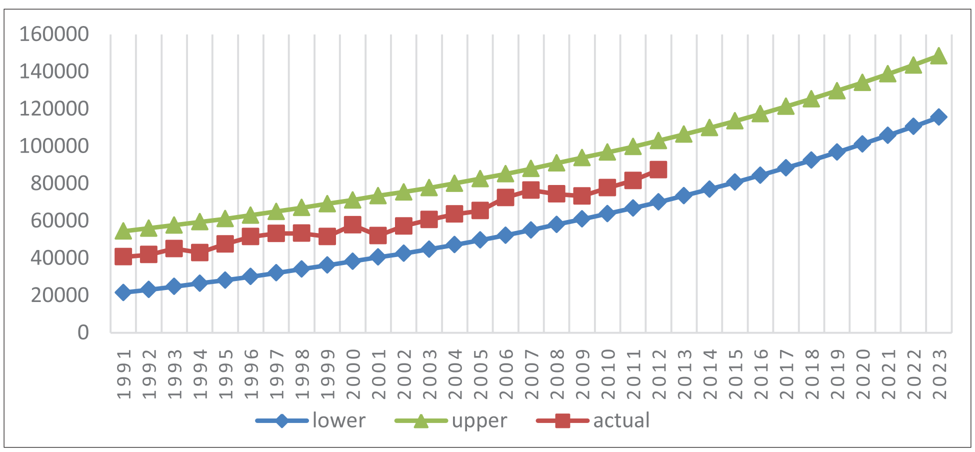
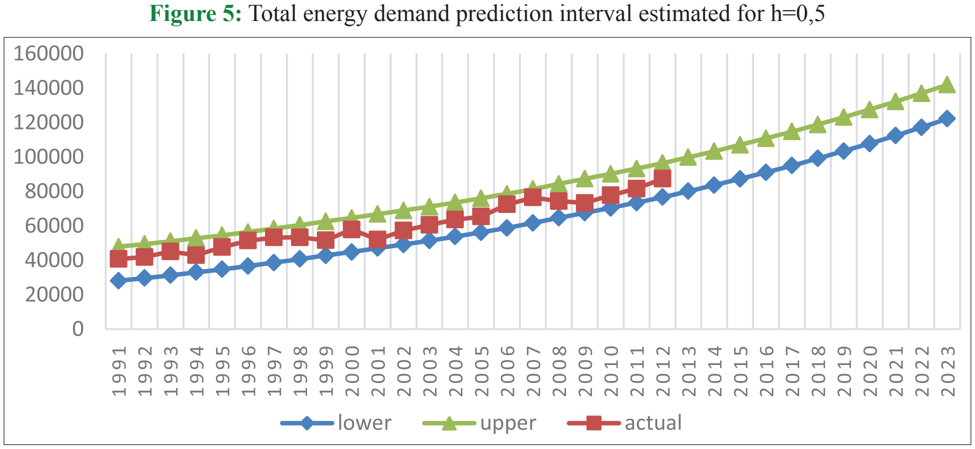


Figure 5: Total energy demand prediction interval estimated for h=0,5



According to study results;

*The total energy demand of Turkey in 2023 is expected to increase by 49% with respect to 2013 and fall within (127138.5, 137021) Ktoe interval.

Examining on a sectorial basis;

- Industrial sector demand is forecasted to increase by 37% and be in (29085.52, 37266.61) Ktoe interval,
- Transportation sector demand is forecasted to increase by 43% and be in (19130.43, 23734.09) Ktoe interval,
- Residence sector demand is forecasted to increase by 26% and be in (26789.91, 32196.49) Ktoe interval,
- Commercial and public services sector demand is forecasted to increase by 90% and be in (14599.95, 26918.09) Ktoe interval, and,

Figure 6: Total energy demand prediction interval estimated for h=0

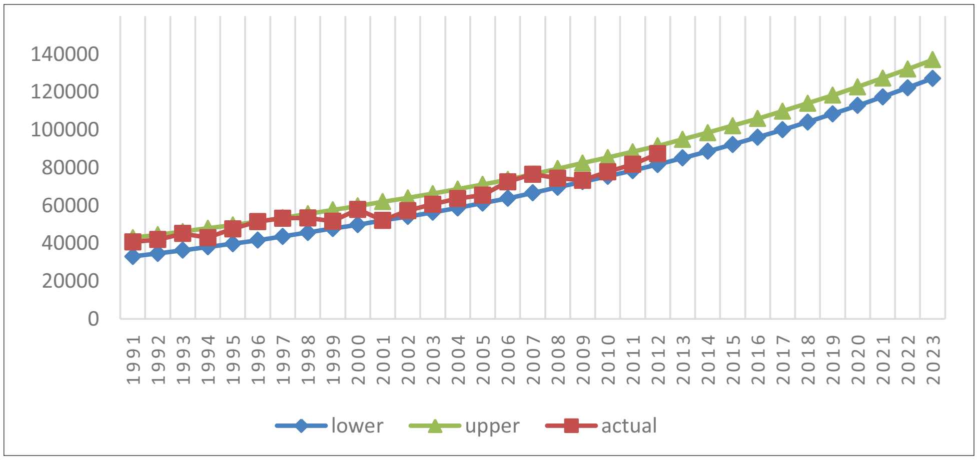


Figure 7: Energy demand prediction interval for the Industrial Sector

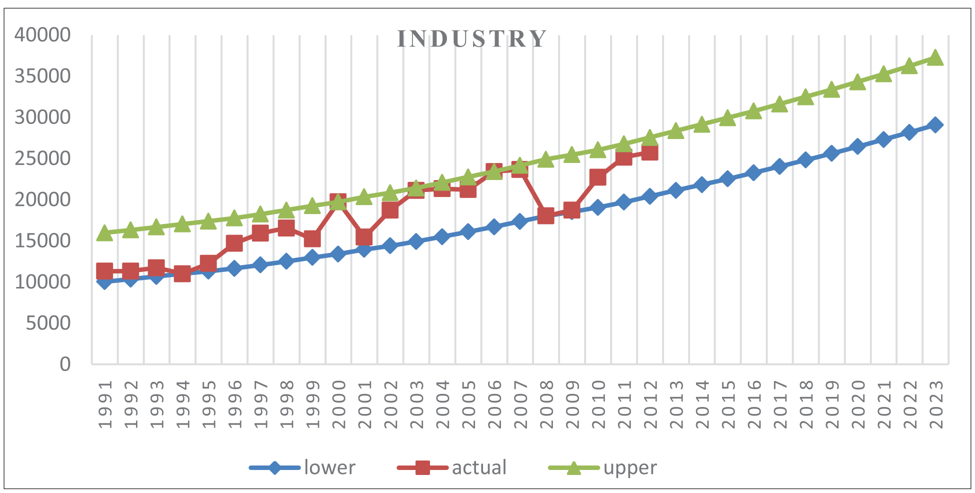


Figure 8: Energy demand prediction interval for transportation sector

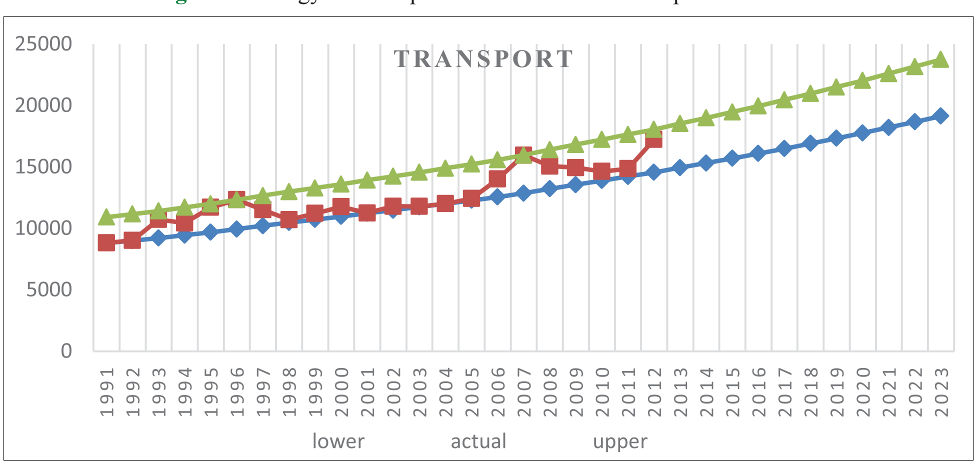


Table 1: Energy demand forecasting studies in Turkey

Year	Authors	Method	Energy
2004	Ersel Canyurt, Ceylan	GA	Energy forecasting
2004	Ceylan and Öztürk	GA	Energy forecasting
2004	Sözen et al.	ANN	Solar energy
2005	Haldenbilen et al.	GA	Transport energy
2006	Ediger et al.	ARIMA	Fossil fuel
2006	Murat and Ceylan	ANN	Transport energy
2007	Ediger and akar	ARİMA	Primary energy
2007	Erdogdu	ARIMA	Electricity demand
2007	Coşkun Hamzaçebi	(ANN)	Net electricity energy consumption
2007	Diyar Akay, Mehmet Atak	GPRM	Electricity demand forecasting of Turkey
2007	Toksarı	ACO	Energy demand
2008	Canyurt and Öztürk	GA	Fossil Fuels demand
2009	Toksarı	ACO	Electricity energy demand
2010	Çınar et al.	ANN ve GA	Hydroelectric energy
2010	Küçükali and Barış	Fuzzy logic methodology	Annual electricity demand
2010	Demirel et al.	ANFIS and ARMA	Electricity energy
2011	Kavaklıoglu	SVR	Electricity energy
2012	Kıran et al.	PSO and ACO	Energy demand (MTOE)
2013	Yılmaz and Yılmaz	The grey predıctıon Method	Türkiye'nin CO_2 emisyon tahmini
2014	Coşkun Hamzaçebi, Hüseyin Avni ES	Optimized Grey modeling OGM (1, 1) technique	Annual total electricity consumption

GA: Genetich algorithm, ANN: Artificial neural networks, PSO: Particle swarm optimization, ACO: Ant colony optimization, GPRM: Grey prediction with rolling mechanism, SVR: Support vector regression

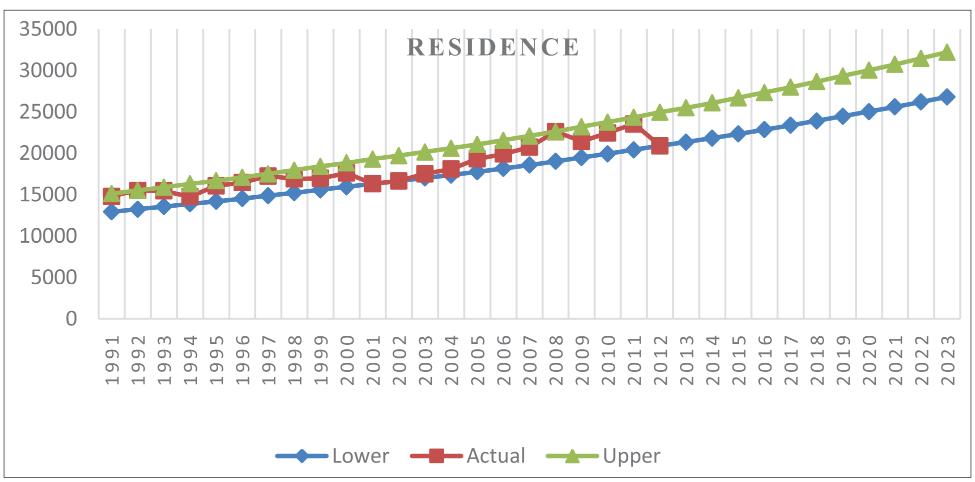
Table 2: Reliability analysis for sectoral energy demand forecasts

Industry	Transport	Residance	Commercial and public service	Other	Unused	Average
88.37	91.61	96.18	87.52	90.84	88.31	91.20

Table 3: Shares of sectors within total energy demand in terms of years

Years	Industry	Transport	Residance	Commercial and public service	Other	Unused	Total (%)
1990	27	23	36	1	5	7	99
2012	29	19	24	12	6	8	98
2023	23-27	15-17	21-23	11-20	5-9	6-8	81-104

Figure 9: Energy demand prediction interval for residential sector



- Demand of other sectors is forecasted to increase by 53% and be in (6523.339, 13152.46) Ktoe interval.

Commercial and public services sector has the demand that most rapidly increases and it is forecasted to have a share of approximately 16% in total energy demand in 2023. Although industrial sector was in the second place in total energy demand in 1990, it is forecasted that this sector will be in the first place in 2023. This is an indicator of future industrialization and development in the country. Deficits in energy import-export balance, unreliable demand forecast and inadequacy of our country in relation to energy efficiency cause amount of unutilized energy to be approximately 8%.

5. CONCLUSION

This study forecasted Turkey's total and sectorial energy demand until 2023 using FGRM approach (Appendix Table 1). This

Figure 10: Energy demand prediction interval for commercial and public services

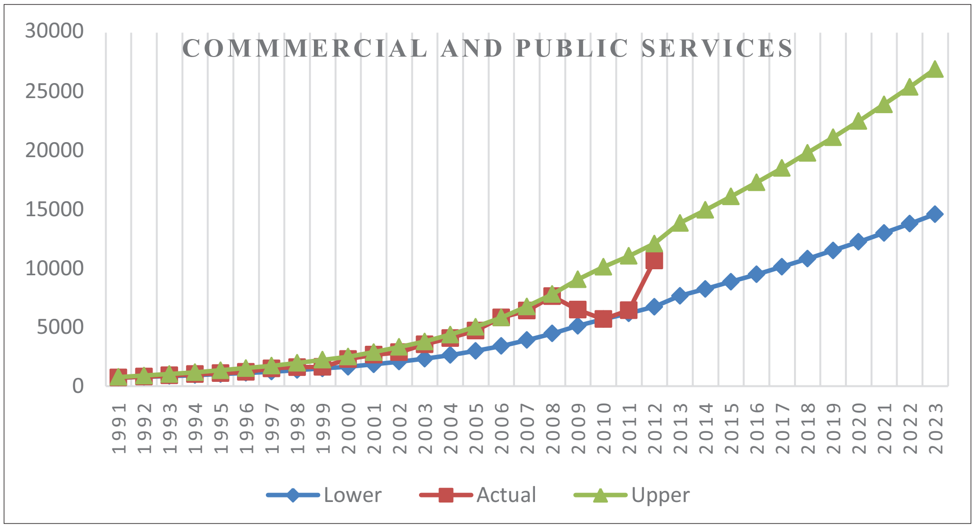


Figure 11: Energy demand prediction interval for Other Sectors (Agriculture/forestry, Fishing, non-spesified)

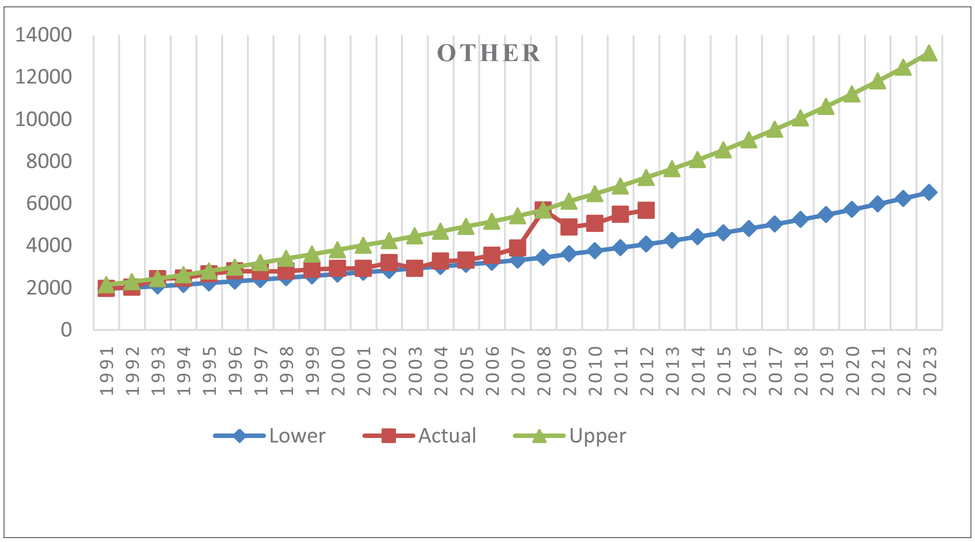
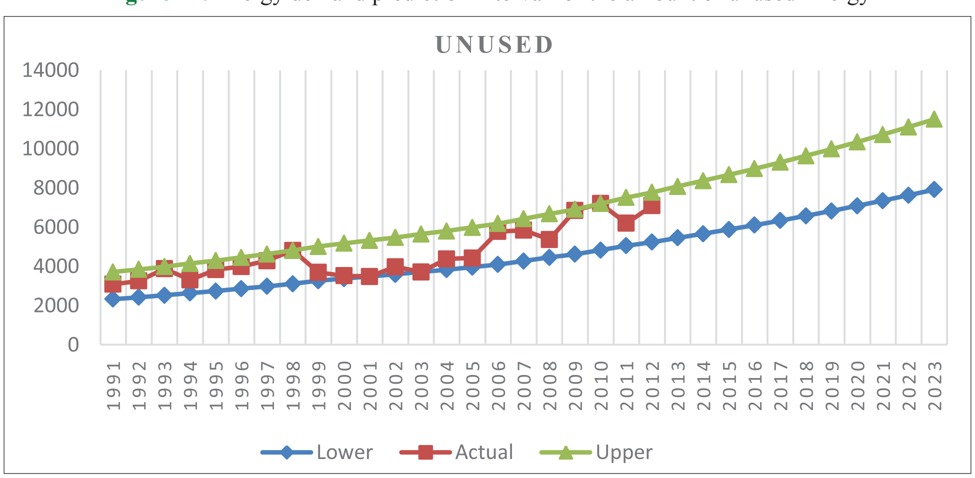


Figure 12: Energy demand prediction interval for the amount of unused Energy



approach was preferred for that it allows obtaining more reliable results with less data. Moreover, FGRM makes the forecast as interval values with lower and upper bounds, therefore the results will help make decisions that are more effective in reducing risk such as those related to supply security, demand surplus and import-export balance, for energy planning. In forecasting the amount of energy that Turkey may demand in the future, our study was not limited to a few sectors, but considered all the sectors. The number of studies that take into consideration all the sectors as this study do is very few. This study is of importance for shaping energy policies and is a guide for MENR. Moreover, the success of the method preferred in forecast reliability and the way the results are interpreted would guide researchers in their own work. The energy demand that will be required until 2023 will be the values in the interval we found in our study with a reliability of 91%. The study can be improved by using Grey Model GM (1, N) methodology which considers the factors affecting energy demand. In addition, the energy demand forecasting analysis that we performed on a sectorial basis can also be performed on energy resource basis.

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APPENDIX

Appendix Table

Table 1: The energy demand projection until 2023 was revealed with fuzzy grey regression model (FGRM) using the data between years 1990-2012

Years	Industry		Transport		Residance		Commercial	
	Left	Upper	Left	Upper	Left	Upper	Left	Upper
2016	23278.69	30774.53	16086.99	19955.25	22834.89	27326.47	9492.439	17290.21
2017	24037.16	31622.51	16490.14	20455.81	23361.42	27974.81	10145.49	18521.24
2018	24818.18	32495.69	16903.4	20968.93	23900.28	28638.33	10822.55	19797.52
2019	25622.4	33394.82	17327.02	21494.92	24451.76	29317.4	11524.49	21120.71
2020	26450.52	34320.67	17761.27	22034.09	25016.16	30012.37	12252.24	22492.54
2021	27303.26	35274.04	18206.4	22586.78	25593.77	30723.62	13006.73	23914.8
2022	28181.34	36255.74	18662.69	23153.33	26184.92	31451.53	13788.96	25389.34
2023	29085.52	37266.61	19130.43	23734.09	26789.91	32196.49	14599.95	26918.09

Years	Other		Non used energy		Total tahmini demand	
	Left	Upper	Left	Upper	Left	Upper
2016	4810.12	9021.343	6103.43	8979.194	96014.26	105896.712
2017	5019.491	9526.202	6334.926	9302.115	99965.24	109847.693
2018	5239.673	10057.13	6574.932	9636.906	104070.8	113953.299
2019	5471.225	10615.48	6823.76	9984.004	108337.1	118219.582
2020	5714.734	11202.66	7081.734	10343.86	112770.4	122652.829
2021	5970.818	11820.16	7349.191	10716.95	117377.1	127259.575
2022	6240.125	12469.54	7626.48	11103.74	122164.2	132046.61
2023	6523.339	13152.46	7913.961	11504.76	127138.5	137020.99