

Determination with Linear Form of Turkey's Energy Demand Forecasting by the Tree Seed Algorithm and the Modified Tree Seed Algorithm

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Abstract—Energy plays an important role in every stage of human life in different forms and variations. Along with the developments in economic, social and industrial fields, the amount of energy that countries need is increasing day by day. Therefore, it is significant to estimate the energy demand for a country's economic activities accurately. In this study, the energy demand forecast (EDF) application optimization problem of Turkey, one of the real-world optimization problems, was performed by MTSA (Modified Tree Seed Algorithm) and TSA (Tree Seed Algorithm) methods. From 1979 to 2005, gross domestic product (GDP), population, export and import values were used as parameter data. Thus, in the presence of three different possible scenarios, Turkey's energy demand from 2006 to 2025, which was estimated by MTSA and TSA methods. To demonstrate the success of MTSA and TSA in the problem of energy demand forecasting (EDF), they are compared with Ant Colony Algorithm (ACO), Particle Swarm Optimization (PSO), Bat Algorithm (BA), Differential Evolution Algorithm (DEA) and Artificial Algae Algorithm (AAA) methods which are in the literature. According to the results of the analysis, it was observed that the MTSA method was a successful estimation tool for energy demand.

Index Terms—algorithms, demand forecasting, energy optimization, heuristic algorithms.

I. INTRODUCTION

Energy plays an important role in the economic and social development of a country from past to present. Along with social, economic and industrial developments, the energy that manifests itself in every stage of human life causes a rise in the amount of energy, which countries need [1] and [2]. In particular, energy has been an important factor in the economic and social development of countries and societies. The place and importance of energy in human life are increasing day by day. Despite the nuclear power plant accidents and financial crises, the demand for energy and the installation of new power plants continue to increase [3]. Today, energy, one of the most important needs, is also an indicator of the level of development of a country [4] and [5]. Estimation of energy demand is of great importance for developed and developing countries. In particular, the need for energy is increasing rapidly due to the increasing

population and developing technology and industrialization. For instance, in Turkey, while per capita energy consumption was 274 kWh in 1974, it increased to 2,682 kWh in 2014 [2].

To ensure the healthy development of the energy sector, distribution, supply, demand, pricing and transmission plans are of great importance for this sector [6]. The most important of these planning studies is to determine the future energy demand by considering the increasing energy demand. Since energy requires high costs and it is not stored, a balance must be established between energy production and consumption [7]. Therefore, the importance of accurate estimation of energy demand increases. If the forecasted energy is lower than the energy needed, it may cause an energy crisis, and if it is high, the energy resources may decrease, while at the same time it may cause harm to the economy [8]. The more accurate the energy demands to be predicted, the more successful the planning work will be. In other words, the success of the planning works is based on the accuracy of the projected energy demand.

When the literature is analysed, researchers have conducted studies on energy demand forecasting (EDF) using various methods for the energy demand of many countries. Some of these studies; Geem and Roper [9] estimated the energy demand of South Korea using an artificial neural network (ANN). Ekonomou [10] have created an estimation model with an artificial neural network for Greece's energy consumption forecast. Yu et al. [11] estimates by proposing a hybrid algorithm for China's EDF. Similarly, Piltan et al. [12] created a prediction model using evolutionary algorithms for Iran's EDF. Sánchez-Oro et al. [13] created a prediction model based on artificial neural network method for the EDF of Spain. Mohamed and Bodger [14] estimated electricity consumption in New Zealand with multiple linear regression. Bianco et al. [15] estimated the electricity consumption of Italy by using the linear regression model. Yu et al. [16] proposed a hybrid algorithm with PSO and GA for projections of China's energy demand. Yu et al. [17] proposed a PSO-GA optimization model to estimate China's primary energy demand. In most countries, although studies related to energy forecast has been continued for a long time, the

forecast studies on energy issues in Turkey gained momentum towards the end of 1990. Turkey Statistical Institute (TSI), the Ministry of Energy and Natural Resources (MoENR), State Planning Organization (SPO) at the end of the 1970s, they started to use mathematical models to forecast energy demand [18].

Not to hinder access to energy resources and investments, advance and industrialization, budget planning, in the long term, the amount of energy needed by Turkey, where 70% of the energy demand is met by the imports, needs to be accurately estimated [19]. For this reason, researchers have developed many heuristic or meta-heuristic algorithms to solve engineering problems that are difficult or impossible to solve [20] and [21]. By modelling these algorithms in a computerized environment, scientists realized that the solution of real-world problems was achieved faster and the

results found were closer to the real value [22]. This has led to the emergence of optimization techniques and improvements through continuous improvements. Optimization is usually described as the handle of using the limited available means to solve a problem and finding the best among the results obtained [23] and [24]. The task of optimization is to determine the optimal result of a function whose constraints are given for continuous or discrete problems.

From past to present, the creatures in nature that inspire science play a huge role in the emergence of new advances. Scientists have advanced lots of algorithms inspired by the behaviours of living things in nature [25]. Such algorithms are also called meta-heuristic methods. As shown in Figure 1, heuristic methods happen six nature-inspired bases [26].

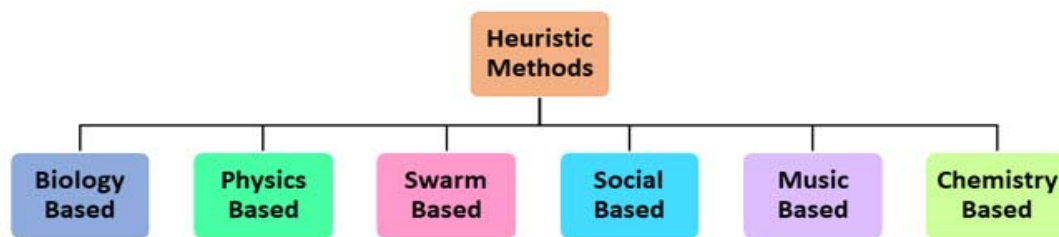


Figure 1. Heuristic methods

A. Sample Application Fields of Heuristic Algorithms

There are many studies about optimization techniques in the literature. When the studies in the literature are examined, it is seen that the algorithm has obtained more successful results as a result of some changes made in the algorithm. Akay and Karaboga [27] adjusted a new parameter to the Artificial Bee Colony algorithm (ABC) and made parameter adjustments along with other parameters of the algorithm. With changes in these parameter values, ABC has been said to be a suitable method to solve optimization problems effectively. In their study, Chen et al. [28] proposed an approach to improve image contrast using the artificial bee colony algorithm. In the proposed approach, they have developed an objective function for a new objective image contrast by adding a new image contrast measure. They suggested that the method they proposed was faster and more efficient than the existing approaches. Ahmad et al. [29] suggested a new hybrid genetic algorithm for workflow timing optimization. They compared hybrid genetic algorithms with different approaches in the literature. According to the test results, they emphasized that the program time of the algorithm they proposed is better. Yilmaz and Kucuksille [30] developed the bat algorithm to solve optimization problems. They used standard benchmark functions and real-world optimization problems to analyse the performance of the developed bat algorithm.

B. Optimization Studies in the Field of Energy

In their study, Kiran, Ozceylan, Gunduz, and Paksoy [31] suggested a hybrid method for forecasting Turkey's electricity demand. The proposed method is the first model that combines two metaheuristic algorithm techniques for particle swarm optimization (PSO) and ant colony optimization (ACO). With the suggested method, using the data of the gross domestic product (GDP), population, import and export in 1979-2005, they estimated energy

demand between 2006 and 2025. As a result, they stated that the proposed method successfully predicted energy demand. In their study, Kiran, Ozceylan, Gunduz, and Paksoy [32] developed a new method with artificial bee colony (ABC) and particle swarm optimization (PSO) techniques to forecasting the electricity demand in Turkey. To demonstrate the applicability and accuracy of the suggested models, they compared the ant colony optimization (ACO) in the literature for the same problem. According to the results obtained, the error rate of the suggested method was lower than ACO and they offered more suitable solutions. Bayrak and Esen [33] suggested the ANN model for Turkey's EDF. They used the 1960-2011 data for the 2012-2020 forecast of energy demand. When comparing the estimation results with MoENR's official estimation results, they stated that there was quite a difference between them and said that the proposed method achieved successful results for energy demand estimation. By using a genetic algorithm-based grey prediction method (GAGM) and particle swarm optimization based grey prediction method (PSOGM), Cayır Ervural and Ervural [34] carried out the EDF in Turkey.

When the studies related to optimization problems in the literature are examined, there are many studies for meta-heuristic algorithms. When these algorithms, in their original form, are applied to real-world problems, they may not always provide the best solution according to the algorithms available in the literature. Researchers have been made some changes to the algorithm to get a better solution to the problems. If the algorithms perform better with the changes made, the solution of the problem will be optimum or the solution approaches the optimum result.

In this study, it is aimed to optimally forecasting the energy demand, which is one of the real-world optimization problems, with MTSA which is a result of the modification of TSA, which is one of the meta-heuristic methods.

II. ORIGINAL TSA

In 2015, Kiran [35] proposed a new meta-heuristic algorithm to solve continuous optimization problems. This algorithm has called tree seed algorithm (TSA). There is a certain connection between trees and seeds in the TSA. This connection consists of natural ways. In nature, tree seeds are distributed to the soil and these seeds grow in time and occur new trees [36]. When the soils of the trees are assumed as research areas, the position of trees and seeds express probable solutions for continuous problems [37]. Thus, the significance of seed location in the formation of trees has increased. There are two equations for the search field. The first one is the process of seed production for the best location of the tree population. This process has increased the local search power of the algorithm. In the other equation, the process is carried out using two distinct tree locations for the formation of a new seed [35]. Where $S_{(i,j)}$, the tree will be produced i . seed j . show the dimension. $T_{(i,j)}$ is the j . size of the i . tree. B_j is the j . size of the best tree location ever obtained. $T_{r,j}$ is the j . size of the r . tree randomly selected from the population. α is randomly generated in the range $[-1,1]$. There are two equations for creating the location of a new seed. These equations are controlled by the search trend (ST) in the $[0,1]$ range. Equation 1 is used if the randomly produced number in the range $[0-1]$ is less than ST, otherwise, Equation 2 is used. The flow chart of the TSA is given in Figure 2.

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (B_j - T_{r,j}) \quad (1)$$

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (T_{i,j} - T_{r,j}) \quad (2)$$

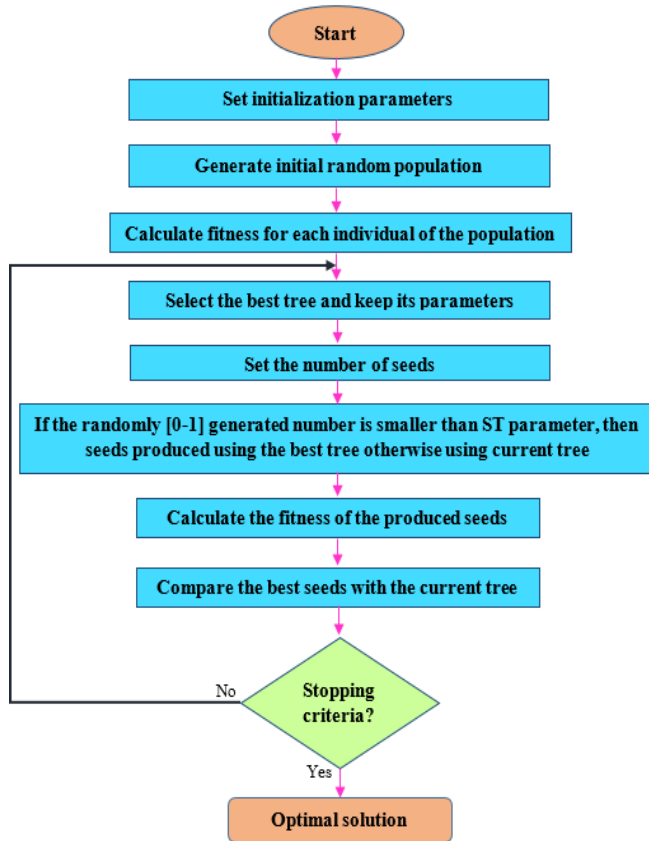


Figure 2. TSA flow chart

III. MODIFIED TREE SEED ALGORITHM

As the complexity of problems rises, it is frequently hard for the algorithm to get the best solution [38]. For the algorithm to produce effective solutions, it is necessary to make some changes in the algorithm. Therefore, it is purposed to expand local and global space of the algorithm by changing the selection method of the trees in TSA. Instead of a randomly selected tree, a tournament selection method is proposed to create seeds. Tournament selection method works with the logic of selecting the strongest of the two randomly selected values. The number of seeds to be formed from the tree is a random N value between 10% and 25% of the population. This N number of trees then participates in a tournament and the best available trees are selected. The modification of TSA's seed selection method and the name of the proposed method were called the modified tree seed algorithm (MTSA) by Beskirli et al. [39].

To produce better quality seeds in Equations 3 and 4, the change in the selection technique of trees is illustrated. Seeds produced with these formulas are selected according to the ST parameter. If the number selected between $[0-1]$ is less than ST, Equation 3 is used, and if the selected number is greater than ST, Equation 4 is used.

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (B_j - T_{t,j}) \quad (3)$$

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (T_{i,j} - T_{t,j}) \quad (4)$$

In this Equation, $S_{(i,j)}$ symbolize the size j . of the tree seed i . $T_{(i,j)}$ is the j . size of the i . tree. B_j contains the size j . of the best-obtained tree locations. $T_{t,j}$ is the j . size of tree t . which is selected from the population by the tournament selection method and α , represents the randomly generated in the $[-1,1]$ range.

In Equations 3 and 4, the seed production stage is reformulated. Instead of randomly selecting (T_r) the trees in the formula of the original TSA, innovation has been made in the selection of trees using the tournament selection method (T_t). To produce quality solutions and to make effective scanning in the search space, a change was made in the seed selection method.

IV. APPLICATION OF RECOMMENDED METHODS TO THE EDF PROBLEM

An energy demand forecasting model is formed by using the Economy-based gross domestic product (GDP), population, import and export data, which have the greatest effect on a country's energy demand and have been mentioned in the literature. This model consists of three scenarios. At the same time, by using this model, the estimation of the energy demand of the different countries can be made. In this study, TSA and MTSA methods were used to estimate Turkey's energy demand. Between 1979 and 2005, GDP for Turkey, population, import and export data, and Turkey's energy demand values are given in Table I. These data are used as input data and the objective function is calculated with them. All these data were collected from Turkey Statistical Institute, Ministry of Energy and Natural Resources, energy reports and literature [19], [40-42].

TABLE I. TURKEY'S ENERGY DEMAND, GDP, POPULATION, IMPORT AND EXPORT DATA

Year	Energy Demand (TWh)	GDP (\$10^9)	Population (10^6)	Imports (\$10^9)	Export (\$10^9)
1979	30.71	82	45.53	5.07	2.26
1980	31.97	68	44.44	7.91	2.91
1981	32.05	72	45.54	8.93	4.70
1982	34.39	64	46.69	8.84	5.75
1983	35.70	60	47.86	9.24	5.73
1984	37.43	59	49.07	10.76	7.13
1985	39.40	67	50.31	11.34	7.95
1986	42.47	75	51.43	11.10	7.46
1987	46.88	86	52.56	14.16	10.19
1988	47.91	90	53.72	14.34	11.66
1989	50.71	108	54.89	15.79	11.62
1990	52.98	151	56.10	22.30	12.96
1991	54.27	150	57.19	21.05	13.59
1992	56.68	158	58.25	22.87	14.72
1993	60.26	179	59.32	29.43	15.35
1994	59.12	132	60.42	23.27	18.11
1995	63.68	170	61.53	35.71	21.64
1996	69.86	184	62.67	43.63	23.22
1997	73.78	192	63.82	48.56	26.26
1998	74.71	207	65.00	45.92	26.97
1999	76.77	187	66.43	40.67	26.59
2000	80.50	200	67.42	54.50	27.78
2001	75.40	146	68.37	41.40	31.33
2002	78.33	181	69.30	51.55	36.06
2003	83.84	239	70.23	69.34	47.25
2004	87.82	299	71.15	97.54	63.17
2005	91.58	361	72.97	116.77	73.48

In Table I, it is observed that Turkey has been in a constant state of development and economic values have raised over the years. Also, when Table II is examined, it can be said that there is a connection between the rise in economic values and the rise in energy consumed [43]. When these connections are taken into consideration, the formula is formed by using the linear form for energy demand estimation and modelled as in Equation 5.

The linear form Equation can be expressed as follows;

$$E_{linear} = w_1 + w_2 X_1 + w_3 X_2 + w_4 X_3 + w_5 X_4 \quad (5)$$

The main goal of EDF is to find an optimum result by processing the available data. The values X_1 , X_2 , X_3 and X_4 in Equation 5 indicate the GDP, population, import and export values, respectively. According to these values, weight values (w_i) are calculated which will make the most appropriate EDF for the given years. The objective function used is given in Equation 6.

$$\min f(v) = \sum_{r=1}^R (E_r^{observed} - E_r^{estimated})^2 \quad (6)$$

Here $E_r^{observed}$ and $E_r^{estimated}$ represent true and predicted values, while R holds the number of observations.

A. Comparison of MTSA and TSA through methods in the literature.

To demonstrate the success of MTSA and TSA methods on the EDF problem, it was compared with the results of the methods performed by Toksari [44], Unler [8], Hakli [45], Beskirli [43], Beskirli [46].

To compare the proposed methods within the literature and to analyse them healthily, as in the methods in the literature, for the MTSA and TSA methods, the data from 1979-2005 in Table I were taken into consideration and forecasting model for energy demand. For MTSA and TSA

methods, it was determined that the number of populations was 100, the ST value was 0.1, and the maximum number of function evaluations (MaxFEs) was 200,000. Weights of MTSA for linear form are given in Equation 7 and weights of TSA are given in Equation 8. Also, all coding was performed with MATLAB 2014 (8.3) and the best solution obtained by running 10 times under the same conditions was taken into consideration.

Weights for linear form:

$$E_{MTSA_linear} = 0.00380X_1 + 1.91227X_2 + 0.37354X_3 - 0.48351X_4 - 55.89907 \quad (7)$$

$$f(v)_{MTSA_linear} = 41.71200$$

$$E_{TSA_linear} = 0.01032X_1 + 1.90057X_2 + 0.25111X_3 - 0.31693X_4 - 55.62818 \quad (8)$$

$$f(v)_{TSA_linear} = 46.27831$$

TABLE II. COMPARISON OF COEFFICIENTS AND RELATIVE ERRORS FOR LINEAR FORM

	w1	w2	w3	w4	w5	Error
MTSA	-55.8991	0.0038	1.9123	0.3735	-0.4835	41.7120
TSA	-55.6282	0.0103	1.9006	0.2511	-0.3169	46.2783
DEA	-55.8991	0.0038	1.9123	0.3735	-0.4835	41.7120
AAA	-55.8991	0.0038	1.9123	0.3735	-0.4835	41.7120
BA	-57.7676	0.00002	1.9549	0.4023	-0.5316	42.4890
PSO	-55.9022	0.0021	1.9126	0.3431	-0.4240	42.6139
ACO	-51.3046	0.0124	1.8102	0.3524	-0.4439	45.7239

MTSA, TSA, DEA, AAA, BA, PSO and ACO algorithms coefficients and error values are given in Table II. The coefficients and error values of the algorithms other than MTSA and TSA were added to the table through obtaining from related studies.

In Table II, while the MTSA method performed

successfully as it had the least error value as in the DEA and AAA methods, the other methods fell behind the MTSA.

The amount of energy demand and amount of energy observed which were estimated by MTSA and TSA methods

between the years 1996-2005 are presented in Table III. Also, the amount of error between the forecasting energy demand and the observed value for both MTSA and TSA and relative error rates are given in Table III.

TABLE III. ENERGY DEMAND FORECASTS FOR MTSA AND TSA METHODS

Years	Observed Energy Demand (OED)	Estimated Energy Demand		Error Quantity		Error (%)	
		MTSA	TSA	MTSA	TSA	MTSA	TSA
1996	69.86	69.71	68.98	0.15	0.89	0.21	1.27
1997	73.78	72.32	71.52	1.46	2.26	1.99	3.07
1998	74.71	73.30	73.03	1.41	1.68	1.89	2.25
1999	76.77	74.18	74.34	2.59	2.43	3.37	3.16
2000	80.50	80.71	79.45	-0.21	1.05	-0.27	1.30
2001	75.40	75.71	76.29	-0.31	-0.89	-0.42	-1.18
2002	78.33	79.13	79.47	-0.80	-1.14	-1.02	-1.45
2003	83.84	82.37	82.75	1.47	1.09	1.76	1.30
2004	87.82	87.19	87.15	0.63	0.67	0.72	0.76
2005	91.58	93.10	92.81	-1.52	-1.23	-1.66	-1.35

The mean relative error rates of the recommended methods to solve the EDF problem and the existing methods in the literature between 1996 and 2005 are presented in Table IV.

TABLE IV. MEAN RELATIVE ERRORS OF THE RECOMMENDED AND OTHER METHODS

Algorithms	Mean Relative Error
TSA	1.71
PSO	1.43
ACO	1.41
BA	1.35
DEA	1.33
AAA	1.33
MTSA	1.33

The lower the mean relative error rate for the EDF problem, the forecast results obtained will be as close to the OED values. In other words, an accurate estimation of the recommended method depends on the mean relative error. In the light of this information, it was seen that DEA, AAA and MTSA which is the recommended method in Table V had the lowest mean relative error with 1.33 value. TSA, PSO, ACO and BA methods fell behind the MTSA. Thus, it can be said that MTSA, DEA and AAA methods are closer to the OED values since they had at least mean relative error rate. Therefore, MTSA has obtained more successful estimates of energy demand than other methods (TSA, PSO, ACO and BA). Estimated energy demand amounts of MTSA, DEA, AAA, TSA, BA, PSO and ACO algorithms between 1996-2005 and the OED quantities in those years are shown in Figure 3.

When Figure 3 is examined, it is seen that DEA, AAA and MTSA, which is the proposed method, make similar estimations and get close to the OED according to other algorithms. The original TSA was found to be below the observed value. Original TSA, compared with the proposed method MTSA, it was seen that MTSA achieved a better result.

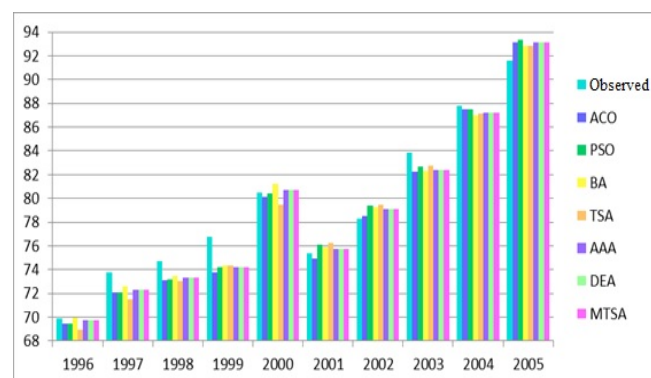


Figure 3. Comparison of EDF of algorithms

B. Future Projections of EDF Using MTSA and TSA Methods

After showing the success of the proposed methods according to the existing methods in the literature, between the years 1979-2005 with current data for calculating linear forms scenario, EDF was carried out in Turkey for the years between 2006 and 2025.

Three different scenarios were used to forecasting the energy demand of Turkey between the years 2006-2025 [43].

1st Scenario: It is presumed that between the years 2006-2025, the average GDP growth ratio is 4%, the population growth ratio is 0.5%, the import growth ratio is 2.5% and export growth ratio is 3%.

2nd Scenario: It is presumed that between the years 2006-2025, the average GDP growth ratio is 5%, the population growth ratio is 0.6%, the import growth ratio is 3.5% and export growth ratio is 3.5%.

3rd Scenario: It is presumed that between the years 2006-2025, the average GDP growth ratio is 6%, the population growth ratio is 0.7%, the import growth ratio is 4% and export growth ratio is 5.5%.

The energy demand estimation values obtained between 2006 and 2025 by using the coefficients obtained by MTSA and TSA method and the scenarios given are given in Table

V. The OED between 2006 and 2014 was used as test data.

When Table V is evaluated in general, it is seen that the 2nd Scenario, especially for the MTSA method, makes estimations closer to the OED compared to other scenarios. The second closest estimate to the test data was obtained by the 2nd Scenario in the TSA method. Other scenarios fall

behind these two scenarios and are expected to have low success in the EDF for the coming years. Therefore, it can be said that the MTSA method will predict energy demand in the coming years more successfully with the 2nd Scenario.

TABLE V. FUTURE PROJECTIONS OF THE TOTAL ENERGY DEMAND OF PROPOSED METHODS ACCORDING TO SCENARIO 1, 2 AND 3

Years	OED	MTSA			TSA		
		1 th Scenario	2 nd Scenario	3 rd Scenario	1 th Scenario	2 nd Scenario	3 rd Scenario
2006	99.59	94.68	104.41	94.13	94,13	100,48	93,71
2007	107.63	96.33	105.64	95.20	95,50	101,55	94,65
2008	106.34	98.06	106.93	96.32	96,95	102,66	95,63
2009	106.14	99.88	108.28	97.50	98,46	103,82	96,65
2010	109.27	101.80	109.68	98.73	100,05	105,02	97,72
2011	114.48	103.81	111.14	100.02	101,72	106,28	98,83
2012	120.09	105.92	112.66	101.37	103,47	107,59	99,98
2013	120.29	108.14	114.25	102.78	105,30	108,95	101,19
2014	123.94	110.47	115.91	104.27	107,23	110,37	102,45
2015	129.3	112.92	117.64	105.82	109,25	111,85	103,77
2016	136.2	115.49	119.45	107.45	111,37	113,40	105,14
2017	143.4	118.19	121.34	109.16	113,60	115,01	106,58
2018	N/A	121.02	123.31	110.96	115,93	116,70	108,08
2019	N/A	124.00	125.37	112.84	118,39	118,45	109,64
2020	N/A	127.13	127.52	114.81	120,96	120,29	111,28
2021	N/A	130.41	129.77	116.88	123,67	122,21	112,99
2022	N/A	133.86	132.12	119.06	126,51	124,21	114,79
2023	N/A	137.48	134.58	121.34	129,49	126,30	116,66
2024	N/A	141.28	137.15	123.74	132,62	128,49	118,62
2025	N/A	145.27	139.84	126.25	135,90	130,77	120,67

The comparison of the EDF results of the proposed methods with the OED data is given in graphs for all scenarios in Figures 4, 5 and 6. Since the MTSA method provided a closer approximation to the OED compared to

the TSA method, a graphical analysis of the MTSA according to 1st Scenario, 2nd Scenario and 3rd Scenario was made and is presented in Figure 7.

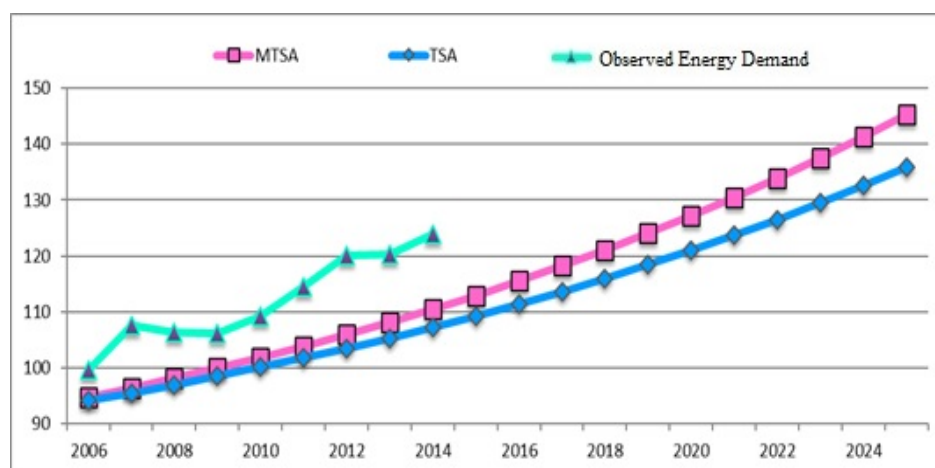


Figure 4. Future EDF of proposed methods for Scenario 1

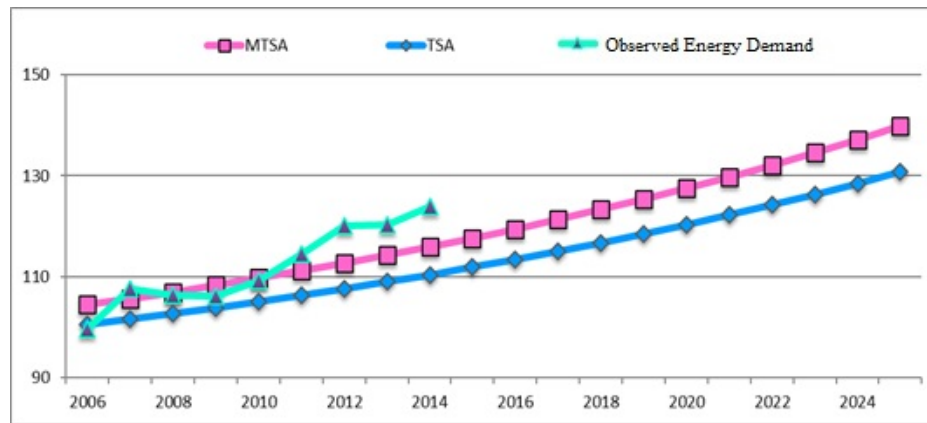


Figure 5. Future EDF of the proposed methods for Scenario 2



Figure 6. Future EDF of the proposed methods for Scenario 3

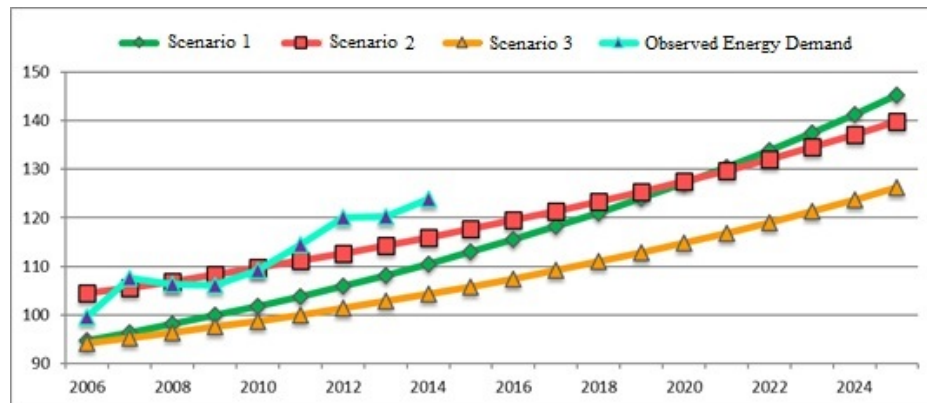


Figure 7. Prediction of MTSA's future energy demand according to scenarios

V. CONCLUSION

MTSA and TSA methods were applied to the EDF optimization problem. It was determined that the population number for MTSA and TSA methods was as 100, ST value was as 0.1 and MaxFEs was as 200.000. To compare the proposed methods and the methods in the literature (ACO, PSO, BA, DEA and AAA) and to analyse them healthily, as in the methods in the literature, the gross domestic product (GDP) in 1979-2005 for MTSA and TSA methods, population, import and export data were taken into consideration and an estimation model was created for energy demand. Also, to ensure the validity of the model, the energy demand values used in 2006-2014 were used for testing purposes. The energy demand generated by the proposed methods is modelled under three possible scenarios and compared with the energy demand values observed in those years. Estimation success of MTSA and

TSA methods for energy demand varies depending on the scenarios and data set used in the study. When the scenarios are analysed, it is seen that the energy demand values obtained by the MTSA method for Scenario 2 are closer to the OED. As a result, it was observed that MTSA method is a successful estimation tool for energy demand since MTSA method has a lower average relative error compared to TSA with 1.33 value.

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