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Energy Reports 8 (2022) 18–32

www.elsevier.com/locate/egyr

TMREES22-Fr, EURACA, 09 to 11 May 2022, Metz-Grand Est, France

Realization of Turkey's energy demand forecast with the improved arithmetic optimization algorithm

Murat Aslan*, Mehmet Beşkirli

Department of Computer Engineering, Şırnak University, 73000, Şırnak, Turkey

Received 10 June 2022; accepted 25 June 2022
Available online xxxx

Abstract

Due to the increasing energy consumption, energy has become a constant problem in the world. Rapidly increasing population, urbanization and economic activities increase the pressure of countries on energy. In a world where consumption is increasing, energy management has become a more important and challenging issue. For this reason, it is necessary to make proper estimations that will reduce the pressure of energy demand on this issue. In order to realize the estimation of energy demand, Turkey application is carried out in this study and arithmetic optimization algorithm (AOA) which is a stochastic metaheuristic algorithm has used to for solving energy demand problem. AOA is inspired from four substantial math functions such as subtraction, multiplication, addition and division for searching process of candidate solutions. The current position update rules of AOA are not powerful enough for solving the problem dealt with this study. Therefore, an improved version of AOA named as IAOA is proposed for solving energy demand problem. In the proposed algorithm, a new position update rule is incorporated to basic AOA in order to enhanced the exploration and exploitation capability of AOA. The linear regression model is used for the estimation of the energy demand and the population, domestic product, import and export data are used in estimation process. In the proposed model, Turkey's real data samples for the years 1979–2011 have been used, and Turkey's long-term energy demand has been estimated for the years 2012–2030. While performing the estimation process, Turkey's energy data of the years 1979–2011 have processed, and then Turkey's long-term energy demand estimations are realized for three different scenarios. Firstly, the experimental results of the proposed model are analyzed, then the results are compared with different studies proposed in the literature. As a result of the comparisons, it is seen that the IAOA method has achieved better or similar results than compared methods. For this reason, it can be said that the IAOA method is competitive and successful in realizing the energy demand forecast for Turkey's future years.

Peer-review under responsibility of the scientific committee of the TMREES22-Fr, EURACA, 2022.

Keywords: Arithmetic optimization algorithm; Energy demand; Estimation; Linear regression model; Optimization

1. Introduction

It is expected that the energy demand in the world will continuously increase until at least 2030 [1–3]. Especially, the energy demand of developing countries is more than the developed countries [4,5]. For this reason, the role and

* Corresponding author.
E-mail address: murataslan@sirnak.edu.tr (M. Aslan).

https://doi.org/10.1016/j.egyr.2022.06.101

Peer-review under responsibility of the scientific committee of the TMREES22-Fr, EURACA, 2022.

Nomenclature

A	Addition
AAA	Artificial algae algorithm
ABC	Artificial bee colony
ACO	Ant colony optimization
ANN	Artificial neural networks
AOA	Arithmetic optimization algorithm
ARIMA	Autoregressive integrated moving average
D	Division
DE	Differential evolution
EED	Estimated energy demands
ER	Error
GA	Genetic algorithm
GDP	Gross domestic product
GSA	Gravitational search algorithm
HAPE	Hybrid method-based particle swarm optimization and ant colony optimization
HPA	Hybrid approach based on particle swarm optimization and artificial bee colony algorithm
IAOA	Improved arithmetic optimization algorithm
IWO	Invasive weed optimization
M	Multiplication
MERN	Ministry of energy and natural resources
MOA	Math optimizer accelerated
OED	Observed energy demands
PSO	Particle swarm optimization
RE	Relative error
S	Subtraction
SARIMA	Seasonal autoregressive integrated moving average
TUIK	Turkish statistical institute
TLBO	Teaching–learning-based optimization
TSA	Tree seed algorithm
TSA	Tunicate swarm algorithm
VS	Vortex search
WEC-TNC	World energy council Turkish national committee

importance of energy in production and consumption is constantly increasing around the world [6]. In Turkey, urbanization, industrialization and socioeconomic developments increase the demand for energy due to rising of the young population [7,8]. An efficient energy planning is based on the best analysis of the energy consumed in the past and the present years, and the creation of predictions for the future with the least error. As a result, each country has its own prediction model for efficient energy production and consumption [9]. Planning and forecasting of future energy demand with modern statistical methods has been carried out officially in Turkey since 1984 [4]. The ministry of energy and natural resources (MENR), the Turkish statistical institute (TUIK) and the government planning organization are carried out their studies for energy demand forecasting in Turkey [10–12]. In many recent studies, some of the researchers have tried to predict the energy demand that Turkey will need in the coming years, using statistical methods [3,4,13–15], some using artificial neural networks (ANN) [11,16,17] and some using population-based metaheuristic approaches [7,8,18–29].

Metaheuristic methods are very effective methods in solving many real-world problems based on optimization. Since metaheuristics are problem-free algorithms, they can be easily adapted to many different problems [30–33].

Arithmetic Optimization Algorithm (AOA) is a math-based stochastic algorithm and was proposed by Abualigah et al. [34] for solving optimization tasks. In this study, an approach based on the AOA has improved in order to prediction the future energy demand of Turkey. In the proposed improved AOA-based approach (in short IAOA), the gross domestic product (GDP), population, import and export data of the MENR and TUIK for the years 1979–2011 are used in the training and testing process [35–37]. Then, the future energy demands of Turkey for three different scenarios have realized by using the proposed model.

The remainder of this paper is organized as follows; the literature review is detailed in Section 2. The steps of basic AOA method are explained in Section 3. The improved version of AOA (IAOA) is detailed in Section 4. The linear regression model used for estimation process of Turkey's future energy demands is detailed in Section 5. The experimental results of basic AOA, proposed IAOA and comparisons are presented in Section 6. Finally, conclusions are presented in Section 7.

2. Literature review

With a proper energy demand forecasting, the current energy resources can be utilized in effective, and some future plans can be considered such as renewable energy, energy conservation, reliability in supply, integrated with different energy production systems and etc. In energy demand management problem some technical, organization and behavioral solutions are should be considered for reduce the energy demand and consumption [38]. Energy management problem consists from production, consumption and distribution and has a major role for a proper energy forecasting and consumption and there are many precious study in literature in last decades for solving energy demand problem [39–42]. There are different solution approaches such as statistical methods [3,4,13–15], artificial neural networks (ANN) [11,16,17] and population-based metaheuristic techniques [7,8,18–29] have been proposed for in the field of estimation of Turkey's future energy demands.

Ediger and Tatlıdil [4] have made the estimation of Turkey's primary energy demand by considering the supply of annual additional energy demand with a cycle analysis. In addition, exponential smoothing method was used for seasonal events. Dilaver and Hunt [13] have established a relational model between industrial value supplement and electricity prices for prediction the Turkey's industrial energy demand in the upcoming years. Thus, they were created an energy demand function by applying the structural temporal technique to the annual data in a certain period and performed a successful forecasting process. In another study, Ediger and Akar [14] have proposed some statistical methods for estimation the Turkey's future energy demand by using the autoregressive Integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) methods. According to their study, it is stated that the ARIMA method estimated the total primary energy demand more safely than SARIMA. In another study, Yumurtacıand Asmaz [15] created a projection of energy use for the future estimations with taking into account the population growth and per capita energy consumption of Turkey in certain years. According to their study, the evaluations of 2050 have been interpreted with the use of all hydroelectric energy potential.

Kankal et al. [3] have proposed a solution technique based on artificial neural networks (ANN) by using the gross domestic product, population, imports, exports and employment data instances. They have improved four different estimation models for forecasting the future energy demand of Turkey. According to the experimental analysis of their study the Model-2, which estimates Turkey's energy consumption in an attached form, is the most successful among compared models. In other study, Biçer [16] has proposed a model based on ANN in the MATLAB program for estimation the short-term energy demand of a special area. Firstly, Biçer has created the model based on ANN, then the developed model was applied to the Urla region of Turkey. Es et al. [17] have improved an approach based on ANN model by using the gross domestic product (GDP), population, imports, exports, building area and number of vehicles for estimating the Turkey's future energy demand. In accordance with the results of their proposed ANN model with the multiple regression technique, they stated that their proposed model is an acceptable and highly competitive model.

Canyurt and Özkan [7] have proposed an estimation model for Turkey's future fuel consumption based on the genetic algorithm (GA) method by analyzing the Turkey's current fuel consumption. According to their study, they stated that the GA based method was found successful results for the estimation process. In another study, Sonmez et al. [8] have proposed a forecasting model by using the artificial bee colony (ABC) technique ın order to estimation the Turkey's future transportation energy demand. They were used Turkey's data instances of last 44 years for the process of the creation the estimation model. They said that ABC based estimation model was found proper results for transportation energy demand problem. Beşkirli et al. [11] have combined the basic artificial algae algorithm (AAA) with regression model for estimation the Turkey's future energy demand process. They said that, according to the comparison with the results of the other studies in literature, AAA based model were obtained the best results. Beşkirli et al. [12] have estimated Turkey's long-term energy demand by using the gravitational search algorithm (GSA). They said that their proposed modified GSA method has achieved better results than the algorithms in comparison by considering the economic data of Turkey. In another study, Beşkirli et al. [18] have estimated the future energy demand of Turkey by using the differential evolution (DE) method. In their study, firstly, linear model with DE has created, then the experimental outcomes have compared with the literature. They said that, they were estimated the Turkey's future energy demand with least error rate according to the compared methods. Ceylan and Öztürk [19] have proposed an approach based on GA for estimating the energy demand of Turkey for incoming years by using the economic indicators. They said that the experimental results of GA based solution approach were found the lowest errors when compare the results of MENR. In another study, Gulcu and Kodaz [20] created a forecasting model for Turkey's electricity demand problem by using the particle swarm optimization (PSO) algorithm. After, they realized the forecast of the future energy demand of Turkey with their proposed PSO based model. They said that the results obtained by PSO algorithm showed that the model was very efficient and durability. Kiran and Gunduz [21] have proposed a hybrid solution method based on PSO and ABC algorithms called as HPA for solving continuous optimization tasks. They implemented the HPA algorithm on some numerical benchmark functions and an energy demand estimation problem for showing the performance of HPA. According to their study, they point out that their proposed HPA is an alternative and competitive algorithm for solving the numerical benchmark problems and energy demand estimation problems. In another study, Kıran et al. [22] have proposed a hybrid algorithm based on PSO and ant colony algorithm (ACO) called HAPE for solving energy estimation demand problem. They implemented their proposed method on Turkey's future energy demand problem. Then, they compared their experimental results with some study in literature and they said that the best results were obtained with HAPE algorithm. Kıran et al. [23] have proposed a hybrid approach by adding different neighborhood selection mechanisms to ABC and PSO methods for solving Turkey's future energy demand problem. Kıran et al. said that their proposed approaches have obtained better results than the results of ACO algorithm. Özkış [24] has proposed an energy demand estimation model based on vortex search (VS) algorithm for solving energy demand problem. Then, Özkış has implemented the VS based energy demand estimation model on Turkey's future energy demand problem with three different scenarios. Toksarı [25] has proposed a linear and a quadratic regression models by using the ACO method. Then, Toksarıhas realized the Turkey's future energy demand by using the proposed regression models. In another study, Toksarı [26] has estimated the Net electrical energy by using the ACO method. Uğuz et al. [27] have proposed a new solution method called as ABCVSS by using ABC algorithm and variable search strategies for estimating the Turkey's long-term energy demand problem. Uğuz et al. have implemented ABCVSS algorithm to energy demand problem and they compared their results with the results of ACO, HAPE and PSO algorithms. They said that the ABCVSS method has reached the best results among of the compared algorithms. Ünler [28] has proposed an energy demand estimation model for realizing Turkey's future energy demand with the original PSO algorithm. Ünler compared the results of the PSO based model with the results of ACO model and said that the proposed PSO based model obtained efficient results for the energy demand forecasting problem. In another study, Beşkirli [29] has proposed a hybrid energy demand estimation model called as LF-IWO by using the invasive weed optimization (IWO) algorithm with levy flight (LF) function. Then, Beşkirli has applied the LF-IWO method on Turkey's long-term energy demand problem and said that LF-IWO algorithm has found quality and efficient results when compared with the solution approaches in literature. Tefek et al. [36] have estimated Turkey's long-term energy demand by hybridizing GSA and teaching–learning-based optimization (TLBO) methods. They presented Turkey's long-term energy demand with different scenarios. Then, they compared the results of their proposed algorithm with some state-of-the-art studies in literature and they said that they obtained the better results for Turkey's long-term energy demand than the other methods. They said that with proposed method, more realistic transactions can be carried out on issues such as energy imports and energy policies. Tefek and Uğuz [37] have realized the estimation of Turkey's future primary energy demand with linear and quadratic forms with TLBO method. They stated that the estimation results of their proposed models were consistent with the results in the WEC-TNC 2013 report. Beşkirli et al. [43] have presented a solution approach based on tree seed algorithm (TSA) with the tournament selection method for estimating the Turkey's long-term energy demand problem by using linear regression form. Aslan [44] has proposed a linear regression approach based on the tunicate swarm algorithm (TSA) to forecast Turkey's long-term energy demand. In the phase of creating the linear regression model, the gross domestic product, population, import and export data of Turkey has been used. Then, TSA algorithm was used to find the optimum weight coefficients of these parameters. Aslan said that considering the experimental results and comparisons of the proposed method, TSA is one of the competitive and powerful algorithm for solving the Turkey's long-term energy demand problem.

3. Arithmetic Optimization Algorithm (AOA)

Arithmetic Optimization Algorithm (AOA) is proposed by Abualigah et al. [34] for solving constrained and unconstrained optimization tasks. AOA is used some mathematical operators such as subtraction (S), multiplication (M), addition (A) and division (D) for searching process of candidate solutions. While multiplication and division operators are used in exploration phase of AOA, addition and subtraction operators are used for exploitation phase. The hierarchy of arithmetic operators used in AOA is given in Fig. 1.

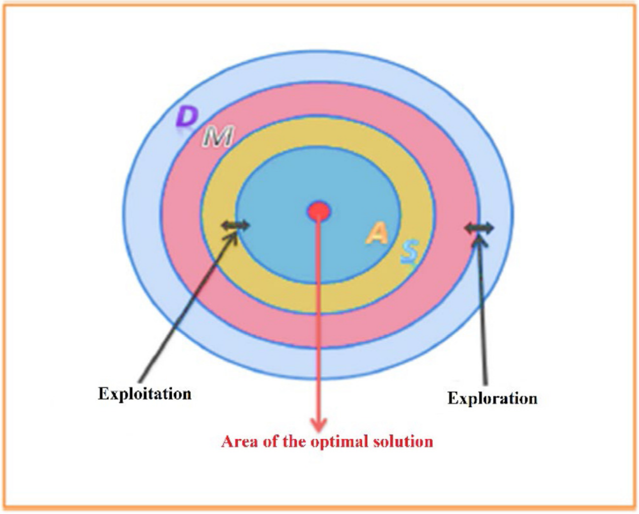

Fig. 1. The hierarchy of Arithmetic operators in AOA [34].

Two different update mechanism are used in AOA for generating candidate solutions in exploration and exploitation phases. Math optimizer accelerated (MOA) function is decided to which update mechanism will be used in generating the candidate solutions and it is calculated according to Eq. (1).

$$MOA(C\_Iter) = Min + C\_Iter \times \left(\frac{Max - Min}{Max\_Iter}\right) \tag{1}$$

In Eq. (1), Min shows the minimum value and Max shows the maximum value of the accelerated coefficients, $MOA(C\_Iter)$ indicates the function value at the tth iteration, C_Iter indicates the current iteration, Max_Iter indicates the number of maximum iterations.

3.1. Exploration phase

In the exploration phase of searching process of candidate solutions, multiplication and division operators are used in order to get a better position for candidate solutions. According to the value of MOA coefficient, exploration phase is carried out or not. If randomly created r_1 value is bigger than MOA value, then exploration phase is started. In exploration phase, if randomly created r_2 value is bigger than 0.5, than division math operator is executed, otherwise multiplication math operator is executed. The update mechanism of exploration phase is given in Eq. (2).

$$x_{i,j}(C\_Iter+1) = \begin{cases} best\left(x_j\right) \div (MOP + \epsilon) \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), r_2 > 0.5 \\ best\left(x_j\right) \times MOP \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), otherwise \end{cases} \tag{2}$$

where, μ indicates a control parameter to adjust the search process, x indicates the population of candidate solutions, $best$ indicates the position of the candidate solution with the best fitness value, i shows the index of a solution and it is a set $(1, 2, \ldots, N)$, j indicates the index of dimensions and it is a set $(1, 2, \ldots, d)$. ϵ is a small integer number, UB_j shows the upper bound of the jth position of a candidate solution and LB_j shows the lower bound of the jth position of a candidate solution. MOP indicates the math optimizer probability, and it is calculated as follows:

$$MOP\left(C_{Iter}\right) = 1 - C\_Iter \times \left(\frac{C\_Iter^{1-\alpha}}{max\_Iter^{1-\alpha}}\right) \tag{3}$$

In Eq. (3), $MOP\left(C_{Iter}\right)$ shows the function value at the tth iteration and α represents a sensitive parameter and defines the exploitation accuracy over the iterations.

3.2. Exploitation phase

In the exploitation phase of searching process of candidate solutions, addition and subtraction operators are used in order to get a better position for candidate solutions. If randomly created r_1 value is smaller than or equal to MOA value, than exploitation phase is started. In exploitation phase, if randomly created r_3 value is bigger than 0.5, then subtraction math operator is executed, otherwise addition math operator is executed. The update mechanism of exploitation phase is given in Eq. (4).

$$x_{i,j}(C\_Iter+1) = \begin{cases} best\left(x_j\right) - MOP \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), r_3 > 0.5 \\ best\left(x_j\right) + MOP \times \left(\left(UB_j - LB_j\right) \times \mu + LB_j\right), otherwise \end{cases} \tag{4}$$

After these explanations, the framework of basic AOA algorithm is given in Fig. 2.

4. Improved Arithmetic Optimization Algorithm (IAOA)

The current update mechanism of AOA algorithm is become insufficient for solving the problems dealt with this study. Therefore, in order to enhancing the exploration and the exploitation capability of AOA, an update mechanism which is a similar strategy used in Zou et al. [45] study is incorporated to the AOA algorithm. The update mechanism used in proposed algorithm is given in Eq. (5).

$$\begin{aligned} \mathrm{Step_{i,j}} &= \mathrm{best}\left(\mathrm{x_j}\right) - \mathrm{x_{i,j}} \\ \mathrm{x_{i,j}}(\mathrm{C\_Iter}+1) &= \mathrm{best}\left(\mathrm{x_j}\right) + \mathrm{rand}() \times \mathrm{Step_{i,j}} \end{aligned} \tag{5}$$

where, $Step_{i,j}$ indicates the step size around the best solution and current candidate solution and $rand()$ is a randomly value between [0,1]. The flowchart of proposed algorithm is given in Fig. 3.

5. Energy demand forecasting problem

In order to determine the total energy demands of a country, the gross domestic product (GDP), population, import and export data samples are very decisive. In this study, a linear regression model based on AOA method has presented for the first time in the literature by using Turkey's energy demand data samples. In the proposed model, GDP, population, import and export are defined as independent variables. Then, while creating the linear regression model, a weight coefficient is determined for each variable and thus the effect of each variable on the total energy demand can be defined. The data samples of MENR and TUIK between 1979–2011 have used as training and test data. The weights of each coefficient to the total energy demand are determined by using the Turkey's energy demand data samples with the AOA. The linear regression model used in this study is given in Eq. (6).

$$E_{linear} = w_1 + w_2 \cdot X_1 + w_3 \cdot X_2 + w_4 \cdot X_3 + w_5 \cdot X_4 \tag{6}$$

The linear regression model obtains from the E_{linear} vector is given in Eq. (6). X1–X4 variables represent the weights of GDP, population, import and export variables, w1 is an independent weight, and $w2 - w5$ the weights showing the effect of each variable on the energy estimation. After the linear regression model is created, the optimum values

Step 1: The initialization of algorithm
Set the dimension of the problem (d)
Set the number of candidate solution (N)
Set the termination condition (Max_Iter)
Set μ, α, Min, Max
Step 2: Generate initial population
Generate N random candidate solution on the d-dimensional search space
Calculate fitness value for each candidate solution
determine the best solution ($best$)
Initialize the iteration counter
Step 3: Searching process in solution space
WHILE $C\_Iter <= Max\_Iter$
Update the MOA value
Update the MOP value
FOR Each candidate solution (x_i)
FOR each dimension of candidate solution ($x_{i,j}$)
Generate a random values between [0, 1] (r_1, r_2 and r_3)
IF r_1>MOA
Exploration phase
IF r_2>0.5
Apply the division math operator and update the ith solution positions
ELSE
Apply the multiplication math operator and update the ith solution positions
END IF
ELSE
Exploitation phase
IF r_3>0.5
Apply the subtraction math operator and update the ith solution positions
ELSE
Apply the Addition math operator and update the ith solution positions
END IF
END IF
Calculate fitness value for ith candidate solution
Update the current position of ith candidate solution
Update the best solution ($best$)
END FOR
END FOR
$C\_Iter = C\_Iter + 1$
Step 4: Testing the termination condition
IF Termination condition is not satisfied
Go to Step 3
ELSE
Report the best solution
END WHILE

Fig. 2. The framework of the basic AOA method [34].

for the weights in the $w1 - w5$ range are tried to be found with proposed IAOA method by using the objective function given in Eq. (7). The total error is calculated according to the difference between the obtained energy demand and the expected energy demand with the linear regression model. It is concluded that the proposed linear regression model will achieve effective results as the total error approaches zero.

$$\min f(v) = \sum_{i=1}^{N} \left(E_i^{observed} - E_i^{predicted} \right)^2 \tag{7}$$

In Eq. (7), $E_i^{observed}$ and $E_i^{predicted}$ the expected and estimated energy values for the data samples, respectively, and the N value represents the total amount of data samples.

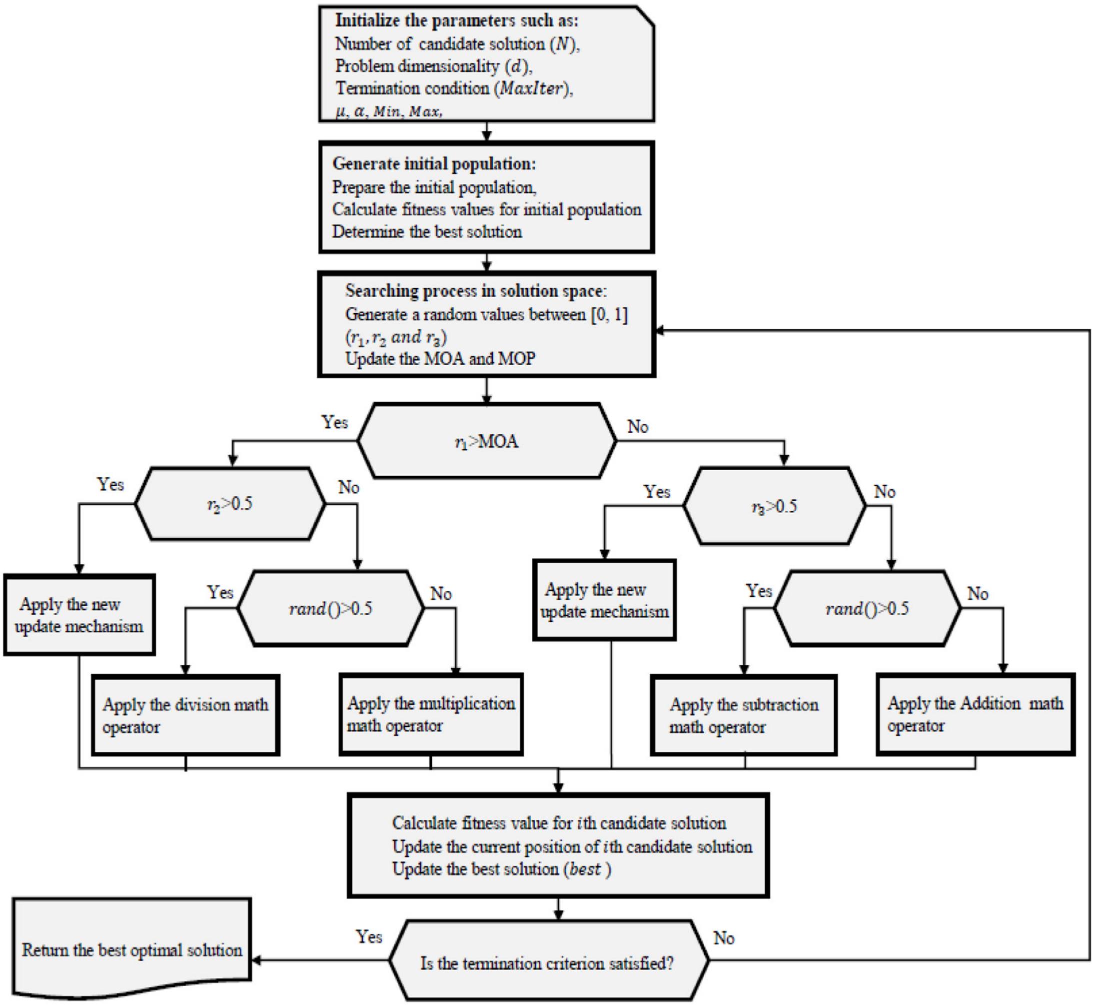

Fig. 3. The flowchart of the proposed algorithm.

6. Experimental results

The amount of energy demand in Turkey between 1979 and 2011 has been observed using the import, population, export and GDP data given in Table 1. The data set in Table 1 are obtained from TUIK and MENR. The improved AOA-based linear regression model has implemented on the data set given in Table 1. Then, the expected energy demand for the years 2012–2030 has estimated on certain scenarios by using the AOA based proposed model. Tunicate swarm algorithm (TSA) [44], gravitational search algorithm (GSA) and invasive weed optimization (IWO) [46], differential evolution (DE) [18], particle swarm optimization and ant colony algorithm based hybrid approach (HAPE) [22], ant colony optimization (ACO) [25], particle swarm optimization (PSO) [28] and vortex search (VS) [24] algorithms also used the data set given in Table 1 in their studies. In order to make a fair comparison with these algorithms, the control parameters of the proposed algorithm are determined to be the same as these algorithms used in the comparisons, and the population size is chosen as 100 and the number of maximum iterations (Max_Iter), which is the stopping criteria is chosen as 5×10^3. μ, α, Min, Max parameters are the algorithmic parameters of AOA and these parameters are chosen as 0.5, 5, 0.2 and 1, respectively according the basic AOA. In addition, as with the compared algorithms, the proposed algorithm is run 10 times independently, and the best results are used in comparisons.

The error amount has obtained by the proposed IAOA-based model and the other models such as AOA, TSA, VS, IWO, GSA, DE, HAPE, ACO and PSO algorithms and the weight coefficient of $w1$, $w2$, $w3$, $w4$ and $w5$ variables

Table 1. Turkey's data samples such as energy demand, GDP, population, import and export for 1979–2011 years.

Year	Energy demand (MTOE)	GDP ($\$10^9$)	Population (10^6)	Import ($\$10^9$)	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	4.7
1982	34.39	64	46.69	8.84	5.75
1983	35.7	60	47.86	9.24	5.73
1984	37.43	59	49.07	10.76	7.13
1985	39.4	67	50.31	11.34	7.95
1986	42.47	75	51.43	11.1	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	56.1	22.3	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	45.92	26.97
1999	76.77	187	66.43	40.67	26.59
2000	80.5	200	67.42	54.5	27.78
2001	75.4	146	68.37	41.4	31.33
2002	78.33	181	69.3	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
2006	99.59	483	72.97	139.58	85.54
2007	107.63	531	70.59	170.06	107.27
2008	106.27	648	71.13	201.96	132.03
2009	106.14	730	73.23	140.93	102.14
2010	109.27	615	74.47	185.54	113.88
2011	114.48	731	74.72	240.84	134.91

Table 2. Error values and weight coefficients obtained by algorithms for the years between 1979–2005.

Weight	IAOA	AOA	TSA	VS	IWO	GSA	DE	HAPE	ACO	PSO
$w1$	−59.2457	0.0000	−59.4149	−59.9676	−57.7420	−53.9784	−55.8991	−55.9091	−51.3046	−55.9022
$w2$	−0.0059	0.0754	−0.0074	−0.0070	0.0037	−0.0093	0.0038	0.0038	0.0124	0.0021
$w3$	1.9861	0.6989	1.9918	2.0019	1.9468	1.8781	1.9123	1.9126	1.8102	1.9126
$w4$	0.4017	0.2049	0.4010	0.4051	0.3430	0.4253	0.3735	0.3734	0.3524	0.3431
$w5$	−0.5118	−0.0002	−0.5082	−0.5197	−0.4562	−0.4738	−0.4835	−0.4833	−0.4439	−0.4240
Error	36.0722	672.1685	36.1146	36.1658	39.1535	43.6001	41.7120	41.7029	45.7239	42.6139

for the estimation of the energy demand of Turkey between 1979–2005 are given in Table 2. The results of the GSA and IWO algorithms are directly taken from the study by Koç et al. [46], the results of the TSA algorithm are directly taken from Aslan study [44], the results of the DE algorithm are directly taken from the study of Beşkirli et al. [18], the results of the HAPE algorithm are directly taken from the study by Kiran et al. [22], the results of the ACO algorithm are directly taken from the study of Toksarı [25], the results of the PSO algorithm are directly taken from Ünler study [28] and finally the results of the VS algorithm are directly taken from Özkış study [24].

When the experimental results given in Table 2 are examined, the total error amount obtained by the proposed model is lower than the total error amount obtained by the other models in compared. Therefore, IAOA has achieved better weight values with compared models. According to the weight values found by IAOA in Table 2, the total error amount of IAOA is 36.0722 and this total error amount is the lowest error amount when compared to other

Table 3. Estimated energy values, error values and relative error percentages obtained by the algorithms for the years between 1996–2005.

Years	OED	IAOA			AOA			TSA			VS			IWO			GSA			DE		
		EED	ER	RE	EED	ER	RE	EED	ER	RE	EED	ER	RE	EED	ER	RE	EED	ER	RE	EED	ER	RE
1996	69.86	69.78	−0.08	−0.11	66.61	−3.25	−4.65	69.75	−0.11	−0.16	69.82	−0.04	−0.06	69.32	−0.54	−0.77	69.56	−0.30	−0.43	69.71	−0.15	−0.21
1997	73.78	72.44	−1.34	−1.82	69.03	−4.75	−6.44	72.41	−1.37	−1.86	72.48	−1.30	−1.76	71.90	−1.88	−2.55	72.30	−1.48	−2.00	72.32	−1.46	−1.99
1998	74.71	73.27	−1.44	−1.93	70.45	−4.26	−5.70	73.23	−1.48	−1.98	73.30	−1.41	−1.89	73.02	−1.69	−2.26	72.92	−1.79	−2.40	73.30	−1.41	−1.89
1999	76.77	74.32	−2.45	−3.19	68.86	−7.91	−10.30	74.31	−2.46	−3.20	74.37	−2.40	−3.12	74.10	−2.67	−3.48	73.74	−3.03	−3.95	74.18	−2.59	−3.37
2000	80.50	81.15	0.65	0.81	73.37	−7.13	−8.86	81.13	0.63	0.78	81.25	0.75	0.93	80.28	−0.22	−0.28	80.79	0.29	0.37	80.71	0.21	0.27
2001	75.40	76.28	0.88	1.17	67.27	−8.13	−10.78	76.37	0.97	1.29	76.37	0.97	1.29	75.81	0.41	0.55	75.83	0.43	0.57	75.71	0.31	0.42
2002	78.33	79.58	1.25	1.60	72.64	−5.69	−7.26	79.63	1.30	1.66	79.65	1.32	1.68	79.08	0.75	0.96	79.32	0.99	1.27	79.13	0.80	1.02
2003	83.84	82.5	−1.34	−1.60	81.31	−2.53	−3.02	82.50	−1.34	−1.60	82.50	−1.34	−1.60	82.1	−1.74	−2.07	82.79	−1.05	−1.25	82.37	−1.47	−1.76
2004	87.82	87.15	−0.67	−0.76	92.26	4.44	5.06	87.10	−0.72	−0.82	87.07	−0.75	−0.85	86.53	−1.29	−1.47	88.41	0.59	0.68	87.19	−0.63	−0.72
2005	91.58	92.85	1.27	1.39	102.14	10.56	11.53	92.74	1.16	1.27	92.72	1.14	1.24	92.19	0.61	0.67	94.55	2.97	3.24	93.10	1.52	1.66

algorithms. The most important reason why IAOA achieved a lower total error compared to other algorithms is, IAOA used the candidate solution which has the best fitness value in update rule. Table 3 shows the observed energy demands (OED), estimated energy demands (EED), error (ER) and relative error (RE) of compared algorithms for the years between 1996–2005 by using the weight coefficients given in Table 2.

When Table 3 is examined, the energy demand estimates of the proposed IAOA algorithm generally close to the observed energy demands. In addition, the errors and relative errors between the estimated energy demand and the observed energy demand of the algorithms for the years 1996–2005 are given in Table 3. Generally, the algorithms made the estimation with the highest relative error values when performing the year 1999 energy estimations. The total error amount obtained by the algorithms for the years between 1996–2005 and the total relative error percentages are given in Table 4.

Table 4. Total error values and total relative error percentages obtained by the algorithms between 1996–2005.

Algorithm	Total error	Total RE (%)
TSA	11.54	14.62
VS	11.42	14.42
IWO	11.80	15.06
GSA	12.92	16.16
DE	10.55	13.31
AOA	58.65	73.60
IAOA	11.37	14.37

When Table 4 is examined, according to the estimated energy demands for the years between 1996–2005, DE algorithm is obtained the best total error and total relative error values, and the second-best results are obtained by IAOA method. The worst total error and total relative error values are reached by basic AOA algorithm.

6.1. Estimating Turkey's long-term energy demand for the years 2012–2030 with the IAOA algorithm

TSA, DE, VS, IWO and GSA algorithms were estimated the long-term energy demand of Turkey by using the data samples for the years between 1979 and 2011. In order to make a fair comparison with the predictions made by the algorithms for the future, firstly, the proposed IAOA-based model is applied on the data set for the years between 1979–2011 and the weight coefficients between $w1 - w5$ has determined for the proposed model. Then, long-term energy demand forecasts for the years between 2012 and 2030 has made for three different future scenarios proposed by Koç et al. [46] study. The obtained results are compared with the results of AOA, TSA, DE, VS, IWO and GSA algorithms. The weight coefficient values, and error amounts found by the algorithms for the data set of the years between 1979 and 2011 are given in Table 5.

When the experimental results given in Table 5 are examined, the total error amount obtained by the proposed model is lower than the total error amount obtained by the other models used in comparison excluding the DE algorithm. IAOA and DE algorithms estimated $w1 - w5$ weight coefficient values with similar error amounts. Future energy demands of Turkey have estimated for three different scenarios for the population, import, GDP and export data given in Table 6 by using the weight coefficient values given in Table 5.

For scenario I, the experimental results obtained by IAOA have compared with the experimental results obtained by the AOA, TSA, VS, IWO and GSA algorithms, and the experimental results of compared algorithms are given in Table 7.

Table 5. Error values and weight coefficients of algorithms for the years between 1979–2011.

Weight	IAOA	AOA	TSA	VS	IWO	GSA	DE
$w1$	−50.1611	−0.6578	−50.29152	−43.35375	−28.14013	−57.15262	−50.13452
$w2$	0.0239	0.0000	0.02513	0.02153	0.00582	0.02461	0.02389
$w3$	1.7581	0.8722	1.76045	1.63557	1.37398	1.89247	1.75763
$w4$	0.0999	0.0809	0.10638	0.09159	0.13009	0.08863	0.09997
$w5$	−0.0362	0.2767	−0.05457	0.01120	0.05630	0.05971	−0.03635
Error	152.6414	1032.6193	152.88368	169.05149	367.45717	180.36962	152.57090

Table 6. Possible scenarios for the years between 2012–2030.

Data	Scenario I	Scenario II	Scenario III
GDP average growth rate (%)	4.0	5.0	6.0
Population growth rate (%)	0.5	0.6	0.6
Growth rate of imports (%)	2.5	3.5	3.0
Growth rate of exports (%)	3.0	3.5	3.0

Table 7. Turkey's future energy demands for scenario I.

Years	OED	IAOA	AOA	TSA	VS	IWO	GSA
2012	120.09	119.64	123.25	119.69	120.00	119.40	117.25
2013	120.29	121.49	125.23	121.55	121.88	121.13	119.01
2014	123.94	123.39	127.26	123.44	123.81	122.90	120.80
2015	129.27	125.33	129.34	125.39	125.78	124.70	122.64
2016	N/A	127.31	131.47	127.38	127.80	126.55	124.52
2017	N/A	129.34	133.66	129.41	129.87	128.43	126.45
2018	N/A	131.43	135.89	131.50	131.99	130.36	128.41
2019	N/A	133.56	138.19	133.64	134.16	132.32	130.43
2020	N/A	135.75	140.54	135.83	136.39	134.33	132.50
2021	N/A	137.99	142.95	138.07	138.67	136.39	134.61
2022	N/A	140.28	145.42	140.38	141.01	138.49	136.78
2023	N/A	142.64	147.95	142.74	143.41	140.64	139.00
2024	N/A	145.05	150.55	145.16	145.88	142.83	141.27
2025	N/A	147.53	153.21	147.64	148.40	145.08	143.61
2026	N/A	150.07	155.94	150.19	151.00	147.37	146.00
2027	N/A	152.68	158.75	152.81	153.66	149.72	148.45
2028	N/A	155.36	161.62	155.49	156.39	152.13	150.97
2029	N/A	158.11	164.56	158.25	159.20	154.58	153.55
2030	N/A	160.93	167.59	161.08	162.08	157.10	156.21

When Table 7 is examined, IAOA-based model and VS algorithm are estimated significant results for years between 2012 and 2030. The graphical energy demand of the compared algorithms for Scenario I by years between 2012–2030 is given in Fig. 4.

The experimental results obtained by proposed IAOA model, and the other models such as AOA, TSA, VS, IWO and GSA algorithms for Scenario II are given in Table 8. When Table 8 is examined, the results of IAOA-based model, VS and TSA algorithms for Scenario II are better than the other compared models. The graphical energy demand of the compared algorithms for Scenario II by years between 2012–2030 is given in Fig. 5. When the results given in Fig. 5 are examined, the results for future energy demand of IAOA, TSA and VS algorithms are better than the other models.

The experimental results obtained by proposed IAOA model, and the other models such as AOA, TSA, VS, IWO and GSA algorithms for Scenario III are given in Table 9. When Table 9 is examined, the results of IAOA-based model, VS and TSA algorithms for Scenario III are better than the other compared models. If Scenario III is chosen for the future energy demand forecasting, the estimated energy demands of the algorithms by years between 2012–2030 are given in Fig. 6. When Fig. 6 is examined, IAOA, TSA and VS algorithms have obtained similar estimations for the years between 2012–2020. However, since the results of years in the 2021–2030 are taken into account, the energy demands found by the proposed model are better than compared algorithms.

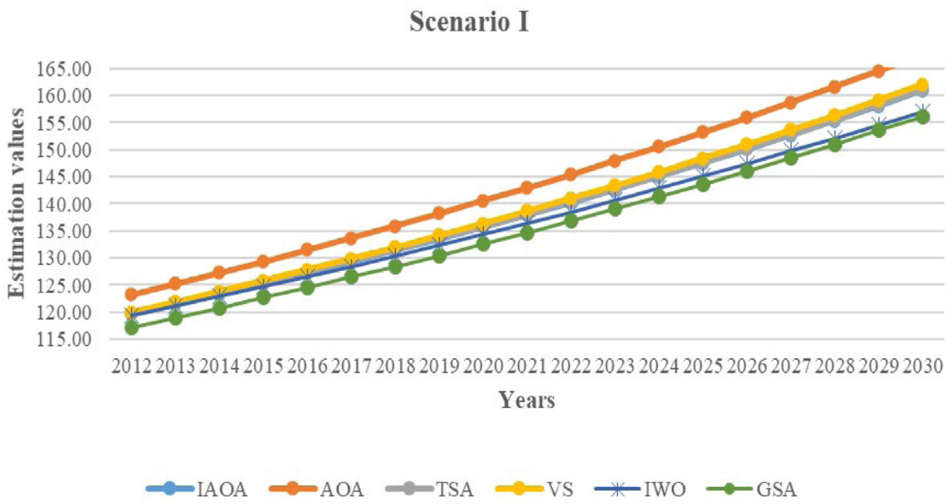

Fig. 4. Estimated energy demands of the algorithms for scenario I for the years 2012–2030.

Table 8. Turkey's future energy demands for scenario II.

Years	OED	IAOA	AOA	TSA	VS	IWO	GSA
2012	120.09	120.16	123.70	120.23	120.51	119.90	117.74
2013	120.29	122.57	126.15	122.65	122.93	122.15	120.02
2014	123.94	125.04	128.68	125.14	125.42	124.47	122.37
2015	129.27	127.60	131.28	127.72	127.99	126.85	124.79
2016	N/A	130.24	133.96	130.38	130.65	129.30	127.29
2017	N/A	132.96	136.73	133.12	133.39	131.83	129.86
2018	N/A	135.77	139.58	135.96	136.22	134.43	132.52
2019	N/A	138.68	142.51	138.88	139.14	137.10	135.26
2020	N/A	141.68	145.54	141.91	142.16	139.86	138.09
2021	N/A	144.78	148.66	145.04	145.28	142.69	141.02
2022	N/A	147.98	151.88	148.28	148.50	145.62	144.04
2023	N/A	151.29	155.20	151.62	151.83	148.63	147.16
2024	N/A	154.72	158.63	155.09	155.28	151.73	150.39
2025	N/A	158.27	162.16	158.67	158.85	154.93	153.73
2026	N/A	161.94	165.80	162.38	162.54	158.22	157.19
2027	N/A	165.74	169.56	166.23	166.36	161.62	160.77
2028	N/A	169.68	173.44	170.21	170.31	165.13	164.47
2029	N/A	173.75	177.44	174.33	174.41	168.74	168.31
2030	N/A	177.98	181.57	178.61	178.65	172.47	172.28

7. Conclusions

Arithmetic Optimization Algorithm is proposed in recent by Abualigah et al. [34] for solving constrained and unconstrained optimization tasks. AOA is inspired from four important math functions such as subtraction, multiplication, addition and division for searching process of candidate solutions. While multiplication and division operators are used in exploration phase of AOA, addition and subtraction operators are used for exploitation phase. And also, the position of best agent is used in update mechanism of AOA. Long-term energy demand estimation is very important in terms of predicting the long-term energy demands of countries and taking planned steps for the future. In this study, a linear model based on improved AOA algorithm has been proposed in order to solve energy demand estimation problem. In the proposed IAOA model, Turkey's GDP, population, export and import data for the period 1979–2011 years have been used in the training and testing phases. Then, for the years between 2012–2030, Turkey's long-term energy demands have tried to be estimated over three different possible scenarios. The experimental results obtained for three different scenarios have compared with the results of the AOA, TSA,

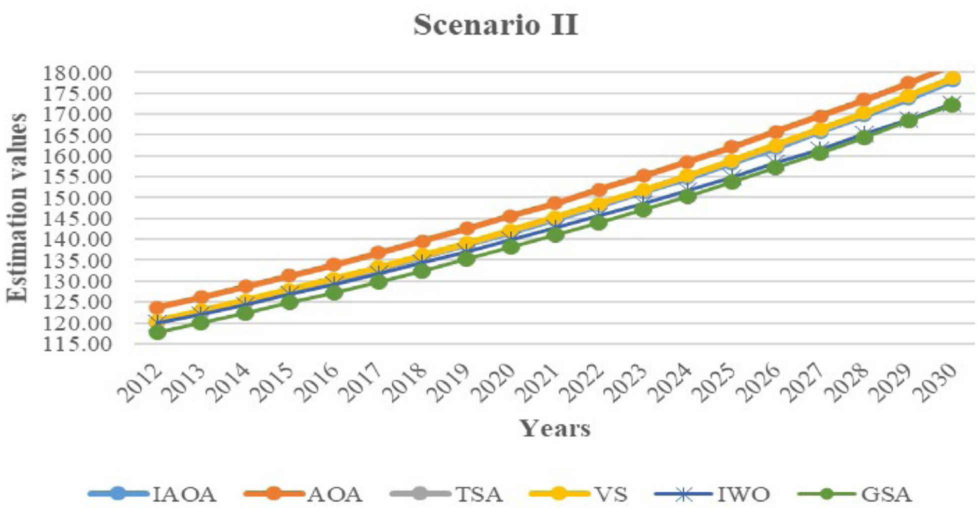

Fig. 5. Estimated energy demands of the algorithms for Scenario II for the years 2012–2030.

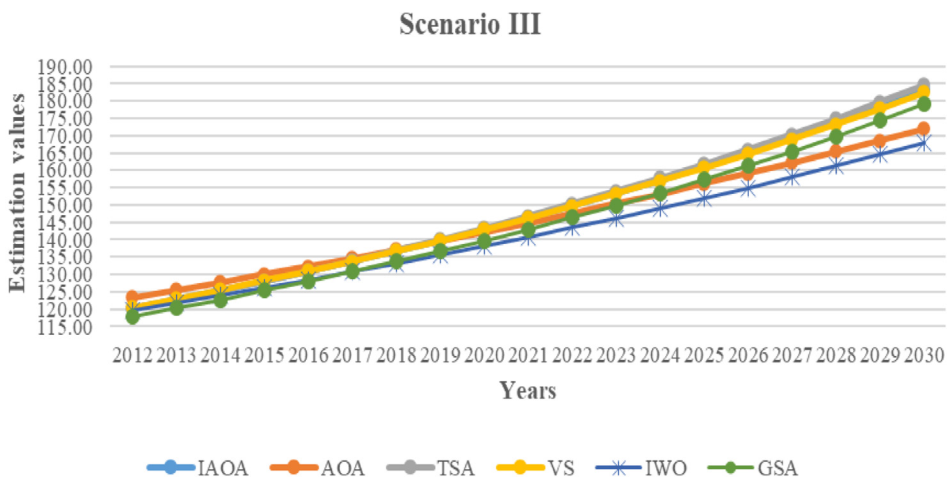

Fig. 6. Estimated energy demands of the algorithms for Scenario III for the years 2012–2030.

Table 9. Turkey's future energy demands for scenario III.

Yıl	OED	IAOA	AOA	TSA	VS	IWO	GSA
2012	120.09	120.24	123.42	120.32	120.55	119.75	117.86
2013	120.29	122.74	125.57	122.85	123.02	121.84	120.27
2014	123.94	125.32	127.77	125.46	125.57	123.99	122.76
2015	129.27	128.00	130.03	128.18	128.21	126.19	125.35
2016	N/A	130.77	132.35	131.00	130.95	128.46	128.03
2017	N/A	133.66	134.73	133.92	133.79	130.79	130.81
2018	N/A	136.64	137.17	136.95	136.74	133.19	133.69
2019	N/A	139.75	139.67	140.11	139.79	135.65	136.69
2020	N/A	142.97	142.24	143.39	142.96	138.18	139.81
2021	N/A	146.32	144.88	146.80	146.25	140.79	143.05
2022	N/A	149.81	147.58	150.35	149.67	143.47	146.42

(continued on next page)

Table 9 (*continued*).

Yıl	OED	IAOA	AOA	TSA	VS	IWO	GSA
2023	N/A	153.44	150.36	154.04	153.23	146.23	149.92
2024	N/A	157.21	153.21	157.89	156.92	149.07	153.57
2025	N/A	161.14	156.13	161.89	160.77	151.99	157.38
2026	N/A	165.23	159.14	166.07	164.77	155.01	161.34
2027	N/A	169.50	162.22	170.43	168.94	158.11	165.48
2028	N/A	173.95	165.38	174.98	173.28	161.31	169.80
2029	N/A	178.60	168.63	179.73	177.80	164.61	174.30
2030	N/A	183.44	171.97	184.68	182.52	168.01	179.00

VS, GSA and IWO algorithms, which have made the energy demand estimation using the same scenarios. When the experimental results and comparisons are examined, it can be seen that the AOA-based linear regression model is obtained competitive and effective results in predicting Turkey's long-term energy demand. In future studies, different regression models and algorithms can be proposed to provide more effective and robust results for Turkey's long-term energy demands.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgment

The author also would like to thank "The Scientific Projects Coordinatorship of Şırnak University" for their institutional supports (Project number: 2022.FNAP.06.01.02).

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