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ORIGINAL ARTICLE

A new hybrid gravitational search–teaching–learning-based optimization method for energy demand estimation of Turkey

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Abstract In this study, energy demand estimation (EDE) was implemented by a proposed hybrid gravitational search–teaching–learning-based optimization method with developed linear, quadratic and exponential models. Five indicators: population, gross domestic product as the socio-economic indicators and installed power, gross electric generation and net electric consumption as the electrical indicators, were used in analyses between 1980 and 2014. First, the developed models were trained by the data between 1980 and 2010, and then, accuracy of the models was tested by the data between 2011 and 2014. It is found that the obtained results with the proposed method are coherent with the training data with correlation coefficients in three models as 0.9959, 0.9964 and 0.9971, respectively. Root mean square error values were computed 1.8338, 1.7193 and 1.5497, respectively, and mean absolute percentage errors were obtained as 2.1141, 2.0026 and 1.6792%, respectively, in the three models. These values calculated by the proposed method are better than the results of standard gravitational search algorithm and teaching–learning-based optimization methods and also classical regression analysis. Low, expected and high scenarios were proposed in terms of various changing rates between 0.5 and 1.5% difference in socio-economic and electrical indicators. Those scenarios were used in the EDE study of Turkey between 2015 and 2030 for a comparison with other related studies in the literature. By the proposed method, the strategy in energy importation can be regulated and thus more realistic energy policies can be made.

Keywords Energy demand estimation · Hybrid optimization method · Estimation models · Scenarios · Turkey

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1 Introduction

Energy demand estimation (EDE) is crucial for the management of energy and economic sources. Moreover, it is vital to sustain uninterrupted and reliable energy generation to make cost-efficient investments in capacity planning and consistent energy policies such as the energy agreements between countries [1]. The EDE is also important for policymakers for the future energy investments in terms of the renewable energy generation and economic growth [2]. The EDE in the developed countries is more consistent and more predictable with respect to the developing countries because of lower unpredictable changes in economic increase, industrialization rate and economic turmoil [3]. Therefore, there is a need to heuristic methods to implement the EDE analyses with higher accuracy.

Turkey is the eighteenth biggest economy in the world with its 718.2 billion $ gross domestic product (GDP) [4]. The development in the Turkish economy impacts the generation and consumption in electricity. Moreover, the increase in primary energy supply in a period of 24 years between 1990 and 2013 came true as 54, 17 and 14% in the World, OECD and the USA, respectively, while it is 117% in Turkey for that period [5]. Although energy demand doesn't increase much, fluctuations can be observed in some developing countries like Turkey due to government policies, local or global crises. The development of primary energy supply in the world and the situation of Turkey are shown in Table 1.

The energy balance of Turkey is affected by some factors such as the transition in the use of energy sources, the increase in population as a rate of 13.3‰ in 2014 [7], the natural gas dependence to the foreign countries as 47.9% and renewables as 21% [8] and dynamic economy in the last decade with the increased GDP rate as 66% reaching up to 799.4 billion $ from 481.5 billion $ [9]. In consideration of these changes, there is a need for a long-term EDE to supply the energy sources reliably in Turkey.

The growth in the economy and population, development in industries under the influence of the powerful tendency of Turkish Government and regional energy security policies are the main parameters increasing the electric generation.

EDE has an important role on the energy agreements between countries. In this context, Ministry of Energy and Natural Resources (MENR) of Turkey has been run the primary EDE in the future. In Fig. 1, excessive deviations have been shown between actual and MENR estimation values over 2008 and 2014 years [6, 10].

The purpose of this paper is to estimate the EDE for the years between 2015 and 2030 by a proposed hybrid gravitational search–teaching–learning-based optimization (HGT) method. The EDE was done by optimizing the weighing coefficients of three forms of models in the proposed method. The forms of the models, namely linear, quadratic and exponential (LQE), used GDP and population as the socio-economic indicators, installed power, gross electric generation and net electric consumption as the electrical indicators in model inputs. These five indicators between 1980 and 2014 are the input data for the LQE models to develop and test. The future study of the EDE between 2015 and 2030 was estimated under the low, expected and high (LEH) scenarios. This is the first study

Table 1 Development in the primary energy supply and increase rates (Mtoe) between 1990 and 2013

Country	Years		Increase (%)
	1990	2013	
China	879	3057	248
India	316	770	144
Turkey [6]	53	120	117
USA	1915	2185	14
OECD	4525	5293	17
World	8790	13,579	54

Mtoe million tons of oil equivalent

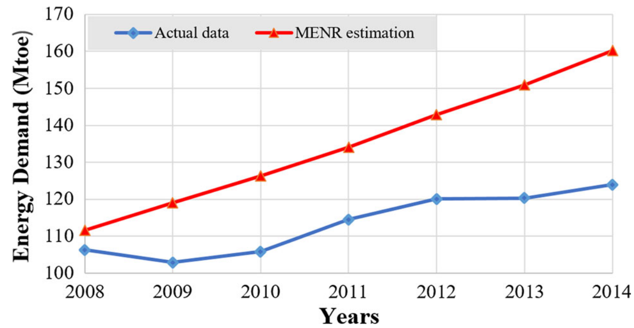


Fig. 1 Actual values and MENR demand estimations between 2008 and 2014 [6, 10]

using the proposed method and LQE models among the EDE studies for Turkey.

The scenarios were proposed in terms of various changing rates between 0.5 and 1.5% difference in socio-economic and electrical indicators. In the expected scenario, GDP is taken from the government at the medium-term programme [11], population is provided from the Turkish Statistical Institute (TURKSTAT) [12], electrical indicators are taken from the Turkish Electricity Transmission Company [13]. GDP and electrical indicators in the low scenario are determined, respectively, as 0.5 and 1.5% lower than the expected scenario. In the high scenario, GDP and electrical indicators in the low scenario are determined, respectively, as 0.5 and 1.5% higher than the expected scenario. Projection results were used with other estimating studies for a comparison.

2 Literature review

Classical regression analysis, which is a statistical method used in EDE studies in the literature, is a simple and well-known method [14–18]. Recently, different artificial intelligence (AI) techniques have been applied to EDE, which are alternative to classical regression methods with less statistical error and more reliable estimation. As AI techniques, many studies related to the EDE are available to forecast the future energy demand by using some estimation models. These are the studies about artificial neural networks (ANNs), meta-heuristic optimization algorithms and hybrid meta-heuristic optimization algorithms.

EDE studies using the ANN method have been implemented widely for different countries as in South Korea EDE [19], estimation of Taiwan's electricity consumption [20], energy consumption prediction of Greece [21], transportation energy demand of Thailand [22] and South Africa's energy consumption [23].

For Turkey, annual gross electricity demand of Turkey [24], net EDE of Turkey [25], net energy consumption of

Turkey [14, 26, 27], net electric consumption of Turkey on sectoral basis [28], basic energy sources and net electricity energy consumption of Turkey [29] and transport energy demand modelling of Turkey [30] were studied by using ANN methods for this purpose.

EDE studies using meta-heuristic optimization algorithms were studied on the subject by using genetic algorithm (GA) as in estimating the Turkish residential–commercial energy [31], oil demand estimation of Turkey [32], demand estimation of fossil fuels in Turkey [33], total EDE of Turkey [34], energy and exergy production and consumption of Turkey [35], estimating petroleum exergy production and consumption [36], electricity estimation of Turkey [37], estimating transport energy demand in Turkey [38] and electricity consumption forecasting with genetic programming (GP) [39].

EDE and net electricity energy generation of Turkey by ant colony algorithm (ACO) [40, 41], energy demand of Turkey by particle swarm optimization (PSO) [42], net electricity energy demand of Turkey by artificial bee colony (ABC) and PSO techniques [43], prediction of electricity energy consumption of Turkey by ABC algorithm [44], transport energy forecasting in Turkey by meta-heuristic harmony search algorithm (HSA) [45], electricity demand estimation in Iran by different PSO variants [46], forecasting future oil demand of Iran by gravitational search algorithm (GSA) [47], estimation of electricity demand of Iran by PSO and GA [48] and demand estimation of oil in Iran [49] were studied in the past for this purpose.

Various papers published using hybrid meta-heuristic optimization methods to forecast the electricity or energy demand as in estimating electricity domestic consumption in Turkey by hybrid algorithm of ACO and iterated local search (ILS) [50], energy consumption of Turkey by the hybrid ANN with TLBO model [51, 52], EDE of Turkey by hybrid PSO and ACO methods [53], EDE of Turkey by a neural network (NN)-based PSO algorithm (PSOM-NN) [54], estimates of hydroelectric generation ANN with ABC for Turkey [55], electricity consumption of China by the hybrid ANN–PSO model [56], prediction of annual electricity demand in China by hybrid PSO- and GA-optimized radial basis function (RBF) neural network model [57], primary EDE of China by hybrid PSO–GA model [58], primary EDE of China by hybrid mix-encoding PSO and RBF network-based algorithm [59], annual electricity demand, natural gas demand and oil products demand in Iran by cooperative ACO–GA [60].

In the past studies, models were developed with one or two estimation models [24, 25, 42–44, 50–54] but in this study, three estimation models were first used altogether in Turkey. Many of the studies were done until 2025 [42, 51–54], but this study was implemented until 2030 for a longer period. Also, the proposed HGT method was first implemented in the study. The study is important for the future studies related to the energy estimation in Turkey especially in point of estimation models created, indicators and the use of other hybrid methods in this area.

3 Variable selection and datasets used

In the EDE studies, different variables have been used. GDP, population, import and export data are the common variables [19, 26, 34, 37, 42, 43, 50, 51, 53, 54, 61]. Apart from these variables, gross generation [62, 63], installed power [27, 62, 64], net consumption [29], temperature [21, 24], unemployment rate [24, 58], registered vehicle number [22, 25, 65] and total number of subscribers [62] are some other variables.

In this study, the EDE was made between the years 2015 and 2030 by using the data between 1980 and 2014 by using population, GDP as socio-economic indicators and total power installed, gross generation and net consumption as electrical indicators. Population and GDP data were taken from the report of Turkish Ministry of Development [9]. Electrical indicators were taken from Turkish Electricity Transmission Company [13]. Primary energy demand between 1980 and 2014 was taken from the MENR of Turkey [6]. In Table 2, actual data used in the study between 1980 and 2014 are given. As it can be seen from Table 2, in the years 1995 and 2007 when the total installed power has increased slightly, GDP, gross generation and net consumption have greatly increased. On the contrary, GDP, gross generation and net consumption have decreased in 2001 and 2009 years but the total installed power has increased much. Generally, it can be said that despite of the increase or decrease in other variables, population and total installed power have increased continuously. The changes of the GDP, total power installed, gross generation and net consumption versus energy demand (Mtoe) in terms of R^2 correlation coefficient between 1980 and 2014 are given in Fig. 2 which shows R^2 correlation coefficients of 0.98, 0.90, 0.95, 0.99 and 0.98 for population, GDP, total power installed, gross generation and net consumption, respectively, versus energy demand. Therefore, it can be concluded that there is a strong correlation between the socio-economic and electrical indicators selected in this study and energy demand.

The reason of a weaker GDP versus energy demand correlation is derived from the profound economic turmoils in some years (1994, 2001, 2009). The increase in the

Table 2 Actual data used between the years 1980 and 2014 for the future estimations

No.	Years	Actual MTOE	Population 10^6	GDP 10^9 $	Installed power (GW)	Gross generation (TWh)	Net consumption (TWh)
1	1980	31.97	44.44	90.68	5.12	23.28	20.40
2	1981	32.05	45.54	94.64	5.54	24.67	22.03
3	1982	34.39	46.69	85.35	6.64	26.55	23.59
4	1983	35.7	47.86	81.13	6.94	27.35	24.47
5	1984	37.43	49.07	78.82	8.46	30.61	27.64
6	1985	39.4	50.31	89.26	9.12	34.22	29.71
7	1986	42.47	51.48	100.87	10.12	39.69	32.21
8	1987	46.88	52.37	115.10	12.50	44.35	36.70
9	1988	47.91	53.27	121.67	14.52	48.05	39.72
10	1989	50.71	54.19	142.64	15.81	52.04	43.12
11	1990	52.98	55.12	200.55	16.32	57.54	46.82
12	1991	54.27	56.06	200.50	17.21	60.25	49.28
13	1992	56.68	56.99	210.58	18.72	67.34	53.98
14	1993	60.26	57.91	238.38	20.34	73.81	59.24
15	1994	59.12	58.84	176.96	20.86	78.32	61.40
16	1995	63.68	59.76	225.94	20.95	86.25	67.39
17	1996	69.86	60.67	243.41	21.25	94.86	74.16
18	1997	73.78	61.58	253.71	21.89	103.30	81.89
19	1998	74.71	62.46	270.95	23.35	111.02	87.70
20	1999	76.77	63.36	247.54	26.12	116.44	91.20
21	2000	80.5	64.27	265.38	27.26	124.92	98.30
22	2001	75.4	65.17	196.74	28.33	122.72	97.07
23	2002	78.33	66.00	230.49	31.85	129.40	102.95
24	2003	83.84	66.80	304.90	35.59	140.58	111.77
25	2004	87.82	67.60	390.39	36.82	150.70	121.14
26	2005	91.58	68.44	481.50	38.84	161.96	130.26
27	2006	99.59	69.30	526.43	40.56	176.30	143.07
28	2007	107.63	70.16	648.75	40.84	191.56	155.14
29	2008	106.27	71.05	742.09	41.82	198.42	161.95
30	2009	102.92	72.04	616.70	44.76	194.81	156.89
31	2010	105.83	73.14	731.61	49.52	211.21	172.05
32	2011	114.48	74.22	773.98	52.91	229.40	186.10
33	2012	120.09	75.18	786.28	57.06	239.50	194.92
34	2013	120.29	76.06	823.04	64.01	240.15	198.05
35	2014	123.937	76.90	800.11	69.52	251.96	207.38

number of electric-powered devices with the increasing population and the increase in the energy demand has created an inverse effect with GDP in terms of correlation coefficient.

4 Methodology

In this study, a new method is proposed with the combination of standard gravitational search algorithm (GSA) [66] and standard teaching–learning-based optimization (TLBO) [67] algorithms and LQE models of the proposed method are developed for the EDE study.

4.1 Gravitational search algorithm (GSA)

GSA is one of the physical meta-heuristic techniques [66] based on Newton's gravity and motion laws. Every particle (agent) in search space is accepted a mass in GSA. Therefore, GSA is defined an artificial mass system [66]. In search space, result of the greater mass attracts the other results and affects them. As a result of this attraction,

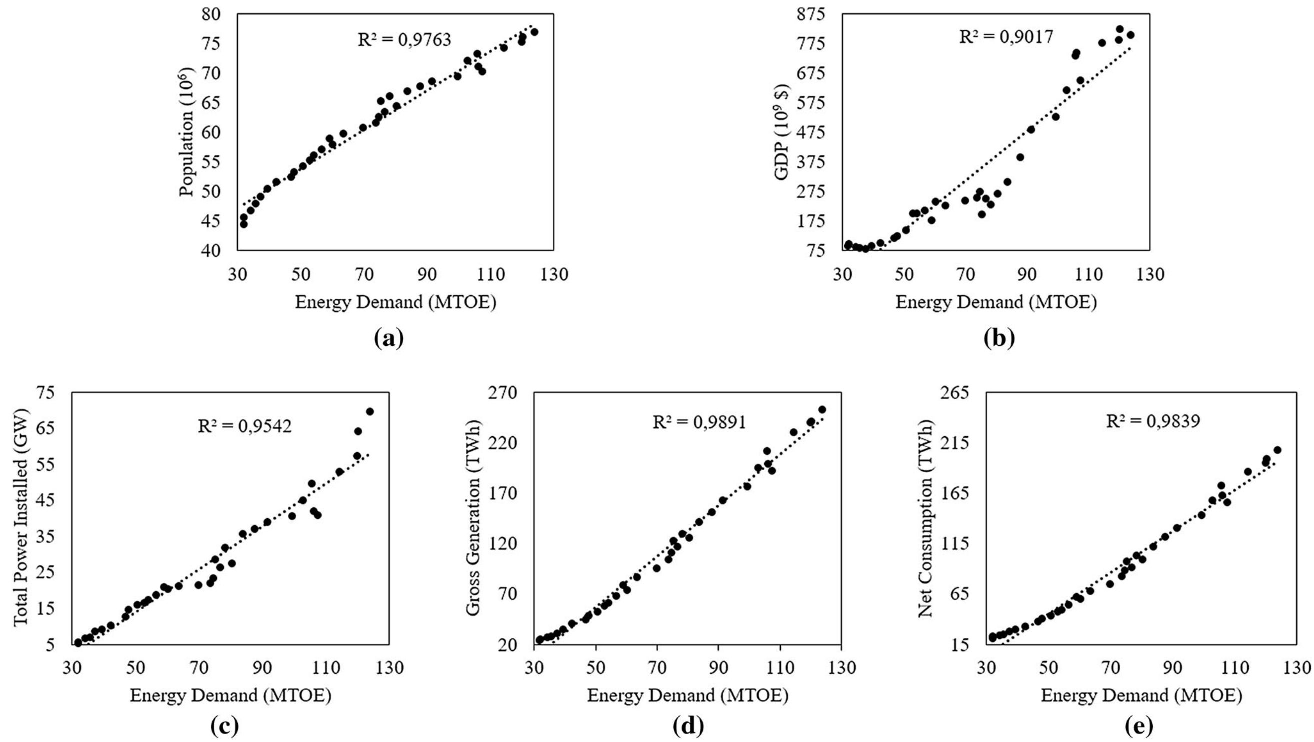


Fig. 2 Variables used in this study and R^2 correlation coefficients versus energy demand: **a** population [9], **b** GDP [9], **c** total power installed [13], **d** gross generation [13] and **e** net consumption [13]

search space has been moved to the global minimum or maximum from local minimum or maximum and then the optimum result has been obtained. GSA has some steps such as fitness function, mass, force and acceleration calculations, velocity and position updates [66, 68].

Steps of the standard GSA algorithm is following:

To describe the standard GSA, let us to consider a system with N objects (agents) in which the position of the ith object is present in Eq. (1):

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^N\right) \quad \text{for } i = 1, 2, \ldots, N, \tag{1}$$

where x_i^d presents the position of ith agent in the dth dimension.

At a specific time "t", the force which acts on the ith mass due to jth mass is defined in Eq. (2):

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t)M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right), \tag{2}$$

where M_{aj} is agent j's active gravitational mass, M_{pi} is agent i's passive gravitational mass, $G(t)$ is gravitational constant at any time t, ε is a miniscule constant defined by the user, $x_j^d(t)$ and $x_i^d(t)$ are the positions of i and j agents in the dth dimension at a specific time "t" and $R_{ij}(t)$ is the Euclidian distance between two agents i and j at the generation t.

Total force of agent i in the dth dimension is calculated as in Eq. 3:

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} rand_j F_{ij}^d(t), \tag{3}$$

where $rand_j$ is a random number and its values change between 0 and 1.

Hence, the acceleration of the agent i is given in Eq. 4:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}, \tag{4}$$

where M_{ii} is the inertial mass of ith agent.

Updated velocity and position are calculated as in Eqs. (5) and (6).

$$v_i^d(t+1) = rand_i v_i^d(t) + a_i^d(t), \tag{5}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \tag{6}$$

4.2 Teaching–learning-based optimization algorithm (TLBO)

TLBO is one of the social optimization techniques [67] based on teaching and learning processes of teachers and students. It is inspired by taking the effect of a teacher on the students in a class. In the TLBO, teacher is a man who gives the best information and students are people who take the information and interact between themselves. The quality of learning in the TLBO is related to teacher's information. As soon as a teacher develops his information nearer to his local best position, all students are closed towards that value to search a solution with higher interaction on learning. The technique is composed of two stages as teacher and learner phases as given in the following two sections [67, 69].

4.2.1 Teacher phase

At teacher phase of the algorithm, teacher is generally supposed to be the best-informed person and gives his information to every student. In this process, teacher tries to increase the average learning level of his class. Teacher is accepted as the most knowledgeable person so the best students can learn as much as the teacher. There is a mean value between teacher and student learning levels and it is given as in Eq. (7)

$$Difference\_Mean_i = r_i\left(M_{\text{new},i} - T_F M_i\right), \tag{7}$$

where $M_{\text{new},i}$ is the mean value of new teacher as the best learner value at every iteration i, M_i is the mean result value of the learners at any iteration i and r_i is the random number in the range [0, 1]. T_F is the teaching factor which decides the value of mean to be changed. The value of T_F is decided randomly with equal probability as Eq. (8)

$$T_F = round[1 + rand(0,1)],\ (T_F \text{ value can be } 1 \text{ or } 2). \tag{8}$$

The existing solution is updated in the teacher phase according to the following Eq. (9) based on the $Difference\_Mean_i$

$$X'_{\text{new},i} = X'_{\text{old},i} + Difference\_Mean_i, \tag{9}$$

where $X'_{\text{new},i}$ is the updated value of $X'_{\text{old},i}$ and it is the best acceptable function result for the teacher phase.

The best function values of the teacher phase are kept in a memory to use them as inputs at the learner phase.

4.2.2 Learner phase

At this stage, the application of the learning process is implemented by two different values: one through input from the teacher and the other through interaction between learners.

If a X_i student is more knowledgeable than a X_i student, the X_j student updates himself by interacting the following Eqs. (10) and (11),

$$X''_{\text{new},i} = X''_{\text{old},i} + r_i\left(X_i - X_j\right), \quad \text{if } f\left(X_i\right) < f\left(X_j\right) \tag{10}$$

$$X''_{\text{new},i} = X''_{\text{old},i} + r_i\left(X_j - X_i\right), \quad \text{if } f\left(X_j\right) < f\left(X_i\right) \tag{11}$$

At the end of the learner phase, when the stopping criteria completed, $X''_{\text{new},i}$ is accepted as a better function value.

4.3 The proposed hybrid GSA–TLBO (HGT) method

Hybrid optimization algorithms are based on the combinations of two or more standard techniques which work interactively as a unique algorithm structure to reach the best solutions in both local and global search space. In this context, hybrid algorithms are developed to reach the global optimum points as soon as possible by using minimum iteration numbers [70].

The proposed method was developed by a combination of two standard calculation techniques. The first is the standard GSA [66, 68] which is based on Newton's gravity and motion laws and the second is the standard TLBO algorithm [67, 69] which is inspired from teaching and learning processes of teachers and learners in a class.

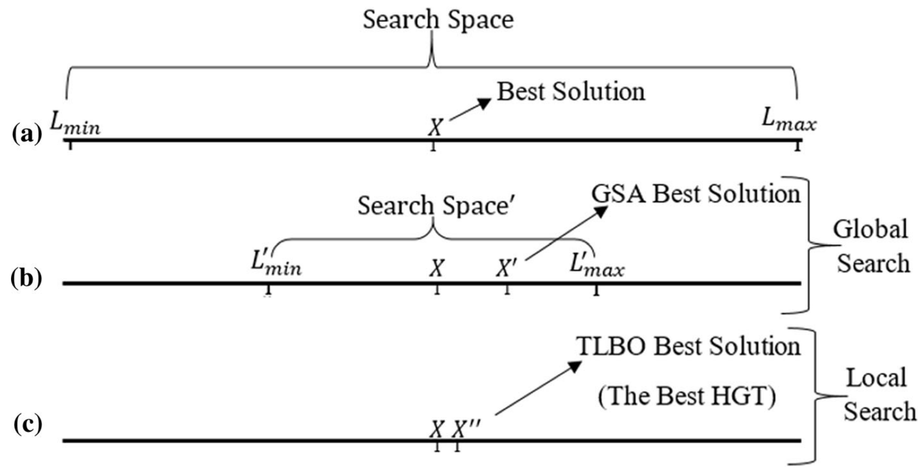
The reasons selecting the GSA and TLBO methods in this study are global searching, easy execution and implicit parallelism in GSA and good learning abilities and parameter-free in TLBO [47, 71]. TLBO has a good performance in solving large-scale optimization problems with little computational efforts [71–75].

In the proposed method, standard GSA searches the optimum points in the global search space and then the standard TLBO finds the best solution in the local search space. That result of the standard TLBO is the best result of the proposed method at the same time. After reaching a determined iteration number, the standard GSA calculates every weighing parameter as the inputs of the standard TLBO algorithm so the best result is obtained by using these weighing parameters in the proposed method.

In Fig. 3, reaching the optimal solution by the proposed method is shown. $L_{\min}$ and $L_{\max}$ are accepted as the limit values in search space. X is accepted as the best solution in the search space between the $L_{\min}$ and $L_{\max}$ limits as shown in Fig. 3a. The objective in the proposed method is to obtain a local search area with the possible standard GSA best solutions X or X' in the area narrowed by $L'_{\min}$ and $L'_{\max}$ limits as shown in Fig. 3b. The next step is given in Fig. 3c, and the objective in this step is to reach the best solution X or to reach the one of the nearest solution (X'') to the best solution X in the local search area.

At the first step, the proposed method calculates the X' value which is the nearest point to the optimal solution by the standard GSA. According to the X' value, the new search space values $L'_{\min}$ and $L'_{\max}$ are calculated by

Fig. 3 Scheme for the proposed method. **a** The best result accepted, **b** the search space (global search) in standard GSA and **c** the best result obtained by standard TLBO algorithm in the local search



Eqs. (12–13). Therefore, the search space for the standard TLBO algorithm has been narrowed and the best X or the nearest X'' value is obtained.

$$L'_{\min}(k) = X'(k) + rand(L_{\min}(k) - X'(k)) \quad (12)$$

$$L'_{\max}(k) = X'(k) + rand\left(L_{\max}(k) - X'(k)\right) \quad (13)$$

where k is $(1, 2, \ldots, d)$ in search space with d dimension.

Steps of the proposed method for the EDE are given as follows:

1. Enter the standard GSA parameters and $L_{\min}(k)$ ve $L_{\max}(k)$ limit values and maximum iteration number (max_iter).
2. Determine N objects (agents) randomly as the number of every design variable
3. Let $pop = 1$.
4. Apply objective function for every objects (agents).
5. for $i = 1$ to N

$$\text{Update } G(t) = G(G_0, t), \quad (14)$$

$$\text{Update } m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}, \quad (15)$$

$$\text{Update } M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}, \quad (16)$$

end for

where $G_0(t)$ is the value of the gravitational constant, $fit_i(t)$ represents the objective function value of the agent i at time t, and, $worst(t)$ and $best(t)$ are defined as follows:

$$best(t) = \min_{j \in \{1,\ldots,N\}} fit_j(t), \quad (17)$$

$$worst(t) = \max_{j \in \{1,\ldots,N\}} fit_j(t). \quad (18)$$

6. According to Eq. (3), calculate the total force in different directions.
7. Apply Eqs. (4) and (5) in turn to calculate the acceleration and velocity.
8. Apply Eq. (6) to update the agent's position.
9. $pop = pop + 1$.
10. If $pop <= max\_iter$, step 4 is carried out; otherwise, GSA termination and carry out step 11.
11. for $i = 1$ to k

Apply the Eqs. (12–13) in turn,

end for

12. Determine the TLBO search space between the $L'_{\min}(k)$ and $L'_{\max}(k)$ limits.
13. Create the learner population (P_n) randomly which is composed of every design variable.
14. $gen = 1$.
15. Apply the objective function for every learner.
16. Teacher phase.

Apply Eqs. (7–9).
Accept the student (learner) as the new better function value.

17. Learner phase.

for $i = 1$ to P_n

randomly select two learners X_i'' and X_j'', where $i \neq j$,

if $f(X_i'') < f(X_j'')$

$$X_{new,i}'' = X_{old,i}'' + r_i(X_i'' - X_j'')$$

else

$$X_{new,i}'' = X_{old,i}'' + r_i(X_j'' - X_i'')$$

end if

end for

18. Accept X''_{new} if it gives a better function value.
19. $gen = gen + 1$.
20. If $gen <= \max\_iter$, step 15 is carried out; otherwise, stop if the maximum generation number is achieved.

4.4 Energy demand estimation (EDE) with the proposed method

Calculation of weighing coefficients with the proposed method based on the LQE models was developed as given in Eqs. (19–21), respectively:

Linear model of the proposed method (HGT_L):

$$\text{HGT}_L = \sum_{i=1}^{T} w_i X_i + w_0 \tag{19}$$

Quadratic model of the proposed method (HGT_Q):

$$\begin{aligned}\text{HGT}_Q = {} & \sum_{i=1}^{T} w_i X_i + \sum_{i=1}^{T-3}\sum_{j=i+1}^{T} w_{(3i+j+1)} X_i X_j + \sum_{i=3}^{T-2}\sum_{j=i+1}^{T} w_{(3i+j)} X_i X_j \\ & + \sum_{i=4}^{T-1}\sum_{j=i+1}^{T} w_{(3i+j-2)} X_i X_j + \sum_{i=1}^{T} w_{(i+15)} X_i^2 + w_0\end{aligned} \tag{20}$$

Exponential model of the proposed method (HGT_E):

$$\text{HGT}_E = \sum_{i=1}^{T} \left(w_{(2i-1)} X_i^{w_{2i}} + w_0 \right) \tag{21}$$

The multiple linear regression method (MLR) as a classic regression analysis model:

$$E(y) = \sum_{i=1}^{T} \beta_i X_i + \beta_0 \tag{22}$$

where w_0, w_i and w_{ij} are the weighing coefficients; T is the number of demand-affecting factors and its value is 5 ($T = 5$). In Eq. (22), $E(y)$ is the estimated energy demand in the MLR method, β_0 and β_i are the regression coefficients. X_i and X_j denote the socio-economic and electrical indicators. X_1, X_2, X_3, X_4 and X_5 are the independent variables; population, GDP, installed power, gross generation and net consumption, respectively. There are five economical and electrical indicators as the input parameters in Eqs. (19–22), so the weighing coefficients in Eqs. (19–21) are calculated as 6, 21 and 11 in the developed LQE models, respectively. The regression coefficients that should be calculated in Eq. (22) are 6. The models were applied by using the proposed method to Eq. (23) as an objective function to minimize the RMSE in the EDE.

$$\min \text{RMSE} = \left[\frac{1}{n} \sum_{i=1}^{n} \left(y_o - y_p \right)^2 \right]^{1/2} \tag{23}$$

where, n is the number of trying (training data), y_0 is the actual energy demand value and y_p is the calculated or predicted energy demand value according to the HGT models and MLR in Eqs. (19–22). The MAPE value in Eq. (24) was used to comment the results between the actual and predicted values.

$$\text{MAPE} = \frac{1}{n} \left(\sum_{i=1}^{n} \left| \frac{y_o - y_p}{y_p} \right| \right) 100 \tag{24}$$

In the proposed method, total number of agents (N), student number (P_n) and total maximum iteration are taken as 50, 50 and 1000, respectively. $L_{\min}(k)$ and $L_{\max}(k)$ values of the input at the start are limited between [−100, 100] in the search space.

5 Estimation results

In this study, 35-year data were used between 1980 and 2014. Training and testing data were selected at the rate of 90 and 10%, respectively. The proposed and MLR methods were applied to the training data between 1980 and 2010, and the data were tested by the data between 2011 and 2014.

Every algorithm was executed 30 times. R^2 and MAPE (%) results are given in Table 3 as a result of the minimum RMSE objective function with the training data. In Table 3 better R^2, RMSE and MAPE values are shown in bold.

According to the training data given in Table 3, the HGT method proposed calculates lower RMSE values than other standard GSA and TLBO algorithms in LQE models in the training data. In all models, the objective function, the lowest RMSE value, is calculated in the exponential model of the HGT method. In a similar way, according to the testing data, the lowest value of RMSE is calculated as 1.171 by the HGT exponential model of the proposed method.

The LQE models in the HGT method, designed according to the testing data, performed better than the standard GSA, TLBO and MLR with less RMSE and less MAPE (%). At the same time, the proposed HGT method and other standard GSA and TLBO methods give better results than the MLR method in testing data.

Between four models, it is observed that exponential model of the proposed HGT method calculates better values than other four models. The exponential model created by the proposed method gives the best results for both training and testing data.

In this study, the reason for the preference of optimization methods is that R^2, RMSE values and MAPE (%) parameters which are the most important parameters of energy estimation give better results than the classical regression as seen in the test data in Table 3. It is seen that the classical regression is a faster method, but it is less effective than the method proposed in calculating the error values.

Weight and regression coefficient values calculated for the EDE are given below.

$$\begin{aligned} w_{\mathrm{HGT}_L} &= [w_1, w_2, \ldots, w_5, w_0] \\ &= [0.9964, 0.0149, -0.0861, 0.6237, -0.4824, -17.4501] \\ w_{\mathrm{HGT}_Q} &= [w_1, w_2, \ldots, w_{20}, w_0] \\ &= [0.0382, -0.0513, -0.0199, 0.4578, 0.0155, 0.0016, -0.0044, \\ &\quad -0.0048, 0.0006, 0, -0.0004, 0.001, 0.0009, 0.0009, 0.0007, \\ &\quad 0.0117, -0.0001, -0.0051, -0.0016, 0.0011, -0.0006] \\ w_{\mathrm{HGT}_E} &= [w_1, w_2, \ldots, w_{10}, w_0] \\ &= [-5.4109, -6.2275, 26.7415, 0.0854, -25.8193, -1.2078, \\ &\quad -25.5476, -0.329, 1.8185, 0.7341, -11.6416] \end{aligned}$$

The regression coefficients calculated by the MLR method are as follows:

$$\begin{aligned} \beta_{E(y)} &= [\beta_1, \beta_2, \ldots, \beta_5, \beta_0] \\ &= [1.6079, 0.0195, -0.6509, 0.4704, -0.2650, -44.1231] \end{aligned}$$

Actual primary energy demand values and estimated results of the LQE models with the proposed and MLR methods between 1980 and 2014 are shown in Fig. 4. Especially during 2011–2014 (testing), the MLR method deviates much from the actual values. A considerable decrease is shown from Fig. 4 in the energy demand of Turkey in 1994, 2001 and 2009. In these years, it can be said that the economic crisis impacts the energy demand profoundly. A considerable increase is shown in 2007. From Fig. 4, it can be shown that deflections due to the economic crisis and non-routine increase in the energy demand.

In Fig. 5, the MAPE values calculated by the LQE models of the proposed method are shown between 1980 and 2014. From Fig. 5, the maximum deviation was calculated in the training data by 4.89% in the HGT_L model in 1981. Similarly, the maximum deviation in the testing data was obtained in the HGT_L model by 2.01% in 2011. From Fig. 5, it can also be seen that the MAPE values of the testing data as a percentage between 2010 and 2014 are lower than the values of many years. Lower value of the MAPE than 10% has been explained as a successful ("very good") and highly accurate forecast [76].

6 Scenario settings and future estimation

In this study, LEH scenarios were developed for the future EDE. The scenarios were determined according to possible increase rates in socio-economic and electric indicators.

Statistical studies with the installed power, gross generation and net consumption were produced for more realistic scenarios. As shown from Table 4, over the past decade, installed power, gross generation and net consumption growths were increased on an average of 6.6, 5.3 and 5.6%, respectively. Electrical indicators of those statistical studies were taken as the expected scenario by taking the average value of the past electrical data. The government at the medium-term programme [77] aimed the growths for the GDP as 4.5 and 5% in 2016 and 2017, respectively. Scenarios for the GDP are determined in accordance with the policy of the government. Population data by years are provided from the Turkish Statistical Institute (TURKSTAT) for population forecasting scenarios [12].

6.1 Low scenario

Low scenario is constituted to estimate the energy demand under the implications of negative energy policy at a lower growth rate in the economy. Low scenario is determined according to 4% growth as a percentage for GDP in accordance with the government medium-term programme [11]. In the past decade, for the electrical indicators 5.1, 3.8 and 4.1% growths were accepted as a percentage as installed power, gross generation and net consumption, respectively. Low scenario is determined by analysing the past data in the electrical indicators with a lower growth rates than the expected values by a 1.5-point decrease. Increase rates of the low scenario are given in Table 5.

Table 3 Comparison of the results from various energy demand models

Models	Methods	R^2	Training set (90%) (1980–2010)		Testing set (10%) (2011–2014)	
			RMSE	MAPE (%)	RMSE	MAPE (%)
Linear	GSA	0.9952	1.9502	2.6162	1.7018	1.1910
	TLBO	0.9956	1.8690	2.3813	1.8043	1.3729
	HGT	0.9959	**1.8338**	2.1141	1.5350	1.1501
Quadratic	GSA	0.9962	1.7631	2.0774	1.2325	0.9494
	TLBO	0.9963	1.7508	1.9964	1.2766	1.0510
	HGT	0.9964	**1.7193**	2.0026	1.2680	0.9839
Exponential	GSA	0.9962	1.7535	1.9572	1.4976	1.1225
	TLBO	0.9964	1.7223	1.9549	1.3162	1.0073
	HGT	**0.9971**	**1.5497**	**1.6792**	**1.1710**	**0.9204**
Classical regression analysis	MLR	0.9952	1.6232	1.9951	6.6970	4.8034

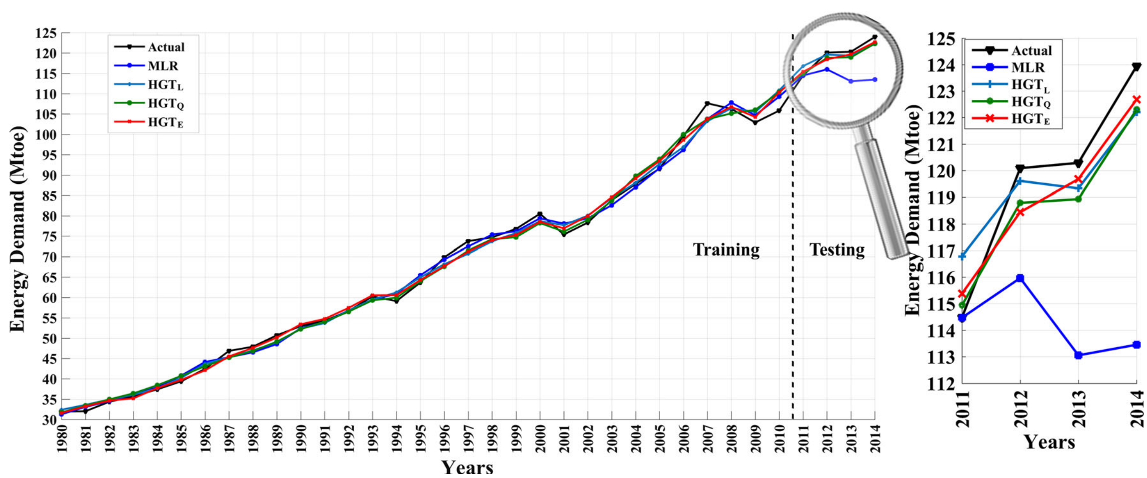
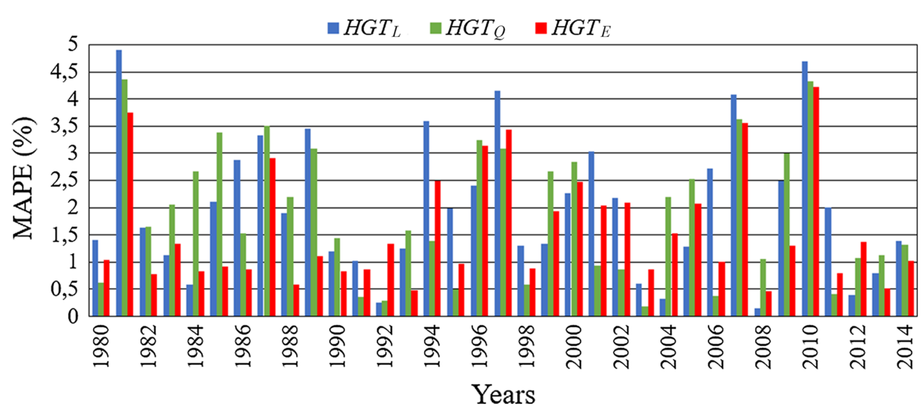


Fig. 4 A comparison between actual demand values [6] and estimates of the models with the proposed method and MLR (1980–2014)

Fig. 5 Trends of the MAPE (%) in the estimation models (1980–2014)



6.2 Expected scenario

Expected scenario is determined according to 4.5% growth as a percentage for GDP in accordance with the government medium-term programme [77], 6.6, 5.3 and 5.6% growths as a percentage as installed power, gross generation and net consumption, respectively, for the electrical indicators in the past decade. Increase rates of the expected scenario are given in Table 5.

6.3 High scenario

High scenario is constituted to estimate the energy demand under a developing economy and increasing electric energy investments. It is determined according to 5% growth as a percentage for GDP in 2017 and 2018 years in accordance with the government medium-term programme [77]. In the past decade, for the electrical indicators there are 8.1, 6.8 and 7.1% growths as the installed power, gross generation and net consumption, respectively. High scenario is determined by analysing the past data in the electrical indicators with a higher growth rates than the expected values by a 1.5-point increase. Increase rates of the high scenario are given in Table 5.

6.4 Future estimation for the years between 2015 and 2030

EDE results with the LEH scenarios calculated by the developed HGT_L, HGT_Q and HGT_E models are given in Table 6. In the literature, the EDE for Turkey was done until 2025 in Kiran et al. [53], until 2020 in Uzlu et al. [51] and MENR [10]. This study contains the estimations until 2030. According to the LEH scenarios, the results are given for a comparison in Figs. 6, 7 and 8, respectively. In Table 6, results of the EDE for every LEH scenarios according to the results of the HGT_L, HGT_Q and HGT_E models have been given.

In Figs. 6, 7 and 8, the estimation results of the proposed HGT_E model are coherent with the results of Uzlu et al. [51] and Kiran et al. [53]. Also, MENR [10] results are higher than the proposed models and other studies. Deviations in the MENR [10] increases the dependency and importation of Turkey in energy, so more fossil fuels cause more harmful energy generation for the environment. According to the result of every scenario with respect to the MENR [10], less amount of energy should be imported.

Table 4 Increase rates of the electrical indicators as a percentage between 2005 and 2014 [13]

Years	Installed power % Growth	Gross generation % Growth	Net consumption % Growth
2005	5.48	7.47	7.53
2006	4.43	8.86	9.83
2007	0.67	8.65	8.43
2008	2.40	3.58	4.39
2009	7.04	−1.82	−3.12
2010	10.64	8.42	9.66
2011	6.84	8.61	8.17
2012	7.84	4.40	4.74
2013	12.18	0.27	1.6
2014	8.61	4.92	4.71
Average	6.6	5.3	5.6

For example, in Table 7, MENR estimations [10] and the results of the LEH scenarios in HGT exponential model (HGT_E) are shown. Total difference in 6 years is estimated as 367, 342.7 and 317.7 for different LEH scenarios. As 123.94 Mtoe energy demand in 2014 is taken into consideration, it can be concluded that there is 2.6–3-fold gain between MENR [10] and the proposed method estimations. In such a case, it can be seen that the less natural gas importation and less environmental pollution are possible in future energy policies of Turkey which has a 47.9% of natural gas dependence to the foreign countries in its all energy map [8].

This study is compared with the Uzlu et al. [51] and Kiran et al. [53] which are the latest studies implemented hybrid methods in the EDE studies for Turkey in terms of data sets, MAPE and R^2 correlation values. Uzlu et al. [51] and Kiran et al. [53] used 33 and 27 years of data, respectively, with GDP, population, import and export indicators. This study uses a more extensive data set comprised of 35 years and three more different electrical indicators which are total power installed, gross generation and net consumption.

Between 1996 and 2009 years, in the training set, RMSE for the linear model (HAPEL) was calculated as 4.19 and 3.77 in the quadratic model (HAPEQ) in Kiran et al. [53] 's study. The training set RMSE value is 2.192 by ANN–TLBO model in Uzlu et al. [51]. This study calculates the RMSE value as 1.8338, 1.7193 and 1.5497 in the proposed HGT_L, HGT_Q and HGT_E models, respectively.

Between 1996 and 2009 years, in the training set, MAPE value for the linear model (HAPEL) was calculated as 2.31 and 2.82% for the quadratic model (HAPEQ) in Kiran et al. [53] 's study in scenario 1. The MAPE value in training set is 2.1566% by ANN–TLBO model in Uzlu et al. [51]. This study calculates the MAPE in the training set as 2.1141, 2.0026 and 1.6792% in the proposed HGT_L, HGT_Q and HGT_E models, respectively.

The RMSE and MAPE values obtained with this study are less than other studies. At the same time, there is a strong relationship between the actual values and the estimation results of this study with 0.9971 of R^2 correlation coefficient in the training set in the HGT_E model.

For the testing set, between the years 2011 and 2014, it can be seen from Table 8, the proposed method with HGT_E model has better RMSE and MAPE values. In Table 8, better RMSE and MAPE values are shown in bold. The percentage used in the test set is less than the other studies and that the crisis years such as 2008 and 2009 are not in

Table 5 LEH scenario settings

Scenarios	Growth rate per year (%)				
	GDP	Population	Installed power	Gross generation	Net consumption
Low	4%	The population data obtained from TURKSTAT [12]	5.1%	3.8%	4.1%
Expected	4.5%		6.6%	5.3%	5.6%
High	5%		8.1%	6.8%	7.1%

Table 6 Future projection of total energy demand in Mtoe according to the LEH scenarios

Years	Low scenario (Mtoe)			Expected scenario (Mtoe)			High scenario (Mtoe)		
	HGT (models)			HGT (models)			HGT (models)		
	L	*Q*	*E*	*L*	*Q*	*E*	*L*	*Q*	*E*
2015	125.5	126.1	125.6	126.3	126.9	126.7	126.3	127.7	127.7
2016	128.4	129.2	128.7	130.1	130.9	130.8	130.1	132.6	133
2017	131.4	132.3	131.8	134.1	135.1	135.1	134.1	137.9	138.5
2018	134.4	135.5	135	138.1	139.4	139.6	138.1	143.5	144.2
2019	137.5	138.7	138.3	142.3	143.9	144.2	142.3	149.5	150.3
2020	140.6	142	141.7	146.6	148.7	149	146.6	156.1	156.7
2021	143.8	145.3	145.1	151	153.7	154	151	163.1	163.3
2022	147	148.7	148.7	155.6	159	159.2	155.6	170.8	170.3
2023	150.3	152.1	152.4	160.3	164.7	164.5	160.3	179.3	177.6
2024	153.7	155.5	156.2	165.2	170.6	170.1	165.2	188.5	185.3
2025	157	158.9	160	170.2	176.9	175.9	170.2	198.6	193.4
2026	160.5	162.4	164	175.4	183.6	182	175.4	209.9	201.9
2027	164	165.9	168.1	180.8	190.9	188.2	180.8	222.3	210.8
2028	167.5	169.4	172.4	186.3	198.7	194.7	186.3	236.2	220.2
2029	171.2	173	176.7	192	207.1	201.5	192	251.7	230
2030	174.9	176.6	181.2	198	216.2	208.5	198	269	240.3

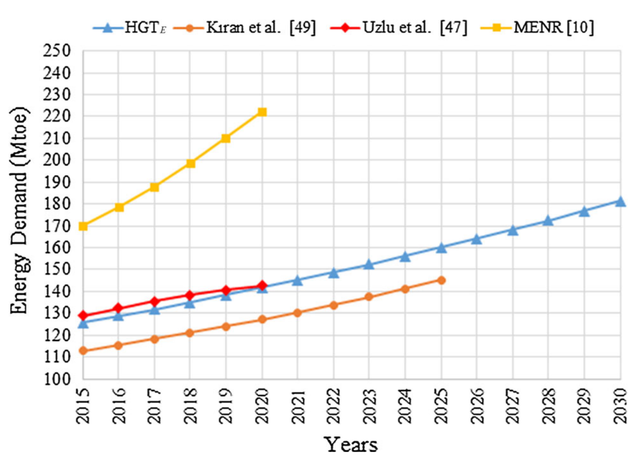


Fig. 6 EDE according to low scenario

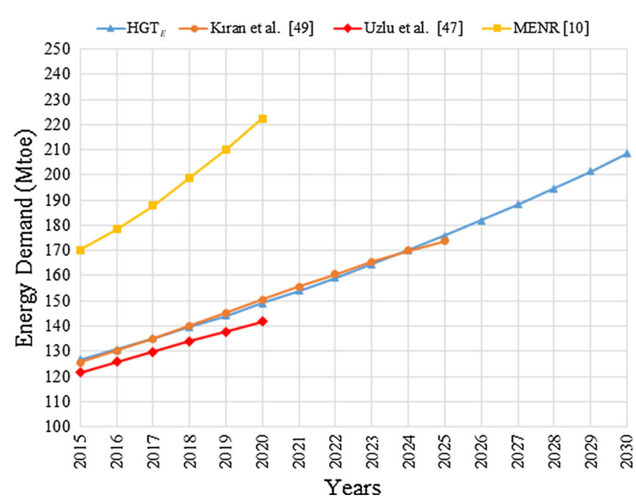


Fig. 7 EDE according to expected scenario

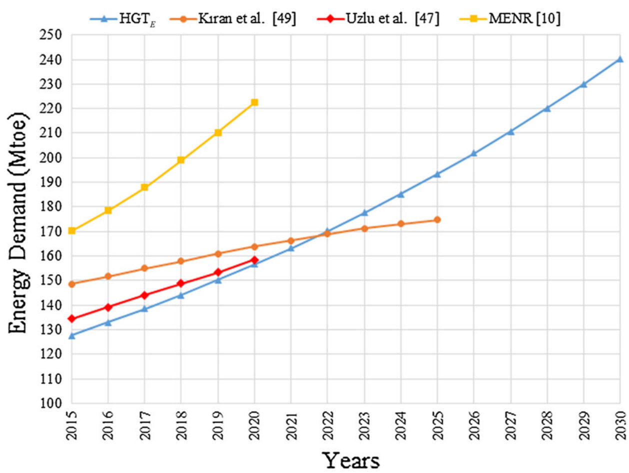


Fig. 8 EDE according to high scenario

the test set and therefore it is normal for the error values to be less. RMSE and MAPE values in Table 8 were calculated in this study from the 2011–2014 values of [10, 25, 53]. The other values of RMSE and MAPE were directly taken from the [14, 51]. In 2011–2014 (testing), it is seen that the MLR method appears to deviate too much from the actual values.

7 Conclusions

Energy estimation studies are important for the future energy policies for developing countries. In this study, the primary EDE of Turkey until 2030 was implemented with the socio-economic and electrical indicators. Developed LQE models with a new proposed hybrid method were first applied together. The results of the study are the most proper results with the actual energy demand values until today. Contrary to the irrelevant variables in energy estimation, the data used as the electrical indicators are installed power, gross generation and net consumption. These indicators influence the energy demand directly and were kept together first here. Therefore, the results of this study are important to use these indicators for the future studies.

The aim to develop a hybrid model is utilizing the specific properties of the standard techniques in one structure. In this study, it expected to have more accurate estimation results. Lower RMSE and MAPE values are the main indicators to make more accurate estimation, and the results of the proposed method for the EDE are very successful for these reasons. In estimation studies, more input parameters are a reason to remove the better estimation

Table 7 Comparison between MENR estimation and LEH scenarios of the HGT$_E$ model

Years	Energy demand estimation (Mtoe)				Gain (Mtoe)		
		Scenarios			Difference in MENR scenarios		
	MENR [10]	*L*	*E*	*H*	MENR-*L*	MENR-*E*	MENR-*H*
2015	170.15	125.6	126.7	127.7	44.55	43.45	42.45
2016	178.46	128.7	130.8	133	49.76	47.66	45.46
2017	187.92	131.8	135.1	138.5	56.12	52.82	49.42
2018	198.91	135	139.6	144.2	63.91	59.31	54.71
2019	210.24	138.3	144.2	150.3	71.94	66.04	59.94
2020	222.42	141.7	149	156.7	80.72	73.42	65.72
Total	1168.1	801.1	825.4	850.4	367	342.7	317.7

Table 8 Comparison of the methods in terms of RMSE and MAPE values between 2011 and 2014 years

Years	Actual (Mtoe)	Proposed method HGT$_E$	Classical regression MLR	Es et al. [25] ANN	Uzlu et al. [51]		Kankal et al. [14] ANN-Regression	Kiran et al. [53] HAPEQ	MENR [10] LEAP
					ANN-BP	ANN-TLBO			
2011	114.48	115.38	114.47	115.79	N/A	N/A	N/A	109.25	133.98
2012	120.09	118.44	115.97	120.91	N/A	N/A	N/A	112.96	142.86
2013	120.29	119.68	113.05	126.16	N/A	121.62	N/A	116.91	150.89
2014	123.94	122.68	113.45	131.51	N/A	125.73	N/A	121.1	160.21
	RMSE	**1.171**	6.6970	4.8586	2.419	2.192	1.46	4.941	18.137
	MAPE	**0.9204**	4.8034	3.2097	1.726	1.499	1.222	3.901	22.676

results. But, although five input parameters are used, the proposed method gives better results than other studies. The study was done for a 16-year long estimation time, from that point this method can be used for long-term estimation studies.

Lower RMSE and MAPE values are highly recommended to make highly accurate forecast. The estimation results suggest that the proposed method has better RMSE and MAPE performances than standard, ANN-based methods and MENR estimations. In conclusion, because of all reasons above mentioned, the proposed HGT method can be recommended as an estimation model for the future studies. Obtained estimation values by the proposed method with the developed models can help determining the consistent energy policies of Turkey for a long term.

Compliance with ethical standards

Conflict of interest There is no conflict of interest in this study.

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