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Modified Gravitational Search Algorithm for Energy Demand Estimation of Turkey

Mehmet BEŞKİRLİ[1*], Mehmet Fatih TEFEK[2], Harun UĞUZ[3]

[1]Şırnak University, Department of Computer Engineering, Şırnak, Turkey
[2] Osmaniye Korkut Ata University, Department of Computer Engineering, Osmaniye, Turkey
[3]Konya Technical University, Department of Computer Engineering, Konya, Turkey
(ORCID: 0000-0002-4842-3817) (ORCID: 0000-0003-3390-4201) (ORCID: 0000-0003-4617-202X)

Abstract
Estimation of energy demand beforehand is a quite significant problem in respect of economy and sources of country. In this study, Gravitational Search Algorithm (GSA) was modified by making some innovations in GSA and called as Modified Gravitational Search Algorithm (MGSA). Energy demand estimation is conducted through the relationship between the increase in economic indicators in Turkey and energy consumption. Estimation was actualized by using gross domestic product (GSYH), importation, exportation and demography for energy demand estimation and both linear and exponential equations. Energy demand between the years 2017-2037 was predicted by using the data belong to 1997-2011. The years between 2012 and 2016 were used as test data. It was observed that the results acquired via MGSA estimate better compared to GSA results.

Anahtar kelimeler: Gravitational search algorithm, Energy demand, Estimation, Turkey.

Türkiye'nin Enerji Talebi Tahmini için Modifiye Yerçekimi Arama Algoritması

Öz
Ülke ekonomisi ve kaynakları bakımından enerji talebini önceden tahmin etmek çok önemli bir problemdir. Bu çalışmada, Yerçekimi Arama Algoritması (YAA) ile YAA'da yapılan bazı yenilikler yapılarak modifiye edilmiş ve Modifiye Yerçekimi Arama Algoritması (MYAA) olarak adlandırılmıştır. Enerji talep tahmini, Türkiye'deki ekonomik göstergelerin artışı ile enerji tüketimi arasındaki ilişki ile gerçekleşmektedir. Enerji talep tahmini için gayri safi yurtiçi hasıla (GSYH), ithalat, ihracat ve nüfus bilgileri hem lineer hem de üssel denklemler kullanılarak tahmin işlemi gerçekleştirildi. 1997-2011 yılları arasındaki veriler kullanılarak 2017-2037 yılları arasındaki enerji talebi tahmin edilmiştir. 2012 ile 2016 yılları ise test verisi olarak kullanılmıştır. MGSA ile elde edilen sonuçlar GSA sonuçlarına göre daha iyi bir tahmin gerçekleştirdiği görülmüştür.

Keywords: Yerçekimi arama algoritması, Enerji talebi, Tahmin, Türkiye.

1. Introduction

Being an indicator of economic and social development from past till today in all phases of life, energy still continues to be an indispensible energy factor [1]. Furthermore, countries may need more energy together with the developments in the field of industry. Therefore, energy analysis and policies determine the amount of energy needed by countries [2]. As energy becomes a source, importance of which consistently increase and which becomes more of importance in life, determination of estimation of amount of energy to be consumed plays a substantial role [3]. Being significant for all developed and developing countries, energy demand estimation is also important for Turkey, having part among developing countries [4]. It is necessary to arrange energy demand in a good manner in long term for a

[*]Sorumlu yazar: mehmetbes@sirnak.edu.tr
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powerful Turkish economy. Energy production becomes cheaper because of the increase in energy production with domestic opportunities currently; however, this case shall be dealt in a manner that it will not lead to energy waste. In case of wrong calculations on estimation of prospective energy demand, the country may have serious problems due to deficient energy production or available sources are wasted in case of over production. Relationship between energy consumption and income was established by means of various mathematical formulas or various techniques for estimation of this procedure and thereby various models were formed to estimate primary energy demand of Turkey. These studies were conducted basing on statistical techniques [5-10], artificial intelligence techniques [11-13] and intuitional techniques [1, 4, 14-21].

2. Gravitational Search Algorithm (GSA)

GSA method is a physics based optimization algorithm designed by Rashedi et al. [22]. GSA was inspired by Newton's laws on gravity and inertia. Each particle in search universe in GSA is accepted as a mass. All masses in search universe pull one another according to Newton's law of universal gravitation and apply force to one another with force of gravity. The result with the biggest mass in search universe pulls other results towards it and affects them. In this manner, search universe is pulled towards global minimum and most appropriate solution can be reached.
GSA is comprised of following steps:

If N is assumed as a system with mass, position of the masses are randomly determined first of all. i. Position of the mass is defined as in equation 1.

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

Here, n defines the size of the problem, x_i^d i. position of the mass in d. in dimension. Force effect of i mass from j mass at a certain t time is defined as in equation 2.

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

Here, M_{aj} shows active gravity mass of j mass; M_{pi} shows passive gravity mass of i mass; ε shows a constant defined by user, $x_j^d(t)$ and $x_i^d(t)$ show positions of i and j masses at d. dimension at a certain t time; $R_{ij}(t)$ shows the distance between i and j masses at t time. $G(t)$ is gravity constant at t time and formula was given in equation 3.

$$G(t) = G_0 \exp(-\alpha \frac{t}{T}) \tag{3}$$

Here, G_0 shows initial value of gravity constant randomly selected; α shows the constant value defined by user; t shows the iteration value at that time and T shows maximum number of iteration. Total forces affecting i mass at d. size is calculated as in equation 4.

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} rand_j F_{ij}^d(t) \tag{4}$$

Here, $rand_j$ is a random figure varying between [0,1] range. According to Newton's law on acceleration, acceleration of i mass at d. size to activate the mass depending on the total force in equation 4 is given in Equation 5.

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{5}$$

Here, M_{ii} value shows inertia mass of i agent. Depending on acceleration value, speed of the mass at d. size is updated as in Equation 6 and position is updated depending on the speed as in Equation 7.

$$v_i^d(t+1) = rand_i v_i^d(t) + a_i^d(t) \tag{6}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{7}$$

Here, $rand_i$ is a random value varying between [0,1]. When algorithm interruption criterion is provided, the mass being most appropriate for the objective function is selected for solution.

3. Proposed Modified Gravitational Search Algorithm (MGSA)

Position of the mass is determined randomly in standard GSA as in equation 1. As a result of this random determination in first search universe, positions of the masses may be too far from one another. This may result in convergence to optimum result in a much more number of iteration in solution of problem. It is required that the positions of the masses shall be closer and homogeneous distribution with the purpose of achieving optimum result at shorter operating time and less iteration. For this, modified GSA (MGSA) was designed by adding w, as in equation 1 and equation 7, being a linear decreasing inertia weight [23] function as in equation 8.

$$w = w_{max} - \frac{w_{max} - w_{min}}{Iter_{max}} x\ k \tag{8}$$

In Equation 8, $\mathrm{w_{max}}$ and $\mathrm{w_{min}}$ refer to constant values varying between 0.9 and 0.1 and refers to k instant iteration number, $\mathrm{Iter_{max}}$ refers to total number of iteration. In MGSA, w function was applied as in equation 9 and equation 10.

$$X_i = w\ (x_i^1, \ldots, x_i^d, \ldots, x_i^n) \tag{9}$$

$$x_i^d(t+1) = w\ x_i^d(t) + v_i^d(t+1) \tag{10}$$

It was provided that MGSA searches global optimum result at less iteration through Equation 9 and 10. In this manner, it was targeted to converge the optimum result among the solutions rather than making search far and wide in search universe.

4. Test Functions

Ten different test functions were used in this study. These are given in Table 1, function names, formulation, values of the search space range, characteristics and minimum values, respectively.

Table 1. Test functions D: Dimension U: Unimodal M: Multimodal F: Feature

Function	Formulation	Search Space	F	f_{min}
Sphere	$F_1(x) = \sum_{i=1}^{D} x_i^2$	$[-100, 100]^D$	U	0
Schwefel 2.22	$F_2(x) = \sum_{i=1}^{D} \lvert x_i \rvert + \prod_{i=1}^{D} \lvert x_i \rvert$	$[-10, 10]^D$	U	0
Schwefel 1.2	$F_3(x) = \sum_{i=1}^{D} (\sum_{j=1}^{i} x_j)^2$	$[-100, 100]^D$	U	0
Schwefel 2.21	$F_4(x) = \max\{\lvert x_i \rvert, 1 \le i \le D\}$	$[-100, 100]^D$	U	0
Rosenbrock	$F_5(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	$[-30, 30]^D$	U	0
Schwefel	$F_6(x) = \sum_{i=1}^{D} -x_i \sin(\sqrt{\lvert x_i \rvert})$	$[-500, 500]^D$	M	-12569,5
Rastrigin	$F_7(x) = \sum_{i=1}^{D} [x_i^2 - 10\cos(2\pi x_i) + 10]$	$[-5,12, 5,12]^D$	M	0
Ackley	$F_8(x) = -20 \exp\left(-0,2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D} \cos(2\pi x_i)\right) + 20 + e$	$[-32, 32]^D$	M	0
Griewank	$F_9 = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$[-600, 600]^D$	M	0
Penalized	$F_{10}(x) = \frac{\pi}{D}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{D-1} (y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_D - 1)^2\right\} + \sum_{i=1}^{D} u(x_i, 10, 100, 4)$ $y_i = 1 + \frac{1}{4}(x_i + 1)$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	$[-50, 50]^D$	M	0

5. Analysis of Test Functions

For ten different test functions, the number of populations was taken as 50 and the problem size was taken as 30 and each test function was run thirty times independently. The results are given in Table 2.

Table 2. The analysis results of ten different test functions

Function		GSA	MGSA
F_1	Best	2.8435e-17	2.3343e-43
	Mean	8.4468e-17	**1.5875e-42**
	Worst	1.4902e-16	4.0350e-42
	Std. S.	2.9470e-17	8.3720e-43
F_2	Best	3.3117e-08	1.6170e-21
	Mean	4.5278e-08	**3.8795e-21**
	Worst	6.3573e-08	5.7226e-21
	Std. S.	7.6129e-09	1.0101e-21
F_3	Best	7.1512e+01	6.1911e-43
	Mean	2.7875e+02	**2.5321e-42**
	Worst	5.7872e+02	6.5421e-42
	Std. S.	1.0845e+02	1.4165e-42
F_4	Best	4.7688e-09	2.2885e-22
	Mean	6.6455e-09	**6.5041e-22**
	Worst	1.0165e-08	9.1134e-22
	Std. S.	1.3713e-09	1.2608e-22

F_5	Best	2.5571e+01	2.8706e+01
	Mean	2.9380e+01	**2.8783e+01**
	Worst	1.3111e+02	2.8808e+01
	Std. S.	1.9214e+01	2.1880e-02
F_6	Best	-3.7929e+03	-3.7277e+03
	Mean	**-2.8194e+03**	-2.5657e+03
	Worst	-2.0244e+03	-1.9966e+03
	Std. S.	4.4020e+02	4.2976e+02
F_7	Best	7.9597e+00	0.0000e+00
	Mean	1.5986e+01	**0.0000e+00**
	Worst	2.8854e+01	0.0000e+00
	Std. S.	5.2384e+00	0.0000e+00
F_8	Best	4.7232e-09	8.8818e-16
	Mean	7.0974e-09	**8.8818e-16**
	Worst	9.4370e-09	8.8818e-16
	Std. S.	9.8758e-10	0.0000e+00
F_9	Best	0.0000e+00	0.0000e+00
	Mean	2.6378e-02	**0.0000e+00**
	Worst	1.0736e-01	0.0000e+00
	Std. S.	3.1403e-02	0.0000e+00
F_{10}	Best	3.0035e-19	2.1261e-01
	Mean	**3.1126e-02**	3.3457e-01
	Worst	5.1912e-01	5.9922e-01
	Std. S.	1.0254e-01	8.7988e-02

In Table 2, ten functions were solved by both GSA and MGSA. When the average value of each solution result was examined, MGSA was successful in eight functions and GSA was successful in two functions. Thus, MGSA performed better than GSA.

After analyzing the function results, Wilcoxon statistical test was applied on the results. The statistical analysis results obtained are given in Table 3.

Table 3. The analysis results of Wilcoxon test

	GSA-MGSA *f1-f10*
p-value	4.51E-02

Wilcoxon means that there is a significant difference if the statistical analysis result is less than 0.05. if it is above 0.05 it means that there is no significant difference. When we look at Table 3, it is seen that there is a significant difference between the modified algorithm results and the original algorithm results, since the value obtained in the statistical test is below the critical value.

6. Applications of Energy Demand Estimation Via MGSA

MGSA-linear ($MGSA_L$) and MGSA-exponential ($MGSA_E$) models were created basing on socio-economic indicators between 1997-2016 years. Equations of the models formed in (11) and (12) equilibriums are given below.

$$GSA_L = w_1.X_1 + w_2.X_2 + w_3.X_3 + w_4.X_4 + w_0 \quad (11)$$
$$GSA_E = w_1.X_1^{w_2} + w_3.X_2^{w_4} + w_5.X_3^{w_6} + w_7.X_4^{w_8} + w_0 \quad (12)$$

w_i $(i \in [0,4])$ in Eq. (11) and w_i $(i \in [0,8])$ in Eq. (12) are the weight values calculated by the GSA. These weight values are unconstrained ($-\infty \leq w_i \leq +\infty$). X_1, X_2, X_3 and X_4 are the population, GDP, import and export values, respectively.

Table 4. Energy demand between 1997-2016 and indicators

Years	Energy demand (MTOE)	Population 106	GDP 109($)	Importation 109($)	Exportation 109($)
1997	73.78	61.58	253.71	48.56	26.26
1998	74.71	62.46	270.95	45.92	26.97
1999	76.77	63.36	247.54	40.67	26.59
2000	80.5	64.73	265.38	54.5	27.77
2001	75.4	65.6	196.74	41.4	31.33
2002	78.33	66.4	230.49	51.55	36.06
2003	83.84	67.19	304.9	69.34	47.25
2004	87.82	68.01	390.39	97.54	63.17
2005	91.58	68.86	481.5	116.77	73.48
2006	99.59	69.73	526.43	139.58	85.53
2007	107.63	70.59	648.75	170.06	107.27
2008	106.27	71.52	742.09	201.96	132.03
2009	102.92	72.56	616.7	140.93	102.14
2010	105.83	73.72	731.61	185.54	113.88
2011	114.48	74.72	773.98	240.84	134.91
2012	120.09	75.63	786.28	236.55	152.46
2013	120.29	76.67	823.04	251.66	151.8
2014	123.94	77.7	800.11	242.18	157.61
2015	126.94	78.74	861.46	207.23	143.84
2016	129.24	79.82	862.74	198.62	142.53

These models formed were applied to make the root mean square error (RMSE), being the objective function, minimum. Data of 75% between 1997-2011 was used for training purposes and data of 25% between 2012-2016 for test purposes. Min RMSE was provided in Equation (13).

$$\min RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(y_o - y_p\right)^2\right]^{\frac{1}{2}} \quad (13)$$

G0 value was taken as 20, α value as 100, mass number as 50, iteration number as 1000 for MGSA and GSA. All algorithms were activated for 30 times and weights were calculated as per the value making RMSE value minimum. Comparison of the models was shown in Table 5 by min RMSE conclusions. MGSA method calculated min RMSE value lower in test results compared to linear and exponential estimation models in Table 5. Convergence curve of linear and exponential estimation models are seen in Figure 1 and Figure 2.

Weight values for linear estimation:
$w_{GSA_L} = w_1, w_2, w_3, w_4, w_0$
$w_{GSA_L} = 0.94917, 0.042319, 0.048961, 0.08302, 0.61253$
$w_{MGSA_L} = w_1, w_2, w_3, w_4, w_0$
$w_{MGSA_L} = 0.8444, 0.060782, 0.012616, 0.020678,$
Weight values for exponential estimation:
$w_{GSA_E} = w_1, w_2, \ldots, w_8, w_0$

$w_{GSA_E} = -2.7815, -2.8483, 4.966, 0.44316,$

$w_{MGSA_E} = w_1, w_2, \ldots, w_8, w_0$

$w_{MGSA_E} =$ $0.0040895, 2.3645, -0.00068864, -0.00033574, 0.0013665, 1.433, -6.654e-05, 0.00018682, 0.00072226$

Table 5. Min RMSE results for linear and exponential models

Models		Training set (75%) (1997-2011)	Testing set (25%) (2012-2016)
		RMSE	RMSE
Linear	(GSA_L)	7.0383931435	9.1886921300
	$(MGSA_L)$	5.3226597211	2.7983117641
Exponential	(GSA_E)	4.5094487411	4.7251591706
	$(MGSA_E)$	3.9470073355	1.8124215981

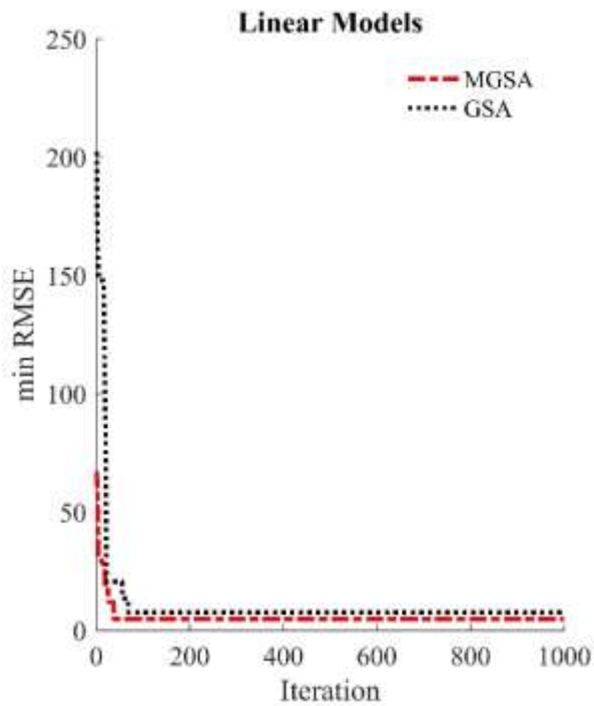

Figure 1. MGSA and GSA linear estimation model convergence curve

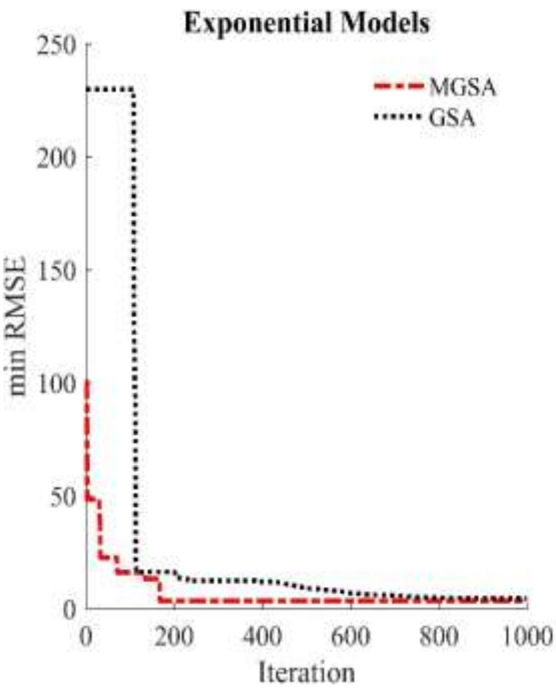

Figure 2. MGSA and GSA Exponential estimation model convergence curve

The values estimated by means of the actual values between 1997 and 2016 are provided in Figure 3. 1997-2011 were shown for training and 2012-2016 for test purposes. When the test results in Figure 3 are handled, it is observed that MGSAE energy estimation and actualized energy demand value coincide. It is observed in Figure 3 that the difference between the value calculated with GSAL and actual energy demand is high.

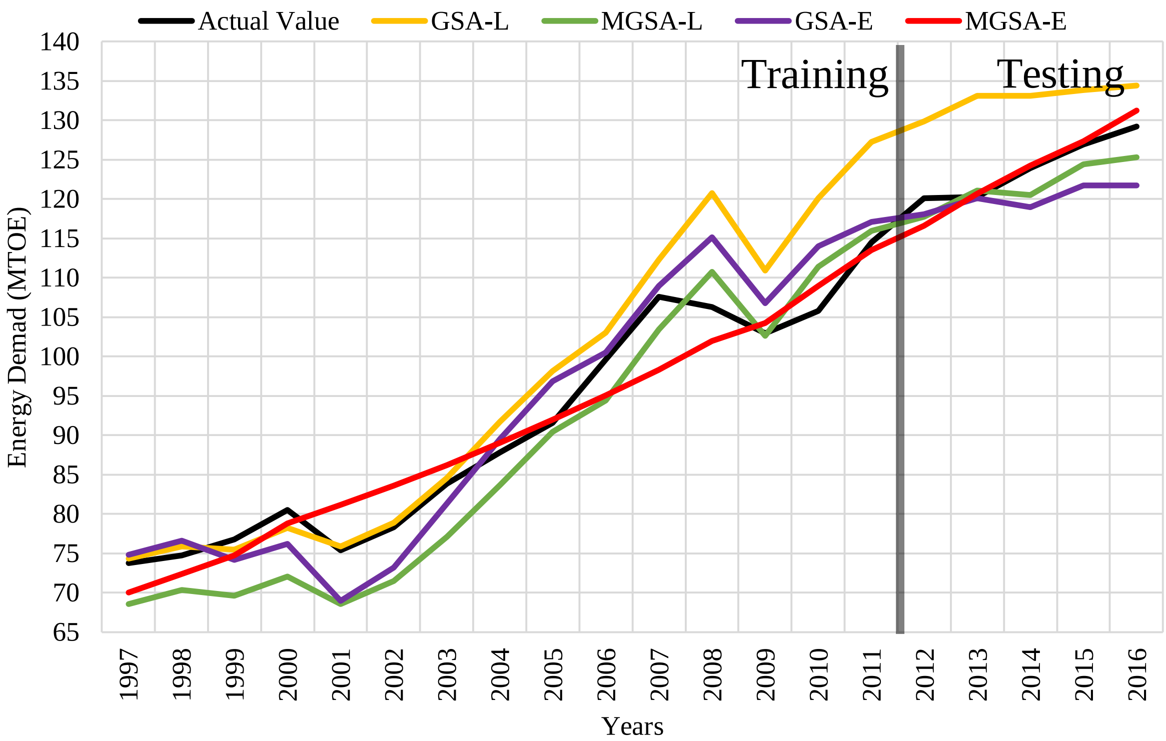

Figure 3. Estimations of the models developed with actual values between the years 1997 and 2016

6.1. Scenarios and Estimation

Scenario studies were conducted for 21-years term between 2017 and 2037. Low, expected and high probability scenarios were established for energy demand estimation. Medium-term estimation increase rates of Ministry of Development (MOD) were taken for GDP in all scenarios [24]. Data on population were received from Turkish Statistical Institute (TSI) [25]. Expected scenario was formed by taking mean increase or decrease rates actualized in last 10 years for importation and exportation. Importation and exportation data in low and medium probability scenarios was determined as 1.5 points more or less than the expected scenario. Scenarios were given in Table 6.

Table 6. Scenario settings

Scenarios	GDP	Population	Import	Export
	Growth rate per year (%)			
Low	4%	The population data obtained from TURKSTAT [26]	3.9%	4.7%
Expected	4.5%		5.4%	6.2%
High	5%		6.9%	7.7%

MGSAE model, developed for estimations studies was used for the scenarios created. The reason for selecting MGSAE model was the parallelism between min RMSE error in test results in Table 5 and actual values in Figure 2. Estimation results were indicated in Table 7. Estimation results calculated with MGSAE model were given in Figure 4.

Table 7. Energy demand estimation results between the years 2017 and 2037 through MGSAE model

	MGSA$_E$ Model Estimation Results (MTOE)		
	Scenarios		
Years	Low	Expected	High
2017	128.46	128.81	129.15
2018	131.79	132.51	133.23
2019	135.17	136.30	137.44
2020	138.66	140.22	141.83
2021	142.24	144.29	146.40
2022	145.93	148.50	151.16
2023	149.74	152.86	156.13
2024	153.64	157.38	161.30
2025	157.65	162.04	166.68
2026	161.77	166.87	172.30
2027	166.02	171.87	178.16
2028	170.39	177.06	184.28
2029	174.88	182.43	190.67
2030	179.50	188.00	197.34
2031	184.26	193.77	204.30
2032	189.16	199.76	211.59
2033	194.21	205.97	219.21
2034	199.41	212.42	227.18
2035	204.78	219.13	235.54
2036	210.31	226.09	244.28
2037	216.02	233.34	253.45

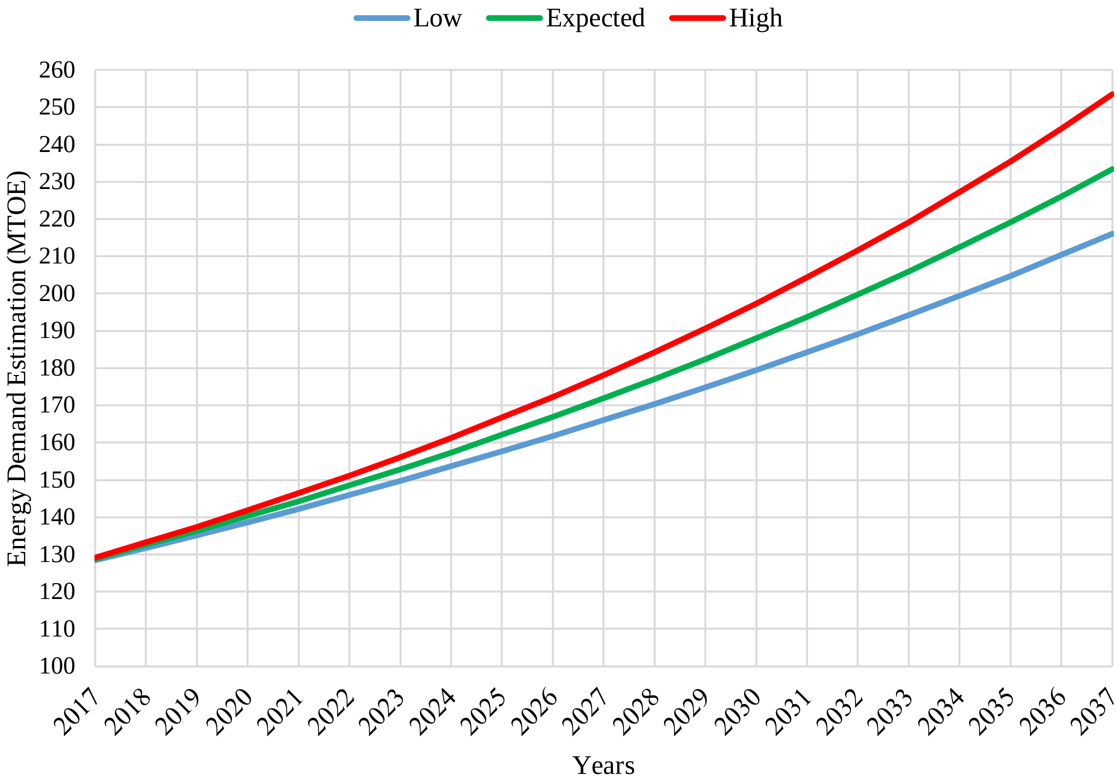

Figure 4. Energy demand estimation between 2017-2037 with MGSAE model

7. Conclusions

Energy demand estimation of Turkey between 2017 and 2037 was conducted in this study. Modified gravitational search algorithm (MGSA) was developed for energy demand estimation. Through MGSA developed, linear and exponential energy demand estimation models were established. The models formed were trained with population, GDP, importation and exportation data of Turkey between 1997 and 2011 and tested between 2012 and 2016. It was shown in test results that improved MGSAL and MGSAE models calculate lower RMSE error than standard GSA. When RMSE error convergence curves are analyzed, it is seen that developed MGSA method converge quicker than the GSA both in linear and exponential models. In this study, minimum RMSE value was calculated by established MGSAE model. Therefore, MGSAE model was used for estimation studies. Low, expected and high scenarios were formed for scenarios. 21-years energy demand estimation was carried out by means of MGSAE model between the years 2017 and 2037. It was observed that energy demand estimation conducted with developed MGSA method is applicable in this study.

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