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A NEW META-HEURISTIC FRAMEWORK FOR FORECASTING OIL DEMAND IN IRAN

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ABSTRACT
Energy is a central element to achieve the interrelated economic, social, and environmental goals toward sustainable development of each country. Detailed, complete, timely and reliable statistics are essential to monitor the energy situation and develop energy demand estimation models at a country as well as at international level to make sound energy policy decisions.
In this study, a novel approach for oil consumption modeling is presented. For this purpose, following demand estimation models are developed using Cuckoo Search (CS) algorithm to forecast oil consumption:
PGIE Model: Oil consumption is estimated based on population, GDP, import and export.
PGML Model: Oil consumption is estimated based on Population, GDP, export minus import, and number of light-duty vehicles (LDVs).
PGMH Model: Oil consumption is estimated based on population, GDP, export minus import, and number of heavy-duty vehicles (HDVs).
Linear and non- linear forms of equations are developed for each model.
Eventually, In order to show the accuracy of the CS algorithm, a comparison is made with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA) estimation models which are developed for the same problem. Oil demand in Iran is forecasted up to year 2030.

KEYWORDS: Cuckoo Search (CS) Algorithm; Oil; Projection; Demand; IRAN.

INTRODUCTION
The geostrategic situation of Iran and its access to the huge hydrocarbon resources placed the country among important areas and resulted in the investment development of oil and gas industry [1].
Iran, one of OPEC's founding members, holds the world's third-largest proven oil reserves and the world's second-largest natural gas reserves [2, 3].
Iran's total recoverable oil reserves has increased due to recent discoveries and reached to around 138.22 billion barrels in 2006. This figure declares an increase about 2.1 billion barrels, something about 1.5% compared to its previous year [1]. In contrary to the public's perception, Iran's share of the market for high quality oil is as little as 2%.More specifically, the oil produced in Iran is ranked 14th in terms of the quality [3].
Oil industry plays a crucial role in Iran's economy, GDP, and government's annual budget. It is also influential in foreign trade, national capital, and developments in non-petroleum exports. For the Iranian government, it is also very important to effectively allocate oil revenues in the rest of its economy [1]. This study presents application of Cuckoo Search (CS) algorithm to forecast oil demand in Iran based on the Iran's socio-economic structure. Linear and non-linear forms of equations are developed. Eventually, In order to show the accuracy of the algorithm, a fair comparison is made with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA) estimation models which are developed for the same problem. Oil consumption in Iran is forecasted up to year 2030.

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LITERATURE REVIEW

Several studies are presented to propose some models for energy demand policy management using different techniques. In order to estimate total energy demand based on economic indicators in Turkey, Unler developed Particle Swarm Optimization (PSO) demand estimation models [4]. Canyurt and Ozturk presented Turkey's fossil fuels demand estimation models by using the structure of the Turkish industry and economic conditions based on Genetic Algorithm (GA) [5]. Toksari developed Ant Colony Optimization (ACO) demand estimation models to forecast total energy demand in Turkey [6]. Azadeh et al. presented an Artificial Neural Network (ANN) for forecasting monthly electrical energy consumption in Iran [7]. In a different study, Azadeh et al. compared GA, ANN and Fuzzy Regression Algorithm (FRA) to estimate seasonal and monthly changes in electricity consumption in developing countries [8]. Amjadi et al. used PSO and GA to forecast electricity demand in Iran [9]. Zhang et al. applied Partial Least Square Regression (PLSR) method to estimate transport energy demand in China [10]. Azadeh et al. compared Adaptive Neuro-Fuzzy Inference System (ANFIS), Auto Regression, and GA-Time Series methods to forecast oil consumption in Canada, United Kingdom, and South Korea [11]. Assareh et al. presented application of PSO and GA on demand estimation of oil in Iran [12]. Behrang et al. used Bees Algorithm (BA) to forecast total energy demand in Iran [13]. Behrang et al. applied GA and PSO to forecast electricity demand in Iran's industrial sector [14]. Behrang et al. proposed an integrated Neural Network-Bees Algorithm framework to forecast global fossil fuels consumption (oil, natural gas, and coal) and its related carbon dioxide emission [15]. Recently, Behrang et al. presented Gravitational Search Algorithm (GSA) method to forecast oil consumption in Iran [16].

Other studies about energy demand policy management using intelligent techniques are mentioned in [17-30]. Literature Review only revised techniques to forecast energy demand that are mainly based on econometric approaches. Econometric approaches are not the solely technique to forecast oil demand. For example, end-use simulation models, optimization models, such as Message (IIASA), Markal, LEAP, have been also used to build energy demand scenarios. For more details about other approaches the readers are refereed to [31-44]. Literature review also indicates that CS algorithm has never been used for such a study.

GENETIC CUCKOO SEARCH (CS) ALGORITHM

Cuckoo search (CS) is an optimization algorithm was proposed by Yang and Deb in 2009 [45] inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds.

In CS algorithm, each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim is to use the new solutions (cuckoos) to replace a week solution in the nests [45].

CS algorithm is based on the following idealized rules [45, 46]:

1. Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest.
2. The best nests with high quality of eggs (solutions) will carry over to the next generation.
3. The number of available host nests is fixed, and a host can discover an alien egg with a probability $P_a \in (0,1)$. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

Lévy flight is an important issue for generating new solutions in CS algorithm. A cuckoo i updates its solution (i.e. $x^{(t+1)}$), by performing Lévy flights, as follow:

$$x_i^{(x+t)} = x_i^{(t)} + \alpha \text{ Lévy}(\lambda) \quad \text{where} \quad \text{Lévy}(\lambda) = t^{-\lambda}, \quad 1 < \lambda \le 3 \tag{1}$$

where $\alpha > 0$ is the step size which determines how far a random walker can go for a fixed number of iterations. A proper step size is important because a large step size generates new solutions far away from old solutions while a small step size causes small and insignificant changes in solutions. In most cases it can be assumed that α=1 [45, 46].

An important advantage of CS algorithm comparing with other population- or agent-based meta-heuristic algorithm is its simplicity as there are essentially only two user-specified parameters (i.e. population (n) and P_a) in CS. For more details about Cuckoo breeding behavior and Lévy flight the readers are referred to [45- 52].

The pseudo-code of the Cuckoo Search (CS) algorithm can be summarized as follow:

Objective function: $f(x)$, $x = (x_1, x_2, ..., x_d)$;

Initialize population of n host nests x_i;

While (t<MaxGeneration) or (stop criterion);

Get a cuckoo randomly (say, i) and update its solution by performing Lévy flights;
Evaluate its fitness F_i
[For minimization];
Choose a nest among n (say, j) randomly;
if ($F_i < F_j$),
Replace j by the new solution;
end if
A fraction (P_a) of the worse nests are abandoned and new ones are built;
Keep the best solutions/nests;
Rank the solutions/nests and find the current best;
Pass the current best to the next generation;
end while
Post-processing the results and visualization;

For more details about intelligent optimization techniques the readers are refereed to [53]**.**

PROBLEM DEFINITION

This study applies CS algorithm to develop oil consumption models in Iran based on socio- economic indicators. Although there are many different socio-economic indicators in order to use as basic energy indicators of oil demand, for the fact that total consumption of oil in 2008 was 555.47 Mboe and in this period the highest share belongs to gasoline that about 98.9% of gasoline consumption was in transportation sector [1], present study uses population, gross domestic product (GDP), export, import, export minus import, number of light-duty vehicles (LDVs), and number of heavy-duty vehicles (HDVs) to develop following oil consumption forecasting models:

Model 1 (PGIE): In first model, population, GDP, import and export are used as indicators to estimate oil consumption.

Model 2 (PGML): In second model, population, GDP, export minus import, and number of light-duty vehicles (LDVs) are used as indicators to forecast oil consumption.

Model 3 (PGML): In third model, population, GDP, export minus import, and number of heavy-duty vehicles (HDVs) are used as indicators to estimate oil consumption.

Forecasting of oil demand based on socio-economic indicators is modeled by using linear and exponential forms of equations. The linear and exponential forms of equations for the demand estimation models are written as follow:

$$Y_{linear} = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5 \tag{2}$$

$$Y_{exponential} = w_1X_1^{w_2} + w_3X_2^{w_4} + w_5X_3^{w_6} + w_7X_4^{w_8} + w_9 \tag{3}$$

where, w_i are the corresponding weighting factors and X_1, X_2, X_3 and X_4 are defined as follow:

For Model 1 (PGIE): X_1, X_2, X_3 and X_4 are population, GDP, import and export.

For Model 2 (PGML): X_1, X_2, X_3 and X_4 are population, GDP, export minus import, and number of light-duty vehicles (LDVs).

For Model 3 (PGMH): X_1, X_2, X_3 and X_4 are population, GDP, export minus import, and number of heavy-duty vehicles (HDVs).

The data related to the design parameters of Iran's population, GDP, import, export, and oil consumption figures are obtained from [3] while the related data for number of vehicles (light and heavy) are obtained from [54].

CS Algorithm is applied in order to find optimal values of weighting parameters based on actual data in order to estimate oil consumption in Iran.

Following steps are carried out to find optimal values of weighting parameters of each model:

(a): All input and output variables (i.e. population, GDP, import, export, export minus import, number of LDVs, number of HDVs, and oil consumption) in Eqs. (2) and (3) are normalized in the (0, 1) range.

(b): The related data from 1981 to 1999 are used in the proposed algorithm (i.e. CS) to find candidates of the best weighting parameters (w_i). The criteria to select candidates for optimal weighting parameters is the minimum fitness function defined by

$$\text{Min } F(x) = \sum_{j=1}^{m} (E_{actual} - E_{predicted})^2 \quad (4)$$

Where E_{actual} and $E_{predicted}$ are the actual and predicted oil consumption, respectively, m is the number of observations.

(c): Best results (optimal values of weighting parameters) for each model are chosen according to **(b)** and less average relative errors in testing period (i.e. the related data from 2000 to 2005).

(d): Demand estimation models are proposed using the optimal values of weighting parameters.

(e): In order to use obtained models for future projections, each input variable should be forecasted in future time domain. Following scenarios are defined for forecasting each indicator in the future:

Scenario I: It is assumed that the annual average growth rates of population, GDP, import, export, number of light-duty vehicles (LDVs), and heavy-duty vehicles (HDVs) are 1.6%, 4.5%, 6%, 3.5%, 5.3%, and 15.7% during 2006-2030.

Scenario II: It is assumed that the annual average growth rates of population, GDP, import, export, number of light-duty vehicles (LDVs), and heavy-duty vehicles (HDVs) are 1.4%, 4.5%, 6.5%, 4.5%, 5.8%, and 15.7% during 2006-2030.

Scenario III: It is assumed that the annual average growth rates of population, GDP, import, export, number of light-duty vehicles (LDVs), and heavy-duty vehicles (HDVs) are 1.5%, 5%, 7.5%, 2.5%, 5.8%, and 16.6% during 2006-2030.

(f): Finally, oil demand is forecasted up to year 2030, using the proposed models **(d)** and scenarios **(e)**.

RESULTS AND DISCUSSION

In this section, a code was developed in MATLAB 2008 (Math Works, Natick, MA) based on the CS algorithm and applied for finding optimal values of weighting parameters regarding actual data (1981–2005). The sensitivity analysis and convergence of the objective function were examined for varying user-specified parameters of CS.

The performance of CS is satisfactory using the following user- specified parameters for all models: Population of host nests (n): 15

Fraction of the worse nests (P_a): 0.25

Number of Iteration (t): 200

Table 1. The best obtained weighting factors by CS for PGIE, PGML and PGMH models.

Model	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
CS-PGIE$_{linear}$	0.6159	0.2398	-0.0454	0.0029	0.0288	-	-	-	-
CS-PGIE$_{exp}$	0.4298	1.0397	0.4299	0.7830	-0.0953	0.3310	-0.0110	0.3751	0.0924
CS-PGML$_{linear}$	0.3469	0.3199	0.0908	-0.0187	0.1574	-	-	-	-
CS-PGML$_{exp}$	-0.0528	0.0404	0.3336	1.0456	0.1142	0.9383	-0.0101	0.1061	0.4715
CS-PGMH$_{linear}$	0.3705	0.378	-0.1991	-0.0372	0.2729	-	-	-	-
CS-PGMH$_{exp}$	0.1875	0.3682	0.474	0.8117	0.5521	0.5101	-0.1692	0.3614	-0.1834

In order to make a fair comparison between CS, GSA, PSO, and GA same data are used with [11, 16].

As it can be seen in Table 2, CS, GSA, PSO, and GA demand estimation models are in good agreement with the observed data but CS-PGIE$_{linear}$ outperformed other models (presented here and by [11, 16]).

The average relative errors on testing data for the best model (i.e. CS-PGIE$_{linear}$) is 1.02%.

In Figs. 1 to 3, oil consumption is projected through 2030.

Table 2. Comparison of the CS, GSA[b], PSO[c], and GA[c] demand estimation models for oil consumption in testing period (2000-2005).

Years	2000	2001	2002	2003	2004	2005	Average
Actual Data [a]	382.7	392.4	406	414.1	427.1	457.4	-
CS-PGIE$_{linear}$	385.6	392.9	406.3	419.0	425.2	441.2	-
Relative error (%)	0.75	0.13	0.07	1.19	-0.44	-3.55	**1.02**
CS-PGIE$_{exponential}$	387.0	394.2	409.5	424.6	434.1	449.9	-
Relative error (%)	1.14	0.45	0.86	2.55	1.63	-1.65	1.38
GSA-PGIE$_{linear}$[b]	385.22	392.51	404.14	419.96	427.1	437.91	-
Relative error (%)	0.66	0.03	-0.46	1.42	0	-4.26	1.14
GSA-PGIE$_{exponential}$[b]	389.34	390.12	402.06	419.67	429.37	439.42	-
Relative error (%)	1.74	-0.58	-0.97	1.34	0.53	-3.93	1.52
GA-PGIE$_{linear}$[c]	393.35	391.00	403.34	426.91	437.10	452.48	-
Relative error (%)	2.78	-0.36	-0.66	3.09	2.34	-1.08	1.72
GA-PGIE$_{exponential}$[c]	392.10	394.70	413.50	433.20	448.19	469.13	-
Relative error (%)	2.46	0.59	1.85	4.61	4.94	2.56	2.83
PSO-PGIE$_{linear}$[c]	386.77	389.44	404.60	425.57	436.78	452.99	-
Relative error (%)	1.06	-0.76	-0.35	2.77	2.27	-0.97	1.36
PSO-PGIE$_{exponential}$[c]	384.05	388.32	401.88	421.50	431.96	443.35	-
Relative error (%)	0.35	-1.04	-1.02	1.79	1.14	-3.07	1.40
CS-PGML$_{linear}$	384.8	390.8	404.7	422.5	432.5	446.2	-
Relative error (%)	0.55	-0.40	-0.32	2.03	1.27	-2.44	1.17
CS-PGML$_{exponential}$	376.0	379.7	394.9	414.6	427.5	440.4	-
Relative error (%)	-1.76	-3.23	-2.74	0.12	0.08	-3.71	1.94
GSA-PGML$_{linear}$[b]	386.85	390.82	400.70	419.63	427.05	437.20	-
Relative error (%)	1.08	-0.40	-1.30	1.34	-0.01	-4.42	1.43
GSA-PGML$_{exponential}$[b]	395.85	413.03	423.94	426.23	428.51	443.89	-
Relative error (%)	3.44	5.26	4.42	2.93	0.33	-2.95	3.22
CS-PGMH$_{linear}$	380.0	394.1	412.3	421.5	427.7	445.2	-
Relative error (%)	-0.71	0.43	1.55	1.78	0.14	-2.68	1.22
CS-PGMH$_{exponential}$	392.3	391.2	405.2	429.5	437.9	451.4	-
Relative error (%)	2.50	-0.30	-0.19	3.72	2.52	-1.31	1.76
GSA-PGMH$_{linear}$[b]	385.90	395.57	407.88	421.20	428.07	439.55	-
Relative error (%)	0.84	0.81	0.46	1.72	0.23	-3.90	1.33
GSA-PGMH$_{exponential}$[b]	394.14	400.34	411.35	418.16	416.66	429.72	-
Relative error (%)	2.99	2.02	1.32	0.98	-2.44	-6.05	2.63

[a] actual data is in million barrel oil equivalent (Mboe)
[b][16]
[c][12]

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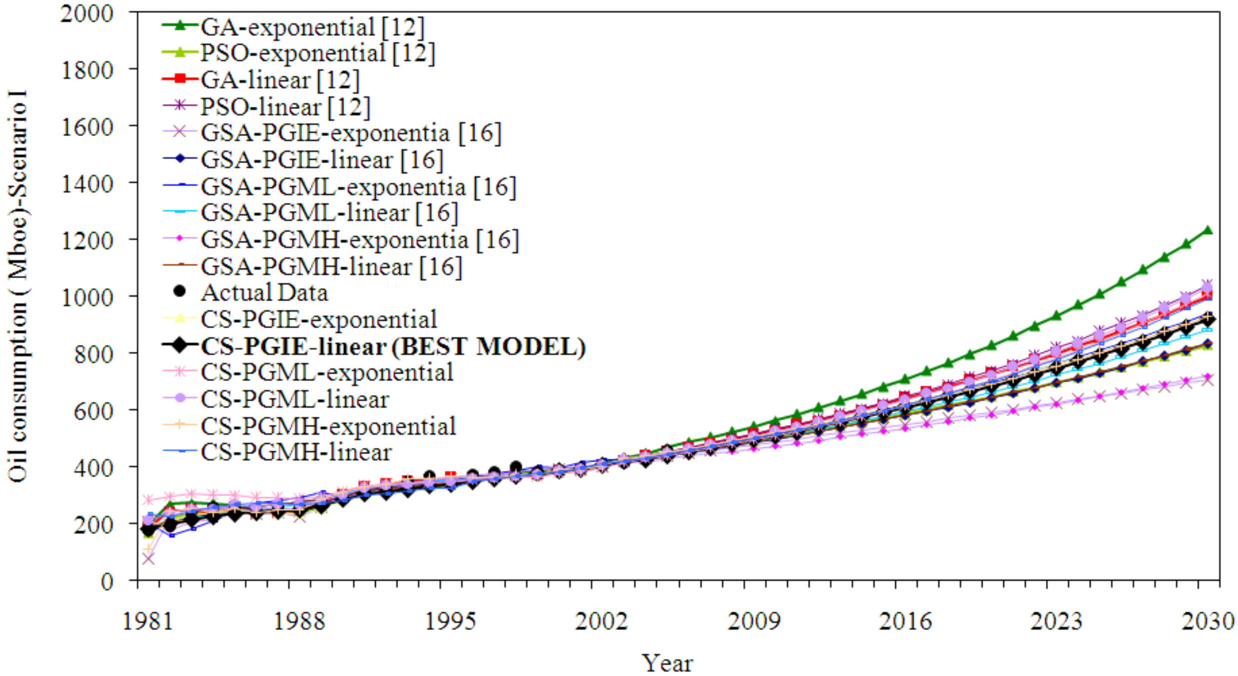

Figure 1. Comparison between observed and estimated values for oil demand (1981-2005) and future projection according to scenario I (2006-2030).

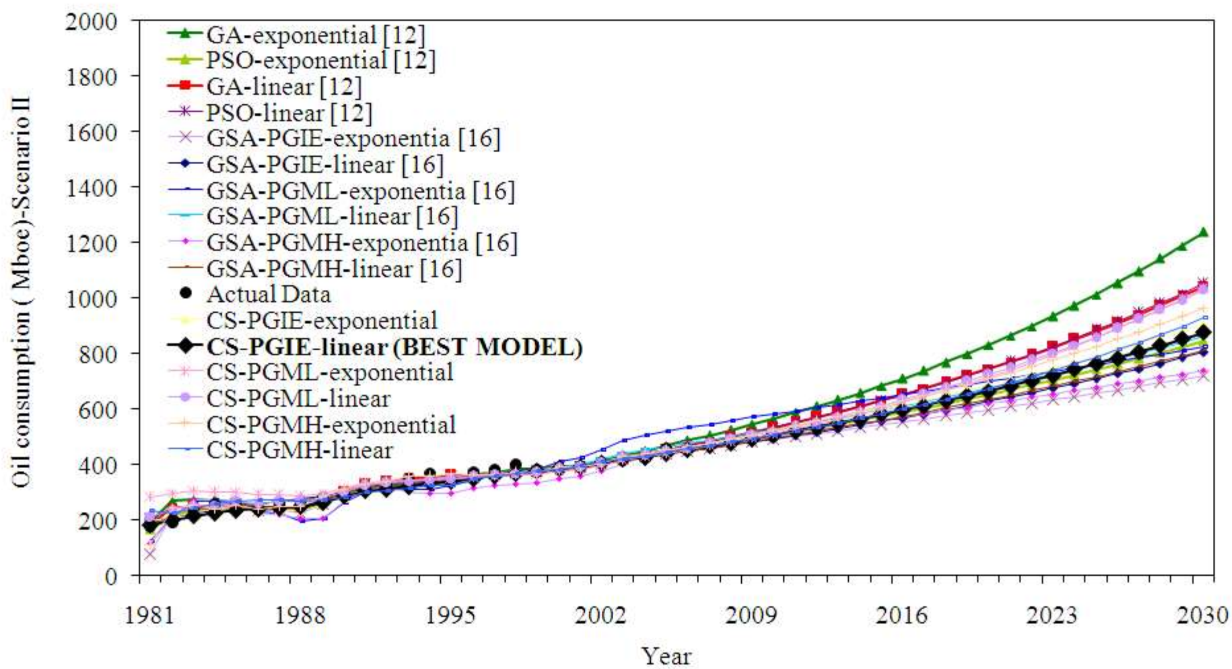

Figure 2. Comparison between observed and estimated values for oil demand (1981-2005) and future projection according to scenario II (2006-2030).

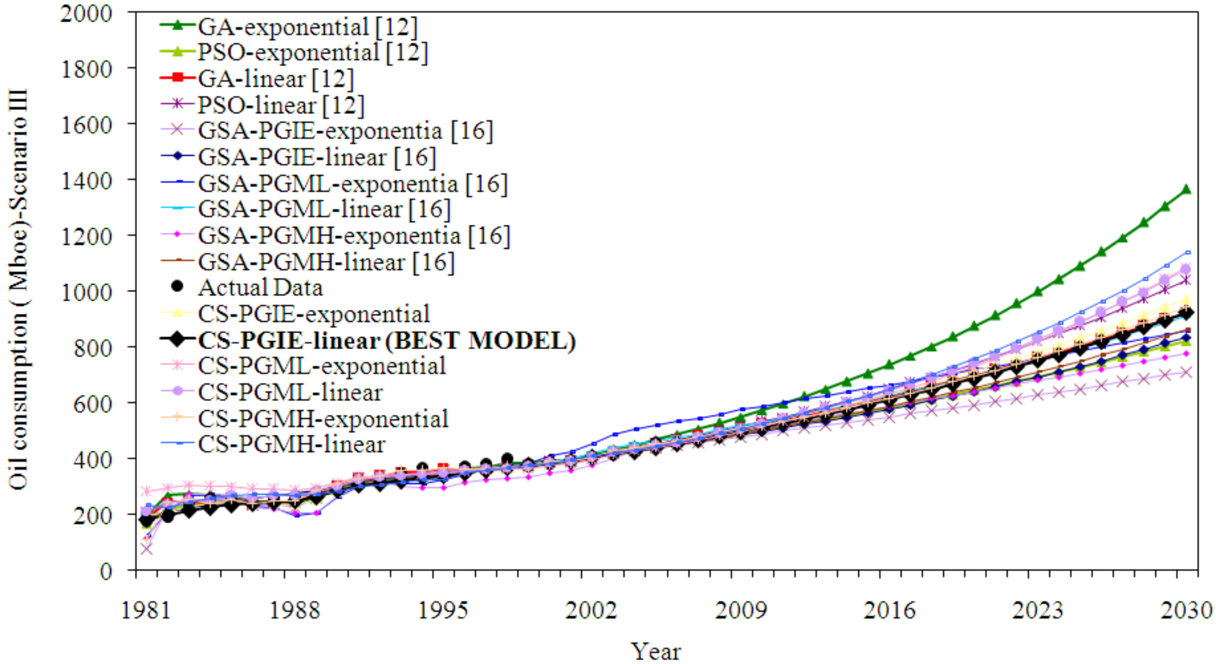

Figure 3. Comparison between observed and estimated values for oil demand (1981-2005) and future projection according to scenario III (2006-2030).

According to the best model (i.e. CS-PGIE$_{linear}$) and developed scenarios (i.e. Scenarios I to III), the oil consumption values by 2030 are 917.99, 875.02, and 924.07 million barrels, respectively.
Forecasting of Iran's oil demand using the CS-PGIE$_{linear}$ models are overestimated when the results are compared with the GSA results in [16] for all scenarios.
Comparison between presented models in the literature and presented models in this study is shown in Table 3.

CONCLUSION

This paper presented a novel approach for oil consumption modeling by using Cuckoo Search (CS) algorithm. The algorithm has been successfully used to estimate Iran's oil demand based on the structure of the Iran socio- economic conditions. Two forms of equations (linear and exponential) were developed based on 25 years data (1981–2005). Three models are designed to estimate oil consumption in Iran. In first model (PGIE) oil consumption is estimated based on population, GDP, import, and export. In second model (PGML) population, GDP, export minus import, and number of light-duty vehicles (LDVs) are used to forecast oil consumption and in third one (PGMH) population, GDP, export minus import, and number of heavy-duty vehicles (HDVs) are used to estimate oil consumption. Validation of models shows that obtained demand estimation models are in good agreement with the observed data but $CS - PGIE_{linear}$ outperformed other presented models. Three scenarios are designed in order to estimate Iran's oil demand during 2006-2030. In order to show the accuracy of the proposed algorithm, a comparison is made with the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Gravitational Search Algorithm (GSA) oil demand estimation models which are developed for the same problem. It is concluded that the suggested models are satisfactory tools for successful oil demand forecasting. The results presented here provide helpful insight into energy system modeling.
This paper developed energy demand forecasting models that were mainly based on econometric approaches. Econometric approaches are not the solely technique to forecast oil demand.
Future work is focused on comparing the models presented here with other available models. End-use simulation models, optimization models, such as Message (IIASA), Markal, LEAP, can be also used to build energy demand scenarios. Technical variables (such as the efficiency of devices, the number of devices or appliances, and the industrial process description) can be used for oil consumption modeling.

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Table 3. Comparison of different models presented in the literature and present study[a].

Source	Method	Target- Country	Average relative errors (%)
[4]	Particle Swarm Optimization	Total Energy-Turkey	0.83
[5]	Genetic Algorithm	Oil- Turkey	2.97
	Genetic Algorithm	Natural Gas- Turkey	2.10
	Genetic Algorithm	Coal- Turkey	3.22
[6]	Ant Colony Optimization	Total Energy- Turkey	1.07
[7]	Artificial Neural Networks	Electricity-Iran	1.20
[8]	Genetic Algorithm	Electricity-Iran	1.4
	Artificial Neural Networks	Electricity-Iran	1.56
	Fuzzy Regression Algorithm	Electricity-Iran	0.82
[9]	Genetic Algorithm	Electricity-Iran	1.36
	Genetic Algorithm	Electricity-Iran	1.51
	Particle Swarm Optimization	Electricity-Iran	3.92
	Particle Swarm Optimization	Electricity-Iran	0.98
[10]	Partial Least Square Regression	Transport energy- China	2.30
[11]	Adaptive Neuro-Fuzzy Inference System	Oil –Canada	2.29
	Auto Regression	Oil –Canada	2.3
	GA-time series	Oil –Canada	2.59
[11]	Adaptive Neuro-Fuzzy Inference System	Oil- United Kingdom	2.17
	Auto Regression	Oil- United Kingdom	2.39
	GA-time series	Oil- United Kingdom	3.55
[11]	Adaptive Neuro-Fuzzy Inference System	Oil-South Korea	3.85
	Auto Regression	Oil-South Korea	3.66
	GA-time series	Oil-South Korea	4.06
[12]	Genetic Algorithm	Oil-Iran	2.83
	Genetic Algorithm	Oil-Iran	1.72
	Particle Swarm Optimization	Oil-Iran	1.40
	Particle Swarm Optimization	Oil-Iran	1.36
[13]	Bees Algorithm	Total Energy- Iran	1.07
	Bees Algorithm	Total Energy- Iran	1.83
[14]	Genetic Algorithm	Electricity-Iran	1.13
	Genetic Algorithm	Electricity-Iran	1.29
	Particle Swarm Optimization	Electricity-Iran	1.03
	Particle Swarm Optimization	Electricity-Iran	1.69
[16]	Gravitational Search Algorithm	Oil-Iran	1.14
	Gravitational Search Algorithm	Oil-Iran	1.52
	Gravitational Search Algorithm	Oil-Iran	1.43
	Gravitational Search Algorithm	Oil-Iran	3.32
	Gravitational Search Algorithm	Oil-Iran	1.33
	Gravitational Search Algorithm	Oil-Iran	2.63
Present Study	Cuckoo Search Algorithm	Oil-Iran	**1.02**
	Cuckoo Search Algorithm	Oil-Iran	1.38
	Cuckoo Search Algorithm	Oil-Iran	1.17
	Cuckoo Search Algorithm	Oil-Iran	1.94
	Cuckoo Search Algorithm	Oil-Iran	1.76
	Cuckoo Search Algorithm	Oil-Iran	1.33

[a] Average relative errors are on testing period of each model.

Forecasting of oil demand can also be investigated with Bees Algorithm, Artificial Bee Colony, Ant Colony, fuzzy logic, neural networks or other meta-heuristic such as tabu search, simulated annealing, etc. The results of the different methods and models can be compared with the CS, GSA, PSO and GA.

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