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Forecasting future oil demand in Iran using GSA (Gravitational Search Algorithm)

M.A. Behrang [a,*], E. Assareh [a], M. Ghalambaz [a], M.R. Assari [c], A.R. Noghrehabadi [b]

[a] Department of Mechanical Engineering, Dezful Branch, Islamic Azad University, Dezful, Iran
[b] Department of Mechanical Engineering, Engineering Faculty, Shahid Chamran University, Ahvaz, Iran
[c] Department of Mechanical Engineering, Engineering Faculty, Jundi Shapour University, Dezful, Iran

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ABSTRACT

Growing energy demand of the world, made the major oil and gas exporting countries to have critical role in the energy supply. 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.

In this study, a novel approach for oil consumption modeling is presented. Three demand estimation models are developed to forecast oil consumption based on socio-economic indicators using GSA (Gravitational Search Algorithm). 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 LDVs (light-duty vehicles) are used to forecast oil consumption and in third one (PGMH) population, GDP, export minus import, and number of HDVs (heavy-duty vehicles) are used to estimate oil consumption. Linear and non-linear forms of equations are developed for each model.

In order to show the accuracy of the algorithm, a comparison is made with the GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) estimation models which are developed for the same problem. Oil demand in Iran is forecasted up to year 2030.

1. Introduction

Iran is considered as a case study in the present work. As such, its logistics, population, and energy outlook are briefly described. 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].

Iran, with population of more than 68 million [2] is one of the largest producers of crude oil in the world. In contrary to the public's perception, Iran's share of the market for high quality oil is as little as 2%. More specifically, while Iran has the fourth highest oil production rate, 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 GSA (Gravitational Search Algorithm) to forecast oil demand in Iran based on the structure of the Iran's socio-economic condition. 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 GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) estimation models which are developed for the same problem. Oil consumption in Iran is forecasted up to year 2030.

2. Literature review

Several studies are presented to propose some models for energy demand policy management using different techniques. Unler developed PSO (Particle Swarm Optimization) energy demand models to estimate energy demand based on economic indicators in Turkey [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 GA (Genetic Algorithm) [5]. Toksari developed ACO (Ant Colony Optimization) energy demand estimation models for Turkey [6]. Azadeh et al. presented an ANN (Artificial Neural Network) for forecasting monthly electrical energy consumption [7]. In a different work, Azadeh et al. compared GA, ANN and FRA (Fuzzy Regression Algorithm) to estimate seasonal and monthly changes in electricity consumption in developing countries [8]. Amjadi et al. used PSO and GA to forecast electricity demand of Iran [9]. Zhang et al. applied PLSR (Partial Least Square

* Corresponding author. Tel.: +98 916 343 7316; fax: +98 641 2232110.
E-mail address: Mohammadali.behrang@gmail.com (M.A. Behrang).

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Regression) method to estimate transport energy demand in China [10]. Assareh et al. presented application of PSO and GA on demand estimation of oil in Iran [11]. Recently, Behrang et al. used BA (Bees Algorithm) to forecast total energy demand in Iran [12]. Behrang et al. applied GA and PSO to forecast electricity demand in Iran's industrial sector [13]. In another study, same authors estimated global fossil fuels consumption (oil, natural gas, and coal) and its related carbon dioxide emission using an integrated Neural Network-Bees Algorithm method [14]. Some studies about energy demand policy management using intelligent techniques are mentioned in [15–31]. 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 [32–45]. Literature review also indicates that GSA algorithm has never been used for such a study.

3. GSA (Gravitational Search Algorithm)

Heuristic algorithms mimic biological or physical processes. One of the newest heuristic algorithms that has been inspired by the physical laws is GSA (Gravitational Search Algorithm) [46].

In GSA, Newtonian laws of gravity and motion are applied to find the optimum solution by a set of agents called masses [47].

To describe the GSA consider a system with s masses in which position of the ith mass is defined as follows:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \quad i = 1, 2, \ldots, s$$

where X_i^d is position of the ith mass in the dth dimension and n is dimension of the search space.

Mass of each agent is calculated after computing current population's fitness as follows [46,47]:

$$q_i(t) = \frac{\mathrm{fit}_i(t) - \mathrm{worst}(t)}{\mathrm{best}(t) - \mathrm{worst}(t)} \tag{2}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{s} q_j(t)} \tag{3}$$

where $M_i(t)$ and $\mathrm{fit}_i(t)$ represent the mass and the fitness value of the agent i at t, respectively. For a minimization problem, worst(t) and best(t) are defined as follows [47]:

$$\mathrm{best}(t) = \min_{j \in \{1,\ldots,s\}} \mathrm{fit}_j(t) \tag{4}$$

$$\mathrm{worst}(t) = \max_{j \in \{1,\ldots,s\}} \mathrm{fit}_j(t) \tag{5}$$

To compute acceleration of an agent, total forces from a set of heavier masses that apply on an agent should be considered based on the law of gravity (Eq. (6)), which is followed by calculation of agent acceleration using the law of motion (Eq. (7)). Afterward, velocity and then position of an agent are updated according to Eqs. (8) and (9):

$$F_i^d(t) = \sum_{j \in k\ \mathrm{best}\ j \neq i} \mathrm{rand}_j G(t) \frac{M_j(t) M_i(t)}{R_{ij}(t) + \varepsilon} \left(x_j^d(t) - x_i^d(t)\right) \tag{6}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} = \sum_{j \in k\ \mathrm{best}\ j \neq i} \mathrm{rand}_j G(t) \frac{M_j(t)}{R_{ij}(t) + \varepsilon} \left(x_j^d(t) - x_i^d(t)\right) \tag{7}$$

$$v_i^d(t+1) = \mathrm{rand}_i \times v_i^d(t) + a_i^d(t) \tag{8}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{9}$$

where rand_i and rand_j are two uniformly distributed random numbers in the interval [0,1], ε is a small value, $R_{ij}(t)$ is the Euclidean distance between two agents i and j, defined as $\|X_i(t), X_g(t)\|_2$, kbest is the set of first K agents with the best fitness value and biggest mass, which is a function of time, initialized to $K0$ at the beginning and decreasing with time. Here $K0$ is set to s (total number of agents) and is decreased linearly to1. In GSA, the gravitational constant, G, will take an initial value, $G0$, and it will be reduced with time [47]:

$$G(t) = G(G_0, t) \tag{10}$$

The GAS algorithm is composed of following steps:

(a) Search space identification.
(b) Randomized initialization.
(c) Fitness evaluation of agents.
(d) Update $G(t)$, best(t), worst(t) and $M_i(t)$ for $i = 1,2,\ldots,N$.
(e) Calculation of the total force in different directions.
(f) Calculation of acceleration and velocity.
(g) Updating agents' position.
(h) Repeat steps (c) to (g) until the stop criteria is reached.
(i) End.

User-specified parameters of GSA are number of population for each group (p), number of groups (n), portions of old member (r_1), portions of Leader member (r_2), portions of random (r_3) and iteration number (t). For more details about intelligent optimization techniques the readers are refereed to [48].

4. Problem definition

In this study, a novel approach for oil consumption modeling is presented. The demand estimation models are developed to forecast oil consumption based on socio-economic indicators using GSA (Gravitational Search Algorithm).

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, GDP (gross domestic product), export, import, export minus import, number of LDVs (light-duty vehicles), and number of HDVs (heavy-duty vehicles) to develop following oil consumption forecasting models:

Model 1 (PGIE): In first model (PGIE) oil consumption is estimated based on population, GDP, import and export.

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

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

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

$$Y_{\mathrm{linear}} = w_1 X_1 + w_2 X_2 + w_3 X_3 + w_4 X_4 + w_5 \tag{11}$$

$$Y_{\mathrm{exponential}} = w_1 X_1^{w_2} + w_3 X_2^{w_4} + w_5 X_3^{w_6} + w_7 X_4^{w_8} + w_9 \tag{12}$$

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

Table 1
The best obtained weighting factors by GSA for *PGIE*, *PGML* and *PGMH* models (for the general forms of Eqs. (11) and (12)).

Model	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
GSA-PGIE$_{linear}$	0.6786	0.1059	−0.0026	0.0295	0.0729	–	–	–	–
GSA-PGIE$_{exponential}$	0.4407	0.3192	0.7253	0.4464	−0.142	0.2133	0.308	0.4821	−0.439
GSA-PGML$_{linear}$	0.6575	0.1233	0.1595	−0.0146	−0.0063	–	–	–	–
GSA-PGML$_{exponential}$	1.0499	0.9887	0.2083	0.9341	−0.4105	0.6329	−0.1837	0.3483	0.2486
GSA-PGMH$_{linear}$	0.7243	0.1142	−0.0511	0.0058	0.0873	–	–	–	–
GSA-PGMH$_{exponential}$	0.646	0.433	0.6022	0.5892	−0.531	0.0081	−0.275	0.3356	0.3406

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 LDVs (light-duty vehicles).

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

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 [49].

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

For this purpose, the following steps are carried out to find optimal values of empirical coefficients 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. (11) and (12) are normalized in the (0, 1) range.
(b) The related data from 1981 to 1999 are used in the proposed algorithm (i.e. GSA) to find candidates of the best empirical coefficients (w_i). The criteria to select candidates for optimal coefficients is the minimum fitness function defined by

$$\text{Min}\, F(x) = \sum_{j=1}^{m} \left(E_{\text{actual}} - E_{\text{predicted}}\right)^2 \tag{13}$$

Where E_{actual} and $E_{\text{predicted}}$ 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 LDVs (light-duty vehicles), and HDVs (heavy-duty vehicles) 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 LDVs (light-duty vehicles), and HDVs (heavy-duty vehicles) 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 LDVs (light-duty vehicles), and HDVs (heavy-duty vehicles) 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).

5. Results and discussions

In this section, a code was developed in MATLAB 2008 (Math Works, Natick, MA) based on the GSA algorithm and applied for finding optimal values of weighting factors regarding actual data

Table 2
Comparison of the GSA, PSO, and GA 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	–
GSA–PGIE$_{linear}$	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$_{exponential}$	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$_{linear}$[b]	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$_{exponential}$[b]	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$_{linear}$[b]	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$_{exponential}$[b]	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
GSA-PGML$_{linear}$	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$_{exponential}$	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
GSA-PGMH$_{linear}$	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$_{exponential}$	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] [11].