Energy 35 (2010) 5223–5229

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Application of PSO (particle swarm optimization) and GA (genetic algorithm) techniques on demand estimation of oil in Iran

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

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

A R T I C L E I N F O

Article history:
Received 20 November 2009
Received in revised form
25 July 2010
Accepted 26 July 2010
Available online 9 September 2010

Keywords:
GA (genetic algorithm)
PSO (particle swarm optimization)
Oil
Projection
Demand

A B S T R A C T

This paper presents application of PSO (Particle Swarm Optimization) and GA (Genetic Algorithm) techniques to estimate oil demand in Iran, based on socio-economic indicators. The models are developed in two forms (exponential and linear) and applied to forecast oil demand in Iran. PSO–DEM and GA–DEM (PSO and GA demand estimation models) are developed to estimate the future oil demand values based on population, GDP (gross domestic product), import and export data. Oil consumption in Iran from 1981 to 2005 is considered as the case of this study. The available data is partly used for finding the optimal, or near optimal values of the weighting parameters (1981–1999) and partly for testing the models (2000–2005). For the best results of GA, the average relative errors on testing data were 2.83% and 1.72% for GA–DEM$_{exponential}$ and GA–DEM$_{linear}$, respectively. The corresponding values for PSO were 1.40% and 1.36% for PSO–DEM$_{exponential}$ and PSO–DEM$_{linear}$, respectively. Oil demand in Iran is forecasted up to year 2030.

1. Introduction

The outlook of energy in Iran shows the importance of the need for systematic optimization of the energy use in Iran. Energy resources are limited and depleting [1]. Furthermore, Iran's population is steadily increasing. The energy consumption in Iran is also rapidly increasing [2].

Iran, with population of more than 68 million [3], 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 [2].

Oil, natural gas, electric power, solar, wood, animal and plant waste are Iran's primary energy sources [4].

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 [5]. 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) [6]. Toksari developed Ant Colony energy demand estimation models for Turkey [7]. Azadeh et al. presented an ANN (Artificial Neural Network) for forecasting monthly electrical energy consumption [8]. In a different work, Azadeh et al. compared GA, ANNs and fuzzy regression algorithm to estimate seasonal and monthly changes in electricity consumption in developing countries [9]. Amjadi et al. used PSO and GA to forecast electricity demand of Iran [10]. Zhang et al. applied partial least square regression method to estimate transport energy demand in China [11]. Other studies about energy demand policy management are mentioned in Refs. [12–21].

This study presents application of PSO and GA techniques to forecast oil demand in Iran based on the structure of the Iran socio-economic conditions. Exponential and linear forms of equations have been developed. Oil consumption in Iran is forecasted up to year 2030.

3. GAs

The formulation of GAs was made about a decade after the first Evolutionary Strategies and Evolutionary Programming applications.

* Corresponding author. Tel.: +98 916 9478017; fax: +98 611 3336642.
E-mail address: Ehsanolah.Assareh@gmail.com (E. Assareh).

0360-5442/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.energy.2010.07.043

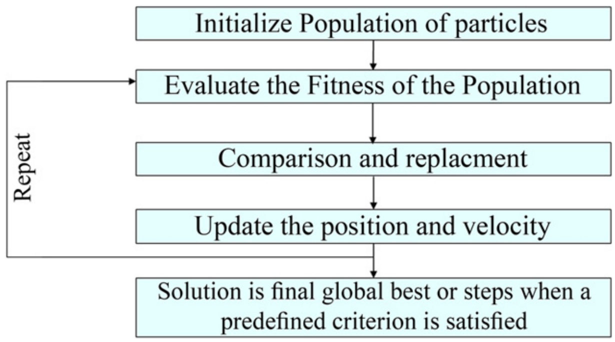

Fig. 1. Flowchart of the Particle Swarm Optimization.

The theoretical basis of GAs lies in the concept of schema (plural schemata) [22]. Schemata represent solution templates where each location can be defined or left unspecified. The larger the number of uninstantiated location is, the greater the number of potential solutions that a schema represents. Schemata leading to higher fitness individuals are propagated through the generations and their number is increased as an effect of the selection process. The ability to process several possible solutions through a single schema is believed to determine the search power of GAs and is given the name implicit parallelism [23,24]. High fitness schemata whose uninstantiated locations occupy a short and compact portion of the encoding are considered to be the building blocks [23] of the optimization process. GAs are designed to multiply and differently recombine these building blocks in order to grow the final optimal solution (building blocks hypothesis) [23]. The schemata theorem [22] allows the estimation in a probabilistic way of the number of criteria schema instances that are transmitted to the following generations.

Over more than 30 years of research, several modifications have been proposed to the original GA structure defined in Ref. [22]. Unless otherwise stated this section will explain Holland's original algorithm, often referred as the canonical GA.

GAs encode candidate solutions as binary strings. Each string (chromosome) is built by chaining a number of sub-strings, each sub-string representing one of the candidate solution's features. Biological genes are in this case equivalent to the sub-strings encoding the parameters, while each binary digit can be related to the nucleotides composing the DNA. In most of the cases, one individual is fully described by a single bit-string, thus leading to the identification of the genotype with one single chromosome. Several other encoding procedures have been explored leading to a debate on the most appropriate choice. Holland showed that binary coding allows the maximum number of schemata to be processed per individual [22]. On the other hand, the mapping to binary coding introduces Hamming cliffs onto the search surface. Moreover, non-binary representations may be more natural for some problem domains and may reduce the computational burden of the search. The canonical binary-coded GA as described here is now rarely used for continuous function optimization as it has been shown that solutions are too easily disrupted (the Hamming cliff issue). Therefore researchers tend to use less disruptive coding such as Gray coding [25].

Similarly to the other EAs (Evolutionary Algorithms), canonical GAs use generational replacement. Popular alternatives are elitism and steady-state replacement [26]. In the first case, the best solution(s) are directly copied into the new population while in the second case only a fraction of the population is replaced at each generation. Both variants aim to improve the preservation of good genetic material at the expense of a reduced search space exploration. A comparison between the behavior of generational and steady-state replacement is given in Ref. [27].

Individuals are selected for reproduction with a probability depending on their fitness. Canonical GAs allocate the mating

Table 2
Values for normalization.

	X_{min}	X_{max}
Population (Thousand persons)	40,825.6	62,736
GDP (billion Iranian rials)	170,281.2	304,941.2
Import (Mboe)	21.4	72.9
Export (Mboe)	339.8	1058.6
Oil consumption (Mboe)	176.2	402.8

Table 1
Oil demand, GDP, population, import and export data of Iran between 1981 and 2005 (from Ref. [2]).

Year	Oil consumption (Mboe)	Population (Thousand persons)	GDP (10^9 Iranian rials)	Import (Mboe)	Export (Mboe)
1981	176.2	40,825.6	170,281.2	21.4	339.8
1982	191.9	42,420	191,666.8	31.2	787.7
1983	234.4	44,076.6	212,876.5	61.7	764.3
1984	257.6	45,720.7	208,515.9	39.6	610.6
1985	264.6	47,541.4	212,686.3	65.3	652.3
1986	241	49,445	193,235.4	62	566.5
1987	262.8	50,650	191,312.4	72.9	635
1988	264.5	51,890	180,822.5	69.6	682.5
1989	280	53,167	191,502.6	50	765.5
1990	284.5	54,483	218,538.7	46.8	919.5
1991	306.1	55,837	245,036.4	48.4	964.8
1992	330.9	56,963	254,822.5	64.6	1023.3
1993	349.4	58,114	258,601.4	57.9	1058.6
1994	366.8	59,290	259,876.3	42.6	991
1995	344.8	59,151	267,534.2	28.5	1002.8
1996	370.9	60,055.5	283,806.6	29.1	880.4
1997	383.5	60,936.5	291,768.7	28.7	855.1
1998	402.8	61,830	300,139.6	24.6	854.6
1999	379.8	62,736	304,941.2	26.9	810.6
2000	382.7	63,663.9	320,068.9	39.6	955.9
2001	392.4	64,528.2	330,565	51.3	901.1
2002	406	65,540.2	355,554	67.3	928.4
2003	414.1	66,991.6	379,838	99.6	1109.6
2004	427.1	67,477.5	398,234.6	121.6	1184.9
2005	457.4	68,467.4	419,705	116.7	1182.3

Table 3
Comparison of the GA–$DEM_{exponential}$ and GA–DEM_{linear} models.

Year	Actual data (Mboe)[a]	GA–$DEM_{exponential}$	Relative error (%)	GA–DEM_{linear}	Relative error (%)
2000	382.700	392.103	2.457	393.349	2.783
2001	392.400	394.697	0.585	390.998	−0.357
2002	406.000	413.502	1.848	403.335	−0.656
2003	414.100	433.202	4.613	426.912	3.094
2004	427.100	448.191	4.938	437.095	2.340
2005	457.400	469.126	2.564	452.484	−1.075
Average	_	_	2.83	_	1.72

1 barrels of oil equivalent (boe) = 6119×10^6 joule(J).
[a] Mboe:Million barrel of oil equivalents.

probability of each individual proportionally to its fitness (proportional selection) and draw the parents set (mating pool) through the roulette wheel selection procedure [23]. Other popular selection schemes are fitness ranking [28] and tournament selection [29]. For a comparison of selection procedure, the reader is referred to Ref. [29].

Crossover is the main search operator in GAs, creating offsprings by randomly mixing sections of the parental genome. The number of sections exchanged varies widely with the GA implementation. The most common crossover procedures are one-point crossover, two-point crossover and uniform crossover [26]. In canonical GAs, a crossover probability is set for each couple. Couples not selected for recombination will generate two offsprings identical to the parents.

A small fraction of the offsprings are randomly selected to undergo genetic mutation. The mutation operator randomly picks a location from a bit-string and flips its contents. The importance of this operator in GAs is however secondary, and the main aim of mutation is the preservation of the genetic diversity of the population.

GAs require the tuning of some parameters such as the mutation rate, crossover rate and replacement rate in the case of steady-state replacement. This task is often not trivial as the chosen values may strongly influence the search process [30,31]. Moreover, the optimal value for the GA parameters may vary according to the evolution of the search process. For all these reasons, several adaptive schemes have been investigated. A survey of adaptation in GAs is given in Refs. [32,33] proposed an off-line tuning approach giving an optimal mutation rate schedule.

Problem-specific operators are sometimes employed in addition to the canonical ones. The introduction of such operators results in an increase in the search power of the algorithm but a loss of general applicability. This issue is analyzed in Ref. [34].

Number of population, methods of selection, reproduction, crossover, mutation and generation are considered as important factors in GA.

4. PSO

The PSO algorithm was first proposed by Eberhart and Kennedy [35], inspired by the natural flocking and swarming behavior of birds and insects. The concept of PSO gained in popularity due to its simplicity. Like other swarm-based techniques, PSO consists of a number of individuals refining their knowledge of the given search space. The individuals in a PSO have a position and a velocity and are denoted as particles. The PSO traditionally has no crossover between individuals, has no mutation and particles are never substituted by other individuals during the run. The PSO algorithm works by attracting the particles to search space positions of high fitness. Each particle has a memory function, and adjusts its trajectory according to two pieces of information, the best position that it has so far visited, and the global best position attained by the whole swarm. If the whole swarm is considered as a society, the first piece of information can be seen as resulting from the particle's memory of its past states, and the second piece of information can be seen as resulting from the collective experience of all members of the society. Like other optimization methods, PSO has a fitness evaluation function that takes each particle's position and assigns it a fitness value. The position of highest fitness value visited by the swarm is called the global best. Each particle remembers the global best, and the position of highest fitness value that has personally visited, which is called the local best.

Many attempts were made to improve the performance of the original PSO algorithm and several new parameters were introduced such as the inertia weight [36]. The canonical PSO with inertia weight has become very popular and widely used in many science and engineering problems [37–40].

In the canonical PSO, each particle i has position z_i and velocity v_i that is updated at each iteration according to Eq. (1)

$$\vec{v}_i = \omega \vec{v}_i + c_1 \vec{\varphi}_{1i}(\vec{p}_i - \vec{z}_i) + c_2 \vec{\varphi}_{2i}\left(\vec{p}_g - \vec{z}_i\right) \tag{1}$$

where ω is the inertia weight described in Refs. [41,42], $\vec{p}_i$ is the best position found so far by particle $\vec{p}_i$, and $\vec{p}_g$ is the global best so far found by the swarm. $\vec{\varphi}_1$ and $\vec{\varphi}_2$ weights that are randomly generated at each step for each particle component. c_1 and c_2 are positive constant parameters called acceleration coefficients (which control the maximum step size the particle can achieve). The position of each particle is updated at each iteration by adding the velocity vector to the position vector.

$$\vec{z}_i = \vec{z}_i + \vec{v}_i \tag{2}$$

Table 4
Comparison of the PSO–$DEM_{exponential}$ and PSO–DEM_{linear} models.

Year	Actual data (Mboe)[a]	PSO–$DEM_{exponential}$	Relative error (%)	PSO–DEM_{linear}	Relative error (%)
2000	382.700	384.045	0.351	386.773	1.064
2001	392.400	388.317	−1.041	389.436	−0.755
2002	406.000	401.876	−1.016	404.594	−0.346
2003	414.100	421.502	1.787	425.571	2.770
2004	427.100	431.958	1.137	436.778	2.266
2005	457.400	443.353	−3.071	452.985	−0.965
Average	_	_	1.40	_	1.36

1 barrels of oil equivalent (boe) = 6119×10^6 joule(J).
[a] Mboe:Million barrel of oil equivalents.

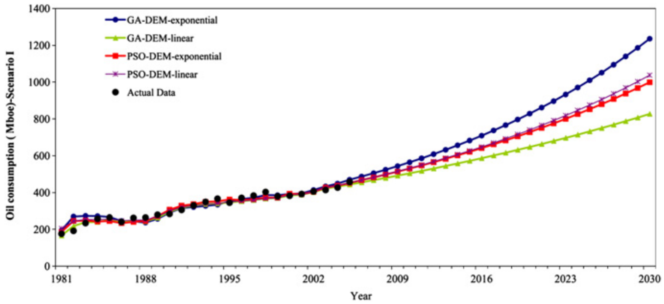

Fig. 2. Comparison between observed and estimated values for oil demand (1981–2005) and future projection according to scenario I (2006–2030).

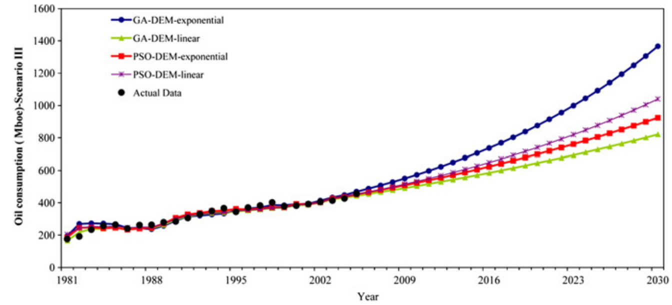

Fig. 4. Comparison between observed and estimated values for oil demand (1981–2005) and future projection according to scenario III (2006–2030).

The inertia weight ω (which is a user-defined parameter), together with c_1 and c_2, controls the contribution of past velocity values to the current velocity of the particle. A large inertia weight biases the search towards global exploration, while a smaller inertia weight directs towards fine-tuning the current solutions (exploitation). Suitable selection of the inertia weight and acceleration coefficients can provide a balance between the global and the local search [36]. The PSO algorithm is composed of 5 main steps:

1. Initialize the position vector z and associated velocity v of all particles in the population randomly. Then set a maximum velocity and a maximum particle movement amplitude in order to decrease the cost of evaluation and to get a good convergence rate.
2. Evaluate the fitness of each particle via the fitness function. There are many options when choosing a fitness function and trial and error is often required to find a good one.
3. Compare the particle's fitness evaluation with the particle's best solution. If the current value is better than previous best solution, replace it and set the current solution as the local best. Compare the individual particle's fitness with the population's global best. If the fitness of the current solution is better than the global best's fitness, set the current solution as the new global best.
4. Change velocities and positions by using Eqs. (1) and (2).
5. Repeat step 2 to step 4 until a stopping criterion is satisfied or a predefined number of iterations is completed. Flowchart of the PSO is shown in Fig. 1.

Particle size (n), inertia weight (ω) and maximum iteration number (t) are considered as important factors in PSO.

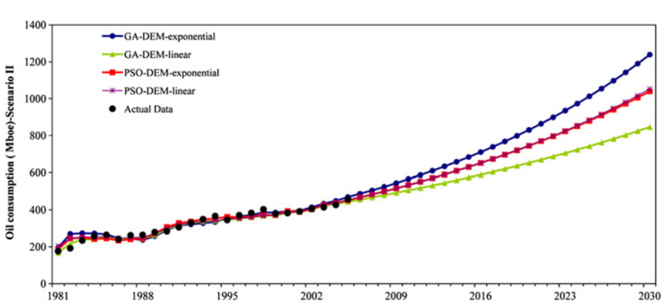

Fig. 3. Comparison between observed and estimated values for oil demand (1981–2005) and future projection according to scenario II (2006–2030).

5. Problem definition

Iran's oil demand by using the structure of the Iran socio-economic conditions is the main objective of this study. GA and PSO demand estimation models (GA–DEM and PSO–DEM) are developed to estimate the future oil demand values based on population, GDP (gross domestic product), import and export figures.

The fitness function, $F(x)$, takes the following form:

$$\text{Min } F(x) = \sum_{j=1}^{m} \left(E_{\text{actual}} - E_{\text{predicted}}\right)^2 \tag{3}$$

where E_{actual} and $E_{\text{predicted}}$ are the actual and predicted oil demand, respectively, m is the number of observations. The data related to the design parameters of Iran's population, GDP, import, export and oil consumption figures are obtained from Ref. [2] and shown in Table 1.

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

$$Y_{\text{linear}} = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5 \tag{4}$$

The exponential form of equations for the demand estimation models is written as follows:

$$Y_{\text{exponential}} = w_1X_1^{w_2} + w_3X_2^{w_4} + w_5X_3^{w_6} + w_7X_4^{w_8} + w_9 \tag{5}$$

where X_1, X_2, X_3, and X_4 are the population, GDP, import and export figures, respectively, and w_i are the corresponding weighting factors.

GA and PSO are applied in order to finding optimal values of weighting parameters based on actual data in order to estimate oil consumption in Iran.

For aiming this purpose, following stages are done:

(a) Population, GDP, import, export and oil consumption need normalizing according to Eq. (6)

$$X_{\text{N}} = (X_{\text{R}} - X_{\text{min}})/(X_{\text{max}} - X_{\text{min}}) \tag{6}$$

X_{min}: Normalized value; X_{R}: The value to be normalized; X_{min}: The minimum value in all the values for related variable; X_{max}: The maximum value in all the values for related variable.

The X_{min} and X_{max} values for each variable are selected between 1981 and 1999 and shown in Table 2.

(b) The proposed algorithms are applied in order to determine corresponding weighting factors (w_i) for each model according

Table 5
Comparison of different models presented in the literature and present study.[a]

Source	Method	Target/Country	Average relative errors (%)
Unler (2008)	Particle Swarm Optimization	Total Energy-Turkey	0.83
Canyurt and Ozturk (2008)	Genetic Algorithm	Oil-Turkey	2.97
	Genetic Algorithm	Natural Gas-Turkey	2.10
	Genetic Algorithm	Coal-Turkey	3.22
Toksari (2007)	Ant Colony Optimization	Total Energy-Turkey	1.07
Azadeh et al. (2008)	Artificial Neural Networks	Electricity-Iran	1.20
Amjadi et al. (2010)	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
Azadeh et al. (2010)	Genetic Algorithm	Electricity-Iran	1.4
	Artificial Neural Networks	Electricity-Iran	1.56
	Fuzzy regression algorithm	Electricity-Iran	0.82
	Partial least square regression	Transport energy demand–China	2.30
Present study	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

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

to the lowest objective functions. The related data (in normalized form according to (a)) from 1981 to 1999 are used in this stage.

(c) Best results (optimal values of weighting parameters) for each model are chosen according to (b) and less average relative errors in testing period. The related data (in normalized form according to (a)) from 2000 to 2005 are used in this section.
(d) Demand estimation models (GA–DEM and PSO–DEM) are proposed using the optimal values of weighting parameters.
(e) In order to use GA–DEM and PSO–DEM models for future projections, each input variable should be forecasted in future time domain. Following scenarios are defined for forecasting each socio-economic indicator in the future:

Scenario I
It is assumed that the annual average growth rates of population, GDP, import and export were 1.6%, 4.5%, 6%, and 3.5% during 2006–2030.

Scenario II
It is assumed that the annual average growth rates of population, GDP, import and export were 1.4%, 4.5%, 6.5%, and 4.5% during 2006–2030.

Scenario III
It is assumed that the annual average growth rates of population, GDP, import and export were 1.5%, 5%, 7.5%, and 2.5% during 2006–2030.

(f) Finally, oil demand is forecasted up to year 2030, using the proposed GA–DEM and PSO–DEM models (d) and scenarios (e).

6. Results and discussions

The PSO algorithm was coded with MATLAB 2007 and for GA algorithm, toolbox of MATLAB 2007 was used. The convergence of the objective function and sensitivity analysis were examined for varying user-specified parameters of GA (population size, methods of selection, reproduction, crossover, mutation and generation) and PSO (particle size (n), inertia weight (ω) and maximum iteration number (t)). Each user-specified parameter combination (for each algorithm) was tested 10 times.

It was found that in GA, the variations in population size, creation function, crossover fractions and mutation scale had most effect on fitness function while number of generation had minimum effect on it.

For PSO, the variations in the t parameter had no major effect as other parameters (n and ω) on fitness function.

The GA and PSO models are implemented using the following user-specified parameters:

GA:

Population: (Population size: 20, Population type: Double vector, Creation function: Uniform).
Selection: (Selection function: Stochastic uniform).
Reproduction: (Elite count: 2.0, Crossover fractions: 0.8).
Crossover: (Crossover function: Scattered).
Mutation: (Mutation function: Gaussian, Scale: 1.0, Shrink: 1.0).
Stopping criteria: (Generation: 100).

PSO:

Maximum Iteration number (t): 200.
Particle size (n): 36.
Inertia weight (ω): 0.2.

Following GA and PSO demand estimation equations (Eqs. (7)–(10)) have been obtained for oil consumption. In the linear form of the GA–DEM and PSO–DEM models, coefficients obtained are given below:

$$Y_{\text{GA-DEM}_{\text{linear}}} = 0.3185X_1 + 0.2912X_2 - 0.0874X_3 + 0.3382X_4 + 0.0434 \quad (7)$$

$$Y_{\text{PSO-DEM}_{\text{linear}}} = 0.2713X_1 + 0.3443X_2 - 0.0528X_3 + 0.181X_4 + 0.127 \quad (8)$$

In the exponential form of the GA–DEM and PSO–DEM models, coefficients obtained are given below:

$$Y_{\text{GA-DEM}_{\text{exponential}}} = 0.0051X_1^{1.0517} + 0.5731X_2^{0.9819} - 0.2769X_3^{0.2235} + 0.461X_4^{0.1628} - 0.0811 \quad (9)$$

$$Y_{\mathrm{PSO-DEM_{exponential}}} = 0.42725X_1^{0.8301} + 0.41675X_2^{0.635} - 0.0334X_3^{0.4651} + 0.111X_4^{1.1191} - 0.0437 \quad (10)$$

These equations were obtained from the general forms of Eqs. (4) and (5).

For the best results of GA, the average relative errors on testing data were 2.83% and 1.72% for GA–DEM$_{\mathrm{exponential}}$ and GA–DEM$_{\mathrm{linear}}$, respectively. The corresponding values for PSO were 1.40% and 1.36% for PSO–DEM$_{\mathrm{exponential}}$ and PSO–DEM$_{\mathrm{linear}}$, respectively.

Tables 3 and 4 show that PSO and GA demand estimation models are in good agreement with the observed data but PSO–DEM$_{\mathrm{exponential}}$ outperformed other models presented here.

In Figs. 2–4, oil consumption is projected through 2030, respectively.

The annual average of growth rate for oil consumption based on best model (PSO–DEM$_{\mathrm{linear}}$) between 2006 and 2030 for scenario I, scenario II and scenario III were 4.60%, 5.30% and 5.18%, respectively.

The annual average of growth rate for oil consumption from 1981 to 2005 was 5.04%.

Comparison between presented models in the literature and presented models in this study is shown in Table 5.

7. Conclusion

Energy consumption growth rate shows the importance of the need for systematic optimization of the energy consumption in Iran.

Artificial intelligence methods have been successfully used to estimate Iran's oil demand based on the structure of the Iran socio-economic conditions. 25 Years' data (1981–2005) has been used for developing two forms (linear and exponential) of the GA and PSO demand estimation models. Three scenarios are designed in order to estimate Iran's oil demand during 2006–2030. Validations of models show that PSO and GA demand estimation models are in good agreement with the observed data but PSO–DEM$_{\mathrm{linear}}$ outperformed other models presented here. 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. They are also instrumental to scholars and policy makers as a potential tool for developing energy plans.

Future work is focused on comparing the methods presented here with other available tools. Forecasting of oil demand can also be investigated with Bees Algorithm, Artificial Bee Colony, Ant Colony, fuzzy logic, neural networks or other metaheuristic such as tabu search, simulated annealing, etc. The results of the different methods can be compared with the GA and PSO methods.

Acknowledgments

The authors are grateful for the support provided for the present work by the Islamic Azad University, Dezful Branch and Iran's Ministry of Energy. The authors also highly appreciate the constructive comments of the reviewers.

References

[1] Houri Jafari H, Baratimalayeri A. The crisis of gasoline consumption in the Iran's transportation sector. Energy Policy 2008;36:2536–43.
[2] Energy Balance Annual Report. Tehran: Ministry of Energy; 2005.
[3] Karbassi AR, Abduli MA, Mahin Abdollahzadeh E. Sustainability of energy production and use in Iran. Energy Policy 2007;35:5171–80.
[4] Hessari FA. Sectoral energy consumption in Iran. Renewable and Sustainable Energy Reviews 2005;9:203–14.
[5] Unler A. Improvement of energy demand forecasts using swarm intelligence: the case of Turkey with projections to 2025. Energy Policy 2008; 36:1937–44.
[6] Canyurt OE, Ozturk HK. Application of genetic algorithm (GA) technique on demand estimation of fossil fuels in Turkey. Energy Policy 2008; 36:2562–9.
[7] Toksari MD. Ant colony optimization approach to estimate energy demand in Turkey. Energy Policy 2007;35:3984–90.
[8] Azadeh A, Ghaderi SF, Sohrabkhani S. A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. Energy Policy 2008;36:2637–44.
[9] Azadeh A, Saberi M, Seraj O. An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: a case study of Iran. Energy 2010;35:2351–66.
[10] Amjadi MH, Nezamabadi-pour H, Farsangi MM. Estimation of electricity demand of Iran using two heuristic algorithms. Energy Conversion and Management 2010;51:493–7.
[11] Zhang M, Mu H, Li G, Ning Y. Forecasting the transport energy demand based on PLSR method in China. Energy 2009;34:1396–400.
[12] Nava M, Gasca J, Gonzalez U. The energy demand and the impact by fossil fuels use in the Mexico City Metropolitan Area, from 1988 to 2000. Energy 2006;31:3381–90.
[13] Amarawickrama HA, Hunt LC. Electricity demand for Sri Lanka: a time series analysis. Energy 2008;33:724–39.
[14] Askari H, Krichene N. An oil demand and supply model incorporating monetary policy. Energy 2010;35:2013–21.
[15] Cinar D, Kayakutlu G, Daim T. Development of future energy scenarios with intelligent algorithms: case of hydro in Turkey. Energy 2010;35:1724–9.
[16] Akay D, Atak M. Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. Energy 2007;32:1670–5.
[17] Ekonomou L. Greek long-term energy consumption prediction using artificial neural networks. Energy 2010;35:512–7.
[18] Jovanovic M, Afgan N, Bakic V. An analytical method for the measurement of energy system sustainability in urban areas. Energy 2010;35(9): 3909–20.
[19] Tang X, Zhang B, Hook M, Feng L. Forecast of oil reserves and production in Daqing oilfield of China. Energy 2010;35:3097–102.
[20] Amjady N, Keynia F. Short-term load forecasting of power systems by combination of wavelet transform and neuro-evolutionary algorithm. Energy 2009;34:46–57.
[21] Pappas SSp, Ekonomou L, Karamousantas DCh, Chatzarakis GE, Katsikas SK, Liatsis P. Electricity demand loads modeling using AutoRegressive Moving Average (ARMA) models. Energy 2008;33:1353–60.
[22] Holland JH. Adaptations in natural artificial systems. Michigan: University of Michigan Press; 1975.
[23] Goldberg DE. Genetic algorithms in search, optimization and machine learning. Reading: Addison-Wesley Longman; 1989.
[24] Grefenstette JJ, Baker JE. How genetic algorithms work: A critical look at implicit parallelism. In: Proceedings of the third Int. Conf. on Genetic Algorithms; 1989. p. 20–7.
[25] Michalewicz Z. Genetic algorithms + data structures = evolution programs. 3rd rev. and extended. Berlin: Springer-Verlag; 1999.
[26] Davis L. Handbook of genetic algorithms. New York: Van Nostrand Reinhold; 1991.
[27] Syswerda G. Reproduction in generational and steady state genetic algorithm. In: Ratlines G, editor. Foundations of genetic algorithms. Los Altos, CA: Morgan Kaufmann; 1991. p. 94–101.
[28] Baker JE. Adaptive selection methods for genetic algorithms. In: Proceedings of Int. Conf. on genetic algorithms and their applications; 1985. p. 101–11.
[29] Goldberg DE, Deb K. A comparison of selection schemes used in genetic algorithms. In: Rawlins GJ, editor. Foundations of genetic algorithms (FOGA 1); 1991. p. 69–93.
[30] Grefenstette JJ. Optimization of control parameters for genetic algorithms. Systems, Man and Cybernetics, IEEE Transactions on 1986;16(1):122–8.
[31] Schaffer JD, Caruana RA, Eshelman LJ, Das R. A study of control parameters affecting online performance of genetic algorithms for function optimization. In: Proceedings of the Third international conference on Genetic algorithms: Morgan Kaufmann, San Francisco, CA; 1989. p. 51–60.
[32] Hinterding R, Michalewicz Z, Eiben AE. Adaptation in evolutionary computation: a survey. In: Proc IEEE international conference on evolutionary computation; 1997. p. 65–9.
[33] Back T. Optimal mutation rates in genetic search. In: Proc fifth Int. Conf. on genetic algorithm. San Mateo: Morgan Kaufmann, 1993. p. 2–9.
[34] Michalewicz Z. A hierarchy of evolution programs: an experimental study. Evolutionary Computation 1993;1(1):51–76.
[35] Kennedy J, Eberhart R. Particle swarm optimization. Proc Neural Networks. In: Proceedings of IEEE International Conference on vol. 1944; 1995. p. 1942–8.
[36] Engelbrecht AP. Fundamentals of computational swarm intelligence. Hoboken, N.J: Wiley; 2005.
[37] Brits R, Engelbrecht AP, van den Bergh F. Locating multiple optima using particle swarm optimization. Applied Mathematics and Computation 2007;189(2):1859–83.
[38] Liu X, Liu H, Duan H. Particle swarm optimization based on dynamic niche technology with applications to conceptual design. Advances in Engineering Software 2007;38(10):668–76.

[39] Pan H, Wang L, Liu B. Particle swarm optimization for function optimization in noisy environment. Applied Mathematics and Computation 2006;181(2):908–19.
[40] Yang IT. Performing complex project crashing analysis with aid of particle swarm optimization algorithm. International Journal of Project Management 2007;25(6):637–46.
[41] Shi Y, Eberhart R. A modified particle swarm optimizer. In: Proceedings of the IEEE international conference on evolutionary computation. Anchorage, Alaska; 1998. p. 69–73.
[42] Shi Y, Eberhart R. Parameter selection in particle swarm optimization. In: Proceedings of the Seventh Annual conference on evolutionary programming. New York; 1998. p. 591–600.