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Selecting the appropriate scenario for forecasting energy demands of residential and commercial sectors in Iran using two metaheuristic algorithms

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Abstract

This study focuses on the forecasting of energy demands of residential and commercial sectors using linear and exponential functions. The coefficients were obtained from genetic and particle swarm optimization (PSO) algorithms. Totally, 72 different scenarios with various inputs were investigated. Consumption data in respect of residential and commercial sectors in Iran were collected from the annual reports of the central bank, Ministry of Energy and the Petroleum Ministry of Iran (2010). The data from 1967 to 2010 were considered for the case of this study. The available data were used partly to obtain the optimal, or near optimal values of the coefficient parameters (1967–2006) and for testing the models (2007–2010). Results show that the PSO energy demand estimation exponential model with inputs, including value added of all economic sectors, value of made buildings, population, and price indices of electrical and fuel appliances using the mean absolute percentage error on tests data were 1.97%, was considered the most suitable model. Finally, basing on the best scenario, the energy demand of residential and commercial sectors is estimated at 1718 mega barrels of oil equivalent up to the year 2032.

Keywords

Energy demand, Forecasting, Genetic algorithm, Particle swarm optimization algorithm, Residential and commercial sectors.

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Introduction

Today, demand management, including the demand for energy, plays a significant role in a country's planning process. However, it has a vital role to play in satisfying economic security so that as an important factor, it plays a direct/indirect role in the production processes of all economic sectors. On the other hand, some factors, such as the implementation of development projects, trend of industrialization in Iran, and the population growth have highlighted the demand for energy carriers (Assareh, Behrang, Assari, and Ghanbarzadeh, 2010). The abundance of oil reserves in Iran and the polices associated with supplying cheap energy carriers have converted different economic sectors to energy consumer units in recent years, so that the domestic production of energy carriers, namely, domestically produced fuel, was not sufficient for purposes of internal consumption, and a fraction of the foreign exchange is allocated to supply the required fuel (Karbassi, Abduli, and Mahin Abdollahzadeh, 2007). According to the latest data obtained from the portal of the Iranian Ministry of Energy (MOE) in 2011, the energy consumption of residential and commercial sectors was 58.8 mega tons of crude oil equivalent (Mtoe)[1] which is a considerable value compared with other sectors. Therefore, predicting the energy demand of these sectors is an important exercise to be undertaken for a proper planning of demand management ("Ministry of Energy. Energy balance annual report. Tehran, Iran," 2012). Energy consumption modeling and predicting are comprehensive subjects which have attracted the attention of many scientists and engineers, and have highlighted both energy production and energy consumption subjects (Ozturk and Ceylan, 2005). Energy planning cannot be practiced without having an acceptable level of knowledge about energy consumption in the past and present, and in predicting the probable energy demand in the future (Sözen, Gülseven, and Arcaklioğlu, 2007). The demand for energy is estimated based on economic and noneconomic indices obtained, probably via linear and nonlinear

1. Mega tons of crude oil equivalent

statistical and mathematical methods as well as simulated models. The nonlinear indices on the one hand and the demand for energy on the other hand have triggered the process of seeking intelligent solutions such as genetic algorithm, the particle swarm optimization (PSO) algorithm, fuzzy-based regression and neural networks (Azadeh and Tarverdian, 2007). The objectives of the study are: (1) selecting the appropriate scenario to predict the energy demands of residential and commercial sectors in Iran; (2) prediction of the annual energy demand of residential and commercial sectors in Iran up to 2032.

Literature Review

There is no doubt as to the importance of the role that energy plays in the lives of people today, and how significant a role it has been even in international relations among nations. The industrial revolution and much of its fast growth, the development of technologies, and the ever increasing facilities which provide welfare for residents are all in some way dependent on energy. The importance of energy has been even more emphasized especially after the energy crisis, and consequently, its impact on the world economy was investigated by many researchers. Residential and commercial sectors consume the biggest amounts of energy in Iran, achieving about 34% of the total energy consumption in 2012. Thus, forecasting residential and commercial demand for energy becomes an essential function in planning for the future, in order to design more efficient systems and control the demand by a proper price mechanism as well (Shakouri and Kazemi, 2011). Many studies have been carried out on intelligent algorithms in order to predict the demand for energy. In the following section, a number of the studies, empirically and theoretically, are presented in Tables 1 and 2.

Table 1. Summary of energy demand estimation empirical studies

Method used	Author(s)	Forecasting for	Independent variables (period of data for model development)
Ordinary Least Squares (OLS)	(Leticia, Boogen, & Filippini, 2012)	Empirical analysis on the residential demand for electricity-Spain	influence of price, income, weather conditions (2000-2008)

Continue Table 1. Summary of energy demand estimation empirical studies

Method used	Author(s)	Forecasting for	Independent variables (period of data for model development)
Auto Regressive Distributed Lags (ADL)	(Madlener & Alt, 1996)	Empirical analysis on the residential energy demand-Vienna	real disposable income, movements in the real price of energy, temperature variable, heating degree days (1970-1992)
Econometric method	(Labandeira, Labeaga, & López-Otero, 2011)	Energy Demand for Heating in Spain: An Empirical Analysis with Policy Purposes	the relative prices of the three main energy sources for heating influence the discrete decision on the type of energy source in a sort of medium/long term effect
Econometric method	(Poyer & Williams, 1993)	Residential energy demand : additional empirical evidence by minority household type-USA	Non-price and income variables. The price elasticities of demand vary with heating and cooling degree days and the income elasticities with the number of household members

The aims of econometric methods consist of experimental investigation into the economic relationships in economic theories, forecasting and decision making, and also evaluating the forecast made by any new policy. Econometric methods are applicable for the model variables once sufficient historical observations exist. In these models, behaviors of variables in the past were extrapolated using the whole historical data, and then they are generalized in the future. Since on the econometric methods, the future relationships between the variables are based on their past relationships, implementing these methods would require stability in their response to economic behavior. These models are suitable for forecasting in the short term, besides, by the use of these models the interaction of the energy sector and other economic sectors may be analyzed. On the other hand, when the relationships between the variables are linear, these models would perform better. However, when variables follow, fluctuating and nonlinear metaheuristic algorithms are more fitting. Metaheuristic algorithms are indeed one kind of proximate optimization algorithms which involve mechanisms for an application out of locally available optimum material, and are applicable in a wide range of problems (Suganthi, Samuel, 2012). These algorithms impose fewer mathematical necessities and they don't need very exactly defined mathematical models. Metaheuristic algorithms conjointly offer efficacious solutions to the high-scale combinatorial and nonlinear problems. Because of these benefits, applications of metaheuristics fall into an oversized variety of areas; one among them being energy models for demand prediction (Talbi, 2009).

Table 2. Summary of energy demand estimation theoretical studies

Method used	Author(s)	Forecasting for	Independent variables (period of data for model development)
Particle Swarm Optimization (PSO)	(Ünler, 2008)	electricity demand Turkey	Population, GDP, import and export (1979-2005)
	(AlRashidi & El-Naggar, 2010)	maximum annual electricity load Kuwait	Peak demands of Egyptian power network during (1977–1993)
	(Kıran, Özceylan, Gündüz, & Paksoy, 2012)	Energy Demand Turkey	GDP, population, import and export
	(Ardakani & Ardehali, 2014)	electricity load Demand Iran and U.S	GDP, energy import, energy export and population (1967-2009)
Genetic algorithm (GA)	(Canyurt & Ozturk, 2008)	fossil fuels demand Turkey	Population, GDP, import and export (1975-2006)
grey hybrid model and genetic algorithm	(Lee & Tong, 2011)	Energy Demand china	used the data collection of (1990-2007)
colony algorithm (CA)	(Kıran, Özceylan, Gündüz, & Paksoy, 2012)	Energy Demand Turkey	GDP, population, import and export
Artificial Neural Networks (ANN)	(Ardakani & Ardehali, 2014)	electricity load Demand Iran and U.S	GDP, energy import, energy export and population

It is owing to a selection of variables that an estimate of the correct amount is one of the issues that can improve the accuracy of prediction of the energy demand. Most studies that have investigated the prediction of energy demand, whether they examined global or overall energy demand, used global variables as inputs in their model. Carefully considering their results shows that they had only a low accuracy in forecasting the energy demand. Therefore, in this study, we have tried to examine more closely the literature and variables that are not considered in this study, that could be more effective in the estimation of the energy demand in residential and commercial sectors. To the best of our knowledge in this study, with a combination of different models, and choosing the appropriate model with the lowest standard error, we hope the gap may be filled.

We use PSO and GA algorithms to select the best scenario for the residential and commercial sectors of Iran, and try to fill out the gap of other studies.

This study has been structured in six sections. After the Introduction and Literature Review section, the next section introduces the theoretical fundamentals of genetic and PSO algorithms in brief. The section following this discusses Methodology. The next section presents the Results and Discussion, and the final section presents the Conclusion.

Metaheuristic Algorithms

Concepts of Genetic Algorithms

Genetic algorithm (GA) is actually the best known type of evolutionary algorithms created and developed by John Holland *et al*. In the 1960s, Rechenberg introduced the evolutionary computing idea in a book titled "Evolution Strategies". Research on genetic algorithm was exactly initialized after research on artificial neural networks. Both fields have been inspired by biological systems as a motivating and computing model. It is an iterative algorithm, and in any iteration, it deals with a single or several different solutions. In a genetic algorithm the searching process is initialized with a population of primary random solutions. If the final criteria are not satisfied, three different operators, reproduction, mutation and crossover, will apply to update the population. Any iteration of the three mentioned operators is considered as a generation. Since the solutions to this algorithm are very similar to natural chromosomes, and the operators work is similar to that of the genetic operators, this algorithm has been named the "Genetic Algorithm". In fact, genetic algorithm searches solution space by repeating three simple steps. In the first step, it assesses a group of points named as population, in accordance with the target function. In the second step, it selects some points as the nominees of the problem's solutions based on the assessments of the previous step, and in the third step, genetic operators are applied to the selected nominees in order to create the population of the next generation. This process is repeated until the final criterion is achieved. This criterion is achieved when an acceptable solution is obtained or the maximum number of a generation is repeated (Haupt and Haupt, 2004).

Concepts of the Particle Swarm Optimization Algorithm

PSO is an evolutionary algorithm for optimizing functions. It has been designed based on the social behavior of birds. It was introduced by Kennedy in 1995. In this algorithm, a group of particles (such as the variables of an optimization problem) is dispersed in the search environment. Obviously, some particles will occupy better positions than the others. Therefore, according to aggregate particle behaviors, other particles will try to raise their position to the prior particle positions. In this method, the position change is done based on every particle's experience obtained in previous motions as well as the experiences of neighboring particles. In fact, every particle is aware of its priority/nonpriority over neighboring particles, as well as over the whole of the group (Haupt and Haupt, 2004).

Figures 1 and 2 show the flow charts of the mentioned algorithms, respectively.

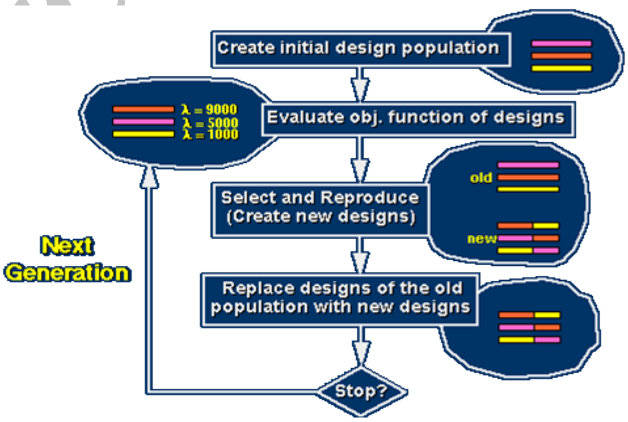

Fig. 1. Genetic algorithm flowchart

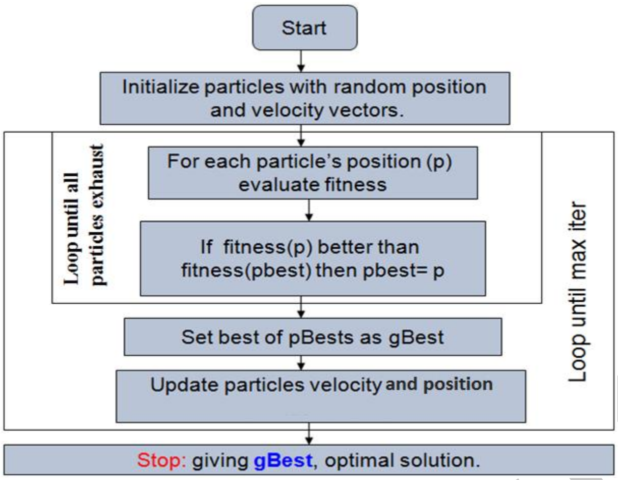

Fig. 2. Particle swarm optimization flow chart[1]

Methodology

Data collection and preprocessing

The data in this study was collected from the annual reports of the central bank, MOE, and the Petroleum Ministry of Iran (2010). These data were divided into the education data (1976–2007) and the test data (2008–2010). First of all, to initialize the computing process using a genetic algorithm and PSO algorithm, the data was converted to normal data with a value between zero and 1. This conversion was performed using Equation (1).

$$z = \frac{x-\mu}{\delta} \tag{1}$$

where z, x, μ and δ are normal distribution function, a variable's value, mean and standard deviation data, respectively.

Development of different scenarios for predicting energy demands of residential and commercial sectors

As was mentioned before, this research assesses different scenarios with different inputs, and selects the best scenario. After studying different researches and acquiring experts' opinions, the model's

1. **Gbest:** The global best location
Pbest: The personal best location

variables, including input and output variables (Shakouri and Kazemi, 2011) were selected as follows.

Output variable

Annual energy consumption in residential and commercial sectors was selected as the output variable of the model. Figure 3 shows the energy consumption rates in residential and commercial sectors from 1967 to 2010.

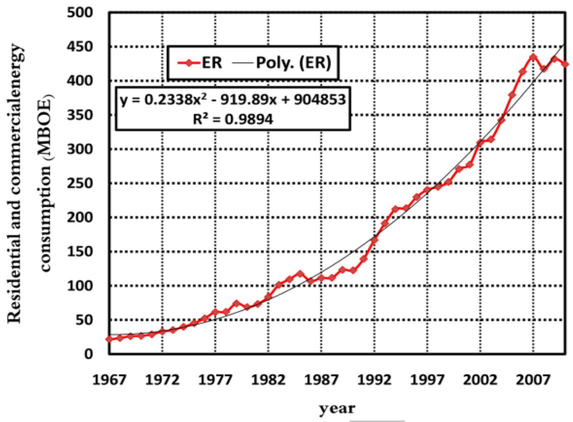

Fig. 3. Energy consumption in residential and commercial sectors

Input variables

Value added

Value added is associated with four economic sectors: oil, industry plus mining, commercial and agriculture. It can serve as an appropriate index for measuring income/welfare of an individual or a family. Regarding the oil sector, income does not directly affect consumption. Therefore, the Value added is divided into two groups: oil and nonoil sectors. Thus, this section's variables are considered as follows. The unit of each variable is determined and its symbol is shown inside parentheses.

- Value added of all economic sectors (total value added): VAT [$10^3 \times$ BIRR]
- The total value added minus that of the oil sector: VAN [$10^3 \times$ BIRR]
- National income: YNI [BIRR]

Figure 4 shows the variables' values from 1967 to 2010.

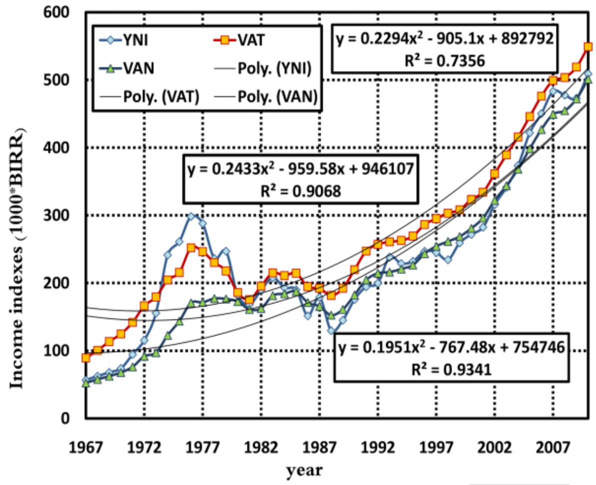

Fig. 4. Income index

Building

The investment in the building sector, or the value of the constructed buildings, shows how many buildings are added annually to previously existing buildings or, in other words, how much energy is required for cooling, heating and ventilation systems of the buildings. On this basis, two variables were considered for this sector:

- Gross fixed capital formation for the constructions: INVC [$10^4 \times$ BIRR]
- Value of made buildings: BLD [$10^4 \times$ BIRR]

Figure 5 shows the variables' values from 1967 to 2010.

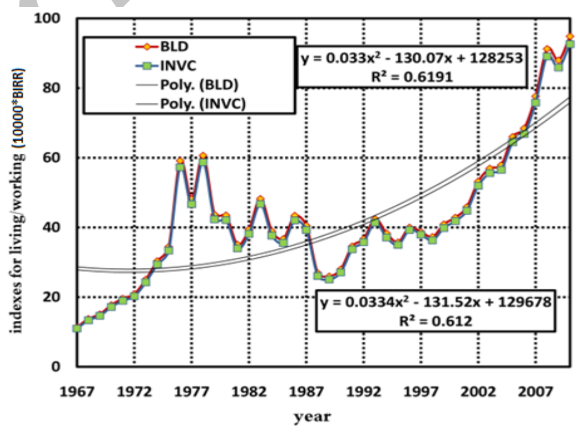

Fig. 5. Living and work space index

Population and Work Force

Undoubtedly, population plays a significant role in the energy consumption of residential and commercial sectors. However, the work force is a part of out-of-home population who affect energy consumption of the sector. Therefore, the influential variables of this section are classified as follows:

- Population: PO [million]
- Total number of households: HNT [million]
- Total labor: LT [million]
- Population minus the labor: PNL [million]

Figure 6 shows the variables' values from 1967 to 2010.

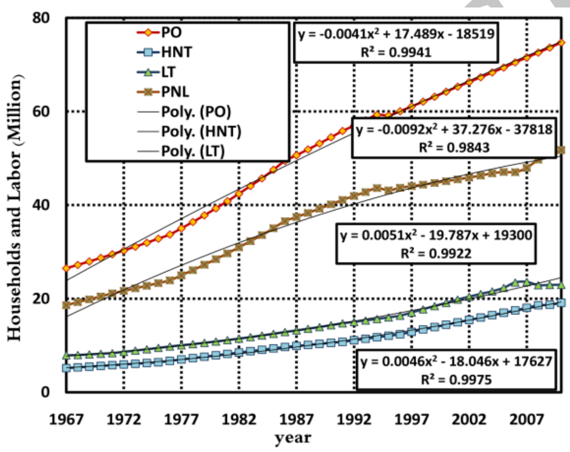

Fig. 6. Population and work force index

Price

The following variables were considered for the price index:

- Electrical and fuel appliances price index: PAPL
- Consumer energy (fuel) price index: PFC
- Energy price index adjusted by the general price index: PFPG

It should be noted that the consumer may not reduce his/her personal rate of consumption even in the event of a price increase, because the residential and commercial sectors' energy is irreplaceable. The consumer, in fact, determines his/her consumption level based on the costs of different fuels, but not based on its previous price. Therefore, the index of energy price adjusted by general price has been taken into account. (Figures 7, 8 and 9) show the variables' values from 1967 to 2010, respectively.

For each socioeconomic indicator, the polynomial trend lines are fitted to the observed data with the highest R^2 (root mean square) values.

Any of the above mentioned input variables can be considered as an input variable. For example, the value addition of all economic sectors, the total added value minus the oil sector and the national income, can be considered as an input variable. Different scenarios assume each of the variables as an input variable and investigate the test data and finally select the best scenario. Regarding 12 input variables (3×2×4×3= 72) leading to 72 parallel models, four were obtained by combining the variables as different scenarios. Table 3 shows the models.

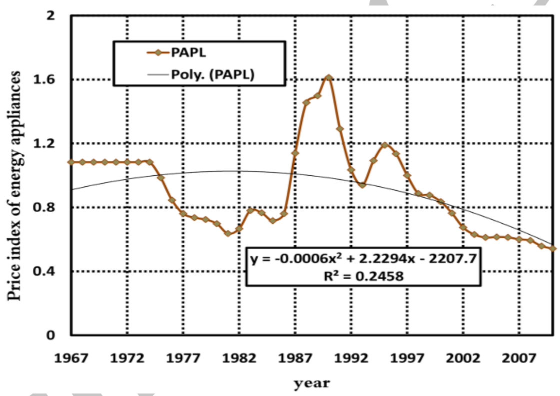

Fig. 7. Electrical appliances and fuel price index (normalized Data)

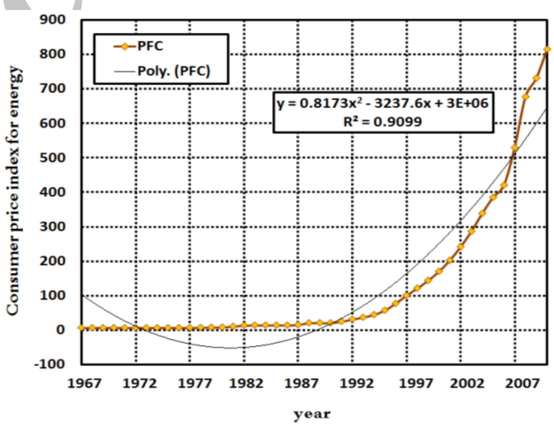

Fig. 8. Energy price for consumer index (1997=100)

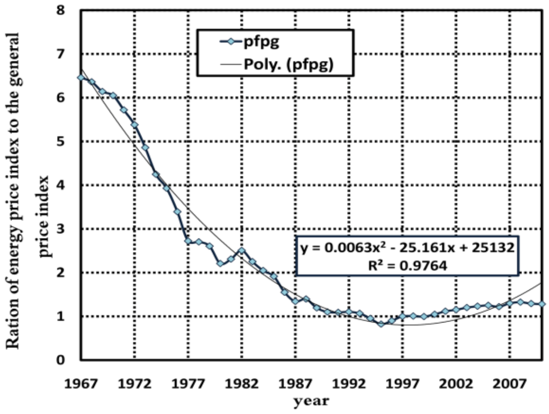

Fig. 9. Energy price adjusted by general price index

Table 3. Models derived from combining the variables

Row	Models				Row	Models			
1	VAN	BLD	HNT	PAPL	37	VAT	INVC	HNT	PAPL
2	VAN	BLD	HNT	PFC	38	VAT	INVC	HNT	PFC
3	VAN	BLD	HNT	PFPG	39	VAT	INVC	HNT	PFPG
4	VAN	BLD	PO	PAPL	40	VAT	INVC	PO	PAPL
5	VAN	BLD	PO	PFC	41	VAT	INVC	PO	PFC
6	VAN	BLD	PO	PFPG	42	VAT	INVC	PO	PFPG
7	VAN	BLD	LT	PAPL	43	VAT	INVC	LT	PAPL
8	VAN	BLD	LT	PFC	44	VAT	INVC	LT	PFC
9	VAN	BLD	LT	PFPG	45	VAT	INVC	LT	PFPG
10	VAN	BLD	PNL	PAPL	46	VAT	INVC	PNL	PAPL
11	VAN	BLD	PNL	PFC	47	VAT	INVC	PNL	PFC
12	VAN	BLD	PNL	PFPG	48	VAT	INVC	PNL	PFPG
13	VAN	INVC	HNT	PAPL	49	YNI	BLD	HNT	PAPL
14	VAN	INVC	HNT	PFC	50	YNI	BLD	HNT	PFC
15	VAN	INVC	HNT	PFPG	51	YNI	BLD	HNT	PFPG
16	VAN	INVC	PO	PAPL	52	YNI	BLD	PO	PAPL
17	VAN	INVC	PO	PFC	53	YNI	BLD	PO	PFC
18	VAN	INVC	PO	PFPG	54	YNI	BLD	PO	PFPG
19	VAN	INVC	LT	PAPL	55	YNI	BLD	LT	PAPL
20	VAN	INVC	LT	PFC	56	YNI	BLD	LT	PFC
21	VAN	INVC	LT	PFPG	57	YNI	BLD	LT	PFPG
22	VAN	INVC	PNL	PAPL	58	YNI	BLD	PNL	PAPL
23	VAN	INVC	PNL	PFC	59	YNI	BLD	PNL	PFC
24	VAN	INVC	PNL	PFPG	60	YNI	BLD	PNL	PFPG
25	VAT	BLD	HNT	PAPL	61	YNI	INVC	HNT	PAPL
26	VAT	BLD	HNT	PFC	62	YNI	INVC	HNT	PFC
27	VAT	BLD	HNT	PFPG	63	YNI	INVC	HNT	PFPG
28	VAT	BLD	PO	PAPL	64	YNI	INVC	PO	PAPL
29	VAT	BLD	PO	PFC	65	YNI	INVC	PO	PFC
30	VAT	BLD	PO	PFPG	66	YNI	INVC	PO	PFPG
31	VAT	BLD	LT	PAPL	67	YNI	INVC	LT	PAPL

Continue Table 3. Models derived from combining the variables

Row	Models				Row	Models			
32	VAT	BLD	LT	PFC	68	YNI	INVC	LT	PFC
33	VAT	BLD	LT	PFPG	69	YNI	INVC	LT	PFPG
34	VAT	BLD	PNL	PAPL	70	YNI	INVC	PNL	PAPL
35	VAT	BLD	PNL	PFC	71	YNI	INVC	PNL	PFC
36	VAT	BLD	PNL	PFPG	72	YNI	INVC	PNL	PFPG

Problem Definition

This study presents the application of the PSO and GA methods to estimate and predict the residential and commercial sectors' energy demand in Iran. The fitness function, F (T), takes the following form as shown in Equation (2):

$$\text{Min F(T)} = \frac{t}{n}|\text{sim}(t) - \text{RE}(t)| \qquad (2)$$

where t, n, sim (t) and re (t) are the time, number of variables, simulated value and actual value of data, respectively.

Forecasting of energy demand in residential and commercial sectors based on economic indicators was modeled by using both linear and exponential models. Moreover, a constant signal and a dummy variable, which indicate the especial conditions of the country in the Revolution years, and the final years of the war, can be added to the model.

The linear form of Equations (3) for the demand estimation models is written as:

$$X_1(t) = \sum_{i=1}^{i=5} \alpha_{1,i}\, t^{\beta_{1.i}}$$

$$..X_4(t) = \sum_{i=1}^{i=5} \alpha_{4,i}\, t^{\beta_{4.i}}$$

$$\text{Ylinear}(t) = c_1X_1(t) + \cdots + c_4X_4(t) + c_5\text{dum}_5(t)$$

$$0 \leq dum \leq 1 \qquad (3)$$

The exponential form of Equations (4) for the demand estimation models is written as:

$$X_1(t) = \sum_{i=1}^{i=5} \alpha_{1,i}\, t^{\beta_{1.i}}$$

$$X_4(t) = \sum_{i=1}^{i=5} \alpha_{4,i}\, t^{\beta_{4.i}}$$

$$\text{Yexponential}(t) = c_1\big(X_1(t)\big)^{\gamma_1} + \cdots + c_4\big(X_1(t)\big)^{\gamma_4} + \ c_5\big(\text{du}m_5(t)\big)^{\gamma_5}$$
$$0 \le dum \le 1 \qquad (4)$$

Here, α, β, γ and c are the coefficients derived from the GA and PSO algorithms. X (t) stands for the model's input variable in terms of time. Y (t) stands for the model's output variable showing the energy consumption of residential and commercial sectors by 1 Mtoe[1]. Moreover, a constant signal and a dummy variable, which indicate the special conditions of the country in the Revolution years and the final years of the war, can be added to the model.

A total of 288 models were designed using genetic and PSO algorithms, and their validity is confirmed using root mean square error (RMSE) fitness function and mean absolute percentage error (MAPE), as Equations (5) and (6) have shown, respectively.

$$\text{RMSE} = \sqrt{\frac{\sum(y_{\text{actual}} - y_{\text{estimated}})^2}{n}} \qquad (5)$$

$$\text{MAPE} = \frac{\sum\left|\frac{y_{\text{actual}} - y_{\text{estimated}})}{y_{\text{actual}}}\right|}{n} * 100 \qquad (6)$$

The y_{actual} and $y_{\text{estimated}}$ are the actual value and estimated value, respectively.

The GA and PSO algorithms were coded with MATLAB R2013a.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). Each user-specified parameter combination (algorithm) was tested 100 times. It was found that in GA, the variations in population size, creation function, crossover fractions and mutation, the scale had most effect on the fitness function, while number of generations had only a minimum effect on it.

The best results of The GA energy demand estimation (GA-DEM) and PSO-DEM models are performed using the following user-specified parameters:

GA:

- Population: Population size: 150.
- Population type: Double vector, creation function: Uniform).
- Selection: (Selection function: Stochastic uniform).
- Reproduction: (Elite count: 2.0, crossover fractions: 0.08).
- Crossover: (Crossover function: Scattered).
- Mutation: (Mutation function: Gaussian, scale: 1.0, shrink: 1.0).
- Stopping criteria: (Generation: 100).

PSO:

- Maximum iteration number (t): 100
- Particle size (n): 40
- Inertia weight (w): 0.6
- $C_1=C_2= 2$

Results

Selecting the Most Appropriate Model for Predicting Energy Demand of Residential and Commercial Sectors

After developing different scenarios and simulating them 100 times, the following four models were selected out of the 288 models to be the best models of linear and exponential states.

The linear Equation (7) was estimated by the GA-DEM:

$$\mathrm{ER} = 8.629045(\mathrm{vat}) + 3.002098(\mathrm{invc}) + 9.642308(\mathrm{PO}) + 6.861753(\mathrm{pfc}) + 0.0315 \quad (7)$$

The exponential Equation (8) was estimated by GA-DEM:

$$\mathrm{ER} = 6.8511\,(\mathrm{vat})^{3.0012} - 7.0299(\mathrm{invc})^{3.6319} + 8.1698(\mathrm{PNL})^{9.6563} + 4.4021(\mathrm{pfc})^{6.4192} + 0.1681 \quad (8)$$

The linear Equation (9) was estimated by the PSO-DEM:

$$ER = 8.054483(vat) + 1.152488(bld) + 1.092040(po) + 6.260510(papl) + 0.0382 \quad (9)$$

The exponential Equation (10) was estimated by the PSO-DEM:

$$ER = -4.0584(vat)^{1.3555} - 3.9628(bld)^{-2.1842} + 2.09336(po)^{7.34966} + 9.4801(papl)^{1.6271} - 0.0041 \quad (10)$$

where ER is energy consumption in residential and commercial sectors, VAT is value addition of all economic sectors (total value added), INVC is the gross fixed capital formation for the constructions, BLD is the value of made buildings, PO is population, PNL is population minus the labor, PFC, consumer energy (fuel) price index, PAPL is electrical and fuel appliances price index.

Figures 10–13 show the curves of the best simulated states of the above four equations.

To select the best model, the test data were assessed using Equations (3) and (4). Tables 4 (a and b) shows the results. According to the results, the best scenario for predicting the energy demand of the residential and commercial sectors of Iran is derived from the exponential model simulated by the PSO algorithm.

The results indicate that among the above possible states, the exponential model derived from the PSO algorithm is the best model with the minimum MAPE and RMSE for predicting the future trend of energy demand of Iran.

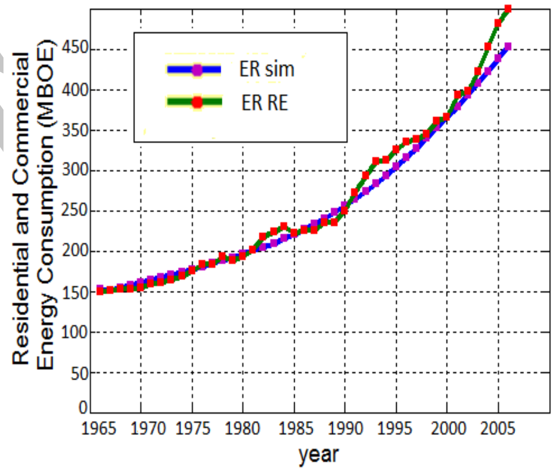

Fig. 10. The best GA-DEM linear model derived from genetic algorithm

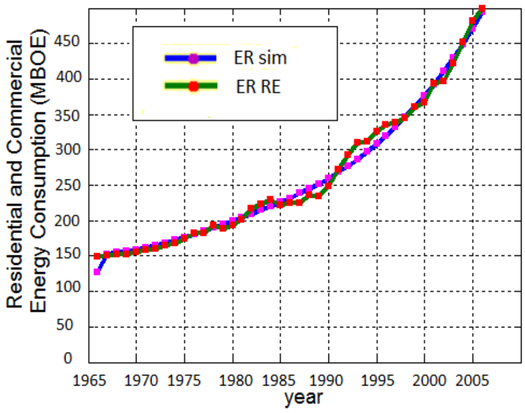

Fig. 11. The best GA-DEM exponential model derived from genetic algorithm

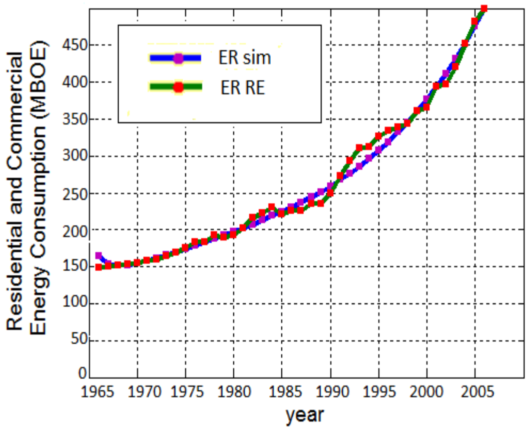

Fig. 12. The best PSO-DEM linear model derived from particle swarm optimization algorithm

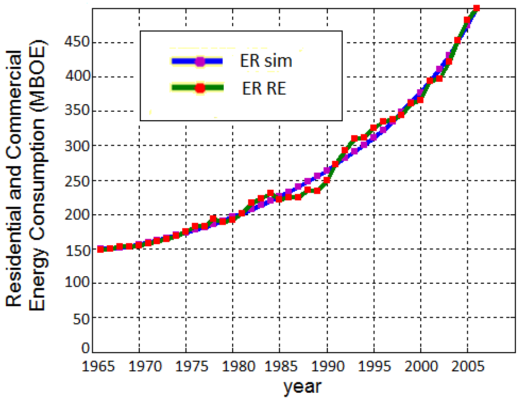

Fig. 13. The best PSO-DEM exponential model derived from particle swarm optimization algorithm

Table 4a. Investigation of test data prediction compared with simulated values with genetic algorithm (by mega barrels of oil equivalent - Mboe)

year	Observed Data, Mboe[a]	GA-DEM exponential	MAPE%	RMSE	GA-DEM linear	MAPE%	RMSE
2007	434.7	433.2	0.003	1.5	441.9	-0.017	7.2
2008	417.4	430.1	-0.03	12.7	443.5	-0.052	26.1
2009	431.9	446.9	-0.037	15	438.2	-0.014	6.3
2010	424.1	440.5	-0.038	16.4	439.5	-0.042	15.4
Average	-	-	2.68	11.4	-	3.25	13.75

Table 4b. Investigation of test data prediction compared with simulated values with particle swarm optimization algorithm (by mega barrels of oil equivalent - Mboe)

year	Observed Data, Mboe[a]	GA-DEM exponential	MAPE%	RMSE	GA-DEM linear	MAPE%	RMSE
2007	434.7	440.7	-0.013	6	440.8	-0.014	6.1
2008	417.4	413.4	0.009	4	431.5	-0.033	14.1
2009	431.9	448.5	-0.038	16.6	445.9	-0.032	14
2010	424.1	416.9	0.016	7.2	442.2	-0.042	18.1
Average	-	-	1.97	8.45	-	3.07	13.07

For the best results of GA, the average relative errors on testing data were 2.68% and 3.25% for GA-DEM$_{exponential}$ and GA-DEM$_{linear}$, respectively. The corresponding values for PSO were 1.97% and 3.07% for PSO-DEM$_{exponentia}$l and PSO-DEM$_{linear}$, respectively.

Validations of models show that PSO-DEM and GA-DEM are in good agreement with the observed data, but PSO-DEM$_{exponential}$ outperformed other models presented here.

These steps are used for forecasting Iran's energy demand in the years 2013–2032.

Prediction of energy demand of residential and commercial sectors up to 2032

Regarding Equation (10), the PSO-DEM $_{exponential}$ model simulated by the PSO algorithm was selected as the best scenario. Therefore, the energy demand of the residential and commercial sectors was predicted up to 2032. According to Figure 14, the energy demand of these sectors will have an increasing trend up to 2032 and grow up to 1718 mega barrels of crude oil equivalent. This value has an exponential growth with the highest R^2 level up to the year 2032.

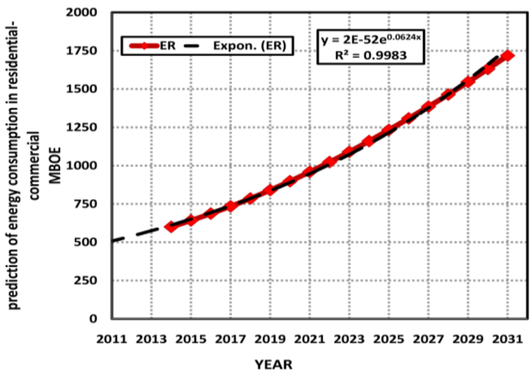

Fig. 14. The prediction of energy consumption in residential and commercial sectors up to 2032

Discussion

In this study, the energy demand of residential and commercial sectors was considered with combining 12 variables as input data and as different models, finally, the suitable models were obtained with the aim of two criteria in error of measurement. Hence, in most of the previous studies in the field of energy, as some of them mentioned in the literature review, they only used 4 variables; export, import, population and gross domestic product as input data, so they couldn't predict the energy demand well.

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

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

Source	Method	Target/Country	[a] MAPE (%)
Ardakani& Ardehali (2014)	PSO -ANN	electricity demand - Iran	5.02
Canyurt & Ozturk (2006)	Genetic Algorithm	Oil- Turkey	0.31 0.99 3.26
Kiran *et al*., (2012)	Particle Swarm Optimization and Ant Colony Algorithm (HAPE)	energy demand -Turkey	1.36 8.34
Ozturk *et al*., (2004)	Genetic Algorithm	energy demand -Turkey	2.72 2.80
Toksari (2007)	Ant Colony Optimization	energy demand -Turkey	1.07
U nler (2008)	Particle swarm optimization Algorithm	energy demand -Turkey	1.41
Present study	Particle swarm optimization Algorithm Genetic Algorithm	Residential commercial-Iran	1.97 3.07 2.68 3.25

[a] Mean Absolute Percentage Error

Conclusion

In this study, different scenarios with various inputs were developed for predicting energy demand of residential and commercial sectors. The scenarios were studied in two linear and exponential states using a genetic algorithm and PSO algorithm. According to our results, the exponential model derived from the PSO model is the best model for the purpose mentioned, with the following inputs:

- Value added of all economic sectors (total value added)
- value of made buildings
- Population
- Electrical and fuel appliance price index

The energy demand of the residential and commercial sectors of Iran was predicted up to 2032, by using the above model. However, different scenarios were developed and the following results were obtained:

- The linear models of genetic and PSO algorithms presented almost the same efficiency. The reason is easy access to optimal results in both algorithms.
- The exponential models of both genetic and PSO algorithms have better efficiency than the linear models providing more accurate solutions. The reason is that the employed variables follow exponential increasing trends.
- The exponential model of PSO has a better efficiency in simulating and predicting energy demand compared with a genetic algorithm. The reason is that a PSO algorithm has a better efficiency in obtaining an optimal point relating to particles' motion when compared with a genetic algorithm.

The prediction of the energy demand in other sectors using the method presented here is highly recommended in future works. However, other metaheuristic algorithms can be used to predict the energy demand of residential and commercial sectors, and the results obtained can be compared with those created from this study. It is also anticipated that this study may be helpful in developing a highly applicable and productive planning for energy policies.

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انتخاب سناریوی مناسب برای پیش‌بینی تقاضای انرژی بخش خانگی- تجاری در ایران با استفاده از دو الگوریتم فرا ابتکاری

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چکیده

این مطالعه با استفاده از توابع خطی و نمایی و با ضرایب به‌دست آمده از الگوریتم‌های ژنتیکی و انبوه ذرات به پیش‌بینی تقاضای انرژی بخش خانگی- تجاری ایران پرداخته است. ۷۲ سناریوی مختلف با ورودی‌های متفاوت بررسی شد. داده‌های مربوط به سال‌های ۱۳۴۶ تا ۱۳۸۹ برای توسعهٔ مدل‌ها و انتخاب سناریوی مناسب استفاده شده است. نتایج نشان داد که مدل نمایی تخمین‌زده شده با استفاده از الگوریتم انبوه ذرات با ورودی‌های ارزش‌افزودهٔ کل منهای بخش نفت، ارزش ساختمان‌های ساخته شده، تعداد کل خانوار و شاخص قیمت مصرف انرژی و درصد میانگین قدرمطلق خطا ۱/۹۷٪ بهترین مدل بوده است که براساس بهترین سناریو، انرژی بخش خانگی- تجاری ایران ۱۷۱۸ میلیون بشکه نفت خام تا سال ۱۴۱۰ پیش‌بینی شده است.

کلیدواژگان

الگوریتم انبوه ذرات، الگوریتم ژنتیکی، بخش خانگی- تجاری، پیش‌بینی، تقاضای انرژی.

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