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The application of particle swarm optimization algorithm in forecasting energy demand of residential - commercial sector with the use of economic indicators

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A B S T R A C T

Energy supply security is one of the strategic issues of all states. Beside the energy supply management, the section that has received less attention is energy demand management. According to importance of residential and commercial sectors in energy consumption, in the present study energy demand of these sectors is estimated using linear and exponential functions and the coefficients are obtained from PSO algorithms. 72 different scenarios with various inputs are investigated. Data from the years 1968 to 2011 are used to develop the models and select the suitable scenario. Results show that an exponential model developed based on particle swarm optimization algorithm has had the best performance. Based on the best scenario the energy demand of residential and commercial sectors is estimated 1718 Mega barrel of crude oil equivalent up to the year 2032.

1. Introduction

Efficient use of energy is a factor that can significantly influence on the sustainable development of countries and not one should disregard this important issue on its way towards development. Due to the increase in population and significant use of energy in various economic sectors in recent years, energy has become the center of attention as the most important production factor (Assareh et al., 2010). Moreover, determining the factors influencing on required energy in a country is necessary in management of energy supplement. According to the fact that the energy demand procedure and factors influencing it follow vague and complicated patterns, identifying efficient tools for proper energy consumption is essential. Therefore, it seems necessary to find efficient tools to identify energy demands, accurately. In Iran, energy estimation in residential and commercial sectors constitutes 34 percent of the total energy consumption (Azadeh & Tarverdian, 2007) .

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This paper predicts the trend of energy demand for residential-commercial sector using linear and exponential models as well as particle swarm optimization algorithm. To this end, different scenarios with various inputs are studied and the best scenario is selected. Several studies are presented to propose some models for energy demand policy management using intelligence techniques. Some of highlighted researches in this field are shown in Table 1.

Table 1

Summary of Iranian energy demand estimation studies

Method used	Author(s)	Forecasting for	Independent variables (period of data for model development)
Particle Swarm Optimization (PSO)	(Assareh et al., 2012)	Forecast World Green Energy	world population, gross domestic product, oil trade movement and natural gas trade movement. (1980-2006)
	(Assareh,et al., 2010)	oil demand	Population, GDP, import and export. (1981–2005)
	(Assareh, Behrang, & Ghanbarzdeh, 2012)	Energy Demand	Population, GDP, import and export. (1981–2005)
	(Piltan, Shiri, & Ghaderi, 2012)	Energy demand in metal industry	electricity tariff, manufacturing value added, prevailing fuel prices, the number of employees, the investment in equipment and consumption in the previous years.(1987-2006)
	(Amjadi et al., 2010) (Bahrami et al., 2014) (Ardakani & Ardehali, 2014)	electricity demand	GDP, population, number of customer's electricity and average price electricity. (1980–2006) temperature average, relative humidity average, wind speed average GDP, energy import, energy export and population (1967-2009)
Genetic algorithm (GA)	(Assareh et al., 2010)	oil demand	Population, GDP, import and export (1981–2005)
	(Assareh, Behrang, & Ghanbarzdeh, 2012)	Energy Demand	Population, GDP, import and export. (1981–2005)
	(Piltan et al., 2012)	Energy demand in metal industry	electricity tariff, manufacturing value added, prevailing fuel prices, the number of employees, the investment in equipment and consumption in the previous years.(1987-2006)
	(Forouzanfar et al., 2010)	natural gas consumption	natural gas consumption in Iran for the 11th, 12th, and 13th year based on the data available for the previous 10 years
Bees Algorithm (BA)	(Behrang et al., 2011)	Total Energy Demand	Population, GDP, import and export (1981–2005)
Gravitational Search Algorithm (GSA)	(Behrang et al., 2011)	oil demand	Population, GDP, import and export, light-duty vehicles, heavy-duty vehicles.(1981-2005)
Artificial Neural Networks (ANN)	(Assareh et al., 2012)	Forecast World Green Energy	world population, gross domestic product, oil trade movement and natural gas trade movement. (1980-2006)
	(Avami & Boroushaki, 2011)	Energy Consumption	gross domestic, product (GDP) and population.(1976–2001)
	(Bahrami et al., 2014) (Ardakani & Ardehali, 2014)	electricity demand	temperature average, relative humidity average, wind speed average
harmony search algorithm (HS)	(Kaveh et al., 2012)	energy demand	Population, GDP and the number of vehicles(1967-2009)

According to the knowledge of these studies, the action of meta-heuristics algorithms to predict the energy demand is essential, but none of the studies has been conducted to evaluate various scenarios to predict energy demand. In the present study, we use particle swarm optimization algorithm (PSO) to select the best scenario for the residential–commercial sector of Iran and try to fill out the gap of other studies.

2. Particle Swarm Optimization Algorithm

Particle swarm optimization is an evolutionary algorithm for optimizing functions, which is designed based on social behavior of birds by Kenedy in 1995. In this algorithm, a group of particles, as the variables of an optimization problem, are dispersed in the search environment. Obviously, some particles will occupy better positions than others do. Therefore, according to aggregative particles' behavior, other particles will attempt to raise their position to the prior particles' positions. In this method, position change is accomplished based on every particle's experience obtained in previous motions as well as the experiences of neighborhood particles. In fact, every particle is aware of its priority/non priority over neighborhood particles as well as over whole the group (Mikki & Kishk, 2008). Fig. 1 shows the flow chart of the mentioned algorithms.

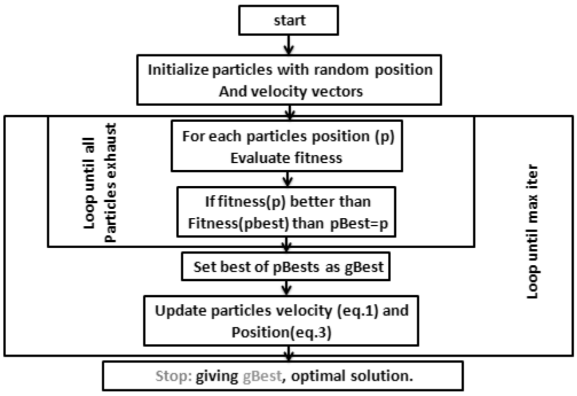


Fig. 1. The proposed study

- Each particle tries to modify its position using the following information:
  - the current positions,
  - the current velocities,
  - the distance between the current position and pbest,
  - The distance between the current position and the gbest.
- The modification of the particle's position can be mathematically modeled according to the following equation :

$$V_i^{k+1} = wV_i^k + c_1 \text{ rand}_1(\ldots) \times (\text{pbest}_i - s_i^k) + c_2 \text{ rand}_2(\ldots) \times (\text{gbest} - s_i^k) \ldots.. \quad (1)$$

where
v_i^k : velocity of agent i at iteration k,
w: weighting function,
c_j : weighting factor,
rand : uniformly distributed random number between 0 and 1,
s_i^k : current position of agent i at iteration k,
pbest_i : pbest of agent i,
gbest: gbest of the group.

The following weighting function is usually utilized in Eq. (1)

$$w = \text{wMax} - [(\text{wMax} - \text{wMin}) \times \text{iter}]/\text{maxIter} \quad (2)$$

where
wMax= initial weight,
wMin = final weight,
maxIter = maximum iteration number,
iter = current iteration number.

$$s_i^{k+1} = s_i^k + V_i^{k+1} \quad (3)$$

3. Materials and methods

As mentioned before, this research evaluates different scenarios with different inputs and selects the best scenario. After studying different research and acquiring experts' opinions, the model's variables including input and output variables Fig. 2B (Shakouri, 2011) are categorized in two sets) described below:

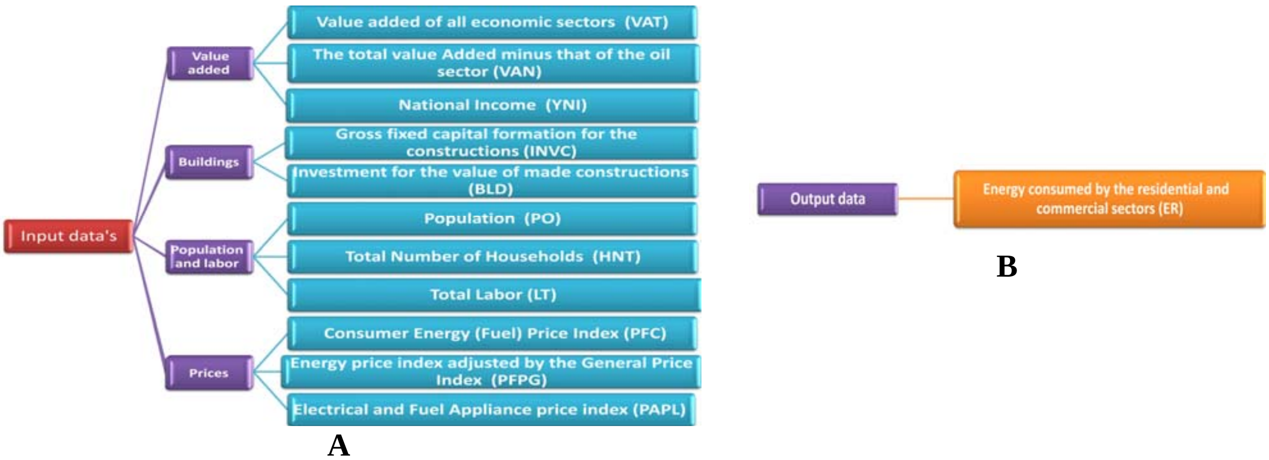


Fig. 2. The prototype of data

Any of the above mentioned inputs can be considered as an input variable. For instance, the added value of all economic sectors, total added value minus petroleum sector and national income can be considered as an input variable. Different scenarios assume each of the variables as an input variable, investigate the test data, and finally select the best scenario. Regarding 12 input variables (Fig. 2A), 72 models of four were obtained by combining the variables as different scenarios. Table 2 shows the models.

Table 2
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
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

Then, each model was investigated in two states: a) linear state as per Eq. (4) and b) exponential state as per Eq. (5). Therefore, it can be argued that 288 scenarios will be investigated.

$$X_1(t) = \sum_{i=1}^{i=5} \alpha_{1,i}\, t^{\beta_{1.i}}$$
$$X_4(t) = \sum_{i=1}^{i=5} \alpha_{4,i}\, t^{\beta_{4.i}} \quad (4)$$
$$y(t) = c_1 x_1(t) + \cdots + c_4 x_4(t)$$
$$y(t) = c_1 (x_1(t))^{\gamma_1} + \cdots + c_4 (x_1(t))^{\gamma_4} \quad (5)$$

Here, α, β, γ and c are the coefficients derived from the genetic algorithm. *x(t)* stands for the model's input variable in terms of time and *y(t)* stands for the model's output variable showing the energy consumption of residential-commercial sector by one mega tons of crude oil equivalent. 288 models were designed using genetic and particle swarm optimization algorithms and their validity is confirmed using root mean square error (RMSE) fitness function and mean absolute percentage error (MAPE) as Eq. (6) and Eq. (7) are shown, respectively.

$$\mathrm{RMSE} = \sqrt{\frac{\sum(\mathrm{y}_{\mathrm{actual}} - y_{\mathrm{estimated}})^2}{\mathrm{n}}} \quad (6)$$

$$\mathrm{MAEP} = \frac{\sum \left| \frac{\mathrm{y}_{\mathrm{actual}} - y_{\mathrm{estimated}})}{\mathrm{y}_{\mathrm{actual}}} \right|}{\mathrm{n}} * 100 \quad (7)$$

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

The data in this study, collected from annual reports of central bank, Iran Ministry of Energy and Iran Ministry of Petroleum. These data were divided into the education data (1976-2007) and the test data (2008-2010). First, to initialize computing process using genetic algorithm and particle swarm optimization algorithm the data were converted to normal data with a value between zero and 1. This conversion was performed using Eq. (8).

$$z = \frac{x - \mu}{\delta} \quad (8)$$

where z, x, μ and δ are normal distribution function, variable's value, data mean and standard deviation, respectively. Since the prediction of energy consumption in residential-commercial sector was the main goal of this study, the competence function, influenced by time, was developed in the form of Eq. (9). This equation enables us for the convergence of the simulated curve to the actual one under the influence of time.

$$minf(t) = \frac{t}{n} |sim(t) - RE(t)| \quad (9)$$

where *t, n, sim(t)* and *re (t)* are the time, number of variables, simulated value and actual value of data, respectively. The software of Matlab version R2013a was used to estimate the optimal coefficients of patterns. The particle swarm optimization algorithm parameters were selected according to Tables 3.

Table 3
Particle swarm optimization algorithm parameters

c_1=c_2	C_0	w	n
2	1*random	0.66	40

4. Results and discussion

4.1. Selecting the most appropriate model for predicting energy demand of residential-commercial sector

After developing different scenarios and simulating them for 100 times, the following four models were selected, out of 288 models, as the best models of linear and exponential states:

The linear form of Eq. (10) was estimated by the particle swarm optimization algorithm:

$$\mathrm{ER} = -8.054483(\mathrm{vat}) + 1.152488(\mathrm{bld}) + 1.092040(\mathrm{po}) + 6.260510(\mathrm{papl}) + 0.0382 \quad (10)$$

The exponential Eq. (11) was estimated by the swarm particle optimization:

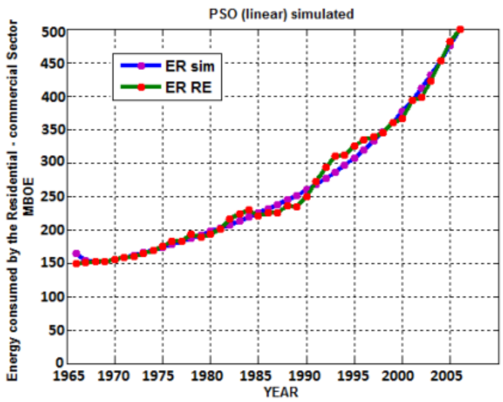
$$\mathrm{ER} = -4.0584(\mathrm{vat})^{1.3555} - 3.9628(\mathrm{bld})^{-2.1842} + 2.09336(\mathrm{po})^{7.34966} + 9.4801(\mathrm{papl})^{1.6271} - 0.0041 \quad (11)$$

where ER, energy consumption in residential-commercial sector, VAT, Value added of all economic sectors (total value added), BLD, Investment for the value of made constructions, PO, Population, PAPL, Electrical and Fuel Appliance price index. Figs. 3 (A and B) show the curves of the best simulated states of the above two equations. To select the best model, the test data were assessed using Eq. (6) and Eq. (7). Tables 4 shows the results. According to the results, the best scenario for predicting the energy demand of residential-commercial sector of Iran is derived from the exponential model simulated by particle swarm optimization algorithm.

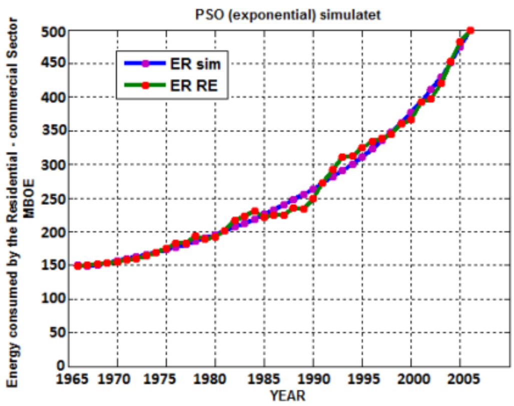
Table 4
Investigation of test data prediction compared with simulated values with particle swarm optimization algorithm (by Mtoe)

year	Observed data, Mboe[a]	PSO-DEM$_{exponential}$	MAPE%	RMSE	PSO- 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

[a]Mboe: Million barrel of oil equivalents.
1 barrels of oil equivalent (boe) = 6,119 × 10^6 joule (J).



A



B

Fig. 3. The curves of the best simulated states of the above two equations

The results indicate that among the above possible states, the exponential model derived from particle swarm optimization algorithm is the best model with the minimum MAEP and RMSE for predicting the future trend of energy demand of Iran. Comparison between presented models in the literature and presented models in this study are shown in Table 5.

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

Source	Method	Target/Country	Average relative Errors (%)
Knave et al. (2012)	Improved Harmony Search	Transport energy/Iran	3.32
	Charged system search	Transport energy/Iran	3.31
Behrang et al (2011)	Gravitational Search Algorithm	Oil-Iran	1.43
	Gravitational Search Algorithm	Oil-Iran	3.32
Behrang et al (2011)	Bees Algorithm	Total Energy-Iran	1.07
	Bees Algorithm	Total Energy-Iran	1.83
Present study	Particle swarm optimization Algorithm	Residential commercial- Iran	1.97
	Particle swarm optimization Algorithm	Residential commercial- Iran	3.07

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

4.2. Prediction of energy Demand of Residential-Commercial Sector up to 2034

According to Eq. (13), the exponential model simulated by the particle swarm optimization algorithm was selected as the best scenario. Therefore, the energy demand of residential-commercial sector was predicted up to 2032. According to the Fig. 4, the energy demand of this sector will have non-decreasing trend up to 2032 and grows up to 1718 Mega barrel of crude oil equivalent.

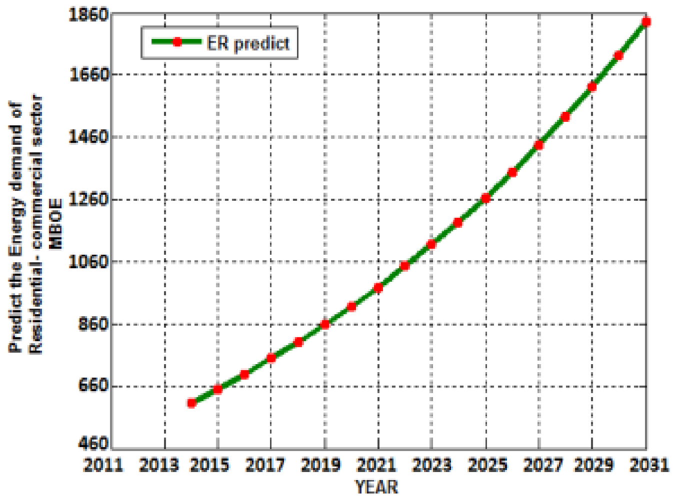


Fig. 4. The results of the proposed study

5. Conclusion

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

1- Value added of all economic sectors (total value added) 2- Investment for the value of made constructions 3- Population 4- Electrical and Fuel Appliance price index.

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