INTERNATIONAL JOURNAL OF
ENERGY AND ENVIRONMENT

Volume 4, Issue 6, 2013 pp.1041-1052
Journal homepage: www.IJEE.IEEFoundation.org

Strategic planning for minimizing CO_2 emissions using LP model based on forecasted energy demand by PSO Algorithm and ANN

M. Yousefi[1], M. Omid[1], Sh. Rafiee[1], S.F. Ghaderi[2]

[1]Department of Agricultural Machinery Engineering, University of Tehran, Karaj, Iran.
[2]Department of Industrial Engineering, University of Tehran, Tehran, Iran.

Abstract
Iran's primary energy consumption (PEC) was modeled as a linear function of five socioeconomic and meteorological explanatory variables using particle swarm optimization (PSO) and artificial neural networks (ANNs) techniques. Results revealed that ANN outperforms PSO model to predict test data. However, PSO technique is simple and provided us with a closed form expression to forecast PEC. Energy demand was forecasted by PSO and ANN using represented scenario. Finally, adapting about 10% renewable energy revealed that based on the developed linear programming (LP) model under minimum CO_2 emissions, Iran will emit about 2520 million metric tons CO_2 in 2025. The LP model indicated that maximum possible development of hydropower, geothermal and wind energy resources will satisfy the aim of minimization of CO_2 emissions. Therefore, the main strategic policy in order to reduce CO_2 emissions would be exploitation of these resources.

Keywords: Artificial Neural Network; CO_2 emissions; Energy demand modeling; Linear programming; Particle Swarm Optimization; Renewable energy; Sensitivity analysis.

1. Introduction
Modeling, estimation and identification of energy demands according to various explanatory parameters are appropriate tools which can help decision makers to implement proper policies and optimize energy consumptions and minimize its relevant pollutants. In 2010, Iran consumed 2% of total primary energy of the world [1]. The country has major fossil fuel energy resources and also, there is a considerable potential of applying renewable energies such as solar, wind, geothermal and etc [2, 3]; thus, it is independent to provide its energy requirement. It is, therefore, necessary to be aware of the amount of the primary energy demand according to effective parameters. Because it can lead us to adapt proper policies in order to optimize energy consumption, enhance related global indices such as greenhouse gas emissions (GHG), and/or increase renewable energy consumption. On the other hand, Iran is a country which has a strong and dynamic economy, so it should provide the cost and technologies to reduce specially GHG emissions which is in accordance with the Kyoto Protocol.
The application of statistical regression is bounded by some strict assumptions about the given data set and this model can be used only if the given data are distributed according to a statistical model and the relation between inputs and outputs is crisp. While, artificial and swarm intelligence methods which are fundamentally different can solve many complex problems accurately because of high flexibility, reasonable estimation and prediction ability dealing with noisy data.

One of the most popular techniques for modelling and/or forecasting the behaviour of nonlinear systems such as economic and financial systems is soft computing. For example, artificial neural networks (ANN) which represent an alternative to standard regression techniques are particularly useful for dealing with nonlinear univariate or multivariate relationships. Hence, these techniques have been applied in many scientific fields, including engineering and financial systems. Several studies were conducted in order to model and predict electricity, gasoline, oil and natural gas demand all over the world. In these studies, various parameters such as population, gross domestic production, the price of energy carrier, number of vehicles, import, export and etc. were applied to model a part of energy demand [4-8]. Amjadi et al. [4] applied PSO and GA techniques to forecast electricity demand for Iran. Assareh et al. [5] applied PSO and GA techniques to forecast oil demand based on the structure of the socioeconomic conditions in Iran. They developed exponential and linear forms of equations to obtain expressions for oil demands. Also, they forecasted energy demand in Iran based on industry and economic condition [8]. In another study, they used Bees algorithm to estimate total energy demand in Iran [9]. Ekonomou [6] employed ANN to predict long-term energy consumption of Greek. There are several studies that researchers have tried to identify the relationships between economic, environmental or meteorological impacts and energy consumption [10-13], so it can be assessed energy consumption sensitivity to various parameters.

Here, Iran's PEC is modeled as a function of five independent variables including population (POP), average minimum temperature (AMT), gross domestic production (GDP), net income (NI) and incremental capital output ratio (ICOR) using PSO and ANN techniques. The results of PSO and ANN models to predict PEC are compared by statistical analysis using mean absolute percentage error (MAPE) and coefficient of determination (R^2). Also, sensitivity analysis is conducted to determine how different values of independent variables impact on PEC under a given set of assumptions. All of these efforts are conducted to represent a model for estimating Iran's energy demand according to socioeconomic and meteorological parameters which are independent of energy resources. Finally, the possible options of using renewable energies that can reduce CO_2 emissions considering energy supply till the year 2025 according to available energy resources in Iran are assessed using the developed linear programming (LP) model.

2. Materials and methods

2.1 Data features structure

Five independent variables including population (POP), gross domestic production (GDP), average minimum temperature (AMT), net income (NI) and incremental capital output ratio (ICOR) were applied to model PEC using PSO and ANN techniques. POP and AMT are in the units of one thousand persons and degree Celsius. Also, GDP and NI are both in the units of billion Iranian Rials (the based cost of 1997). In addition, PEC is in the unit of million barrel crude oil equivalent (Mboe). The data (1973-2006) are represented in Table 1 from the Refs [14-16].

The PEC of Iran equals the difference between the annually energy supply (production or import) and the energy export. Oil and NG were the two main energy resources (which more than 97% of PEC consisted of them) in the last two decades and the consumption of the other energy resources such as coal, hydropower and renewable are not significant in Iran. Population growth and economic development are closely related to energy consumption. Also, incremental capital output ratio (ICOR) is an indicator which reveals the ratio of investment in previous periods to production increase in later periods. In fact, this index is a measure of the productivity of capital. One of the applications of ICOR is to estimate the investment required to achieve the target rate of economic growth. On the other hand, the share of residential and public sector in energy consumption is the highest and the energy is mostly consumed for heating and in electrical form; hence, AMT of ten most populated cities of Iran was used as a meteorological parameter which is identified effective on PEC estimation.

Like previous studies [5,13], inputs and output data were normalized into the range [-0.9, 0.9] in order to greatly improve learning speed according to Eq. (1).

$$x^* = 1.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) - 0.9 \tag{1}$$

where x*, x, x_{min} and x_{max} are the normalized value, the value to be normalized, the minimum value in all the values for related variable and the maximum value in all the values for related variable, respectively. The values for normalization are represented in Table 2.

Table 1. Primary energy consumption (PEC), population (POP), average minimum temperature (AMT), incremental capital output ratio (ICOR), gross domestic production (GDP) and net income (NI) of Iran between 1973 and 2006

Year	POP ($\times 10^3$ person)	AMT (°C)	ICOR	GDP ($\times 10^9$ Iranian Rials)	NI ($\times 10^9$ Iranian Rials)	PEC (Mboe)
1973	31106.3	8.64	4.1	174668.4	115368.8	170.2
1974	31950.7	8.91	2.6	196581.0	155649.4	185.1
1975	32817.9	9.20	7.1	206113.8	241369.7	207.6
1976	33708.7	9.50	2.7	242326.0	261044.0	238.4
1977	35025.2	8.88	-22.8	236645.3	298227.0	265.3
1978	36393.1	8.58	-6.4	219191.0	287920.3	252.1
1979	37814.3	8.38	-9.9	209919.4	236256.5	277.8
1980	39291.1	8.80	-2.0	178149.0	246977.3	252.2
1981	40825.6	9.11	-8.5	170281.2	181690.1	270.2
1982	42420.0	8.05	2.9	191666.8	167943.3	293.8
1983	44076.6	8.16	3.1	212876.5	189465.9	355.9
1984	45720.7	8.20	21.9	208515.9	207798.7	386.7
1985	47541.4	8.52	21.2	212686.3	193059.8	425.4
1986	49445.0	8.71	-3.6	193235.4	190020.6	392.5
1987	50650.0	9.34	-31.2	191312.4	151510.1	414.1
1988	51890.0	9.32	-5.6	180822.5	178770.0	416.9
1989	53167.0	8.61	4.4	191502.6	129657.9	459.2
1990	54483.0	9.13	1.9	218538.7	145080.0	496.0
1991	55837.0	9.35	2.2	245036.4	175631.9	545.7
1992	56963.0	8.13	8.6	254822.5	194495.0	593.1
1993	58114.0	8.83	21.5	258601.4	199788.7	658.3
1994	59290.0	9.39	57.0	259876.3	238445.5	708.0
1995	59151.0	9.19	8.1	267534.2	228785.2	740.6
1996	60055.5	9.39	3.7	283806.6	232124.5	787.4
1997	61070.4	9.50	9.4	291768.7	246865.3	821.8
1998	62102.5	10.05	10.0	300139.6	244857.4	846.6
1999	63152.0	10.06	18.0	304941.2	234347.4	877.0
2000	64219.3	9.86	6.0	320068.9	259203.6	923.7
2001	65301.3	10.43	9.1	330564.8	271785.4	937.1
2002	66300.4	10.02	4.0	357670.9	282526.5	996.4
2003	67314.8	10.07	4.4	385630.3	317877.7	1057.2
2004	68344.7	9.55	5.6	410428.8	341161.0	1138.2
2005	69390.4	7.55	5.3	438899.9	373506.0	1239.9
2006	70495.8	9.65	5.7	467930.0	357594.1	1350.7

Table 2. Values used for input-output data normalization

Parameter	MIN	MAX
POP	31106.3	70495.8
AMT	7.55	10.43
ICOR	-31.2	57
GDP	170281.2	467930.0
NI	115368	373506.0
PEC	170.2	1350.7

2.2 Particle swarm optimization

Particle swarm optimization (PSO), which was first introduced in 1995 [17], is founded on the interaction and social communication of the swarm members such as bird flocking, fish training and etc. PSO is a combined local and global search; and also, low memory and CPU speed are enough to obtain the best solution, because PSO is able to storage the previous solution to compare with new ones. In addition, it is simple to apply; because a few parameters should be defined and/or adjusted. All of these features and obtaining the most accurate and appropriate solutions quickly have made PSO excellent to be used.

At first, PSO algorithm was used to discover the birds flying patterns and their sudden route alteration. Swarm members called particles can be led to obtain the best solution using the experiences of all particles or social intelligence approach. Since all particles cooperate to reach the chief aim, this method is more effective than the methods which individual agents act. In fact, the particles reform their movement toward the aim according to the best previous position of themselves and other neighbours in every iteration.

In PSO, the velocity and position of particles are updated using Eqs. (2) and (3), respectively. These equations are the main part of updating particles experiment in searching space.

$$v_i(t+1) = w \times v_i(t) + C_1 \times rand_1(Pbest_i(t) - x_i(t)) + C_2 \times rand_2(Gbest_i(t) - x_i(t)) \tag{2}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

where '*i*', '*t*', '*v*', '*x*', 'rand', 'Pbest' and 'Gbest' are particle number, iteration number, particle velocity, particle position, random function, the best position ever visited by particle *i* and the best position discovered so far, respectively. In addition, '*w*', 'C_1' and 'C_2' are positive constant, which are called inertia weight and acceleration coefficients. In this paper, '*w*', 'C_1' and 'C_2' were defined 0.01, 2 and 2, respectively. The flowchart of PSO is represented in Figure 1.

The PSO procedure was written in MATLAB 7 (R2010b) software [18]. Also, the random normalized data were divided into two parts: train and test sets by portion of 70% and 30%, respectively. The considered linear model for this problem is represented in Eq. (4).

$$PEC(j) = A_1 Y_1(j) + A_2 Y_2(j) + A_3 Y_3(j) + A_4 Y_4(j) + A_5 Y_5(j) \tag{4}$$

In addition, the mean absolute percentage error (MAPE) was used as fitness function:

$$Fitness\_Function = \frac{100}{n} \sum_{j=1}^{n} \left| \frac{Y_j - \hat{Y}_j}{Y_j} \right| \tag{5}$$

where A_1 to A_5 are PSO coefficients and Y_1 to Y_5 are POP, GDP, ICOR, NI and AMT, respectively. Also, Y_j is the real PEC and $\hat{Y}_j$ is the PSO estimation of PEC of *j*th year, respectively. In Eq. (5), 'n' is the total number of training data. Ultimately, the PSO coefficients were used to estimate PEC of the ten remained test data and the model error was estimated.

2.3 Artificial Neural Networks

Artificial neural networks (ANN) developed in 1950s in order to imitate human brain's biological structure, is a very frequently used method in recent years for modeling and prediction purposes. ANNs are parallel information processing methods which can express complex and nonlinear relationship using number of input-output training patterns from the experimental data.

In this study, NeuroSolutions 5.07 package [19] was used to develop ANN models for predicting Iran's PEC. One hidden layer multilayer perceptron (MLP) networks with different number of processing elements are selected for the present problem. Also, POP, AMT, GDP, NI and ICOR were applied as inputs and Iran's PEC was the network output. Similarly, data were divided into train and test sets by portion of 70% and 30%, respectively. In addition, four data were determined as cross validation in order to improve ANN learning. The MLPs having gradient descent with momentum (GDM) algorithm [20] as learning rule, with one hidden layer, TanhAxon as transfer function for hidden layer and BiasAxon as transfer function for output layer were developed. Leave N Out cross-validation approach was used in order to train the networks. This method randomly splits the dataset into training and validation data. It presents one way to estimate the accuracy of the model without the need for creating additional data [21]. Here, networks are trained multiple times leaving out different sections of data for each run. This training procedure is very useful for testing the robustness of a model on small datasets. Here we divided the 24 data into six (N = 6) subsets of nearly equal size. We then trained the net N times, each time leaving out one of the subsets from training, but using only the omitted subset to compute error criterion.

The data set used to train ANN models were the same as those used to develop PSO model, Eq. (4). In addition, the test data are the same in order to compare the performance of proposed models. An example of MLP network with one hidden layer having 5 neurons in its hidden layer (i.e., a 5-5-1 architecture) to model PEC is represented in Figure 2.

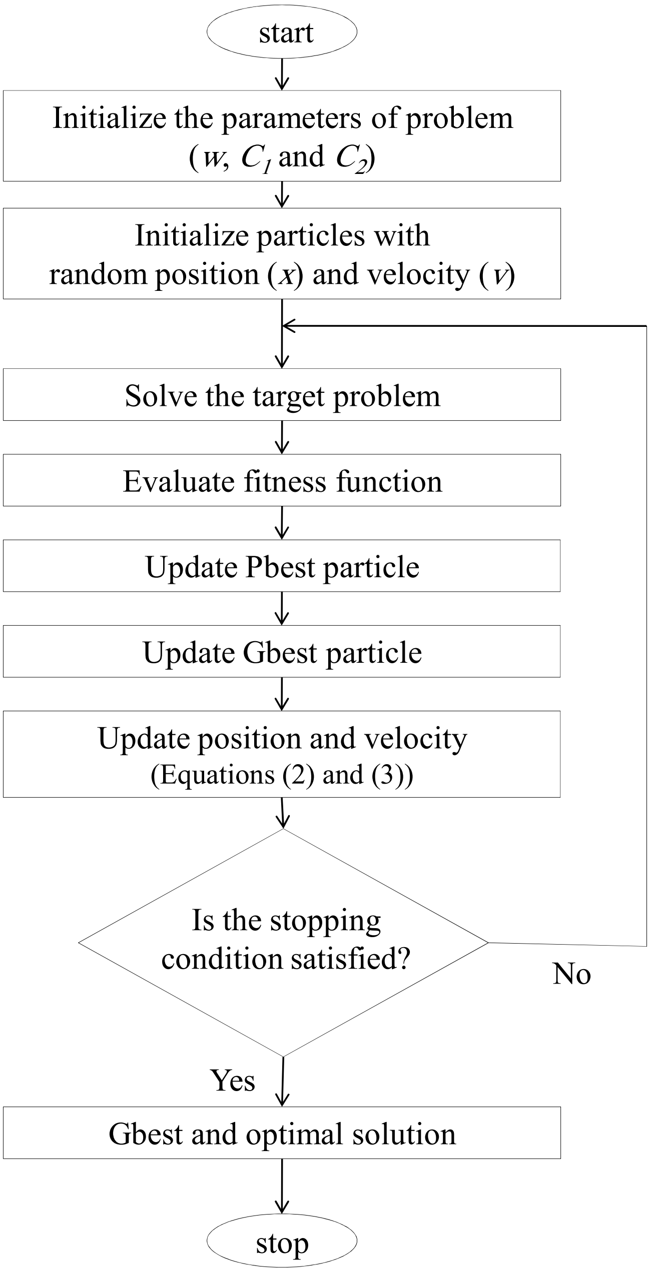

Figure 1. Particle swarm optimization flowchart

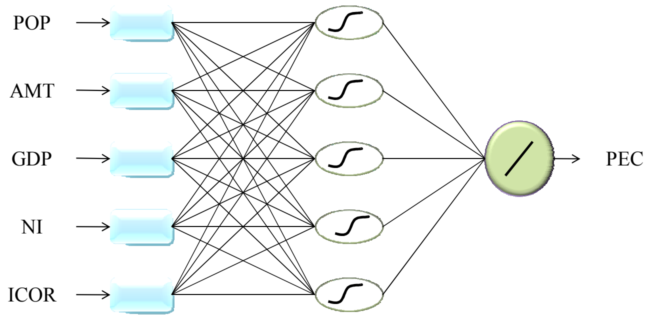

Figure 2. Topology of a simple fully connected by 5-5-1 architecture

2.4 Linear programming

Linear programming (LP) is the most commonly used form of constrained optimization. It is supposed that energy demand follows linear model as it is discussed in previous sections. The following linear constrains as can be used to minimize objective function i.e., CO_2 emissions minimization, in Iran for the year 2025:

1. 10% of total PEC which will be supplied from renewable energy resources (maximum possible rate).
2. According to the necessities of Iran's economic structure, population growth and replacement policy of natural gas (NG) with oil for domestic consumption to boost oil export, annually growth rate of NG and oil are considered 3% and 1%, respectively. Consequently, NG demand would equal 1.7 of oil demand.

In order to determine the objective function, CO_2 emissions coefficients for all accessible energy resources are represented in Table 3. Formulation of LP model is represented as:

$$Min\ CO_2\ Emissions = 1196800\ x_1 + 64600\ x_1 + 812600\ x_2 + 221000\ x_2 + 1507900\ x_3 + 149600\ x_3 + 49300\ x_4 + 18700\ x_5 + 25500\ x_6 + 90100\ x_7 + 49300\ x_8 \tag{6}$$

Subject to:

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 \geq TED$$
$$x_4 + x_5 + x_6 + x_7 + x_8 \leq PERE$$
$$1.7x_1 - x_2 = 0$$

where TED and PERE stand for the total energy demand and the possible exploitation of renewable energy, respectively. This problem was solved using LINDO version 6.1.

Table 3. Direct and indirect CO_2 emissions

Energy Resources	**variable**	**CO_2 emissions coefficients ton CO_2/Mboe**	
		Direct	**Indirect**
Oil	X_1	1196800	64600
Natural gas	X_2	812600	221000
Coal	X_3	1507900	149600
Nuclear	X_4	-	49300
Hydropower	X_5	-	18700
Geothermal	X_6	-	25500
Solar	X_7	-	90100
Wind	X_8	-	49300

2.5 Statistical analysis

In order to quantify the performance of ANN models for predicting the desired output of PEC, some quality parameters including the coefficient of determination (R^2) and the mean absolute percentage error

(MAPE) between the predicted and actual PEC values were used and calculated using the following equations:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} Y_i^2} \right) \tag{7}$$

$$MAPE(\%) = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \tag{8}$$

where Y_j and $\hat{Y}_j$ are the actual and predicted PEC's for ith year, and n is the number of data points.

3. Results and discussion

3.1 PSO model

Various initializations of three parameters including number of particles and iterations were tested to determine the best coefficients for PSO Model. Results revealed that particle's experiment in searching space is more important than parameter initialization during different runs of algorithm. The PSO coefficients for the proposed linear model (Eq. 4) are represented in Eq. (9). The run which was initialized 50 particles and 500 iterations provided the best coefficients.

$$PEC = 10^{-4} \times [3592 \times POP + 6656 \times GDP + 346 \times ICOR + 4 \times NI + 345 \times AMT] \tag{9}$$

The R^2 and MAPE (Eqs. 7 and 8) related to the optimum PSO model were 0.994 and 8.24%, respectively. Correlation between actual PEC and PSO estimations for test data is represented in Figure 3.

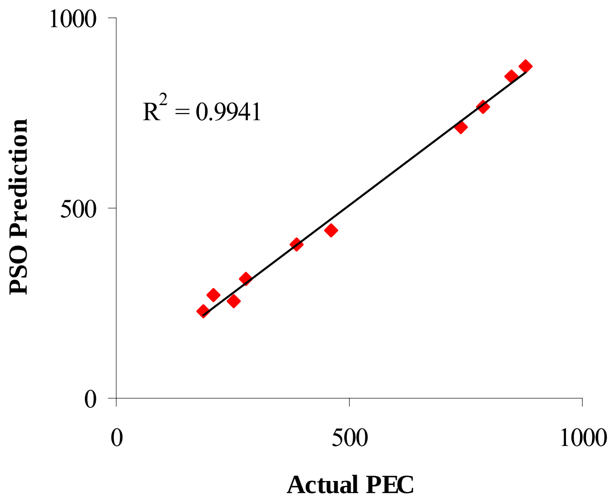

Figure 3. Correlation between actual PEC and PSO prediction

3.2 ANN model

Five different ANNs having 2, 4, 6, 8 and 10 neurons for hidden layer were run to determine the best network topology. The results are represented in Table 4. The R^2 and MAPE (Eqs. 7 and 8) related to the best ANN model were calculated as 0.999 and 3.47%, respectively. The best ANN model has a 5-4-1 architecture, namely, a network having five input variables (POP, AMT, GDP, NI and ICOR), four neurons (with TanhAxon) in the hidden layer and a single (BiasAxon) output variable (Iran's PEC) resulted in the best-suited model predicting Iran's PEC. Figure 4 represents correlation between ANN predictions and actual PEC data.

Table 4. ANN proposed models to predict Iran's PEC

Model	ANN Structure	Test data	
		R^2	MAPE (%)
1	5-2-1	0.997	5.03
2*	**5-4-1**	**0.999**	**3.47**
3	5-6-1	0.999	3.69
4	5-8-1	0.999	3.81
5	5-10-1	0.998	4.93

* Optimal ANN model

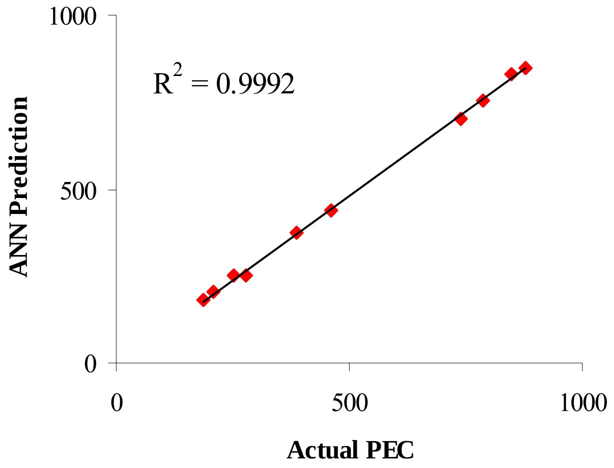

Figure 4. Correlation between actual PEC and ANN prediction

3.3 *Sensitivity analysis*

In order to assess the predictive ability and validity of the developed models, a sensitivity analysis was performed using the best network selected. Here, sensitivity analysis was conducted in order to determine the most effective parameters on Iran's PEC. The robustness of the ANN model was determined by examining and comparing the output produced during the validation stage with the calculated values. The MLP model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. According to the sensitivity analysis which is represented in Table 5, although all parameters are effective on ANN output, Iran's PEC is severely sensitive to AMT. It is evident that AMT had the highest sensitivity on PEC (6.3600), followed by ICOR (0.1377). Also, the sensitivity of NI and GDP was relatively low. Since residential and public sector consumes the highest amount of energy for heating and in electrical form; so, slight changes in weather (or consequently AMT) can be very effective on Iran's energy demand.

Table 5. The sensitivity analysis of the ANN model

Parameter	Sensitivity
AMT	6.3600
ICOR	0.1377
POP	0.0118
GDP	0.0008
NI	0.0003

3.4 Modeling techniques assessment

The first 24 data of the whole randomized data were used to train PSO and ANN models. Then, the PSO coefficients and ANN models were used to predict Iran's PEC according to 10 test data (25 to 34), see Table 6. The best positions which were investigated by PSO particles are compared with ANN estimations for training data. In addition, ability of both models to predict PEC according to test data is compared and represented in Figure 5.

In the other study, Kankal and Akpmar [13] applied ANN and multiple linear regression analysis (MLR) in order to model energy consumption in Turkey. In addition, Assareh et al. [5] concluded that PSO slightly outperforms genetic algorithm (GA). In this study, comparing R^2 and MAPE of the proposed models (Eq. 6 and Table 4), it is seen that both PSO and ANN techniques modeled Iran's PEC with good correlation (see Figures 3 and 4), but ANN slightly outperforms PSO (see Figure 6). However, PSO technique is very simple and provided us with a closed form expression for predicting PEC.
Also, by the represented scenario in Section 3.5, both models were used to forecast Iran's energy demand until 2025. As it is shown in Figure 7 forecasting results of ANN are not reasonable and unlike PSO model, ANN does not indicate any growth rate.

Table 6. Comparison between PSO and ANN models to predict Iran's PEC

Year	Actual data (Mboe)	PSO	PSO relative error (%)	ANN	ANN relative error (%)
1974	185.1	228.02	23.18	181.53	1.93
1975	207.6	268.86	29.51	203.89	1.79
1979	277.8	313.21	12.75	253.75	8.66
1980	252.2	254.86	1.05	252.30	0.04
1984	386.7	406.75	5.18	375.15	2.99
1989	459.2	439.55	4.28	437.53	4.72
1995	740.6	714.78	3.49	704.06	4.93
1996	787.4	768.27	2.43	752.91	4.38
1998	846.6	845.69	0.11	828.67	2.12
1999	877.0	873.49	0.40	849.06	3.18
Average			**8.24**		**3.47**

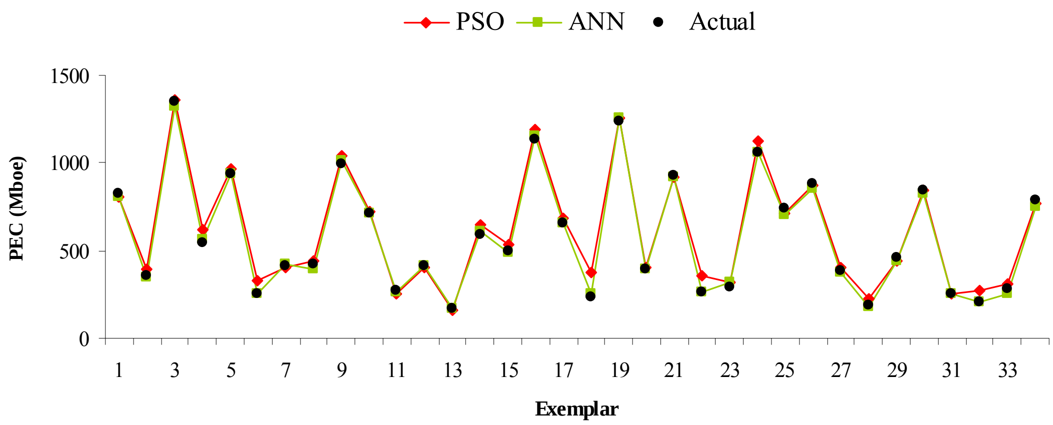

Figure 5. Comparison between the best investigated positions by PSO particles and ANN estimations

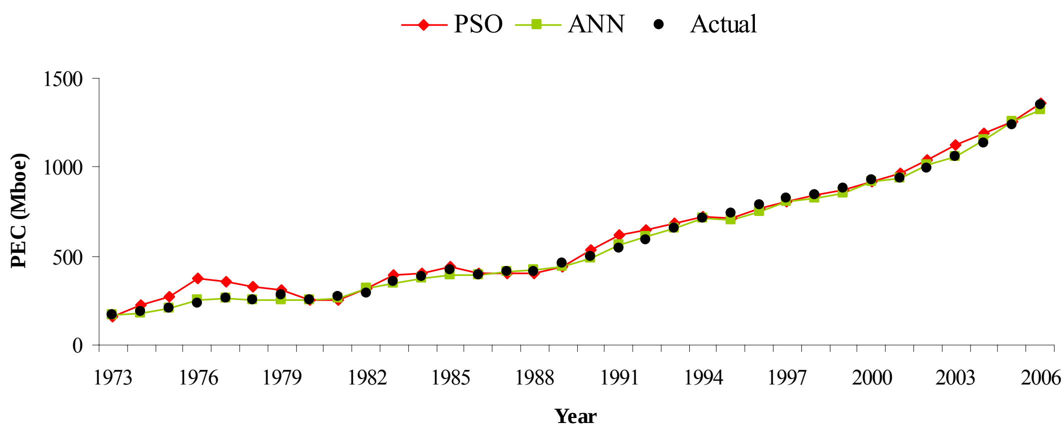

Figure 6. Time series plot of Iran's PEC and performance of PSO and ANN modeling techniques

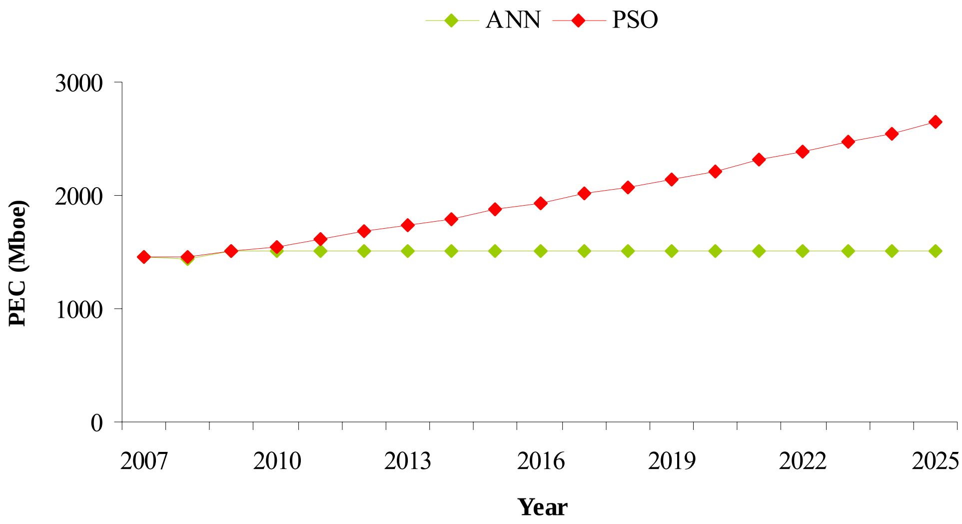

Figure 7. Forecasting energy demand based on represented scenario using PSO and ANN models, 2007-2025

3.5 Energy supply and CO_2 emissions reduction in Iran

The main and accessible of renewable energy (RE) resources are hydropower, wind, solar, geothermal and etc in Iran. Based on recent studies on suitable locations for exploitation of wind energy, the potential for wind energy is estimated 6500 MW considering the efficiency of 33%. Iran has 300 sunny days and 5.5 kWh solar energies on average daily in 90% of its area, too. In addition, there are four strategic locations with an area of 31000 m^2 for geothermal energy in Iran considering that Iran is located on the belt of geothermal energy. CO_2 emission of these energy resources is far lesser than fossil energy resources.

In condition of high CO_2 emission (being ranked 8^{th} country in the world by CO_2 emission) due to excessive consumption of fossil energy resources, there is a need for adapting more clean energy. Therefore, it is crucial for Iran to change its strategic planning in energy debate. The results of studies on the possible options for the use of REs in Iran indicated that the target of using about 10% of total energy demand (TED) from REs is justified till the year 2025 [22].

If it is supposed that after the year 2006, POP, GDP, NI and ICOR will have the growth rate of 1%, 3.5%, 4% and -1%, respectively, and for AMT, Iran will have a repetition of the last 20 years, then the TED will be about 2500 Mboe (same as [5], see Figure 7). Consequently, by replacing about 10% of TED with RE, it is possible to reduce CO_2 emissions. But how much reduction is possible? According to the results of the developed LP model (Eq. 6), in condition of minimum CO_2 emissions, Iran will emit about 2520 million metric tons CO_2. Also LP model indicated that maximum possible development of hydropower, geothermal and wind energy resources will satisfy the aim of minimization of CO_2 emissions. Therefore, Iran should consider exploitation of these three RE resources as the main strategic policy in order to reduce CO_2 emissions.

4. Conclusion

Since there are severe fluctuations and uncertainties for energy consumption, classical method such as regression approach does not provide a suitable prediction for modeling primary energy consumption (PEC). In the study of modeling Iran's PEC, a linear model was defined for PSO procedure. On the other hand, several ANNs were run to compare with PSO and determine the best fitted model. In addition, sensitivity analysis was carried out in order to determine the importance of the socioeconomic and meteorological parameters which were used.

Finally, although different energy resources are available to exploit in Iran, government's policies should concentrate on optimization of energy consumptions especially in residential and industrial sectors and ways of adapting alternative resources.

Acknowledgements

The authors would like to acknowledge the financial support of University of Tehran, Iran, under Grant Number 1305051-6-25 for this research.

References

[1] BP Statistical Review of World Energy xls. www.bp.com. 2011.

[2] Abbaspour M., Rahimi R. Iran atlas of offshore renewable energies. Renewable Energy. 2011, 36(1), 388-98.

[3] Dehghan A.A. Status and potentials of renewable energies in Yazd Province-Iran. Renewable and Sustainable Energy Reviews. 2011, 15(3), 1491-6.

[4] Amjadi M.H., Nezamabadi-pour H., Farsangi M.M. Estimation of electricity demand of Iran using two heuristic algorithms. Energy Conversion and Management. 2010, 51(3), 493-7.

[5] Assareh E., Behrang M.A., Assari M.R., Ghanbarzadeh A. Application of PSO (particle swarm optimization) and GA (genetic algorithm) techniques on demand estimation of oil in Iran. Energy. 2010, 35(12), 5223-9.

[6] Ekonomou L. Greek long-term energy consumption prediction using artificial neural networks. Energy. 2010, 35(2), 512-7.

[7] Azadeh A., Arab R., Behfard S. An adaptive intelligent algorithm for forecasting long term gasoline demand estimation: The cases of USA, Canada, Japan, Kuwait and Iran. Expert Systems with Applications. 2010, 37(12), 7427-37.

[8] Assareh E., Behrang M.A., Ghanbarzdeh A. Forecasting Energy Demand in Iran Using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) Methods. Energy Sources, Part B: Economics, Planning, and Policy. 2012, 7(4), 411-22.

[9] Behrang M.A., Assareh E., Assari M.R., Ghanbarzadeh A. Using Bees Algorithm and Artificial Neural Network to Forecast World Carbon Dioxide Emission. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 2011, 33(19), 1747-59.

[10] Al-mulali U., Binti Che Sab CN. The impact of energy consumption and CO2 emission on the economic growth and financial development in the Sub Saharan African countries. Energy. 2012, 39(1), 180-6.

[11] Niu S., Ding Y., Niu Y., Li Y., Luo G. Economic growth, energy conservation and emissions reduction: A comparative analysis based on panel data for 8 Asian-Pacific countries. Energy Policy. 2011, 39(4), 2121-31.

[12] Zhang C., Xu J. Retesting the causality between energy consumption and GDP in China: Evidence from sectoral and regional analyses using dynamic panel data. Energy Economics. 2012, 34(6), 1782-9.

[13] Kankal M., Akpınar A., Kömürcü M. İ., Özşahin T. Ş. Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables. Applied Energy. 2011, 88(5), 1927-39.

[14] (MOE). MoE. Energy balance annual report Tehran, Iran: Ministry of Energy. 2010.

[15] Bank. IC. www.cbi.ir. 2012.

[16] Organization IM. www.weather.ir.

[17] Wang Y., Li B., Weise T., Wang J., Yuan B., Tian Q. Self-adaptive learning based particle swarm optimization. Information Sciences. 2011, 181(20), 4515-38.

[18] MathWorks MUsG, The MathWork, Inc. www.mathwork.com.

[19] Neurosolutions for excel n, Inc http://www.neurosolutions.com. 2011.

[20] Omid M., Baharlooei A., Ahmadi H. Modeling Drying Kinetics of Pistachio Nuts with Multilayer Feed-Forward Neural Network. Drying Technology. 2009, 27, 1069-77.

[21] Pahlavan R., Omid M., Akram A. Energy input–output analysis and application of artificial neural networks for predicting greenhouse basil production. Energy. 2012, 37(1), 171-6.

[22] Mostafaeipour A., Mostafaeipour N. Renewable energy issues and electricity production in Middle East compared with Iran. Renewable and Sustainable Energy Reviews. 2009, 13(6-7), 1641-5.

M. Yousefi was born in 1988 in Tehran/Iran, received her B.Sc. Degree in Agricultural Mechanization Engineering from the University of Tehran; Iran, in 2011. She is now M.Sc. student in Agricultural Mechanization Engineering in the University of Tehran under supervision of Dr. Mahmoud Omid. Her main research interest are agricultural mechanization, energy consumption and environmental impact modeling and renewable energies
E-mail address: mzyousefi@ut.ac.ir

M. Omid was born in Tehran/Iran, received his B.Sc. degree in Electronic Engineering from the University of Newcastle, Newcastle Upon-Tyne; UK, in 1989 and his M.Sc. and Ph.D. degrees in Telecommunication Engineering from University of Electro-Communications, Tokyo; Japan in 1994 and 1997, respectively. He is currently a Professor in Department of Agricultural Machinery Engineering in University of Tehran. His current research interests are Greenhouse: Design, management, control and automation, Energy and efficiency: Modeling, optimization and renewable energy based technology development; Electronics; Machine Vision; Quality inspection; Optimization and Postharvest Technology.
E-mail address: omid@ut.ac.ir

S. Rafiee was born in Tehran/Iran, received his B.Sc. and M.Sc. degrees in Agricultural Machinery Engineering from the University of Tehran, Iran, in 1993 and 1999, respectively. He received his Ph.D. degree in Agricultural Machinery Engineering from Tarbiat Modares University; Iran. He is currently a Professor in Department of Agricultural Machinery Engineering in University of Tehran. His current research interests are energy, modeling and simulation, and mechanization.
E-mail address: shahinrafiee@ut.ac.ir

S.F. Ghaderi was born in Tehran/Iran. He received his Ph.D. degree in Industrial Engineering from Tokyo Institute of Technology; Iran. He is currently Associate Professor of Socio-economic Systems Engineering in Department of Industrial Engineering, University of Tehran. His current research interests are scientific computing, energy and artificial intelligence.
E-mail address: ghaderi@ut.ac.ir