International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:5, No:7, 2011

Global Electricity Consumption Estimation Using Particle Swarm Optimization (PSO)

E.Assareh, M.A. Behrang, R. Assareh and N. Hedayat

Abstract— An integrated Artificial Neural Network- Particle Swarm Optimization (PSO) is presented for analyzing global electricity consumption. To aim this purpose, following steps are done:

STEP 1: in the first step, PSO is applied in order to determine world's oil, natural gas, coal and primary energy demand equations based on socio-economic indicators. World's population, Gross domestic product (GDP), oil trade movement and natural gas trade movement are used as socio-economic indicators in this study. For each socio-economic indicator, a feed-forward back propagation artificial neural network is trained and projected for future time domain.

STEP 2: in the second step, global electricity consumption is projected based on the oil, natural gas, coal and primary energy consumption using PSO. global electricity consumption is forecasted up to year 2040.

Keywords—Particle Swarm Optimization; Artificial Neural Networks; Fossil Fuels; Electricity; Forecasting

I. Introduction

According to the increasing demand of energy, the assessment of energy is necessary. This assessment could be done based on socio-economic indicators using different methods of mathematical demonstration. The energy demand equations can be expressed as linear or non-linear forms [1, 2]. Intelligent optimization techniques like Particle Swarm Optimization (PSO) are appropriate to forecast these models.

Several studies are presented to propose some models for energy demand policy management using intelligence techniques [3-8].

This study presents an integrated Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) to forecast world's fossil fuels, primary energy and electricity demand.

II. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization algorithm was first proposed by Eberhart and Kennedy [9], 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. For mare details the readers are referred to [9-17].

E. Assareh is with Mechanical Engineering Department, Dezful Branch, Islamic Azad University, Dezful, Iran (e-mail: Ehsanolah.assareh@gmail.com)
M.A. Behrang is with Mechanical Engineering Department, Dezful Branch, Islamic Azad University, Dezful, Iran (e-mail: Mohammadali.behrang@gmail.com).
R. Assareh is a member of Electrical Department of Islamic Azad University, Dezful Branch, Iran (e-mail: Reza_asareh@yahoo.com).
N. Hedayat , Civil Engineering Department, Dezful Branch, Islamic Azad University, Dezful, Iran (e-mail: n.hedayat@yahoo.com).

III. Problem Definition

An integrated Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN) is presented to forecast world's electricity demand. To aim this purpose, following steps are done:

STEP 1: in the first step, PSO is applied in order to determine world's oil, natural gas, coal and primary energy demand equations based on socio-economic indicators. World's population, Gross domestic product (GDP), oil trade movement and natural gas trade movement are used as socio-economic indicators in this study. For each socio-economic indicator, a feed-forward back propagation artificial neural network is trained and projected for future time domain.

STEP 2: in the second step, global electricity consumption is projected based on the oil, natural gas, coal and primary energy consumption using PSO. The Best results of step 1 are used for future forecasting of world green energy consumption (step 2).

The related data from 1980 to 2006 are considered, partly for finding the optimal, or near optimal, values of the weighting parameters (1980-1999) and partly for testing the models (2000–2006).

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

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

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of objective energy carrier (oil, natural gas, coal, primary energy, electricity) consumption, respectively, m is the number of observations. The data related to world's oil trade movement and energy carriers consumption figures are obtained from [18] while world's population, Gross domestic product (GDP) and natural gas trade movement figures are obtained from [19].

Forecasting of each energy carrier demand was modeled by using linear and exponential forms of equations.

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:5, No:7, 2011

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

$$Y_{linear} = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5 \quad (2)$$

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

$$Y_{exponential} = w_1X_1^{w2} + w_3X_2^{w4} + w_5X_3^{w6} + w_7X_4^{w8} + w_9 \quad (3)$$

In Eqs.2 and 3, w_i are the corresponding weighting factors and X_1, X_2, X_3 and X_4 are input variables and defines as follow:
For step 1: X_1, X_2, X_3 and X_4 are population, Gross domestic product (GDP), oil trade movement and natural gas trade movement.
For steps 2: X_1, X_2, X_3 and X_4 are world's oil, natural gas, coal and primary energy consumption.

IV. Estimating parameter values using GA

In this section PSO algorithm which is coded with MATLAB 2007 software, applied in order to finding optimal values of weighting parameters based on actual data (1980-2006).

For aiming this purpose, following stages are done for both steps 1 and 2:

(a) All input variables (for both steps 1 and 2) and objective energy carrier consumptions in Eqs.2 and 3 are normalized in (0 1) range.

(b): The proposed algorithm (PSO) is applied in order to determine corresponding weighting factors (w_i) for each energy carrier model according to the lowest objective functions.

(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 2006 is used in this section.

(d): Demand estimation models are proposed using the optimal values of weighting parameters.

The PSO models (in both steps 1 and 2) are performed using the following user-specified parameters.

PSO:
Iteration number (t): 400
Particle size (z): 39
Inertia weight (w): 0.2

Following PSO demand estimation equations are obtained (NG: natural gas, PE: primary, EL: electricity):

$$Y_{Oil_{linear}} = 0.3618X_1 + 0.0934X_2 + 0.3034X_3 + 0.1463X_4 + 0.0935 \quad (4)$$

$$Y_{NG_{linear}} = 0.3787X_1 + 0.3414X_2 + 0.368X_3 - 0.0452X_4 + 0.0166 \quad (5)$$

$$Y_{Coal_{linear}} = -0.6733X_1 + 0.24495X_2 + 0.75105X_3 + 0.9993X_4 + 0.043 \quad (6)$$

$$Y_{PE_{linear}} = -1.0595X_1 + 0.8768X_2 + 0.3034X_3 - 0.6539X_4 + 0.1795 \quad (7)$$

$$Y_{EL_{linear}} = 0.11857X_1 + 0.68973X_2 + 0.07385X_3 + 0.09183X_4 + 0.01833 \quad (8)$$

In the exponential form of GA models, coefficients obtained are given below.

$$Y_{Oil_{exponential}} = 0.0602X_1^{1.3066} + 0.9295X_2^{0.9201} + 0.2143X_3^{0.4348} - 0.1558X_4^{0.6011} - 0.0066 \quad (9)$$

$$Y_{NG_{exponential}} = -0.1233X_1^{0.4884} + 0.2203X_2^{0.9163} - 0.2366X_3^{0.2761} + 0.7578X_4^{0.8868} + 0.4237 \quad (10)$$

$$Y_{Coal_{exponential}} = 0.1182X_1^{0.066} + 0.6482X_2^{0.2645} + 0.2006X_3^{1.1112} + 0.2362X_4^{3.4175} - 0.0669 \quad (11)$$

$$Y_{PE_{exponential}} = 0.2243X_1^{0.1649} + 0.3025X_2^{0.3238} + 0.1652X_3^{0.97} + 0.379X_4^{1.7809} - 0.1184 \quad (12)$$

$$Y_{EL_{exponential}} = 0.4529X_1^{0.6036} + 0.3177X_2^{2.1309} - 0.0705X_3^{0.6748} + 0.4684X_4^{0.3383} - 0.1785 \quad (13)$$

All presented models are in good agreement with actual data on models installation period (1980 to 1999).

In Tables 1, it can be seen that there is good agreement between the results obtained from PSO method with observed data (on testing period) but Oil_{linear}, $NG_{exponential}$, $Coal_{linear}$, PE_{linear} and $EL_{exponential}$ outperformed other models presented here for oil, natural gas, coal, primary energy and electricity consumption.

V. Future projection

A. Artificial Neural Network (ANN)

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large number of interconnected neurons. Each neuron is capable of performing only simple computation [20]. Any how, the architecture of an artificial neuron is simpler than a biological neuron. ANNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological system. For mare details the readers are referred to [20-23].

B. future projection scenario

In order to use Eqs.6 to15 for future projections, each input variables should be forecasted in future time domain.

For each input variable in step 1 (socio-economic indicators), a feed-forward back propagation artificial neural network is trained and projected for future time domain. The actual data for each variable between 1980 and 1999 were used for training the neural networks while the data for 2000-2006 were used as testing data.

The testing data were not used in training the neural networks

Table 2 shows the best network structure of each input variable (socio-economic indicator) and its training and testing errors.

For step 1, each energy carrier consumption (oil- natural gas- coal- primary energy) are forecasted up to year 2040, using the proposed models (Eqs.4 to 7 and Eqs.9 to 12).

In Figs. 1 to 5, oil, natural gas, coal and primary energy, electricity consumption are projected through 2040.

The best models in step 1 (Oil_{linear}, $NG_{exponential}$, $Coal_{linear}$ and PE_{linear}), are used as input variables for future forecasting of green energy consumption through 2040.

VI. CONCLUSION

Artificial intelligence techniques have been successfully used to estimate world's electricity demand based on the structure of the international industry and economic conditions. 27 years data (1980–2006) has been used for developing both forms (linear and exponential) of PSO demand estimation models. a scenario was designed in order to forecast each socio-economic indicator during 2007-2040. Validations of models show that PSO demand estimation models are in good agreement with the observed data but Oil_{linear}, $NG_{exponential}$, $Coal_{linear}$ and PE_{linear} outperformed other models presented here for oil, natural gas, coal and primary energy consumption. Also $EL_{exponential}$ outperformed other models presented here for

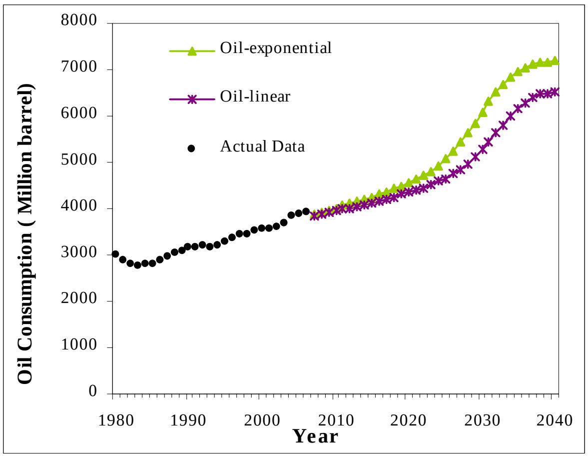

Fig. 1 Future projection for oil consumption

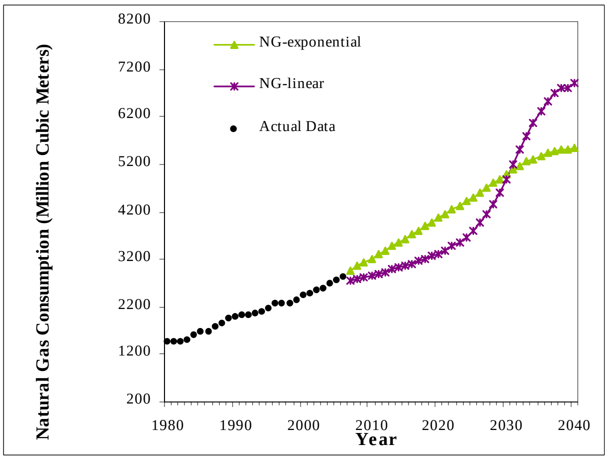

Fig. 2 Future projection for natural gas consumption

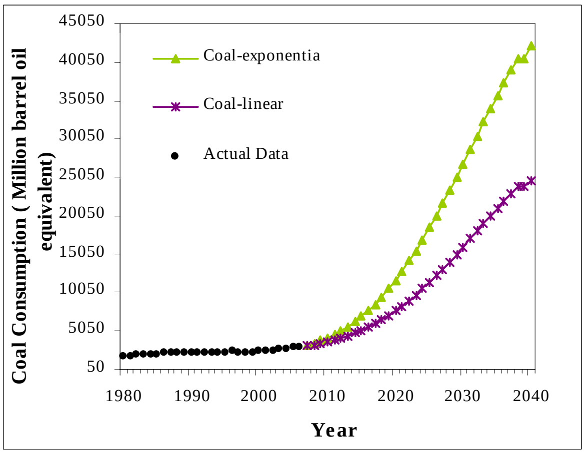

Fig. 3 Future projection for coal consumption.

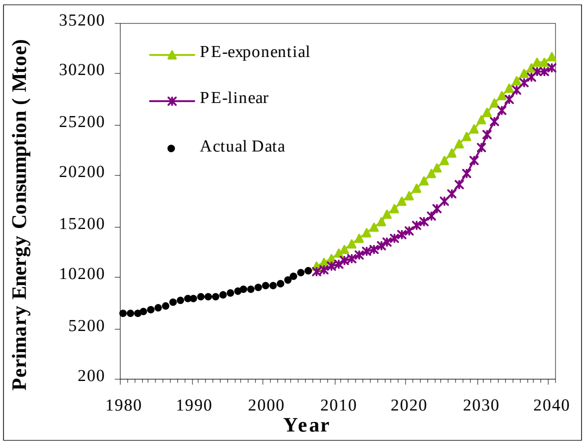

Fig. 4 Future projection for primary energy consumption

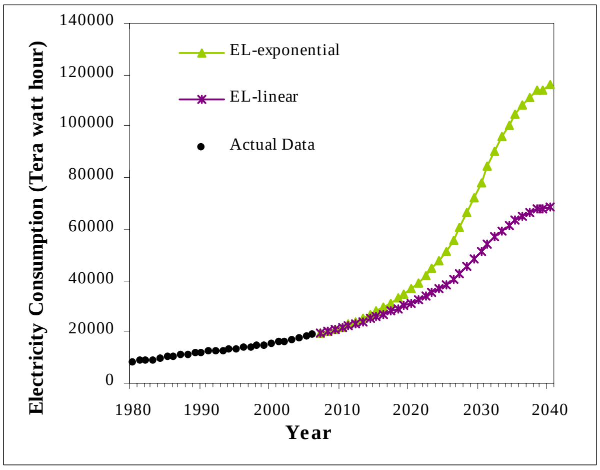

Fig. 5 Future projection for electricity consumption

electricity consumption. It is concluded that the suggested models are satisfactory tools for successful fossil fuels, primary energy and electricity demand forecasting.

Future work is focused on comparing the methods presented here with other available tools.

References

[1] E. Assareh, M.A. Behrang., M.R. Assari., A. Ghanbarzadeh. Application of particle swarm optimization (PSO) and genetic algorithm (GA) techniques on demand estimation of oil in Iran. Energy 2010; 35: 5223-5229.

[2] A. Azadeh, S.F. Ghaderi, S. Sohrabkhani. A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. Energy Policy 2008 ; 36: 2637– 2644

[3] E. Assareh, M.A. Behrang., A. Ghanbarzadeh. Forecasting energy demand in Iran using genetic algorithm (GA) and particle swarm optimization (PSO) methods. Energy Sources, Part B: Economics, Planning, and Policy: 2009 Accepted manuscript.

[4] M.A. Behrang E. Assareh, A. Ghanbarzadeh, A. Total energy demand estimation in Iran using Bees Algorithm. Energy Sources, Part B: Economics, Planning, and Policy: 2009Accepted manuscript.

[5] M.A. Behrang., E. Assareh, M.R. Assari, M.R., and A. Ghanbarzadeh. Assessment of electricity demand in Iran's industrial sector using different intelligent optimization techniques. Applied Artificial Intelligence 2011; 25: 292–304. doi:10.1080/08839514.2011.559572

[6] A. Unler. Improvement of energy demand forecasts using swarm intelligence: The case of Turkey with projections to 2025. Energy Policy 2008; 36: 1937–194

[7] O.E. Canyurt, H.K. Ozturk.. Application of genetic algorithm (GA) technique on demand estimation of fossil fuels in Turkey. Energy Policy2008;36:2562–2569.

[8] Ermis, K., Midilli, A., Dincer, I., Rosen, M.A., 2007. Artificial neural network analysis of world green energy use. Energy Policy 35: 1731-1743.

[9] Kennedy J, Eberhart R. Particle swarm optimization. Proc Neural Networks. Proceedings,vol.1944. IEEE International Conference on, 1995. p.1942-1948 .

[10] Engelbrecht A P. Fundamentals of computational swarm intelligence. Hoboken, N.J.: Wiley, 2005.

[11] Brits R, Engelbrecht AP, van den Bergh F. Locating multiple optima using particle swarm optimization. Applied Mathematics and Computation 2007; 189(2): 1859-1883.

[12] 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): 668-676.

[13] Pan H, Wang L, Liu B. Particle swarm optimization for function optimization in noisy environment. Applied Mathematics and Computation 2006; 181(2): 908-919.

[14] Yang IT.Performing complex project crashing analysis with aid of particle swarm optimization algorithm. International Journal of Project Management 2007; 25(6): 637-646.

[15] Shi Y, Eberhart R. A modified particle swarm optimizer. Proceedings of the IEEE International Conference on Evolutionary Computation. Anchorage, Alaska, 1998a. p.69-73.

[16] Shi Y, Eberhart R. Parameter selection in particle swarm optimization. Proceedings of the Seventh Annual Conference on Evolutionary Programming. New York, 1998b. p.591-600.

[17] M.A. Behrang, E. Assareh, A.R. Noghrehabadi, and A. Ghanbarzadeh. New sunshine-based models for predicting global solar radiation using PSO (particle swarm optimization) technique. Energy 2011; 36: 3036-3049. doi:10.1016/j.energy.2011.02.048.

[18] Workbook, Statistical Review of World Energy. Available online at http://www.bp.com/statisticalreview. 2008.

[19] IEA. Keyword energy statistic. International Energy Agency (IEA).U.S.A. 2008.

[20] Pham DT, Koç E, Ghanbarzadeh A, Otri S. Optimisation of the Weights of Multi-Layered Perceptrons Using the Bees Algorithm. in: Proceedings of 5th International Symposium on Intelligent Manufacturing Systems, Sakarya University, Department of Industrial Engineering, , 2006. May 29-31, pp. 38-46.

[21] Pham DT, Liu X. Neural Networks for identification, prediction and control, Springer verlag, london. , 1995.

[22] Yilmaz AS, Ozer Z. Pitch angle control in wind turbines above the rated wind speed by multi-layer percepteron and redial basis function neural networks. Expert Systems with Applications 36: 9767–9775, 2009.

[23] M.A. Behrang, E. Assareh, A. Ghanbarzadeh, A.R. Noghrehabadi. The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Solar Energy 2010; 84: 1468–1480.

TABLE I
COMPARISON OF THE PROPOSED MODELS FOR OIL, NATURAL GAS, COAL, AND PRIMARY ENERGY CONSUMPTION

Years	2000	2001	2002	2003	2004	2005	2006	Ave.
Oil Consumption (million barrel)								
Actual Data	3559	3576	3611	3682	3824	3871	3911	--
$Oil_{exponential}$	3615	3645	3671	3720	3793	3857	3930	--
Relative error	1.59	1.93	1.65	1.03	-0.81	-0.36	0.50	1.12
Oil_{linear}	3574	3615	3642	3702	3771	3826	3874	--
Relative error	0.44	1.10	0.86	0.54	-1.38	-1.16	-0.94	0.92
NG Consumption (Billion cubic metres)								
Actual Data	2437	2455	2534	2591	2689	2765	2834	--
$NG_{exponential}$	2464	2517	2540	2615	2708	2786	2859	--
Relative error	1.08	2.52	0.27	0.92	0.68	0.74	0.87	1.01
NG_{linear}	2455	2486	2557	2624	2706	2767	2822	--
Relative error	0.73	1.24	0.94	1.28	0.64	0.05	-0.44	0.76
Coal Consumption (million barrel oil equivalent)								
Actual Data	2340	2352	2407	2600	2768	2892	3042	--
$Coal_{exponential}$	2382	2420	2489	2586	2723	2835	2939	
Relative error	0.02	0.03	0.03	-0.01	-0.02	-0.02	-0.03	0.02
$Coal_{linear}$	2500	2540	2577	2660	2763	2835	2892	
Relative error	6.82	8.01	7.07	2.31	-0.19	-1.98	-4.91	4.47
PE Consumption (Billin barrel oil equivalent)								
Actual Data	9.29	9.34	9.52	9.83	10.30	10.56	10.84	--
$PE_{exponential}$	9.30	9.40	9.55	9.84	10.27	10.57	10.87	
Relative error	0.09	0.66	0.28	0.14	-0.23	0.14	0.22	0.25
PE_{linear}	9.22	9.36	9.59	9.89	10.26	10.54	10.77	--
Relative error	-0.80	0.21	0.72	0.62	-0.30	-0.21	-0.64	0.50
Electricity Consumption (Giga watt hour)								
Actual Data	15.45	15.56	16.17	16.76	17.53	18.31	19.00	--
$EL_{exponential}$	15.36	15.51	16.09	16.61	17.65	18.33	18.97	
Relative error	-0.61	-0.31	-0.48	-0.89	0.67	0.11	-0.20	0.47
El_{linear}	15.41	15.54	16.08	16.72	17.65	18.28	18.90	--
Relative error	-0.27	-0.10	-0.57	-0.23	0.70	-0.15	-0.57	0.34

TABLE II
NETWORK STRUCTURE OF EACH INPUT VARIABLE (SOCIO-ECONOMIC INDICA
TRAINING AND TESTING ERRORS

Input Variable	Neurons in 1st hidden layer	Neurons in 2nd hidden layer	Error for train		Error for test
			MSE	SSE	R^2 (%)
Population	3	_	5.45E-8	1.09E-6	99.99
GDP	2	1	3.29E-4	0.0066	99.99
Oil trade movement	2	2	8.89E-4	0.0178	99.96
NG trade movement	2	_	0.0023	0.0395	99.56