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 more details the readers are referred to [9-17].

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:

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

(1)

Where \( E_{\text{actual}} \) and \( E_{\text{predicted}} \) 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.
The linear form of equations for the demand estimation models is written as follows:

\[ Y_{\text{linear}} = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5 \] (2)

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

\[ Y_{\text{exponential}} = w_1X_1^{\alpha_2} + w_2X_2^{\alpha_4} + w_3X_3^{\alpha_6} + w_4X_4^{\alpha_8} + w_5 \] (3)

In Eqs.2 and 3, \( w_i \) are the corresponding weighting factors (NG: natural gas, PE: primary, EL: electricity):

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):

\[ Y_{\text{Oil linear}} = 0.3618X_1 + 0.0934X_2 + 0.3034X_3 + 0.1463X_4 + 0.0935 \] (4)

\[ Y_{\text{NG linear}} = 0.3787X_1 + 0.3414X_2 + 0.368X_3 - 0.0452X_4 + 0.0166 \] (5)

\[ Y_{\text{PE linear}} = -0.6733X_1 + 0.2449X_2 + 0.7510X_3 + 0.9993X_4 + 0.043 \] (6)

\[ Y_{\text{EL linear}} = -1.0595X_1 + 0.8768X_2 + 0.3034X_3 - 0.6539X_4 + 0.1795 \] (7)

\[ Y_{\text{NG exponential}} = 0.0602X_1^{1.3066} + 0.9295X_2^{0.9201} + 0.2143X_3^{0.4348} - 0.1558X_4^{0.6011} - 0.0066 \] (9)

\[ Y_{\text{NG exponential}} = -0.1233X_1^{0.4884} + 0.2203X_2^{0.9163} - 0.2366X_3^{0.2761} + 0.7578X_4^{0.8868} + 0.4237 \] (10)

\[ Y_{\text{Coal exponential}} = 0.1182X_1^{0.066} + 0.6482X_2^{0.2645} + 0.2006X_3^{1.1112} + 0.2362X_4^{1.4715} - 0.0669 \] (11)

\[ Y_{\text{PE exponential}} = 0.2243X_1^{0.1649} + 0.3025X_2^{0.3238} + 0.1652X_3^{0.97} + 0.379X_4^{1.7809} - 0.1184 \] (12)

\[ Y_{\text{EL exponential}} = 0.4529X_1^{0.6036} + 0.3177X_2^{2.1309} - 0.0705X_3^{0.6748} + 0.4684X_4^{3.3383} - 0.1785 \] (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\(_{\text{linear}}\), NG\(_{\text{exponential}}\), Coal\(_{\text{linear}}\), PE\(_{\text{linear}}\) and EL\(_{\text{exponential}}\) 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.

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of biological system. For more details the readers are referred to [20-23].

B. future projection scenario

In order to use Eqs.6 to 15 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) were 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...
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


### TABLE I

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

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### TABLE II

**NETWORK STRUCTURE OF EACH INPUT VARIABLE (SOCIO-ECONOMIC INDICATOR)**

<table>
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<th>Input Variable</th>
<th>Neurons in 1st hidden layer</th>
<th>Neurons in 2nd hidden layer</th>
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<th>Error for test</th>
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