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ORIGINAL ARTICLE

Global Green Energy Consumption Forecasting Using an Integrated Simulated Annealing and Artificial Neural Network

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ABSTRACT

Climate change concerns, coupled with high oil prices, peak oil, and increasing global supports, are driving increasing renewable energy legislation, incentives and commercialization. In the present study, an integrated Simulated Annealing (SA) and Artificial Neural Network (ANN) is applied to forecast global green energy consumption. For this purpose, following steps are done:
***STEP 1**: in the first step, SA 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. In order to forecast each socio-economic indicator in future time domain, for each socio-economic indicator, a MLP network is trained and projected.*
***STEP 2**: in the second step, global green energy consumption is projected based on the oil, natural gas, coal and primary energy consumption using SA.*
Keywords: Simulated Annealing (SA); Artificial Neural Networks (ANN); Green Energy (GE); Prediction.

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INTRODUCTION

About 16% of global final energy consumption comes from renewable resources, with 10% of all energy from traditional biomass, mainly used for heating, and 3.4% from hydroelectricity. New renewables (small hydro, modern biomass, wind, solar, geothermal, and biofuels) accounted for another 3% and are growing very rapidly. The share of renewables in electricity generation is around 19%, with 16% of electricity coming from hydroelectricity and 3% from new renewable [1].

In 21st century, green energy consumption may become an important factor for indicating social, industrial, economic and technological development. Also, an increase in green energy consumption often contributes to sustainable development [2]. So, green energy is considered a catalyst for energy security, sustainable development, and social, technological, industrial and economic development. Globally, energy demand has been increasing due to rapid population growth and technological and societal development [2].

Renewable energy replaces conventional fuels in four distinct areas: grid-connected electricity generation, off-grid (rural) energy services, hot water/space heating, and motor fuels [3].

Renewable energy provides 19% of electricity generation worldwide. Renewable power generators are spread across many countries, and wind power alone already provides a significant share of electricity in some areas: for example, 14% in the U.S. state of Iowa, 40% in the northern German state of Schleswig-Holstein, and 20% in Denmark. Some countries get most of their power from renewables, including Iceland (100%), Norway (98%), Brazil (86%), Austria (62%), New Zealand (65%), and Sweden (54%) [3].

Heating. Solar hot water makes an important contribution to renewable heat in many countries, most notably in China, which now has 70% of the global total (180 GWth). Most of these systems are installed on multi-family apartment buildings and meet a portion of the hot water needs of an estimated 50–60 million households in China. Worldwide, total installed solar water heating systems meet a portion of the water heating needs of over 70 million households. The use of biomass for heating continues to grow as well. In Sweden, national use of biomass energy has surpassed that of oil. Direct geothermal for heating is also growing rapidly [3].

Transport fuels. Renewable biofuels have contributed to a significant decline in oil consumption in the United States since 2006 [3]. The 93 billion liters of biofuels produced worldwide in 2009 displaced the

equivalent of an estimated 68 billion liters of gasoline, equal to about 5% of world gasoline production [3].
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 [4]. Intelligent optimization techniques like Simulated Annealing (SA) are appropriate to forecast these models.
Several studies are presented to propose some models for energy demand policy management using intelligence techniques.
Ermis et al. studied on ANN modeling of primary energy, fossil fuel and green energy consumption [2]. Unler developed Particle Swarm Optimization (PSO) energy demand models to estimate energy demand based on economic indicators [5]. Canyurt and Ozturk presented Turkey's fossil fuels demand models by using the structure of the Turkish industry and economic conditions based on genetic algorithm (GA) [6]. Toksari developed ant colony energy demand estimation models for Turkey [7]. Azadeh et al. presented an integrated algorithm for forecasting monthly electrical energy consumption based on artificial neural network (ANN) [4]. Kermanshahi and Iwamiya investigated the forecasting of peak electric loads in Japan to year 2020 using ANN approach [8].
This study presents an integrated Simulated Annealing (SA) and Artificial Neural Network (ANN) to forecast world's green energy demand.

SIMULATED ANNEALING (SA)

Simulated Annealing (SA) comes from the Metropolis algorithm [9], a simulation of the recrystallization of atoms in metal during its annealing (the process of slow cooling is known as annealing process). In the physical annealing of metals, as the temperature is reduced, the atoms start to get arranged and finally form crystals having the minimum possible energy. It is the basic concept of SA to search the optimal solution in an optimization problem [10]. SA has been successfully applied to solve a variety of optimization problems. For more details about SA the readers are referred to [9, 10].

ARTIFICIAL NEURAL NETWORKS (ANNs)

Artificial 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. Anyhow, 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 [11].

Problem definition

An integrated Simulated Annealing (SA) and Artificial Neural Network (ANN) is used to forecast world's green energy demand. For this purpose, following steps are done:
STEP 1: in the first step, SA 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. In order to forecast each socio-economic indicator in future time domain, for each socio-economic indicator, a MLP network is trained and projected.
STEP 2: in the second step, global green energy consumption is projected based on the oil, natural gas, coal and primary energy consumption using SA. The Best results of step 1 are used for future forecasting of world green energy consumption (step 2).
The related data from 1980 to 2010 are considered, partly for finding the optimal, or near optimal, values of the weighting parameters (1980-2003) and partly for testing the models (2004–2010).
The fitness function, F(x), takes the following form:

$$\text{Min } F(x) = \sum_{j=1}^{m} \left| \left(E_{actual} - E_{predicted} \right) / E_{actual} \right| \tag{1}$$

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of objective energy carrier (oil, natural gas, coal, primary energy, green energy) consumption, respectively, m is the number of observations. The data related to the design parameters of world's oil trade movement and energy carriers' consumption figures are obtained from [12] while world's population, Gross domestic product (GDP) and natural gas trade movement figures are obtained from [13].

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:

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

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

$$Y_{exp\,onential} = w_1X_1^{w_2} + w_3X_2^{w_4} + w_5X_3^{w_6} + w_7X_4^{w_8} + w_9 \quad (3)$$

In Eqs.4 and 5, 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.

USING SA TO DETERMINE WEIGHTING PARAMETERS VALUES

In this section SA algorithm which is coded with MATLAB 2010 software, applied in order to finding optimal values of weighting parameters based on actual data (1980-2010).

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.4 and 5 need normalizing in the interval [0, 1].

(b): The proposed algorithm (SA) is applied in order to determine corresponding weighting factors (w_i) for each energy carrier model according to the lowest objective functions. The convergence of the objective function and sensitivity analysis were examined for varying important factors of SA. After several times running the different combinations of each important factor, the best results were chosen according to the lowest objective functions. The related between 1980 to 2003 is used in this stage.

(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 2004 to 2010 is used in this section.

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

The best obtained weighting factors for oil, natural gas, primary Energy, Green energy (for the general forms of Eqs. (2) and (3)) are shown in Table 1.

Table 1. Best obtained weighting factors for oil, natural gas (NG), Coal, primary Energy (PE), Green energy (GE).

Model	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
Oil_{linear}	-0.1317	0.4948	-0.0457	0.4946	0.2533	-	-	-	-
$Oil_{exponential}$	-0.2276	0.4135	0.5591	0.7586	0.5406	0.7059	0.0725	0.8507	0.082
NG_{linear}	0.5442	-0.0745	0.3549	0.326	-0.157	-	-	-	-
$NG_{exponential}$	-0.0289	0.2432	0.3834	0.274	0.2335	0.4097	0.7891	0.8344	-0.3402
$Coal_{linear}$	0.6441	-0.464	0.7761	0.4941	-0.2268	–	–	–	–
$Coal_{exponential}$	0.186	0.3141	0.9319	1.177	0.458	0.4407	-0.4551	0.4451	0.0337
PE_{linear}	0.5451	0.0764	0.8783	-0.4936	0.0179	-	-	-	-
$PE_{exponential}$	0.6652	1.7107	-0.035	0.7344	0.521	0.2057	0.2803	0.7263	-0.3988
GE_{linear}	0.1112	0.4619	0.0897	-0.003	0.3313	-	-	-	-
$GE_{exponential}$	0.0298	0.7399	0.3868	0.6427	0.1779	0.1679	0.4041	0.7794	-0.0316

All presented models are in good agreement with actual data on models installation period (1980 to 2003).

In Table 2, it can be seen that there is good agreement between the results obtained from presented method with observed data (on testing period) but Oil_{linear}, $NG_{exp\,onential}$, $Coal_{linear}$ and PE_{linear} outperformed other models presented here for oil, natural gas, coal and primary energy consumption.

Also $GE_{exponential}$ outperformed other models presented here for green energy consumption.

Table 2. Comparison of the proposed models for oil, natural gas, coal, primary energy and green energy consumption.

Years	2004	2005	2006	2007	2008	2009	2010	Ave.
Oil Consumption (Mtoe)								
Actual Data	3858.7	3908.5	3945.3	4007.3	3996.5	3908.7	4028.1	_
$Oil_{exponential}$	3810.6	3870.8	3926.5	3976.3	4032.5	4089.5	4147.2	_
Relative error	-1.25	-0.96	-0.48	-0.77	0.9	4.63	2.96	1.71
Oil_{linear}	3844.2	3902	3961.7	3979.8	4033.4	4088.2	4144	_
Relative error	-0.38	-0.16	0.42	-0.69	0.92	4.59	2.88	1.43
NG Consumption (Mtoe)								
Actual Data	2431.8	2511.2	2565.6	2661.3	2731.4	2661.4	2858.1	_
$NG_{exponential}$	2475.1	2534.2	2584	2627.7	2685.5	2743.8	2802.4	_
Relative error	1.78	0.92	0.72	1.26	1.68	3.1	1.95	1.63
NG_{linear}	2437.3	2508.8	2566.7	2680.6	2758.2	2837.2	2917.9	_
Relative error	0.23	0.09	0.05	0.73	0.98	6.61	2.09	1.54
Coal Consumption (Mtoe)								
Actual Data	2858.4	3012.9	3164.5	3305.6	3341.7	3305.6	3555.8	_
$Coal_{exponential}$	2902.4	2993.1	3082.6	3162.8	3253.5	3347.6	3445.2	_
Relative error	1.54	-0.66	-2.59	-4.32	-2.64	1.27	-3.11	2.3
$Coal_{linear}$	2953.2	3060.2	3146.1	3200.6	3308.8	3421.2	3537.9	_
Relative error	3.32	1.57	-0.58	-3.17	-0.98	3.5	-0.5	1.95
PE Consumption (Mtoe)								
Actual Data	10482	10800	11087	11398	11535	11363	12002	_
$PE_{exponential}$	10371.1	10604	10823	11285.9	11547.9	11814.6	12086	_
Relative error	1.06	1.82	2.38	0.99	0.11	3.97	0.7	1.57
PE_{linear}	10371	10617	10815	11307	11574	11849	12132	_
Relative error	1.05	1.7	2.46	0.79	0.34	4.28	1.08	1.67

Table 2. Continued.

Years	2000	2001	2002	2003	2004	2005	2006	Average
Green Energy (ej)								
Actual Data	52.64	54.58	55.4	56.08	57.05	58.02	59.01	_
$GE_{exponential}$	53.5	54.7	55.7	57	57.8	57	59.5	_
Relative error	1.57	0.28	0.67	1.7	1.25	-1.74	0.8	1.15
GE_{linear}	54.8	55.4	55.3	56.6	58	55.8	59.1	_
Relative error	4.05	1.5	-0.06	0.89	1.64	-3.83	0.17	1.99

FUTURE PROJECTION SCENARIOS

For future projections, each input variables should be forecasted in future time domain. For forecasting world's population, Gross domestic product (GDP), oil trade movement and natural gas trade movement in order to use as input variables in step 1 to estimate each energy carrier (oil- natural gas- coal- primary energy) form 2011 to 2030, for each socio-economic indicator 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 2003 were used for training the neural networks while the data for 2004-2010 were used as testing data.

Eventually, for all socio-economic indicators, hyperbolic tangent transfer function (tanh) for hidden layers, linear transfer function (purelin) for output layer and LM (Levenberg–Marquardt) train were found to perform reasonably good.

In Figure 1, oil, natural gas, coal and primary energy consumption are projected through 2030 while global green energy consumption is projected through 2030, in Figure 2.

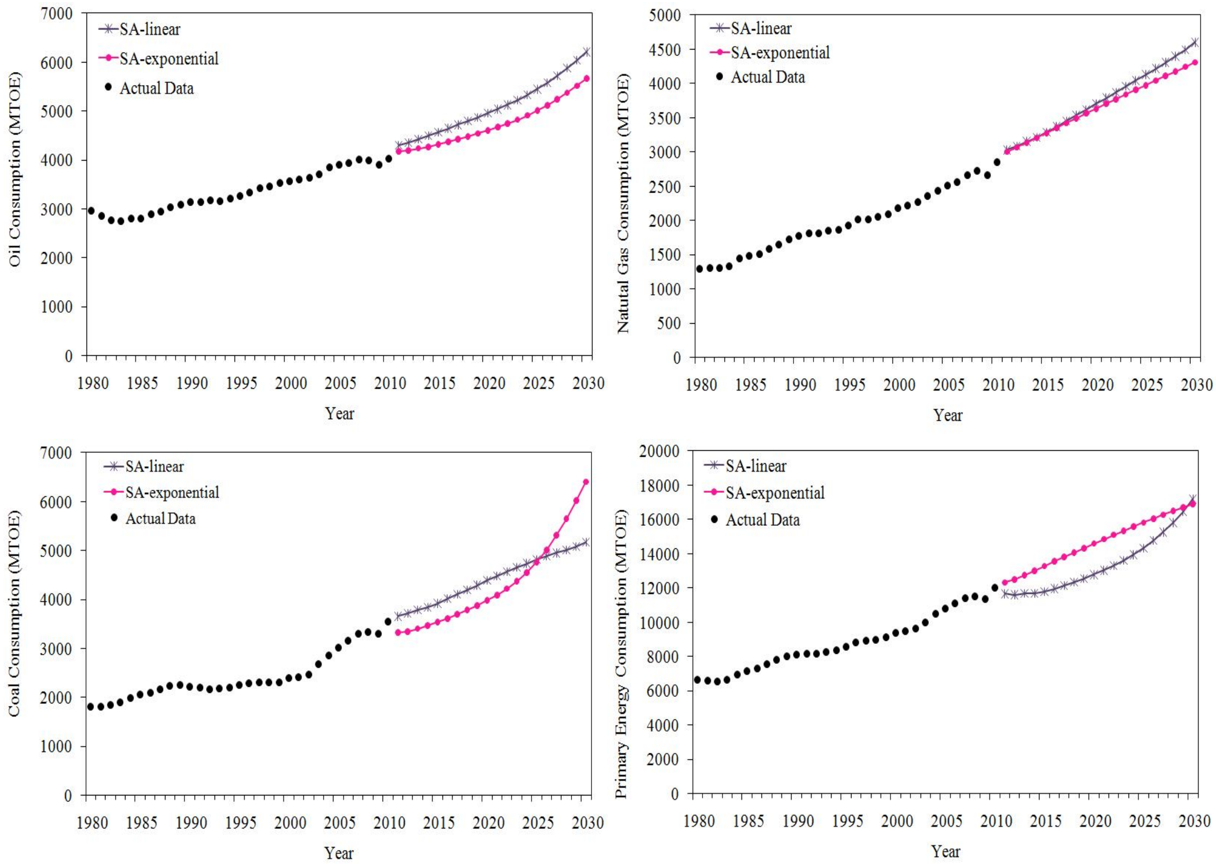

Fig. 1. Future projection for oil, natural gas, coal, and primary energy consumption.

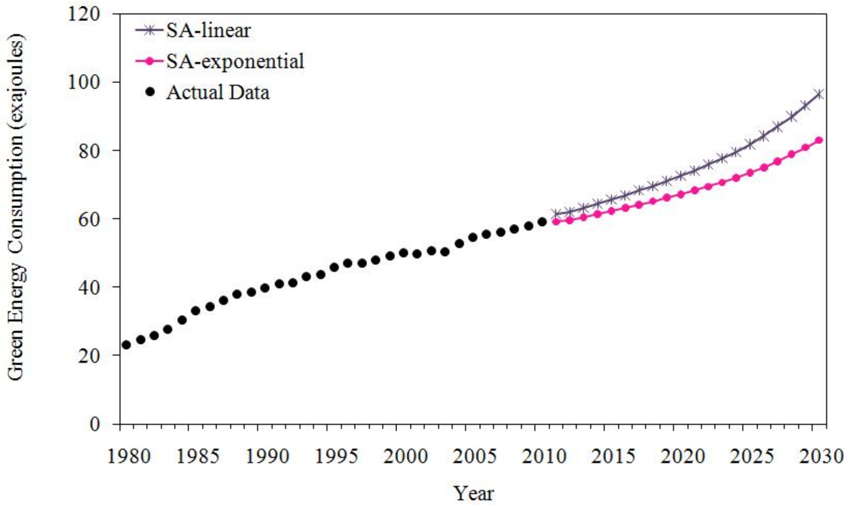

Fig. 2. Future projection for Green Energy consumption.

CONCLUSION

In this study, an integrated Simulated Annealing and Artificial Neural Network has been successfully used to estimate global green energy demand based on the structure of the international industry and economic conditions. 31 years data (1980–2010) has been used for developing linear and exponential forms demand estimation models. Validations of models show that all demand estimation models are in good agreement with the observed data but Oil_{linear}, NG_{linear}, $Coal_{linear}$ and $PE_{exponential}$ outperformed other models presented here for oil, natural gas, coal and primary energy consumption. Also $GE_{exponential}$ outperformed other models presented here for green energy consumption. Future work is focused on comparing the methods presented here with other available tools. Forecasting of green energy demand can also be investigated with Bees Algorithm, Artificial Bee Colony, Ant Colony, Genetic Algorithm, fuzzy logic or other metaheuristic such as tabu search, simulated annealing, etc. The results of the different methods could be compared with the SA technique.

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