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Research Article

Forecasting Iran's Energy Demand Using Cuckoo Optimization Algorithm

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This study deals with the modeling of the energy consumption in Iran to forecast future projections based on socioeconomic and demographic variables (GDP, population, import and export amounts, and employment) using the cuckoo optimization algorithm. For this purpose, four diverse models including different indicators were used in the analyses. Linear and power forms of equations are developed for each model. The related data between 1972 and 2013 were used, partly for installing the models. The result of the models shows that the obtained demand estimation linear models are in closer agreement with the observed data, particularly the linear model with five independent variables including GDP, population, import, export, and employment, which outperformed other linear models. Finally, the future energy demand of Iran is forecasted up to the year 2030 using these models under three scenarios.

1. Introduction

Energy is a foundation element of the modern industrial economy. Over the past few decades, energy has become a very critical element in industries and also a fundamental product and factor in the growth of the economy in different world regions. Ever-increasing dependence of human life on energy has made this factor play a critically crucial role either potentially or actively in the functions of various economic sectors of countries.

In spite of the fact that Iran has the richest sources of energy, squandering and despicable utilization of them cause irrecoverable harm to the national annual financial plan. The cost is evaluated proportionally to the whole national annual development financial plan (around 5 billion $). As indicated by approximately settled raw petroleum generation, increase in the measure of domestic utilization will prompt to diminish in oil fares and therefore will diminish proceeds from the offer of oil incomes. In this manner, energy administration issue has specific significance regarding maintaining oil export capacity, diminishing energy intensity, and sporadic development in utilization, ecological insurance, and monetary limitations for interest in the energy sector.

Therefore, Iranian authorities have to forecast more exactly the energy consumption in the correct arranging and direction utilization so that to manage the way they sought energy demand and supply parameters. So energy demand expectation is vital to auspicious supply. Hence, regulations on the raised issues result in focusing on energy security.

The Ministry of Energy which assessed the amount of energy consumption in Iran during 1972–2013 also prepared the detailed breakdown of energy consumption. For example, in 2013, Iran consumed about 1320.7 million barrels of oil equivalents (Mboe) which consisted of 482.5 Mtoe of petroleum, 696.7 Mboe of natural gas, 3 Mboe of coal,

8.4 Mtoe of biofuel energy, and 130.2 Mboe of electrical energy.

Distinctive techniques acquainted with energy consumption expectation. According to the increasing demand for energy, the assessment of energy is necessary. This assessment can be done based on socioeconomic indicators using different methods of mathematical demonstration. The energy demand equations can be expressed in linear or nonlinear forms. Intelligent optimization technique entities, e.g., birds, bats, and fireflies, are appropriate to forecast these models.

This article focuses on forecasting the energy demand in Iran based on socioeconomic factors using the COA (cuckoo optimization algorithm) technique. Different models are studied to determine the best possible approach in modeling energy demand as a function of various indicators. This study examines the relationship between energy demand and diverse independent variables in four models, utilizing linear and power types of equations. Results arising from this study provide important reference information for the utility companies in assessing energy consumption patterns and selecting a more accurate approach to estimate future energy demand.

Several studies that propose several models for energy demand policy management with different techniques are introduced. Pao [1] developed linear and nonlinear statistical models, including ANN methods, to forecast Taiwan's electricity consumption based on the national income, population, GDP, and consumer price index. For further details on employing ANN to estimate energy consumption, refer Assareh et al. [2] and Azadeh et al.'s [3] study. Bianco et al. [4] employed the Holt–Winters exponential smoothing method and the trigonometric grey model with rolling mechanism (TGMRM) to estimate electricity consumption in Italy. Ceylan et al. [5] used the harmony search (HS) technique to forecast Turkish transport energy demand in tree forms (linear, exponential, and quadratic) and based on population, GDP, and vehicle kilometers driven. Mohamed and Bodger [6] estimated the electricity demand of New Zealand based on economic indicators, including, GDP, electricity price, and population by multiple linear regression analysis. Amjadi et al. [7] presented two forms (exponential and linear) of energy demand equations to forecast the electricity demand for future projections based on PSO and GA techniques (see also Sadeghi et al. [8]). They used population, GDP, number of customer's electricity, and average price electricity as independent variables. The energy consumption in Iran is also determined using the bees algorithm technique by Behrang et al. [9] with independent variables such as population, GDP, import, and export. Kıran et al. [10] applied artificial bee colony (ABC) and particle swarm optimization (PSO) techniques to forecast electricity energy demand in Turkey in two forms, linear and quadratic by using selected economic and demographic variables that include the gross domestic product (GDP), population, import, and export.

The paper is organized as follows: In the next section, we explain the specification of the cuckoo optimization algorithm. Section 3 presents problem definition. In Section 4, the model estimations and forecasting results are done, and finally, in Section 5, the conclusions will be stated.

2. Cuckoo Optimization Algorithm

The cuckoo algorithm has been proposed by Yang and Deb [11]. It was developed by Rajabioun [12]. This algorithm runs like other evolutionary algorithms. The cuckoos used in this modeling are considered in two forms, namely, adult cuckoos and eggs. Thus, the COA begins with an initial population of cuckoos. Each adult cuckoo lays only one egg at a time and dumps it in a randomly selected nest. Some of these eggs grow up and turn into adult birds which are more similar to the host bird's eggs, and other eggs are recognized and thrown out by host birds. Therefore, an egg whose profit function value is smaller is removed. More profit is gained in habitats in which more eggs survive. In fact, the nests (position) in which more eggs remain will be the term that the COA is going to optimize. On the contrary, the remaining eggs grow and turn into adult cuckoos. They form some groups in all different regions of the environment. Then, they migrate to better regions where eggs have higher survival chances. Thus, the group with the best position is chosen as the goal point for all other groups to immigrate.

Therefore, it is necessary that problem values be convened as an array called "habitat" for solving an optimization problem with COA. In a N_{var} dimensional optimization problem, a habitat presents the current living place of a cuckoo and is an array of $1 \times N_{\text{var}}$. The array is indicated as follows:

$$\text{habitat} = [x_1, x_2, \ldots, x_{N\text{var}}]. \tag{1}$$

The suitability of a habitat is estimated by the assessment of profit function f_{b} at a habitat of $(x_1, x_2, \ldots, x_{N\text{var}})$, where

$$\text{profit} = f_{\text{b}}(\text{habitat}) = f_{\text{b}}(x_1, x_2, \ldots, x_{N\text{var}}). \tag{2}$$

To begin the COA, a primary habitat matrix of size $N_{\text{pop}} \times N_{\text{var}}$ is introduced.

Due to the number of eggs each cuckoo has and the cuckoo's distance to the best habitat (the current optimal area), an egg-laying radius (ELR) is assigned to it. Then, the cuckoo begins to lay eggs randomly in several nests inside her ELR. This process reiterates until the best position is obtained.

$$\text{ELR} = \alpha \times \frac{\text{number of current cuckoo's eggs}}{\text{total number of eggs}} \times (\text{var}_{\text{hi}} - \text{var}_{\text{low}}), \tag{3}$$

where α is an integer that adjusts the maximum value of ELR. var_{hi} and var_{low} are the upper and lower bound for the variables, respectively. Since adult cuckoos exist all over the environment, it is a problem to discover which group each cuckoo is dependent on. Grouping of birds is done by using the K-means clustering method to solve this problem. Now that the group's cuckoos are determined, their mean profit value is calculated. Then, other groups migrate to the region with the greatest mean profit. All cuckoos do not migrate the entire path in the movement to the goal point; they just go across a part of the total distance.

To keep the balance between the cuckoo and other birds, the maximum number of cuckoos that may live in a region is finite ($N_{\max}$). After iteration, all cuckoos arrive in an

optimized region with the most similarity of their eggs to the eggs of the host bird. In this location, the number of the removed eggs will be minimal and will gain the greatest objective function. The repeated algorithm to more than 95% of all the cuckoos converges toward a single point. Relation (4) shows the migration function in the COA:

$$X_{\text{Next habitat}} = X_{\text{Current habitat}} + F \times \left(X_{\text{Goal point}} - X_{\text{Current habitat}}\right), \tag{4}$$

where F is a parameter of cause deflection. The cuckoo optimization algorithm (COA) is classified as follows:

Step 1: forming initial cuckoo's habitats by using several random points

Step 2: allocating several eggs to each cuckoo and giving definition ELR for each cuckoo

Step 3: allowing cuckoos to lay eggs inside their corresponding ELR

Step 4: allowing eggs similar to the host bird's eggs to hatch, grow, and remove other eggs that are recognized by the host birds

Step 5: evaluating the habitat of each newly grown cuckoo

Step 6: limiting the maximum number of cuckoos in the environment and ignoring those who exist in the worst habitats

Step 7: clustering cuckoos, determining the best group and selecting goal habitat, and then allowing new cuckoo population immigrates toward a goal habitat

Step 8: checking the convergence, and then if the stop criterion is satisfied, stop. If not, go to step 2.

To check cuckoo optimization algorithm in detail, refer Mellal et al. [13], Shadkam and Bijari [14], and Mellal et al.'s [15] study.

2.1. Multiple Linear Cuckoo Optimization Algorithm (COA_{linear}). The present study uses population, GDP (gross domestic product), import, export, and employment to develop energy consumption models. For estimating the energy consumption, the models have been developed in two forms (linear and power) as follows.

Multiple linear cuckoo optimization algorithm (COA) is used for modeling the energy consumption in Iran. The four models taking different socioeconomic variables into consideration are as follows:

$$\begin{aligned}
&\text{Model 1: } y = a_1x_1 + b_1x_2 + f_1,\\
&\text{Model 2: } y = a_2x_1 + b_2x_2 + c_2x_3 + d_2x_4 + f_2,\\
&\text{Model 3: } y = a_3x_1 + b_3x_2 + e_3x_5 + f_3,\\
&\text{Model 4: } y = a_4x_1 + b_4x_2 + c_4x_3 + d_4x_4 + e_4x_5 + f_4,
\end{aligned} \tag{5}$$

where y represents the estimated energy consumption and $a_1, \ldots, a_4$; $b_1, \ldots, b_4$; $f_1, \ldots, f_4$; c_2; c_4; d_2; d_4; e_3; and e_4 values are the algorithm coefficients. The x_i values represent the five independent variables used as the predictors of y (x_1 is population, x_2 is GDP, x_3 is import amount, x_4 is export amount, and x_5 is employment).

Table 1: Values for normalization.

	$X_{\min}$	$X_{\max}$
GDP (billion Iranian rials)	**162557**	**555436**
Population (thousand persons)	**30284**	**76911**
Import (Mboe)	**0.1440**	**134.9738**
Export (Mboe)	**326.3281**	**2109.0781**
Employment (thousand persons)	**8188**	**21324**
Energy consumption (Mboe)	**94.8216**	**1229.7495**

2.2. Power Cuckoo Optimization Algorithm (COA_{power}). Power cuckoo optimization algorithm (COA) for estimating energy consumption is used as follows:

$$\begin{aligned}
&\text{Model 1: } y = a_1x_1^{b_1}x_2^{c_1},\\
&\text{Model 2: } y = a_2x_1^{b_2}x_2^{c_2}x_3^{d_2}x_4^{e_2},\\
&\text{Model 3: } y = a_3x_1^{b_3}x_2^{c_3}x_5^{f_3},\\
&\text{Model 4: } y = a_4x_1^{b_4}x_2^{c_4}x_3^{d_4}x_4^{e_4}x_5^{f_4},
\end{aligned} \tag{6}$$

where $a_1, \ldots, a_4$; $b_1, \ldots, b_4$; $c_1, \ldots, c_4$; d_2; d_4; e_2; e_4; f_3; and f_4 are the algorithm coefficients, x_1 is population, x_2 is GDP, x_3 is import amount, x_4 is export amount, and x_5 is employment.

The fitness function for selecting candidates for optimal coefficients is defined as

$$\min F(x) = \sum_{j=1}^{k} \left(Y_{\text{observed}} - Y_{\text{predicted}}\right)^2, \tag{7}$$

where Y_{observed} and $Y_{\text{predicted}}$ are the observed and predicted energy consumption, respectively, and k is the number of observations.

3. Estimation

Energy consumption in Iran from 1972 to 2013 is considered as a case in point in this paper. The available data are partly used for finding the optimal, or near-optimal, values of the weighting parameters (1972–2008) and partly for testing the models (2009–2013).

The following steps are conducted for forecasting energy consumption in Iran between 2014 and 2030:

Step 1: population, GDP, import, export, employment, and energy consumption need normalizing according to equation (8):

$$X_N = \frac{\left(X_{\text{R}} - X_{\min}\right)}{\left(X_{\max} - X_{\min}\right)}, \tag{8}$$

where X_N is the normalized value, X_{R} is the value to be normalized, $X_{\min}$ is the minimum value in all the values for the related variable, and $X_{\max}$ is the maximum value in all the values for the related variable. The $X_{\min}$ and $X_{\max}$ values for each variable are selected between 1972 and 2008 and are shown in Table 1.

Table 2: COA-linear model coefficients.

	a	b	c	d	e	f
Model 1	**0.9451**	**−0.0347**	**0.0783**	—	—	—
Model 2	**0.8151**	**−0.3325**	**−0.2272**	**0.5819**	**0.4416**	—
Model 3	**0.7312**	**0.0344**	**0.3379**	**−0.1104**	—	—
Model 4	**1.0659**	**0.4089**	**−0.3118**	**0.8644**	**0.4744**	**−0.2153**

Table 3: COA-linear model coefficients.

	a	b	c	d	e	f
Model 1	**0.9913**	**1.2568**	**−0.1195**	—	—	—
Model 2	**1.0408**	**1.0660**	**−0.6527**	**−0.0990**	**0.1338**	—
Model 3	**1.0665**	**−0.0045**	**0.6311**	**1.9404**	—	—
Model 4	**1.1164**	**1.0714**	**0.5894**	**−0.0769**	**0.0693**	**−0.1325**

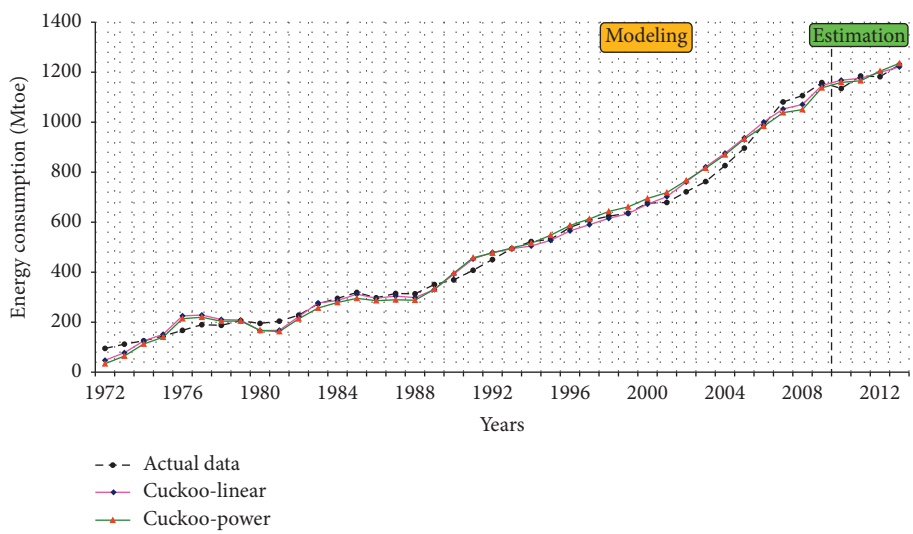

Figure 1: Comparison of the actual data and cuckoo-linear and cuckoo-power results for Model 1.

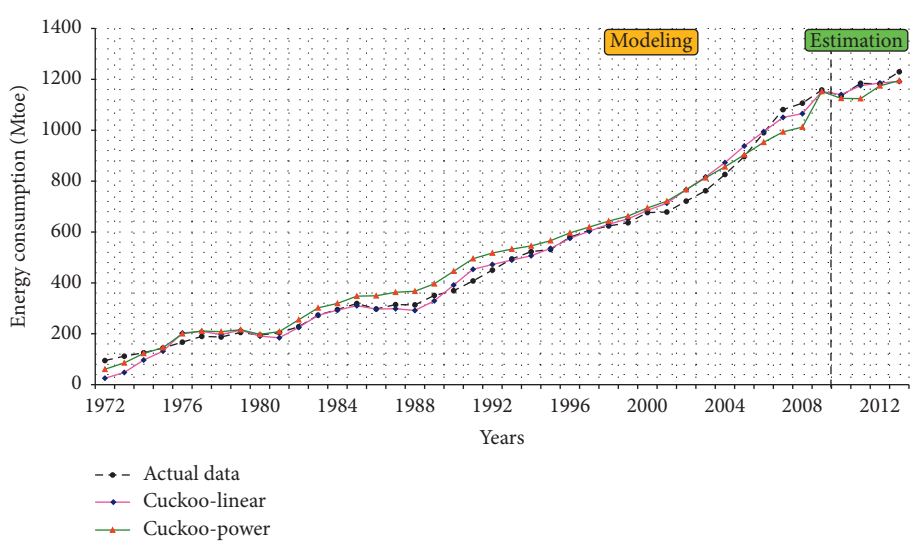

Figure 2: Comparison of the actual data and cuckoo-linear and cuckoo-power results for Model 2.

Step 2: the proposed algorithm is used in order to determine corresponding weighting factors (C_i) for each model according to the lowest objective functions

Step 3: in the second step, the best results of step 1 for each model and less average relative errors in the testing period are chosen (i.e., the related data from 2009 to 2013)

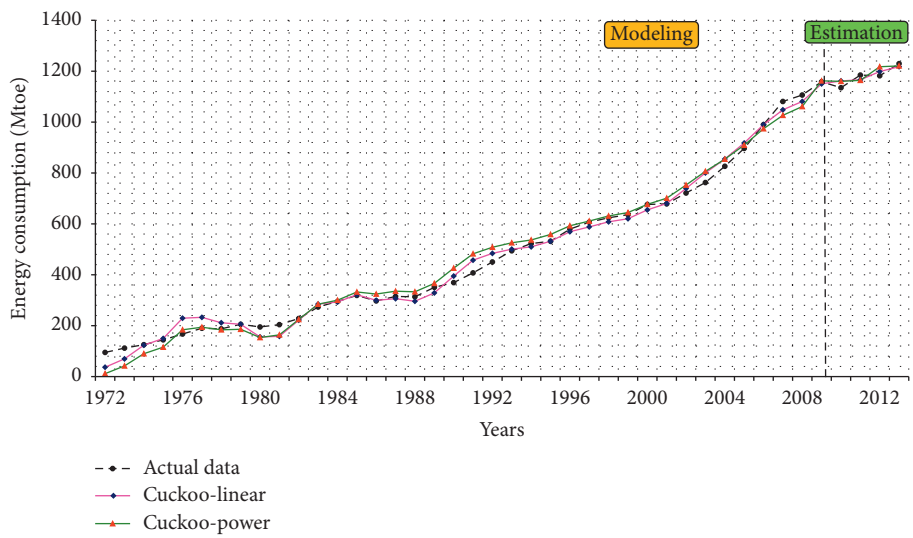

Figure 3: Comparison of the actual data and cuckoo-linear and cuckoo-power results for Model 3.

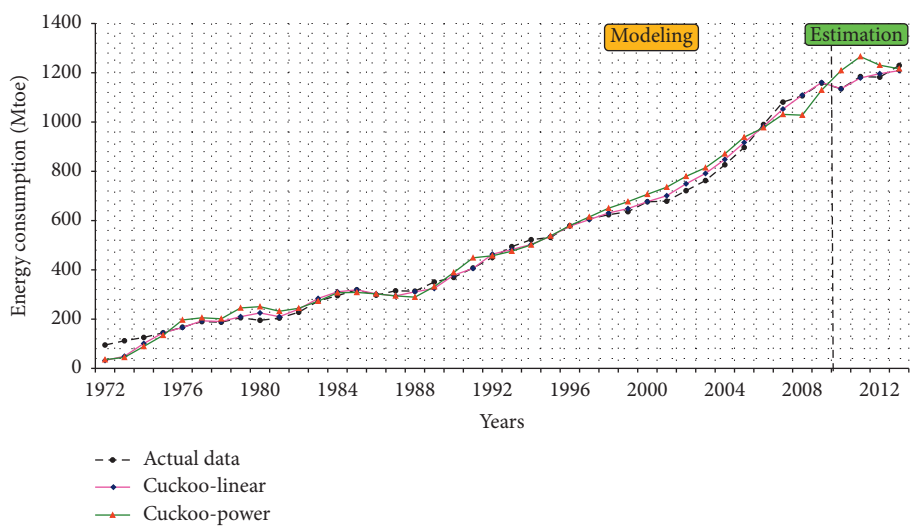

Figure 4: Comparison of the actual data and cuckoo-linear and cuckoo-power results for Model 4.

Table 4: Comparison of the COA estimation models for energy consumption in the testing period (2009–2013).

Years	2009	2010	2011	2012	2013	Average
Actual data[a]	1158.311	1134.874	1184.621	1182.055	1229.75	—
COA-linear model 1	1146.673	1167.896	1175.386	1199.447	1221.124	—
Relative error (%)	−1.01495	2.8275	−0.78565	1.4499	−0.7063	1.3568
COA-linear model 2	1152.347	1140.204	1175.386	1185.487	1192.07	
Relative error (%)	−0.5175	0.4674	−0.7856	0.2894	−3.1608	1.0441
COA-linear model 3	1150.078	1161.654	1166.08	1198.539	1217.719	
Relative error (%)	−0.7159	2.3053	−1.5900	1.3753	−0.9879	1.3948
COA-linear model 4	1160.292	1134.983	1179.132	1196.383	1208.753	
Relative error (%)	0.1707	0.0096	−0.4655	1.1975	−1.7370	0.716
COA-power model 1	1137.48	1158.93	1165.626	1204.1	1235.424	
Relative error (%)	−1.8313	2.0757	−1.6295	1.8308	0.4593	1.5653
COA-power model 2	1152.574	1125.201	1124.201	1174.252	1195.248	
Relative error (%)	−0.49772	−0.9493	−5.3744	−0.6645	−2.8865	2.0745
COA-power model 3	1161.99	1160.065	1163.924	1217.379	1220.67	
Relative error (%)	0.3169	2.1715	−1.7782	2.9015	−0.7438	1.5824
COA-power model 4	1129.422	1208.98	1265.613	1230.657	1216.13	
Relative error (%)	−2.5578	6.1296	6.3994	3.9492	−1.1198	4.0311

[a]Actual data are in million barrel oil equivalent (Mboe).

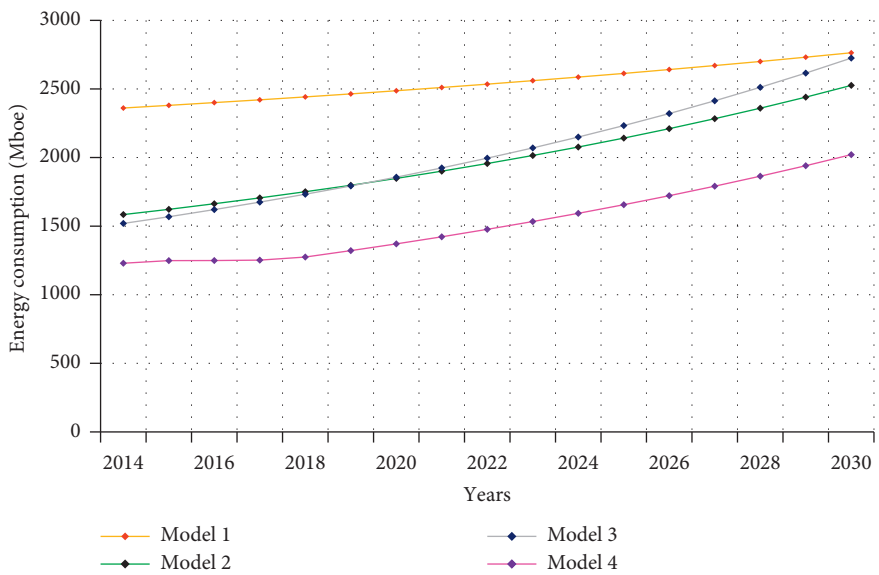

Figure 5: Forecasted values for energy demand in Iran (2014–2030) under scenario 1.

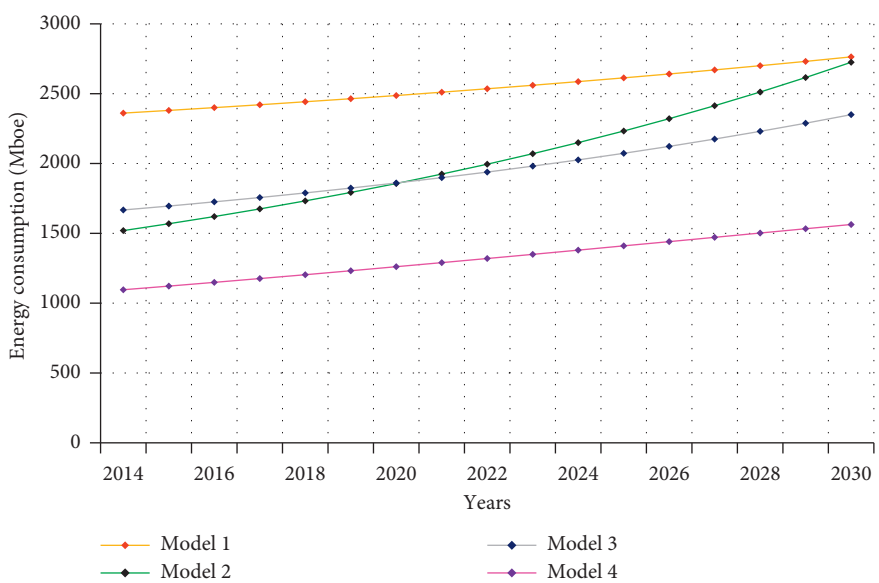

Figure 6: Forecasted values for energy demand in Iran (2014–2030) under scenario 2.

Step 4: to use the obtained models for future projections, each indicator should be forecasted in the future time domain

In this section, COA models are coded with MATLAB 2013 software. Note that all data include 41 annual data (1972–2013). They are used for finding optimal values of weighting factors regarding actual data (1972–2008). Following COA, demand estimation models have been obtained for energy consumption in Iran. The best-obtained weighting factors by the COA for linear and power models are shown in Tables 2 and 3.

It can be seen that there is a good agreement between the results obtained from COA estimation models (COA_{linear} and COA_{power}) but COA-linear models outperformed COA_{power} models.

Figures 1–4 for the modeling and the testing data show the performance of the linear cuckoo optimization algorithm and the power cuckoo optimization algorithm for all models. The findings proved that the recommended linear models were more appropriate tools for effective energy consumption prediction in Iran. For more clarification, Table 4 reports actual and estimated values of testing data by utilizing all models.

Using the COA_{linear} models, which was determined above, the energy consumption predictions are forecasted until 2030 for Iran. For different scenarios, differently forecasted data of GDP, population, employment, and export and import volumes are considered. The following three scenarios are used for forecasting each socioeconomic indicator in the years 2014–2030:

Scenario 1: it is assumed that the average growth rates of population, GDP, import, export, and employment

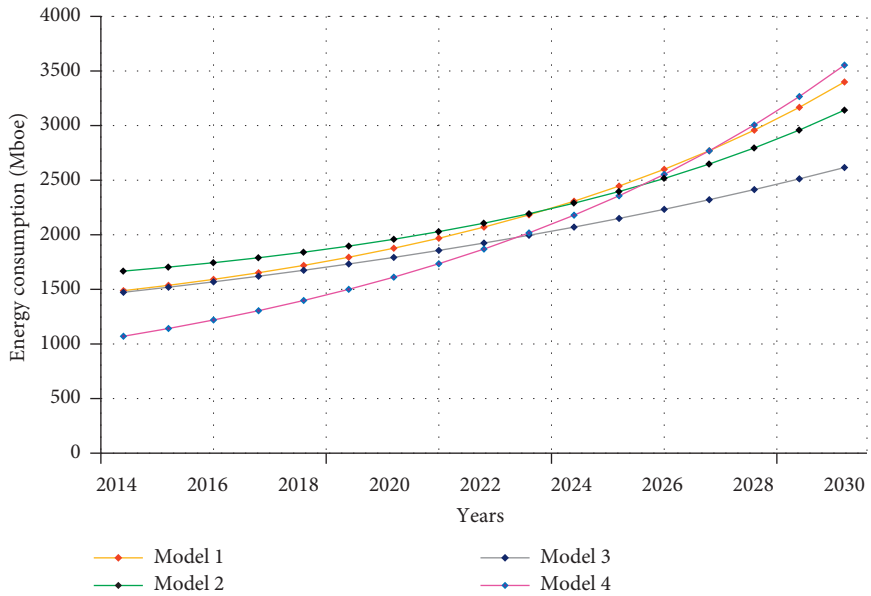

Figure 7: Forecasted values for energy demand in Iran (2014–2030) under scenario 3.

are 2%, 5%, 3%, 3%, and 6%, respectively, during 2014–2030

Scenario 2: it is assumed that the average growth rates of population, GDP, import, export, and employment are 2.2%, 6.7%, 3.3%, 3.3%, and 6.5%, respectively, during 2014–2030

Scenario 3: it is assumed that the average growth rates of population, GDP, import, export, and employment are 2.5%, 8%, 3.5%, 3.5%, and 7.5%, respectively, during 2014–2030

4. Conclusion

The point of this study is to demonstrate to the authorities the significance of utilizing option estimating strategies.

Therefore, in this study, the COA (cuckoo optimization algorithm) has been successfully used to estimate Iran's energy demand based on the structure of the Iran's socio-economic conditions. In the first model, energy consumption is estimated based on population and GDP. In the second model, population, GDP, import, and export are used to forecast energy consumption. In model 3, population, GDP, and employment are used to estimate energy consumption. Finally, in the fourth model, energy consumption is modeled based on population, GDP, export, import, and employment. The proposed linear models anticipated the energy demand superior to anything the power models in terms of relative errors and RMSEs. In addition, approval of models demonstrates that acquired demand estimation linear models are in great concurrence with the watched information, yet the COA_{linear} model 4 outflanked other introduced models. Thus, three scenarios are designed to estimate Iran's energy demand during 2014–2030 using COA-linear models, and the results are shown in Figures 5–7.

In conclusion, this paper presented helpful suggestions and novel insights into experts and policy planners. It recommended a strong tool for developing energy programs. Forecasting energy demand can as well be studied by neural networks or other new metaheuristics including harmony search and simulated annealing. The results of different methods may be compared with the COA method. Further studies should concentrate on the comparison of methods explained in this study with the rest of the available tools. Forecasting energy demand may as well be investigated by using electromagnetism mechanism algorithm, krill herd optimization algorithm, and the rest of intelligent optimization techniques. The results of using different methods could be put into analogy with the COA method.

Data Availability

All data are available in the World Bank depository, Central Bank of the Islamic Republic of Iran, and Iran's Ministry of Energy.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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