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Forecasting Energy Demand in Iran Using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) Methods

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Abstract The main objective of this research is to estimate energy demand in Iran using intelligence techniques based on the structure of Iran’s industry and economic conditions. This study develops a scenario to analyze energy consumption and makes future projections based on particle swarm optimization (PSO) and genetic algorithm (GA) methods. The models are developed in two forms (exponential and linear) and applied to forecast energy demand in Iran. PSO and GA demand estimation models are developed to estimate the future energy demand values based on population, gross domestic product, import, and export data. Energy consumption in Iran from 1981–2005 is considered as the case of this study. The available data is partly used for finding the optimal, or near optimal, values of the weighting parameters (1981–1999) and partly for testing the models (2000–2005). Energy demand in Iran is forecasted up to year 2030.

Keywords energy, genetic algorithm, Iran, particle swarm optimization, projection

1. Introduction

The outlook of energy in Iran shows the importance of the need for systematic optimization of energy use in Iran. Energy resources are limited and depleting (Houri Jafari and Baratimalayeri, 2008). Furthermore, Iran’s population is steadily increasing. Energy consumption in Iran is also rapidly increasing (MOE, 2005).

Iran, with population of more than 68 million (Karbassi et al., 2007), is one of the largest producers of crude oil in the world. Contrary to the public’s perception, Iran’s share of the market for high quality oil is as little as 2% (MOE, 2005). More specifically, while Iran has the fourth highest oil production rate, the oil produced in Iran is ranked 14th in terms of quality (MOE, 2005).

The available reserves of crude oil and liquid gas in Iran at the end of 2005 were 136.99 billion barrels (1 barrel = 0.159 m³) while in 2004 it was 500 million barrels, a 0.36% decrease (MOE, 2005).

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From the point of view of natural gas reserves, Iran is in the second position after the former USSR. The amount of the available natural gas reserves of Iran at the end of 2005 were estimated as 28.17 trillion cubic meters.

In 2005, the total consumed power of Iran was 135,468 million kilowatt hours (GWh) which in comparison with 2004 shows a 4.6% growth (MOE, 2005).

Several studies are presented to propose some models for energy demand policy management using intelligence techniques. Unler (2008) developed a particle swarm optimization energy demand (PSO-DEM) model to estimate energy demand based on economic indicators in Turkey. Canyurt and Ozturk (2008) presented Turkey’s fossil fuel demand by using the structure of the Turkish industry and economic conditions based on genetic algorithm (GA). Toksari (2007) developed an ant colony energy demand estimation model for Turkey. Azadeh et al. (2008) presented an integrated algorithm for forecasting monthly electrical energy consumption based on artificial neural network (ANN). Canyurt and Ozturk (2006) developed three scenarios to analyze oil consumption and made future projections based on the GA notion, and examined the effect of the design parameters on the oil utilization values. Ceylan and Ozturk (2004) developed a GA energy demand model (GA-DEM) to estimate energy demand based on economic indicators in Turkey. Ozturk et al. (2005) developed two different nonlinear estimation models using GAs to forecast Turkey’s electricity demand in the future.

Sozen et al. (2005) also used ANN to forecast Turkey’s net energy consumption.

Haldenbilen and Ceylan (2005) developed three forms of the energy demand equations in order to improve transport energy demand estimation efficiency for future projections based on the GA notion. Sozen and Arcaklioglu (2007) developed the energy sources estimation equations in order to estimate future projections and make correct investments in Turkey using the ANN approach. For more studies in this regard see Assareh et al. (2010; 2012) and Behrang et al. (2011a,b,c,d).

This study presents the application of the particle swarm optimization (PSO) and GA methods to forecast energy demand in Iran based on socio-economic indicators. The socioeconomic indicators used in this study are population, gross domestic product (GDP), import, and export. The models which are developed in two forms (exponential and linear), are applied to forecast energy demand in Iran. Energy consumption in Iran from 1981–2005 is considered as the case of this study.

## 2. Genetic Algorithm

The formulation of GAs was made about a decade after the first evolutionary strategies and evolutionary programming applications.

Over more than 30 years of research, several modifications have been proposed to the original GA structure defined in Holland (1975). Unless otherwise stated this section will explain Holland’s original algorithm, often referred as the canonical GA.

GAs encode candidate solutions as binary strings. Each string (chromosome) is built by chaining a number of substrings, each substring representing one of the candidate solution’s features. Biological genes are in this case equivalent to the substrings encoding the parameters, while each binary digit can be related to the nucleotides composing the DNA. In most of the cases, one individual is fully described by a single bit-string, thus leading to the identification of the genotype with one single chromosome. Several other encoding procedures have been explored leading to a debate on the most appropriate choice. Holland (1975) showed that binary coding allows the maximum number of schemata to be processed per individual. On the other hand, the mapping to binary coding
introduces Hamming cliffs onto the search surface. Moreover, nonbinary representations may be more natural for some problem domains and may reduce the computational burden of the search. The canonical binary-coded GA as described here is now rarely used for continuous function optimization as it has been shown that solutions are too easily disrupted (the Hamming cliff issue). Therefore researchers tend to use less disruptive coding such as Gray coding (Michalewicz, 1999).

Similar to the other evolutionary algorithms, canonical GAs use generational replacement. Popular alternatives are elitism and steady-state replacement (Davis, 1991). In the first case, the best solution(s) are directly copied into the new population while in the second case only a fraction of the population is replaced at each generation. Both variants aim to improve the preservation of good genetic material at the expense of a reduced search space exploration. A comparison between the behavior of generational and steady-state replacement is given in Syswerda (1991).

Individuals are selected for reproduction with a probability depending on their fitness. Canonical GAs allocate the mating probability of each individual proportionally to its fitness (proportional selection) and draw the parents set (mating pool) through the roulette wheel selection procedure (Goldberg, 1989). Other popular selection schemes are fitness ranking (Baker, 1985) and tournament selection (Goldberg and Deb, 1991). For a comparison of selection procedure, the reader is referred to Goldberg and Deb (1991).

Crossover is the main search operator in GAs, creating offspring by randomly mixing sections of the parental genome. The number of sections exchanged varies widely with the GA implementation. The most common crossover procedures are one-point crossover, two-point crossover, and uniform crossover (Davis, 1991). In canonical GAs, a crossover probability is set for each couple. Couples not selected for recombination will generate two offspring identical to the parents.

A small fraction of the offspring are randomly selected to undergo genetic mutation. The mutation operator randomly picks a location from a bit-string and flips its contents. The importance of this operator in GAs is, however, secondary and the main aim of mutation is the preservation of the genetic diversity of the population.

GAs require the tuning of some parameters such as the mutation rate, crossover rate and replacement rate in the case of steady-state replacement. This task is often not trivial as the chosen values may strongly influence the search process (Grefenstette, 1986; Schaffer et al., 1989). Moreover, the optimal value for the GA parameters may vary according to the evolution of the search process. For all these reasons, several adaptive schemes have been investigated. A survey of adaptation in GAs is given in Hinterding et al. (1997); Back (1993) proposed an off-line tuning approach giving an optimal mutation rate schedule. Problem-specific operators are sometimes employed in addition to the canonical ones. The introduction of such operators results in an increase in the search power of the algorithm but a loss of general applicability. This issue is analyzed in Michalewicz (1993).

Population, selection, reproduction, crossover, mutation, and generation are considered as important factors in GA.

### 3. Particle Swarm Optimization

The PSO algorithm was first proposed by Kennedy and Eberhart (1995), 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. The individuals
in a PSO have a position and a velocity and are denoted as particles. The PSO traditionally has no crossover between individuals, has no mutation, and particles are never substituted by other individuals during the run. The PSO algorithm works by attracting the particles to search space positions of high fitness. Each particle has a memory function, and adjusts its trajectory according to two pieces of information, the best position that it has so far visited, and the global best position attained by the whole swarm. If the whole swarm is considered as a society, the first piece of information can be seen as resulting from the particle’s memory of its past states, and the second piece of information can be seen as resulting from the collective experience of all members of the society. Like other optimization methods, PSO has a fitness evaluation function that takes each particle’s position and assigns it a fitness value. The position of highest fitness value visited by the swarm is called the global best. Each particle remembers the global best, and the position of highest fitness value that has personally visited, which is called the local best.

Many attempts were made to improve the performance of the original PSO algorithm and several new parameters were introduced such as the inertia weight (Engelbrecht, 2005). The canonical PSO with inertia weight has become very popular and is widely used in many science and engineering problems (Brits et al., 2007; Liu et al., 2007; Pan et al., 2006; Yang, 2007).

In the canonical PSO, each particle has position and velocity that is updated at each iteration according to Eq. (1):

\[ \vec{v}_i = \omega \vec{v}_i + c_1 \vec{\phi}_{i1} (\vec{p}_i - \vec{x}_i) + c_2 \vec{\phi}_{i2} (\vec{p}_g - \vec{x}_i) \] (1)

where \( \omega \) is the inertia weight described in Shi and Eberhart (1998a,b), \( \vec{p}_i \) is the best position found so far by particle \( \vec{p}_i \), and \( \vec{p}_g \) is the global best so far found by the swarm. \( \vec{\phi}_{i1} \) and \( \vec{\phi}_{i2} \) are weights that are randomly generated at each step for each particle component. \( c_1 \) and \( c_2 \) are positive constant parameters called acceleration coefficients (which control the maximum step size the particle can achieve). The position of each particle is updated at each iteration by adding the velocity vector to the position vector.

\[ \vec{x}_i = \vec{x}_i + \vec{v}_i \] (2)

The inertia weight \( \omega \) (which is a user-defined parameter), together with \( c_1 \) and \( c_2 \), controls the contribution of past velocity values to the current velocity of the particle. A large inertia weight biases the search towards global exploration, while a smaller inertia weight directs toward fine-tuning the current solutions (exploitation). Suitable selection of the inertia weight and acceleration coefficients can provide a balance between the global and the local search (Engelbrecht, 2005). The PSO algorithm is composed of five main steps:

1. Initialize the position vector \( \vec{x} \) and associated velocity \( \vec{v} \) of all particles in the population randomly. Then set a maximum velocity and a maximum particle movement amplitude in order to decrease the cost of evaluation and to get a good convergence rate.
2. Evaluate the fitness of each particle via the fitness function. There are many options when choosing a fitness function and trial and error is often required to find a good one.
3. Compare the particle’s fitness evaluation with the particle’s best solution. If the current value is better than previous best solution, replace it and set the current
solution as the local best. Compare the individual particle’s fitness with the population’s global best. If the fitness of the current solution is better than the global best’s fitness, set the current solution as the new global best.

4. Change velocities and positions by using Eqs. (1) and (2).

5. Repeat Step 2 through Step 4 until a stopping criterion is satisfied or a predefined number of iterations is completed.

Particle size \((n)\), inertia weight \((\omega)\), and maximum iteration number \((t)\) are considered as important factors in PSO. For more details about PSO, the reader is referred to Behrang et al. (2011c).

4. Problem Definition

This study presents the application of the PSO and GA methods to estimate and predict energy demand in Iran. The socioeconomic indicators used in this study are population, GDP, import, and export. The models are developed in two forms (exponential and linear) are applied to estimate energy demand in Iran.

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

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

(3)

where \(E_{\text{actual}}\) and \(E_{\text{predicted}}\) are the actual and predicted energy consumption, respectively, and \(m\) is the number of observations. The data related to the design parameters of Iran’s population, GDP, import and export figures are obtained from MOE (2005). Energy consumption in Iran from 1981–2005 is considered as the case of this study. The testing procedure for the present study was performed in the as: The model was validated using the population, GDP, import, and export figures for the 6-year period 2000–2005.

Forecasting of energy demand based on economic indicators was modeled by using both linear and exponential models. The linear form of equations for the demand estimation models is written as:

\[
Y_{\text{linear}} = w_1 X_1 + w_2 X_2 + w_3 X_3 + w_4 X_4 + w_5
\]  

(4)

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

\[
Y_{\text{exponential}} = w_1 X_1^{w_2} + w_3 X_3^{w_4} + w_5 X_3^{w_6} + w_7 X_4^{w_8} + w_9
\]  

(5)

where \(X_1\), \(X_2\), \(X_3\), and \(X_4\) are the population, GDP, import, and export figures, respectively, and \(w_i\) are the corresponding weighting factors.

5. Results

In Tables 1 and 2, it can be seen that there is good agreement between the results obtained from PSO-DEM and GA-DEM with the observed data. The PSO algorithm is coded in MATLAB 2007 software (The MathWorks, Natick, MA) and for the GA algorithm, the toolbox of MATLAB 2007 (The MathWorks, Natick, MA) is used. Population, GDP, import, export, and energy consumption in Eqs. (7)–(10) needs normalizing according to Eq. (6)

\[
X_N = (X_R - X_{\text{min}})/(X_{\text{max}} - X_{\text{min}})
\]  

(6)
### Table 1
Comparison of the GA-DEM\textsubscript{exponential} and GA-DEM\textsubscript{linear} models

<table>
<thead>
<tr>
<th>Years</th>
<th>Observed data, Mboe\textsuperscript{a}</th>
<th>GA-DEM\textsubscript{exponential}</th>
<th>Relative error, %</th>
<th>GA-DEM\textsubscript{linear}</th>
<th>Relative error, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>623.7</td>
<td>611.1</td>
<td>-2.020</td>
<td>620.7</td>
<td>-0.481</td>
</tr>
<tr>
<td>2001</td>
<td>641.8</td>
<td>636.8</td>
<td>-0.795</td>
<td>640.4</td>
<td>-0.218</td>
</tr>
<tr>
<td>2002</td>
<td>693.8</td>
<td>690.7</td>
<td>-0.461</td>
<td>685.5</td>
<td>-1.196</td>
</tr>
<tr>
<td>2003</td>
<td>726.8</td>
<td>759.7</td>
<td>4.527</td>
<td>747.5</td>
<td>2.848</td>
</tr>
<tr>
<td>2004</td>
<td>780.2</td>
<td>807.4</td>
<td>3.486</td>
<td>786.3</td>
<td>0.782</td>
</tr>
<tr>
<td>2005</td>
<td>857.7</td>
<td>835.8</td>
<td>-2.553</td>
<td>817.0</td>
<td>-4.745</td>
</tr>
<tr>
<td>Average</td>
<td>—</td>
<td>—</td>
<td>2.31</td>
<td>—</td>
<td>1.71</td>
</tr>
</tbody>
</table>

\textsuperscript{a}Mboe: Million barrel of oil equivalents.
1 barrels of oil equivalent (boe) = 6,119 × 10\textsuperscript{6} joule (J).

$X_N$: normalized value  
$X_R$: the value to be normalized  
$X_{\text{min}}$: the minimum value in all the values for related variable  
$X_{\text{max}}$: the maximum value in all the values for related variable.

The $X_{\text{min}}$ and $X_{\text{max}}$ values for each variable are selected between 1981–1999 and shown in Table 3. The convergence of the objective function and sensitivity analysis was examined for varying important factors of each PSO-DEM and GA-DEM model. After 10 times running the different combinations of each important factor, the best results were chosen according to the lowest objective functions. The best results of GA-DEM and PSO-DEM models are performed using the following user-specified parameters:

**GA:**  
Selection (Selection function: Stochastic uniform)  
Reproduction (Elite count: 2.0, Crossover fractions: 0.8)  
Crossover (Crossover function: Scattered)

### Table 2
Comparison of the PSO-DEM\textsubscript{exponential} and PSO-DEM\textsubscript{linear} models

<table>
<thead>
<tr>
<th>Years</th>
<th>Observed data, Mboe</th>
<th>PSO-DEM\textsubscript{exponential}</th>
<th>Relative error, %</th>
<th>PSO-DEM\textsubscript{linear}</th>
<th>Relative error, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>623.7</td>
<td>624.9</td>
<td>0.19</td>
<td>618.6</td>
<td>-0.82</td>
</tr>
<tr>
<td>2001</td>
<td>641.8</td>
<td>638.7</td>
<td>-0.48</td>
<td>632.3</td>
<td>-1.48</td>
</tr>
<tr>
<td>2002</td>
<td>693.8</td>
<td>694.4</td>
<td>0.09</td>
<td>684.1</td>
<td>-1.40</td>
</tr>
<tr>
<td>2003</td>
<td>726.8</td>
<td>750.2</td>
<td>3.22</td>
<td>748.9</td>
<td>3.04</td>
</tr>
<tr>
<td>2004</td>
<td>780.2</td>
<td>797.4</td>
<td>2.20</td>
<td>790.0</td>
<td>1.26</td>
</tr>
<tr>
<td>2005</td>
<td>857.7</td>
<td>871.4</td>
<td>1.60</td>
<td>837.1</td>
<td>-2.40</td>
</tr>
<tr>
<td>Average</td>
<td>—</td>
<td>—</td>
<td>1.27</td>
<td>—</td>
<td>1.73</td>
</tr>
</tbody>
</table>
Table 3

<table>
<thead>
<tr>
<th></th>
<th>(X_{\text{min}})</th>
<th>(X_{\text{max}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population (1,000 persons)</td>
<td>40,825.6</td>
<td>62,736</td>
</tr>
<tr>
<td>GDP (billion Iranian rials)</td>
<td>170,281.2</td>
<td>304,941.2</td>
</tr>
<tr>
<td>Import (Mboe)</td>
<td>21.4</td>
<td>72.9</td>
</tr>
<tr>
<td>Export (Mboe)</td>
<td>339.8</td>
<td>1,058.6</td>
</tr>
<tr>
<td>Energy consumption (Mboe)</td>
<td>196.2</td>
<td>588.4</td>
</tr>
</tbody>
</table>

Mutation (Mutation function: Gaussian, Scale: 1.0, Shrink: 1.0)
Stopping criteria (Generation: 100)
PSO:
- Maximum Iteration number \((t)\): 200
- Particle size \((n)\): 36
- Inertia weight \((\omega)\): 0.2

Following GA and PSO demand estimation equations have been obtained for energy demand. Four demand estimation models (DEM) for energy are shown in Eqs. (7)–(10). In the linear form of the GA-DEM and PSO-DEM, coefficients obtained are given as:

\[
Y_{\text{GA-DEMlinear}} = 0.3296X_1 + 0.42945X_2 + 0.0518X_3 + 0.104X_4 + 0.1536
\]

\[
Y_{\text{PSO-DEMlinear}} = 0.13775X_1 + 0.696653X_2 - 0.0373X_3 + 0.21345X_4 - 0.0113
\]

In the exponential form of the GA-DEM and PSO-DEM, coefficients obtained are given as:

\[
Y_{\text{GA-DEMeponential}} = 0.0637X_1^{0.4921} + 0.684X_2^{0.8263} + 0.1093X_3^{0.9918}
\]

\[+ 0.1562X_4^{0.2614} + 0.057\]

\[
Y_{\text{PSO-DEMeponential}} = 0.0116X_1^{0.386} + 0.4712X_2^{1.6598} - 0.1392X_3^{0.654}
\]

\[+ 0.2326X_4^{0.232} + 0.365\]

These four equations were obtained from the general forms of Eqs. (4) and (5).

For the best results of GA, the average relative errors on testing data were 2.31% and 1.71% for \(Y_{\text{GA-DEMeponential}}\) and \(Y_{\text{GA-DEMlinear}}\), respectively. The corresponding value for PSO were 1.27% and 1.73% for \(Y_{\text{PSO-DEMeponential}}\) and \(Y_{\text{PSO-DEMlinear}}\), respectively. Validations of models show that PSO-DEM and GA-DEM are in good agreement with the observed data but PSO-DEM outperformed other models presented here.

These steps are used for forecasting Iran’s energy demand in the years 2006–2030:

a. For each socio-economic indicator, the polynomial trend lines are fitted to the observed data with the highest \(R^2\) values and shown in Figure 1(a to d).

b. The forecasting for each indicator is made in the years 2006–2030.

c. Finally the energy demand is forecasted using the PSO-DEM and GA-DEM models.

In Figures 2–5, energy consumptions are projected through 2030.
Figure 1. Trend lines and actual data of (a) population, (b) GDP, (c) import and (d) export figures.

(continued)
Figure 1. (Continued).

Figure 2. Comparison between observed data and GA-DEM\textsubscript{exponential} for energy demand values of Iran.

Figure 3. Comparisons between observed data and GA-DEM\textsubscript{linear} for energy demand values of Iran.
6. Conclusion

The relationship between the economic growth of a country and its energy demand is an important subject which requires reasonable estimation for a broad range of parameters including economic, social, and technological. Artificial intelligence models have been successfully used to estimate Iran’s energy demand based on population, GDP, import, and export. Data for 25 years (1981–2005) has been used for developing both forms (linear and exponential) of the GA-DEM and PSO-DEM. A scenario is then designed in order to estimate Iran’s energy demand during 2006–2030. The predictions are compared with the actual values. Validations of models show that PSO-DEM and GA-DEM are in good agreement with the observed data but PSO-DEM\textsubscript{exponential} outperformed other models presented here. It is concluded that the suggested models are a satisfactory tool for successful energy demand forecasting. The range of scenario and related energy demand is small; however, the results presented here provide helpful insight into energy system modeling. They are also instrumental to scholars and policy makers as a potential tool for developing energy plans.
Future work is focused on comparing the methods presented here with other available tools. The forecasting of energy demand can also be investigated with gravitational search algorithm, ant colony, fuzzy logic, neural networks, or other metaheuristic methods such as tabu search, simulated annealing, and so on. The results of the different methods could be compared with the GA and PSO methods.

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References


