Applications of Particle Swarm Optimization in Oil Demand Estimation

Motahareh Moravej Hamedani ,Baharan Mirzasoleiman

School of Electrical and Computer Engineering, University of Tehran,

North Kargar St., P.O. Box 14395-515, Tehran, Iran.
{ m.moravej, b.mirzasoleiman }@ece.ut.ac.ir

Paper Reference Number: **12516700**
Name of the Presenter: Motahareh Moravej

Abstract

Oil consumption is a major factor in country economy decisions. Prediction of this factor can help in adjustment and making long term plans for oil production, import and export values or decision to use another form of energy such as gas, electricity or nuclear energy.

This paper is concerned with the estimation of future oil demands based on particle swarm optimization (PSO) notation which can be used for projection of future oil consumption of any country in terms of different parameters such as Gross National Product (GNP), population, import, export, oil production, oil import and car, truck and bus sales. The models developed in quadratic form are applied to the oil demand of Turkey.

A comparison has been made between the result of particle swarm algorithm and the previous results generated by genetic algorithm (GA). Case studies show that in this application, the PSO can generate optimal results.

Keywords: Genetic algorithm; Oil estimation; Particle swarm;

1. Introduction

In the International Energy Outlook 2007 (IEO2007) reference case [1], total world consumption of marke-ted energy is projected to increase by 57 percent from 2004 to 2030.

The IEO2007 reference case projects increased world consumption of marketed energy from all sources over the 2004 to 2030 period. Fossil fuels continue to supply much of the increment in marketed energy use worldwide throughout the projections. Liquids (primarily, oil and other petroleum products) are expected to continue to provide the largest share of world energy consumption over the projection period, but their share falls from 38 percent in 2004 to 34 percent in 2030, largely because rising world oil prices dampen the demand for liquids after 2015.

Worldwide liquids consumption is projected to increase from 83 million barrels per day in 2004 to 97 million barrels per day in 2015 and 118 million barrels per day in 2030. Liquids remain the most important fuels for transportation, because there are few alternatives that can be expected to compete widely with petroleum-based liquids; however, the role of oil outside the transportation sector continues to be eroded because of high world oil prices in most regions of the world. On a global basis, the transportation sector accounts for 68 percent of the total projected increase in liquids use between 2004 and 2030, followed by the industrial sector, which accounts for another 27 percent of the increment in world liquids demand.

It is estimated that there may be 57 ZJ of oil reserves on Earth (although estimates vary from a low of 8 ZJ [2], consisting of currently proven and recoverable reserves, to a maximum of 110 ZJ) consisting of available, but not necessarily recoverable reserves, and including optimistic estimates for unconventional sources such as tar sands and oil shale. Current consensus among the 18 recognized estimates of supply profiles is that the peak of extraction will occur in 2020 at the rate of 93-million barrels per day (mbd). Current oil consumption is at the rate of 0.18 ZJ per year (31.1 billion barrels) or 85-mbd.

There is growing consensus that peak oil production may be reached in the near future, resulting in severe oil price increases. A 2005 French Economics, Industry and Finance Ministry (FEIFM) report suggested a worst-case scenario that could occur as early as 2013[3]. There are also theories that peak of the global oil production may occur in as little as 2-3 years. The ASPO predicts peak year to be in 2010. Some other theories present the view that it has already taken place in 2005. World oil production decreased from 84.65 mbd in 2005 to 84.60 mbd in 2006 but increased in 2007 to 84.81 mbd, and is projected to increase to 89.22 mbd in 2009[4].

These discussions show the importance of oil demand prediction to make long-term plans for reducing oil consumption and to use other kinds of energy instead of oil. These kinds are usually cleaner than the fossil fuels and have less damage to environment. The estimation of oil demand based on economic indicators may be modeled using various forms of equations. These equations may be linear or non-linear forms. The non-linear form of the equations can better applied to the estimation of the future oil demand of Turkey due to the fluctuation of the economic indicators.

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching for food in an area. There is only one piece of food in the area being searched. All of birds do not know where the food is. But they know how far the food is in each iteration. So what is the best strategy to find the food? The effective one is to follow the bird that is nearest to the food.

PSO developers learned from this scenario and used it to solve the optimization problems. In PSO, each single solution is a ''bird'' in the search space. We call it ''particle''. All the particles have fitness values that are evaluated by the fitness function to be optimized, and have velocities that direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.

In the present study, the particle swarm is used to predict the future oil consumption trends of Turkey. The oil demand may be considered to be influenced by economic growth, GNP, import, export and population and oil related parameters. The results show that the particle swarm approach can successfully estimate almost exact value for oil demand of any selected country.

The remainder of the paper is organized as follows. Section 2 defines the PSO algorithm. Section 3 focuses on the implementation of PSO algorithm for oil consumption estimation (PSODEM). In Section 4, we describe the results and compare them to those of GA oil demand estimation model (GAODEM) and Ministry of Energy and Natural Resources (MENR) [8-10]. Finally, Section 5 concludes the paper.

2. PSO Algorithm

PSO introduced by Kennedy and Eberhart [5] is one of the most recent and hopeful evolutionary metaheuristics, which is inspired from the swarming behaviour of animals and human social behaviour.

Scientists found that the synchrony of animal's behaviour was through maintaining optimal distances between individual members and their neighbours. Thus, velocity plays the important role of adjusting each other for the optimal distance. Furthermore, scientists simulated the scenario in which birds search for food and observed their social behaviour. They perceived that in order to find food the individual members determined their velocities by two factors, their own best previous experience and the best experience of all other members. This is similar to the human behaviour in making decision where people consider their own best past experience and the best experience of the other people around them.

The general principles for the PSO algorithm are stated as follows.

Similarly to evolutionary computation technique, the PSO maintains a population of particles, where each particle represents a potential solution to an optimization problem. Let K be the size of the swarm. Each particle i can be represented as an object with several characteristics.

Suppose that the search space is n-dimensional, then the ith particle can be represented by a n-dimensional vector, $W_i = \{w_{i1}, w_{i2}, ..., w_{in}\}$, and velocity $V_i = \{v_{i1}, v_{i2}, ..., v_{in}\}$, where i = 1, 2,. . .,K.

In PSO, particle i remembers the best position it visited so far, referred to as $P_i = \{p_{i1}, p_{i2}, ..., p_{in}\}$, and the best position of the best particle in the swarm, referred to as $G = \{G_1, G_2, ..., G_n\}$.

The PSO is similar to evolutionary computation algorithm and, in each generation t, particle i adjusts its velocity v_{ij}^t and position through each dimension j by referring to, with random multipliers, the personal

best position and the swarm's best position G_{ij}^{t-1} using Eqs. (1) and (2) as follows:

$$v_{ij}^t = v_{ij}^{t-1} + c_1 r_1 (p_{ij}^{t-1} - w_{ij}^{t-1}) + c_2 r_2 (G^{t-1}{}_j - w_{ij}^{t-1}) \quad (1)$$

and

$$w_{ij}^t = w_{ij}^{t-1} + v_{ij}^t \quad (2)$$

where c1 and c2 are the acceleration constants and r_1 and r_2 are random real numbers drawn from U(0,1). Thus the particle flies through potential solutions toward p_i^t and G^t in a navigated way while still exploring new areas by the stochastic mechanism to escape from local optima. Since there was no actual mechanism for controlling the velocity of a particle, it was necessary to impose a maximum value Vmax on it. If the velocity exceeded this threshold, it was set equal to Vmax, which controls the maximum travel distance in each iteration to avoid this particle flying past good solutions.

The PSO algorithm is terminated with a maximal number of generations or the best particle position of the entire swarm that cannot be improved further after a sufficiently large number of generations.

The aforementioned problem was addressed by incorporating a weight parameter for the previous velocity of the particle. Thus, in the latest versions of the PSO, Eqs. (2) and (3) are changed to the following ones:

$$v = \chi(\omega v_{ij}^{t-1} + c_1 r_1 (p_{ij}^{t-1} - w_{ij}^{t-1}) + c_2 r_2 (G^{t-1}{}_j - w_{ij}^{t-1})) \quad (3)$$

and

$$w_{ij}^t = w_{ij}^{t-1} + v_{ij}^t \quad (4)$$

where ω is called inertia weight and is employed to control the impact of the previous history of velocities on the current one. Accordingly, the parameter ω regulates the trade-off between the global and local exploration abilities of the swarm. A large inertia weight facilitates global exploration, while a small one tends to facilitate local exploration. A suitable value for the inertia weight ω usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution.

χ is a constriction factor, which is used to limit velocity. [6]

The PSO algorithm has shown its robustness and efficacy in solving function value optimization problems in real number spaces.

3. Implementation of PSO Algorithm for Oil Consumption Estimation

For estimation of oil consumption we can use a model either in quadratic or linear form. Because those in quadratic forms can give a better result, we choose one of them in the following form which actually originates from GA proposed for GAODEM in [7]. This model includes each individual effect of the design parameters (Xi) for oil consumption estimation. The quadratic form in $X_1, . . . , X_5$ is a polynomial, and it can be expressed as

$$\begin{aligned} E^{PSODEM} &= w_1 + w_2 X_1 + w_3 X_2 + w_4 X_3 + \\ & w_5 X_4 + w_6 X_5 + w_7 X_1 X_2 + w_8 X_1 X_3 + \\ & w_9 X_1 X_4 + w_{10} X_1 X_5 + w_{11} X_2 X_3 + \\ & w_{12} X_2 X_4 + w_{13} X_2 X_5 + w_{14} X_3 X_4 + \\ & w_{15} X_3 X_5 + w_{16} X_4 X_5 + w_{17} X_1^2 + w_{18} X_2^2 \\ & + w_{19} X_3^2 + w_{20} X_4^2 + w_{21} X_5^2 \end{aligned}$$
(5)

where X_1, X_2, X_3, X_4 and X_5 were selected among the parameters such as population, GNP, import, export, oil production, oil import and car, truck and bus sales; and w_i are the coefficients of the corresponding design variables.

We can implement different scenarios with different views to predict the future oil consumption of a country. We choose population, GNP, import and export which are economic and social parameters for X_1 to X_4 where X_5 is considered to be zero.

The PSODEM finds the weighting values by taking them as particles, set position and velocity constraints i.e. assigning a lower bound and upper bound for particles position, determines inertia and maximum velocity and then tries to find the best positions to estimate the future oil demand. The PSODEM searches for the most fit members by minimizing the square errors. The fitness function, f(x), takes the following form:

Min

$$f(x) = \sum_{j}^{m} s_j (E^{oil}_{j,observed} - E^{oil}_{j,predicted})^2$$

(7)

where $E^{oil}_{observed}$ and $E^{oil}_{predicted}$ represent the observed and predicted oil consumption values, respectively, m is the number of observations and s_i is the weighting factor.

4. Results and Discussion

The values of considered parameters (population, GNP, import, export) which are shown in fig. 1, are collected for Turkey to compare the result of PSODEM with those of GADOEM represent in [7]. The result for weighted factors obtained from PSODEM is shown in the following Eq.

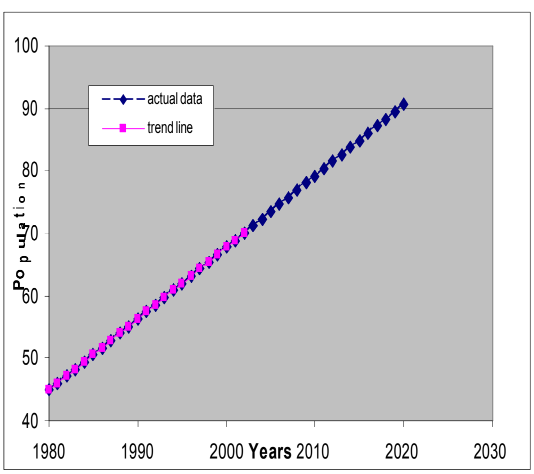
$$E^{PSODEM} = -3.27 + 23.86X_1 + 2.67X_2 + 21.73X_3 + 13.74X_4 + 25X_1X_2 + 21.57X_1X_3 + 32.21X_1X_4 + 21.59X_2X_3 + 21.49X_2X_4 + 11.96X_3X_4 - 2.91X_1^2 + 21.80X_2^2 + 6.42X_3^2 + 26.40X_4^2$$

(6)

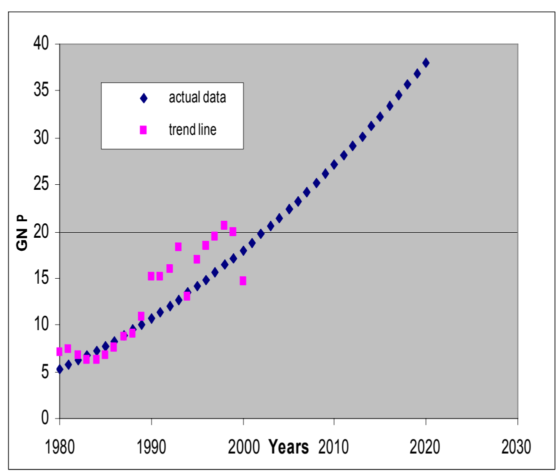
The capability of any model can only be validated through prototype application to mimic a particular case study with accurate depiction of real phenomena. The result of PSODEM is compared to real value of oil consumption in 1997-2003 to validate the model in fig. 2. It can be seen that PSODEM result is a very good estimation for the observed value.

For prediction of future oil demand, we should first predict the design parameters for future years. This can be done using the trend lines. The trend lines (i.e. time series) that are used for prediction of the parameters are shown in fig. 1.

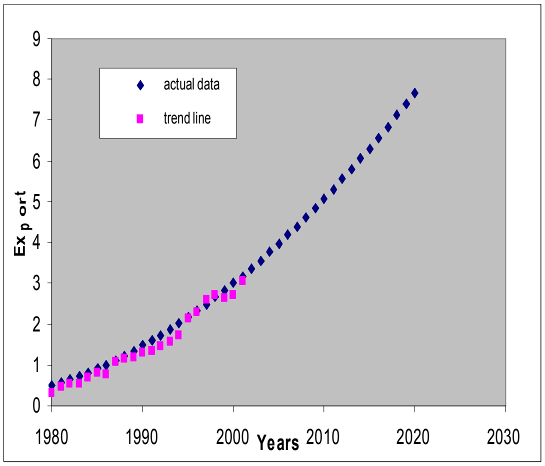
The result obtained from PSODEM and GAODEM and their deviation from observed date are shown in table 1. They are also compared with GAODEM [7] and MENR [8-10] values in fig. 3.



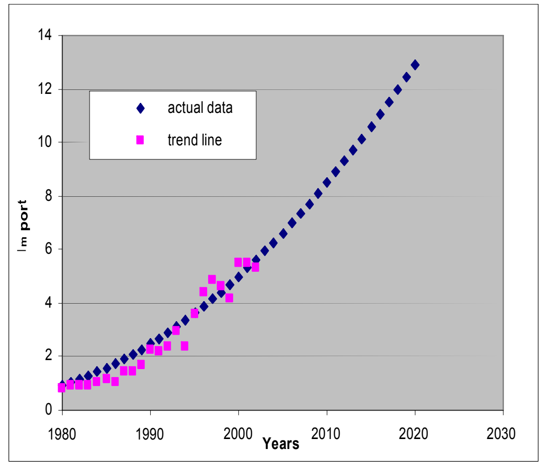
(a)



(b)



(c)



(d)

Fig. 1. (a) Population trend, (b) GNP and its corresponding fitted polynomial trends, (c) import trends, (d) export trends.

It can be shown that the PSODEM is very successful in prediction of oil demand estimation. Its result is very close to the observed data and it can be used for forecasting of oil consumption in the future years. PSODEM can be successfully used to predict the oil consumption of any country.

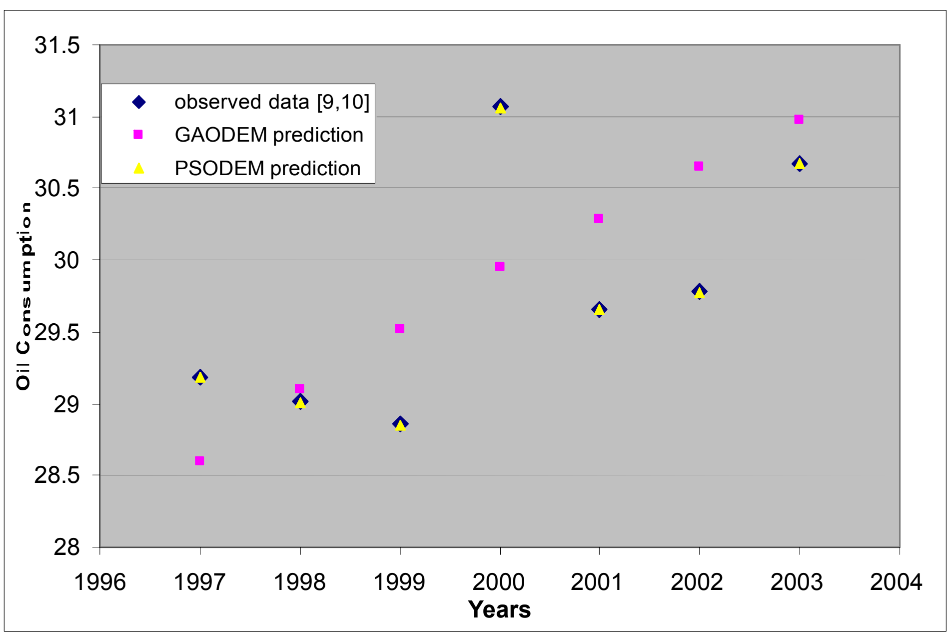


Fig. 2. Validation of GAODEM model.

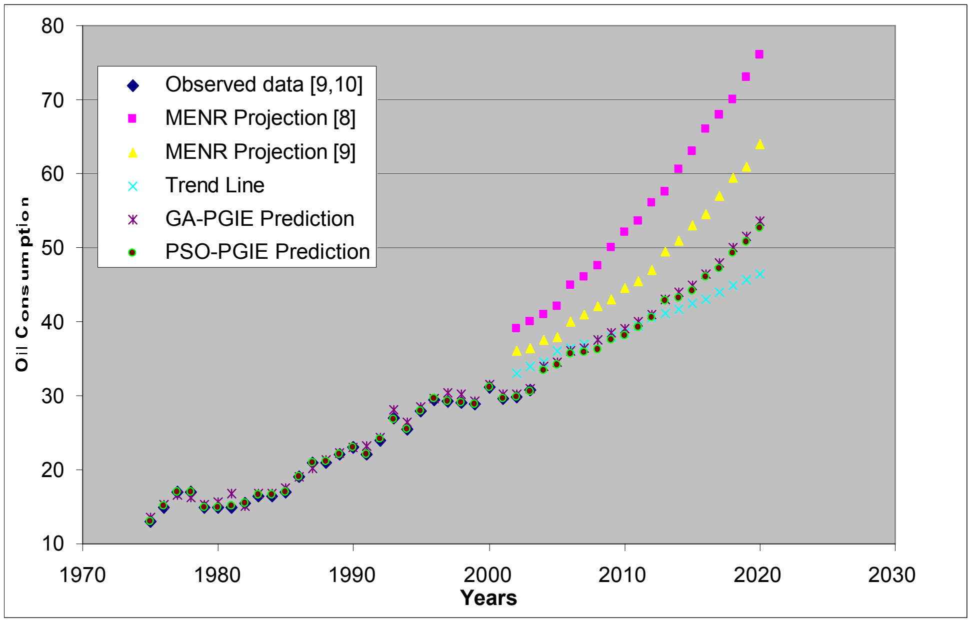


Fig. 3. Observed, fitted data and comparison of PSODEM-PGIE with other references for the oil demand values of Turkey.

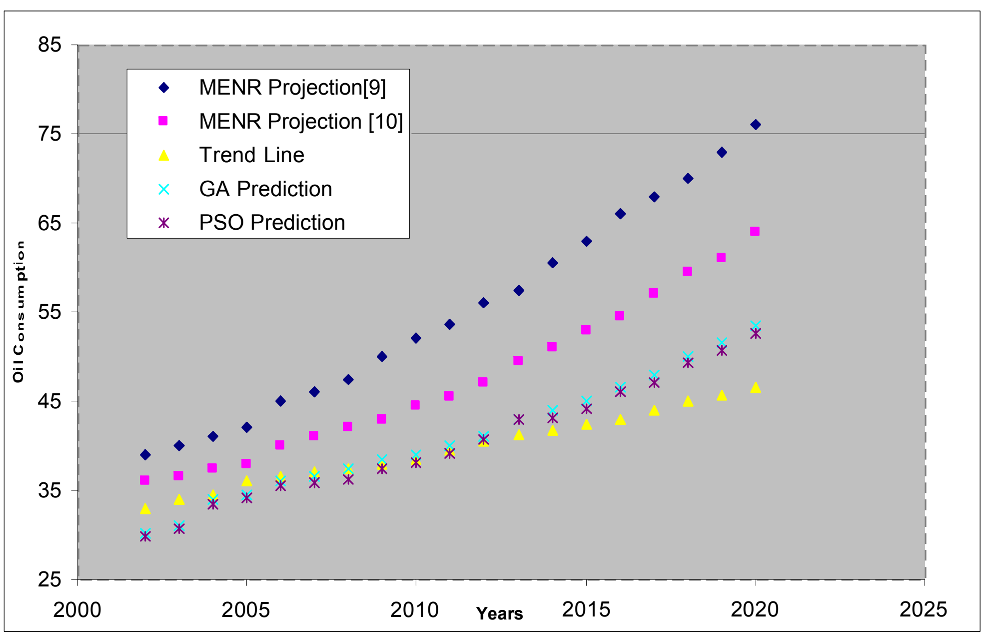


Fig. 4. Comparison of the future oil demand predictions of Turkey obtained by GAODEM scenarios with other references.

Table 1
Comparison of the GAODEM models

Years	Observed data Ref. [9,10]	GA Prediction	Error(%)	PSO prediction	Error(%)
1975	13.02	13.6	4.61	13.02	0.15
1976	14.99	15.27	1.8	15	0.06
1977	17.05	16.64	-2.11	17.04	0.23
1978	17.03	16.24	-4.47	17.03	0.17
1979	14.98	15.34	2.26	14.98	0
1980	14.96	15.6	4	14.96	-0.26
1981	15.03	16.71	11.4	15.02	0.13
1982	15.45	15.02	-3.09	15.45	-0.32
1983	16.55	16.78	1.69	16.55	0.30
1984	16.65	16.73	1.39	16.65	0.90
1985	17.04	17.47	2.76	17.04	0.23
1986	18.93	19.04	0.21	18.93	0.15
1987	20.95	20.23	-3.66	20.95	-0.23
1988	21.06	21.32	1.52	21.06	0.28
1989	22.1	22.18	0.81	22.09	0.40
1990	23.08	22.93	-0.30	23.08	0.34
1991	22.09	23.15	5.22	22.09	0.40
1992	24.1	24.31	1.29	24.09	0.37
1993	26.89	28.17	4.33	26.88	-0.44
1994	25.53	26.41	3.56	25.53	0.11
1995	27.9	28.47	1.67	27.9	-0.3
1996	29.57	29.62	0.40	29.56	0.20
1997	29.18	30.32	3.90	29.17	-0.03
1998	29.02	30.22	4.13	29.02	0
1999	28.86	29.23	1.28	28.85	-0.03
2000	31.07	31.49	1.35	31.07	0
2001	29.66	30.11	1.52	29.65	-0.03
2002	29.78	30.15	1.25	29.77	-0.03
2003	30.67	30.97	0.99	30.66	-0.03
2004		34.16		33.45	
2005		34.67		34.12	
2006		36.06		35.58	
2007		36.42		35.81	
2008		37.36		36.25	
2009		38.82		37.48	
2010		38.94		38.04	
2011		39.87		39.16	
2012		41.36		40.62	
2013		43.41		42.89	
2014		43.88		43.12	
2015		45.15		44.1	
2016		46.59		46.07	
2017		48.39		47.09	
2018		50.12		49.25	
2019		51.45		50.71	
2020		53.57		52.65	

5. Conclusions

In this paper the future oil demand of turkey were predicted with particle swarm optimization algorithm which uses a quadratic model of oil consumption estimation. This method can also be applied to prediction of oil demand of any country.

PSODEM forecasts the oil demand in terms of population, GNP, import, export, oil import, car sales, truck sales, bus sales and oil production factors. In this article we predict the oil demand estimation of Turkey based on population, GNP, import and export. The results were compared with the observed data, MENR prediction and GAODEM. It is shown that the PSODEM outperforms the other ones in terms of accuracy. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust.

This study can help to manage the minimization of oil supply and plan not to depend on oil as the only energy source. It also gives the ability to optimize the oil consumption for reducing the air pollution and environment hazard.

Table 2
The values of main indicators for Turkey

Years	Population 10^6	GNP 10^{10} (USD)	Import 10^{10} (USD)	Export 10^{10} (USD)
1975	40.08	4.75	0.47	0.14
1976	40.92	5.37	0.51	0.20
1977	41.77	6.13	0.58	0.18
1978	42.64	6.68	0.46	0.23
1979	43.53	8.17	0.51	0.23
1980	44.74	6.97	0.79	0.29
1981	45.86	7.28	0.89	0.47
1982	47.00	6.59	0.88	0.57
1983	48.18	6.22	0.92	0.57
1984	49.38	6.08	1.08	0.71
1985	50.66	6.82	1.13	0.80
1986	51.78	7.65	1.11	0.75
1987	52.92	8.77	1.42	1.02
1988	54.08	9.10	1.43	1.17
1989	55.27	10.87	1.58	1.16
1990	56.47	15.24	2.23	1.30
1991	57.50	15.24	2.10	1.36
1992	58.55	16.07	2.29	1.47
1993	59.61	18.20	2.94	1.53
1994	60.70	13.11	2.33	1.81
1995	61.81	17.20	3.57	2.16
1996	62.93	18.47	4.36	2.32
1997	64.08	19.24	4.86	2.63
1998	65.24	20.66	4.59	2.70
1999	66.43	18.53	4.07	2.66
2000	67.64	20.00	5.45	2.78
2001	68.59	14.57	4.14	3.13
2002	69.83	18.09	5.12	3.58
2003	71.11	23.92	6.87	4.69

References

[1] EIA, Energy Information Administration. Available: http://www.eia.doe.gov, 2008

[2] *World Consumption of Primary Energy Type and Selected Country Groups,* 1980-2004.

[3] Porter, Adam. *Peak oil enters mainstream debate,* 2007-02-02

[4] *International Petroleum Supply, Consumption and Inventories,* Aug. 2002, pp. 20-31.

[5] J. Kennedy, RC. Eberhart, *Particle swarm optimization, in: Proceedings of IEEE International Conference on Neural Networks*, Piscataway, NJ, 1995, pp. 1942–1948.

[6] B. Jarboui, N. Damak, P. Siarry, A. Rebai. *A combinatorial particle swarm optimization for solving*

[7] Canyurt OE, Ozturk HK, Hepbasli A, Utlu Z. *Three different applications of genetic algorithm (GA), search techniques on oil demand estimation. Energy Conversion and Management, Sep.* 2006, pp.3138–3148

[8] WECTNC, *World Energy Council Turkish National Committee,* 1996 Energy Report and Statistics, Ankara, 1997 [in Turkish].

[9] WECTNC, *World Energy Council Turkish National Committee,* 1998 Energy Report and Statistics, Ankara, 2000 [in Turkish].

[10] WECTNC, *World Energy Council Turkish National Committee*, 2002 Energy Report and Statistics, Ankara, 2002 [in Turkish].