2Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 2 (6) May 2013: 135- 140

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com

CASE STUDY

NO_x Emission Forecasting: A Case Study for Iran

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ABSTRACT
Industrialization, urbanization, rapid traffic growth and increasing levels of anthropogenic emissions have resulted in a substantial deterioration of air quality over the globe. The main objective of the present study is to forecast NO_x emission in Iran using Particle Swarm Optimization (PSO) based on the values of oil, natural gas, coal, and primary energy consumptions as the energy consumption indicators. Linear and non-linear forms of equations are developed to forecast NO_x emission using PSO based on the Iran's energy consumption indicators. The related data between 1981 and 2009 were used, partly for installing the models (finding candidates of the best weighting factors for each model (1981-2002)) and partly for testing the models (2003–2009). Eventually, NO_x emission in Iran is estimated up to year 2035.
***Keywords**: Particle Swarm Optimization (PSO); Fossil fuels; Primary Energy; Carbon Dioxide Emission; Forecasting.*

Received 20.04.2013 Accepted 11.05.2013

INTRODUCTION

NO_x indirectly influences the radiation budget of the atmosphere through O3, which possibly represents 10–15% of the total anthropogenic greenhouse radiative forcing in the atmosphere [1- 3]. NO_x also influences the oxidation capacity of the atmosphere through OH and nitrate. O3 production in the troposphere is mainly due to the oxidation of CH4, CO and hydrocarbons in the presence of NOx [4]. The 1997 Kyoto protocol had the objective of reducing greenhouse gases (GHGs) which cause climate change. It demanded the reduction of GHG emissions to 5.2% lower than the 1990 level during the period between 2008 and 2012. It came into force in 2005. Many countries have started to develop climate policies but scenario studies indicate that greenhouse gas emissions are likely to increase in the future in most world regions [5]. Global energy consumption and GHGs emission have increased rapidly in the past few years. In 2009, the primary energy consumption in Iran reached 2467 million barrels oil equivalent (boe), with the total No_x emissions reaching 1,836 thousand tons [6].
Many studies are presented to propose some models to forecast future scenarios for GHGs emission (see [7- 12])
This study employs PSO technique to forecast NO_x emission due to energy consumption in Iran.

PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization algorithm was first proposed by Eberhart and Kennedy [13], 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 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 [14]. The canonical PSO with inertia weight, which is used in this study, has become very popular and widely used in many science and engineering applications. In the canonical PSO, each particle i has position x_i and velocity v_i (the velocity of a particle represents the distance traveled from the current position) that is updated at each iteration according to Eq.1

$$\vec{v}_i = \omega\vec{v}_i + c_1\vec{\varphi}_{1i}\left(\vec{p}_i - \vec{x}_i\right) + c_2\vec{\varphi}_{2i}\left(\vec{p}_g - \vec{x}_i\right) \quad (1)$$

Where ω is the inertia weight, $\vec{p}_i$ 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. $\vec{\varphi}_1$ and $\vec{\varphi}_2$ 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.

$$\vec{x}_i = \vec{x}_i + \vec{v}_i \quad (2)$$

The inertia weight w (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 [14]. The PSO algorithm is composed of 5 main steps:

1. Initialize the position vector x and associated velocity 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 to step 4 until a predefined number of iterations is completed.

PROBLEM DEFINITION

In this study, NO_x emission in Iran was forecasted based on the oil, natural gas, coal and primary energy consumption using PSO.
For this purpose, following forms of equations (Linear and exponential) are developed:

$$NO_{x_{linear}} = w_1\,OIL + w_2\,NG + w_3\,COAL + w_4\,PE + w_5 \quad (1)$$

$$NO_{x_{exponential}} = w_1\,OIL^{w2} + w_3\,NG^{w4} + w_5\,COAL^{w6} + w_7\,PE^{w8} + w_9 \quad (2)$$

Where OIL, NG, COAL, PE are the oil, natural gas, coal and primary energy consumptions in Iran and w_i are the corresponding weighting factors.

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

$$\text{Min } F(x) = \sum_{j=1}^{m} \left| E_{actual} - E_{predicted} \right| \quad (3)$$

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of NO_x emission respectively, m is the number of observations.

The related data from 1981 to 2009 were used, partly for installing the models (finding candidates of best weighting factors for each model (1981-2002)) and partly for testing the models (2003–2009). These values are obtained from [6] and [15] and shown in Table 1.

Table 1. The values of oil, natural gas, coal, and primary energy consumption [6] and related NO_x emission [15].

Year	NO_x emission (Kt)	Oil consumption (Mboe)[a]	NG consumption (Mboe)	Coal consumption (Mboe)	PE consumption (Mboe)
1981	306.75	175.46	15.87	3.40	582.45
1982	359.40	191.79	21.95	4.30	1033.34
1983	400.68	232.72	25.16	6.00	1046.06
1984	434.23	246.37	31.15	5.70	935.31
1985	463.07	269.54	30.28	4.90	979.59
1986	489.04	245.19	28.70	5.20	868.27
1987	515.33	256.74	32.90	5.10	977.65
1988	541.70	254.73	33.91	5.40	1024.97
1989	569.39	276.02	45.03	6.00	1188.45
1990	598.79	280.68	55.98	6.50	1340.55
1991	629.90	300.45	73.84	7.40	1423.92
1992	662.72	325.73	89.74	7.40	1535.96
1993	696.80	355.32	99.30	8.10	1636.08
1994	731.82	363.31	118.71	8.10	1691.83
1995	767.41	350.13	140.87	7.70	1741.02
1996	814.70	372.01	162.84	7.90	1753.02
1997	842.18	384.88	175.94	8.30	1767.64
1998	858.25	404.13	172.05	8.60	1790.63
1999	892.05	381.80	203.54	8.30	1785.11
2000	956.18	405.07	216.82	8.60	1858.32
2001	994.42	396.78	224.60	7.80	1808.83
2002	1056.75	405.68	253.45	7.90	1853.39
2003	1111.25	415.74	277.55	8.30	2057.16
2004	1168.39	431.02	320.25	8.40	2146.47
2005	1256.22	462.64	344.05	8.60	2233.33
2006	1346.57	495.86	399.09	8.79	2311.70
2007	1378.96	516.37	470.97	8.70	2426.32
2008	1808.55	533.47	475.24	8.90	2428.42
2009	1836.27	538.52	519.69	9.00	2467.17

[a](Kt): Thousand tone
[b](Mboe): Million barrels oil equivalent

RESULTS AND DISCUSSION

Estimating Weighting Factors Values by PSO

In this section a code was developed in MATLAB 2010 (Math Works, Natick, MA) based on the PSO and applied for finding optimal values of weighting factors regarding actual data (1981-2009). For this purpose, following stages were done:

(a) All input and output variables in Eqs.1 and 2 were normalized in the (0, 1) range.

(b): The proposed algorithm (PSO) was applied in order to determine corresponding weighting factors (w_i) for each model. The related data from 1981 to 2002 were used in this stage.

(c): The best results (optimal values of weighting parameters) for each model were chosen according to (b) and less average relative errors in testing period. The related data from 2003 to 2009 were used in this stage.
(d): Forecasting models were proposed using the optimal values of weighting parameters.
In the linear and exponential forms of PSO models, coefficients obtained are given below:

$$PSO-NO_{x_{linear}} = 0.7685OIL + 1.0095NG + 0.5929COAL - 1.5834PE + 0.3838 \quad (4)$$

$$PSO-NO_{x_{exponential}} = -0.1657\ OIL^{0.924} + 0.659\ NG^{1.2807} - 0.0244\ COAL^{0.6809} + 0.3828\ PE^{0.2135} + 0.0999 \quad (5)$$

Table 2 shows the comparison between the Actual and estimated values of NO_x emission on testing period.

Table 2. Comparison between the Actual and estimated values of NO_x emission on testing period (2003-2009).

Years	2003	2004	2005	2006	2007	2008	2009	Average
Actual Data[a]	1090.52	1205.92	1262.06	1412.60	1631.63	1636.63	1779.73	
$PSO_{exponential}$	1.87	3.21	0.46	4.90	18.32	9.51	3.08	5.91
Relative error (%)	1071.13	1170.59	1261.54	1463.05	1628.75	1700.28	1826.91	
PSO_{linear}	3.61	0.19	0.42	8.65	18.11	5.99	0.51	**5.35**
Relative error (%)	1090.52	1205.92	1262.06	1412.60	1631.63	1636.63	1779.73	

[a] [15]

As it can be seen in this table, the estimation models are in good agreement with the actual data but $PSO-NO_{x_{linear}}$ outperformed another presented model.

Future Projection

In order to use Eqs. (4) and (5) for future projections, each input variable (i.e. oil consumption- natural gas consumption– coal consumption- primary energy consumption) should be forecasted in future time domain (2010–2025). To achieve this, the designed scenarios for future projection of each input variable remained the same scenarios which were developed by Behrang et al. [8] For more details about the values of oil, natural gas, coal, and primary energy consumptions between 2010 and 2035 based on the designed scenarios by Behrang et al. the authors ate refered [8].
Figure 1 to 3 shows the comparison between different projections for NO_x emission based on Scenario I to III.

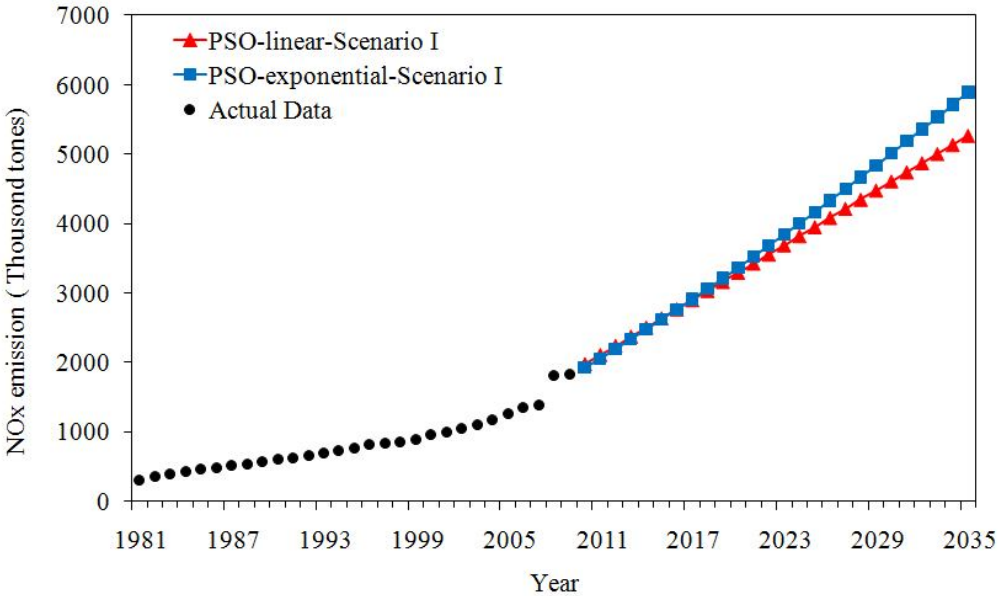

Figure 1. Comparison between different projections for NO_x emission based on Scenario I.

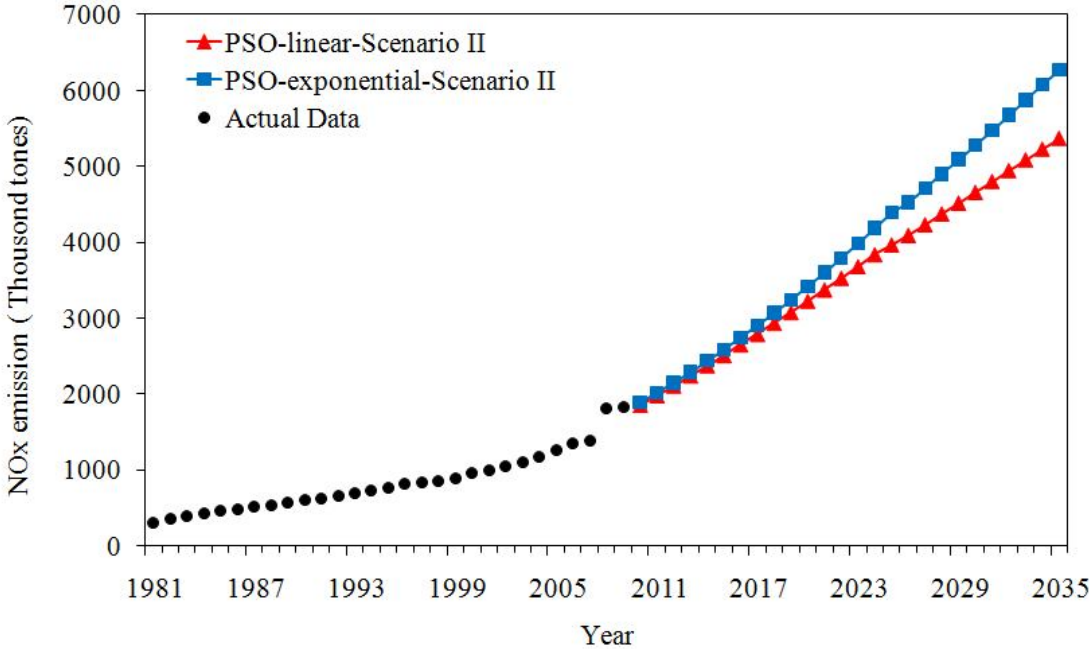

Figure 2. Comparison between different projections for NO_x emission based on Scenario II.

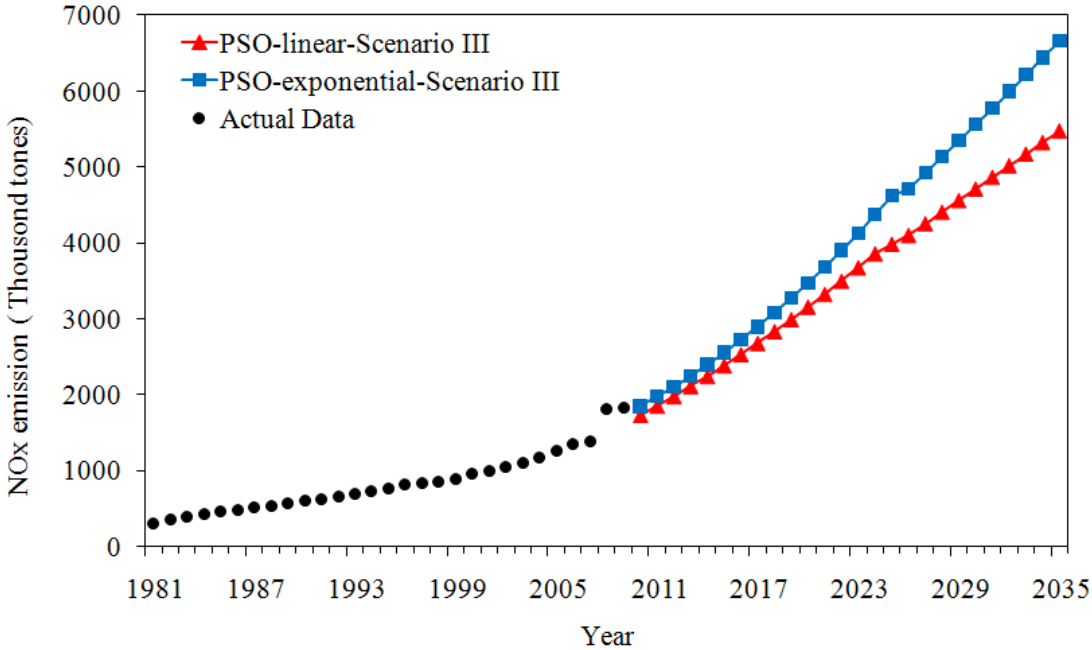

Figure 3. Comparison between different projections for NO_x emission based on Scenario III

CONCLUSION

This paper investigates the causal relationships among carbon emission and energy consumption, using PSO. 30 years data (1981–2009) were used for developing both forms (linear and exponential) of PSO estimation models. Validations of models show that the estimation models are in good agreement with the observed data but PSO_{linear} outperformed another developed model in this study. The results presented here provide helpful insight into energy system and NO_x emission control 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. Forecasting of NO_x emission can also be investigated with Artificial Bee Colony, Genetic Algorithm (GA), or other metaheuristic algorithms. The results of the different methods can be compared with the PSO technique.

ACKNOWLEDGMENTS

The author is grateful for the support provided for the present work by Dezful Branch, Islamic Azad University, Dezful, Iran.

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How to Cite this Article

Reza Samsami. (2013). NO_x Emission Forecasting: A Case Study for Iran. *Bull. Env. Pharmacol. Life Sci.,* Vol 2 (6) May 2013: 135-140