Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 3 [10] September 2014: 126-132

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD
Global Impact Factor 0.533
Universal Impact Factor 0.9804

ORIGINAL ARTICLE

Environmental Pollution Assessment using different intelligent techniques: A case study for Iran

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ABSTRACT
This paper investigates the causal relationships among carbon emission and fossil fuels consumption, using two types of Intelligent Optimization Techniques (IOTs). In this study, Bees Algorithm (BA) and Particle Swarm Optimization (PSO) techniques are applied for analyzing CO_2 emission in Iran based on the values of oil, natural gas, coal, and primary energy consumptions, as the energy indicators. Linear and non-linear forms of equations are developed to forecast CO_2 emission using BA and PSO. The related data between 1981 and 2009 were used, partly for finding the candidates of the best weighting factors for each model (1981-2002)) and partly for testing the models (2003–2009). Eventually, CO_2 emission in Iran is estimated up to year 2025.
Keywords: *Particle Swarm Optimization (PSO), Bees Algorithm (BA), Fossil fuels, Primary Energy, Carbon Dioxide Emission, Forecasting.*

Received 20.05.2014 Revised 09.07.2014 Accepted 22.08. 2014

INTRODUCTION

Due to climatic problems associated with the increased levels of pollution and the deterioration of the environmental quality as a result of increased human activity, environmental issues have attracted renewed interest and more attention during recent years [1].
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 [2, 3]. 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 CO_2 emissions reaching 540 million tons [4].
There are many methods to model and forecast all kinds of energy indicators, but each has its limitations. Division decomposition analysis [5] can simulate the road map of the CO2 emission between relative factors; however, it cannot predict emission. Multiple linear regression models (e.g., ordinary least square [6] and partial least square [7]) have the ability to simulate the relationship between dependent variable and many relevant factors. They often have acceptable quality of fit for historical data, but considering that factors in the forecasting term are unknown, they often are unsuitable for forecasting. If time is selected as the only independent variable [8], the simple regression analysis model can obviously be used to trend extrapolation. However, because the main trend of CO2 emission is more like a non-linear curve, it is impossible to obtain much accuracy using a linear model. Time series methods (e.g.,ARMA [9] and ARIMA [10]) specialize in periodic wave trends with serial correlation but they cannot model a non-linear curve with a small sample (yearly data are very limited). Artificial Neural Network (ANN) has been widely used in modeling and forecasting energy consumption [11]. ANN has the advantages of modeling non-linear relations [12], needing no human supervision in decision making [13] and adapting to changes in the series by self-learning [14].When used to extrapolate trends, ANN needs large sample data that contain similar trend information during the process of training to optimize its parameters. Recently, IOTs are widely used because of their ability to forecast CO_2.
This study employs BA and PSO techniques to forecast CO_2 emission due to energy consumption in Iran.

2. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization algorithm was first proposed by Eberhart and Kennedy [15], 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 [16]. 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

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

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.

$$\vec{x}_i = \vec{x}_i + \vec{v}_i \tag{2}$$

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 [16]. 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 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 [16].

3. Bees Algorithm (BA)

The Bees Algorithm (BA) was first proposed by Pham et al. [17], inspired by the bees foraging behavior in nature. Bees foraging behavior in nature has been discussed in [17 , 18]. This section summarizes the main steps of the Bees Algorithm. The algorithm requires a number of parameters to be set, namely: number of scout bees (s), number of sites selected for neighborhood search (out of s visited sites) (m), number of top-rated (elite) sites among m selected (e), number of bees recruited for the best e sites (nep), number of bees recruited for the other (m-e) selected sites (nsp), the initial size of each patch (ngh) (a patch is a region in the search space that includes the visited site and its neighborhood), and the stopping criterion. These parameters are considered as important factors in BA. The algorithm starts with s scout bees randomly distributed in the search space. The fitness of the sites (i.e. the performance of the candidate solutions) visited by the scout bees are evaluated in step 2.

In next step, the m sites with the highest fitnesses are designated as "selected sites" and chosen for neighborhood search. Then, the algorithm searches around the selected sites, assigning more bees to search in the vicinity of the best e sites. Selection of the best sites is made according to the fitness associated with them. Search in the neighborhood of the best e sites – those which represent the most promising solutions – are made more detailed. As already mentioned, this is done by recruiting more bees for the best e sites than for the other selected sites. Together with scouting, this differential recruitment is a key operation of the Bees Algorithm. For each patch only the bee of highest fitness value is selected to form the next bee population. In nature, there is no such restriction. This restriction is introduced here to reduce the number of points to be explored. In Final step, the remaining bees in the population are placed randomly around the search space to scout for new potential solutions. At the end of each iteration, the colony has two parts to its new population: representatives from the selected patches, and scout bees assigned to conduct random searches. These steps are repeated until a stopping criterion is met. For more details, the reader is referred to [17, 18].

4. Data and models

In this study, CO_2 emission in Iran was forecasted based on the oil, natural gas, coal and primary energy consumption using BA and PSO.

For this purpose, following forms of equations (Linear and exponential) are developed:

$$CO_{2\,linear} = w_1\,OIL + w_2\,NG + w_3\,COAL + w_4\,PE + w_5 \tag{3}$$

$$CO_{2\,exponential} = w_1\,OIL^{w2} + w_3\,NG^{w4} + w_5\,COAL^{w6} + w_7\,PE^{w8} + w_9 \tag{4}$$

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:

$$\text{Min } F(x) = \sum_{j=1}^{m} \left| E_{actual} - E_{predicted} \right| \tag{5}$$

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of CO_2 emission respectively, and *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 Eqs. 3 and 4 and shown in Table 1.

Table 1. The values of oil, natural gas, coal, and primary energy consumption and related CO2 emission [3].

Year	Oil consumption (Mboe)[a]	NG consumption (Mboe)	Coal consumption (Mboe)	PE consumption (Mboe)	CO_2 emission (Mt)[b]
1981	175.46	15.87	3.40	582.45	100.01
1982	191.79	21.95	4.30	1033.34	110.90
1983	232.72	25.16	6.00	1046.06	137.98
1984	246.37	31.15	5.70	935.31	154.01
1985	269.54	30.28	4.90	979.59	168.11
1986	245.19	28.70	5.20	868.27	165.40
1987	256.74	32.90	5.10	977.65	171.38
1988	254.73	33.91	5.40	1024.97	163.24
1989	276.02	45.03	6.00	1188.45	184.65
1990	280.68	55.98	6.50	1340.55	196.71
1991	300.45	73.84	7.40	1423.92	203.06
1992	325.73	89.74	7.40	1535.96	210.95
1993	355.32	99.30	8.10	1636.08	217.39
1994	363.31	118.71	8.10	1691.83	236.38
1995	350.13	140.87	7.70	1741.02	259.32
1996	372.01	162.84	7.90	1753.02	274.16

1997	384.88	175.94	8.30	1767.64	286.80
1998	404.13	172.05	8.60	1790.63	289.79
1999	381.80	203.54	8.30	1785.11	307.81
2000	405.07	216.82	8.60	1858.32	329.07
2001	396.78	224.60	7.80	1808.83	344.46
2002	405.68	253.45	7.90	1853.39	377.96
2003	415.74	277.55	8.30	2057.16	397.50
2004	431.02	320.25	8.40	2146.47	413.09
2005	462.64	344.05	8.60	2233.33	463.80
2006	495.86	399.09	8.79	2311.70	482.70
2007	516.37	470.97	8.70	2426.32	492.48
2008	533.47	475.24	8.90	2428.42	518.06
2009	538.52	519.69	9.00	2467.17	540.28

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

RESULTS

A. Estimating Weighting Factors Values

PSO and BA algorithms were implemented in MATLAB 2010 (Math Works, Natick, MA) 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.3 and 4 were normalized in the (0, 1) range.

[b]: The proposed algorithms were 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.

The best obtained weighting factors for BA and PSO models (for the general forms of Eqs. (3) and (4)) are shown in Table 2.

Table 3 shows the comparison between the actual and estimated values of CO_2 emission on testing period. As it can be seen in this table, the estimation models are in good agreement with the actual data but **BA-CO_2 linear** outperformed the other presented models.

B. Future Projection

In order to use obtained models 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 [4]. Tables 4 and 5 show the values of oil, natural gas, coal, and primary energy consumptions between 2010 and 2035 based on the designed scenarios by [4].

Figure 1 and 2 shows the comparison between different projection models for CO_2 emission based on scenarios I and II.

Table 2. The best obtained weighting factors by BA and PSO for the general forms of Eqs. (3) and (4).

Model	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
CO_2-PSO$_{linear}$	0.7261	0.092	-0.3381	0.5028	-0.0565	-	-	-	-
CO_2-PSO$_{exponential}$	-0.2193	1.0037	0.7775	0.8799	0.3252	0.6599	-0.1128	0.5505	0.2645
CO_2-BA$_{linear}$	0.2522	0.3855	0.5153	-0.2078	0.1285	-	-	-	-
CO_2-BA$_{exponential}$	0.2211	0.9546	0.5347	0.776	-0.0004	0.2337	0.2126	0.6034	0.0265

Table 3. Comparison between the actual and estimated values of CO_2 emission on testing period (2003-2009).

Years	2003	2004	2005	2006	2007	2008	2009	Ave.
Actual Data (Tt)	397.5	413.1	463.8	482.7	492.5	518.1	540.3	_
PSO $_{exponential}$	398.1	427.5	438.8	473.1	519.1	519.9	551.9	_
Relative error (%)	0.14	3.49	-5.4	-1.98	5.4	0.36	2.16	2.7
PSO $_{linear}$	396.7	422.7	458.9	499.2	539.1	551.2	562.8	_
Relative error (%)	-0.2	2.33	-1.05	3.41	9.47	6.39	4.18	3.86
BA $_{exponential}$	396.1	422.3	443.3	478	516.7	522.9	543.5	_
Relative error (%)	-0.35	2.22	-4.42	-0.96	4.93	0.93	0.59	2.06
BA $_{linear}$	394.8	417.5	439.4	476	507	519.5	542.1	_
Relative error (%)	-0.67	1.06	-5.27	-1.39	2.94	0.28	0.33	**1.71**

Table 4. Predicted values of oil, natural gas, coal, and primary energy consumptions between 2010 and 2025 based on ***Scenario I*** designed by [4].				
Year	Oil consumption (Mboe)	NG consumption (Mboe)	Coal consumption (Mboe)	PE consumption (Mboe)
2010	571.97	566.79	9.18	2558.30
2011	593.78	604.89	9.31	2628.98
2012	615.59	642.98	9.43	2699.67
2013	637.40	681.07	9.56	2770.35
2014	659.21	719.17	9.68	2841.03
2015	681.03	757.26	9.81	2911.72
2016	702.84	795.36	9.93	2982.40
2017	724.65	833.45	10.06	3053.08
2018	746.46	871.54	10.18	3123.77
2019	768.28	909.64	10.31	3194.45
2020	790.09	947.73	10.43	3265.13
2021	811.90	985.83	10.56	3335.82
2022	833.71	1023.92	10.68	3406.50
2023	855.52	1062.01	10.81	3477.18
2024	877.34	1100.11	10.93	3547.87
2025	899.15	1138.20	11.06	3618.55

Table 5. Predicted values of oil, natural gas, coal, and primary energy consumptions between 2010 and 2025 based on ***Scenario II*** designed by [4].				
Year	Oil consumption (Mboe)	NG consumption (Mboe)	Coal consumption (Mboe)	PE consumption (Mboe)
2010	550.79	561.29	9.46	2504.54
2011	565.47	605.03	9.63	2560.63
2012	584.78	649.35	9.72	2615.49
2013	598.49	697.45	9.90	2671.84
2014	612.21	747.85	10.08	2728.19
2015	625.92	800.72	10.27	2784.53
2016	639.63	856.27	10.45	2840.88
2017	653.35	914.70	10.64	2897.23
2018	667.06	976.22	10.82	2953.58
2019	680.78	1041.06	11.00	3009.92
2020	694.49	1109.44	11.19	3066.27
2021	708.21	1181.63	11.37	3122.62
2022	721.92	1257.87	11.56	3178.96
2023	735.64	1338.42	11.74	3235.31
2024	749.35	1423.57	11.93	3291.66
2025	763.06	1513.59	12.11	3348.01

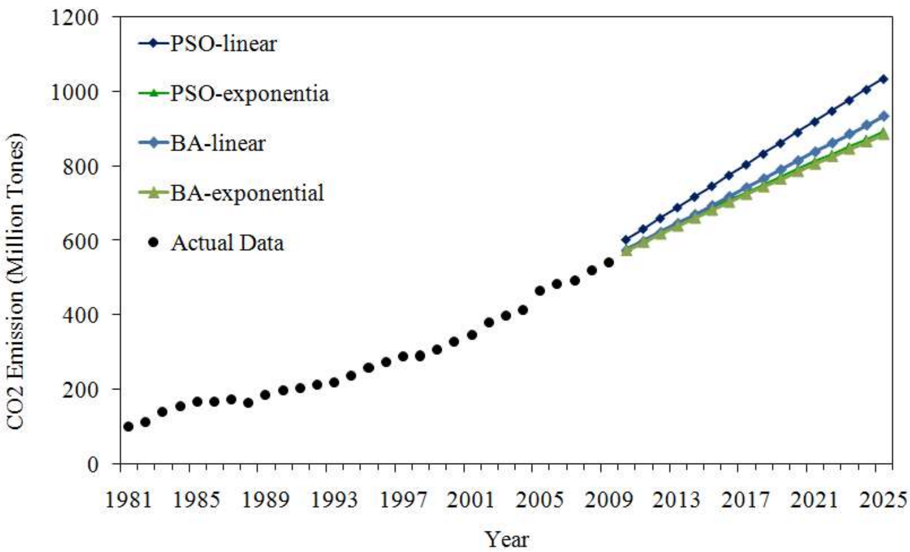

Figure 1. Comparison between different projections for CO_2 emission based on ***Scenario I***.

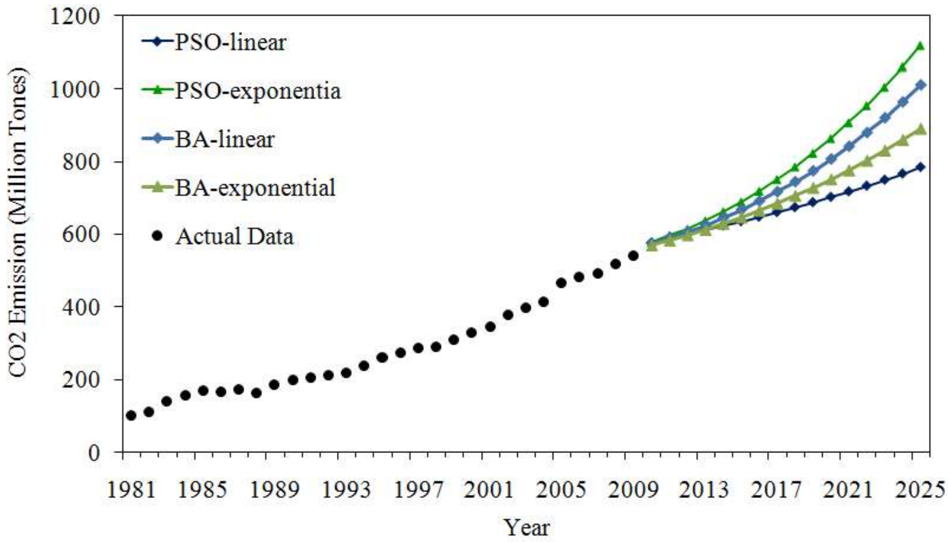

Figure 2. Comparison between different projections for CO_2 emission based on ***Scenario II***.

CONCLUSION

This paper investigates the causal relationships among CO_2 emission and energy consumption, using BA and PSO techniques. 30 years data (1981–2009) were used for developing linear and exponential forms of estimation models. Validations of models show that the estimation models are in good agreement with the observed data but BA-$CO_{2\ linear}$ outperformed other developed models in this study. The results presented here provide helpful insight into energy system and CO_2 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 CO_2 emission can also be investigated with Artificial Bee Colony, Artificial Neural Networks, or other metaheuristic algorithms. The results of the different methods can be compared with the presented techniques in this study.

ACKNOWLEDGMENT

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

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Citation of This Article

Mehrdad Naderian. Environmental Pollution Assessment using different intelligent techniques: A case study for Iran . Bull. Env. Pharmacol. Life Sci., Vol 3 [10] September 2014: 126-132