Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 2 (6) May 2013: 95- 99

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

ORIGINAL ARTICLE

Application of Ant Colony Optimization (ACO) to forecast CO_2 Emission in Iran

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ABSTRACT
In this study, Ant Colony Optimization (ACO) was applied to forecast CO_2 emission in Iran, based on the socio-economic indicators. Linear and non-linear forms of equations were developed to forecast CO_2 emission using ACO based on the Iran's oil, natural gas, coal, and primary energy consumption figures. 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). CO_2 emission in Iran is forecasted up to year 2035.
***Keywords**: Ant Colony Optimization (ACO); Fossil fuels; Primary Energy; Carbon Dioxide Emission; Forecasting.*

Received 10.04.2013 Accepted 07.05.2013

INTRODUCTION

The combustion of fossil fuels is the largest contributor to CO2 emissions. Research on emission trends and further forecasting their further values is important for adjusting energy policies, particularly those relative to low carbon [1].
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].
The outlook of GHGs emission shows the importance of the need for CO_2 emission modeling. Several studies are presented to propose some models to investigate the causal relationships between energy consumption and CO_2 emission [1- 5].
This study presents an Ant Colony Optimization (ACO) approach to forecast global CO_2 emission due to energy consumption.

ANT COLONY OPTIMIZATION (ACO)

In the early 1990s, Ant Colony Optimization (ACO) was introduced by Dorigo et al. as a novel nature-inspired metaheuristic for the solution of combinatorial optimization problems [6]. The inspiring source of ACO is the foraging behavior of real ants. When searching for food, ants initially explore the area surrounding their nest in a random manner. When an ant finds a food source, it carries some of it back to the nest. During the return trip, the ant deposits a chemical pheromone trail on the ground. The quantity of pheromone deposited guides other ants to the food source [7]. As shown by Deneubourg et al. [8], indirect communication between the ants via pheromone trails enables them to find the shortest paths between their nest and food sources. The indirect communication mechanism where ants modify their environment to influence the behavior of other ants is referred to as *stigmergy*. This characteristic of real ant colonies is exploited in artificial ant colonies in order to solve combinatorial and continuous optimization problems. Although an ant colony exhibits complex adaptive behavior, a single ant exhibits a very simple behavior. An ant can be seen as a stimulus-response agent [7, 8], the ant observes pheromone concentrations and produces an action based on the pheromone-stimulus. An ant can therefore abstractly be considered as a simple computational agent. An artificial ant algorithmically models the simple behavior of real ants.
The simple ACO can be formulated as follows [7]. If we define a combinatorial optimization problem that entails the minimization of a given error function, a candidate solution is defined as a sequence of parameters, and can be visualized as a path through several nodes, each node corresponding to one of the solution's parameters.
For more details about intelligent optimization techniques the readers are referred to [6- 8].

PROBLEM DEFINITION

In this study, CO_2 emission in Iran was projected based on the oil, natural gas, coal and primary energy consumption using ACO.
For this purpose, following forms of equations (Linear and exponential) are developed:

$$CO2_{linear} = w_1 OIL + w_2 NG + w_3 COAL + w_4 PE + w_5 \quad (1)$$

$$CO2_{exponential} = w_1 OIL^{w2} + w_3 NG^{w4} + w_5 COAL^{w6} + w_7 PE^{w8} + w_9 \quad (2)$$

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 CO_2 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 [9] and [10] and shown in Table 1.

RESULTS AND DISCUSSION

Estimating Weighting Factors Values by ACO

In this section a code was developed in MATLAB 2010 (Math Works, Natick, MA) based on the ACO 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 (ACO) 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 ACO models, coefficients obtained are given below:

$$ACO - CO2_{linear} = 0.1018 OIL + 0.3765 NG + 0.4013 COAL + 0.2304 PE - 0.1218 \quad (4)$$

$$ACO - CO2_{exponential} = 0.6029 \ OIL^{0.3788} + 9163 \ NG^{0.3831} - 1.5723 \ COAL^{0.6719} + 0.7395 \ PE^{1.2463} + 0.1233 \quad (5)$$

Table 2 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 $ACO - CO2_{exponential}$ outperformed another presented model

Table 1. The values of oil, natural gas, coal, and primary energy consumption [9] and related CO2 emission [10].

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

Table 2. Comparison between the Actual and estimated values of CO2 emission on testing period (2003-2009).

Years	2003	2004	2005	2006	2007	2008	2009	Average
Actual Data[a]	397.50	413.09	463.80	482.70	492.48	518.06	540.28	-
ACO $_{exponential}$	396.36	429.21	452.47	484.13	539.60	533.72	549.64	-
Relative error (%)	0.29	3.90	2.44	0.30	9.57	3.02	1.73	**1.74**
ACO $_{linear}$	390.36	417.69	440.73	477.07	515.11	523.48	547.78	-
Relative error (%)	1.80	1.11	4.97	1.17	4.59	1.05	1.39	2.30

[a] [10]

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 (2010–2035). To achieve this, the designed scenarios for future projection of each input variable remained the same scenarios which were developed by Behrang et al. [11]. 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 to et al. [11].

Figures 1 to 3 show the comparison between different projections for CO2 emission based on Scenario I to III.

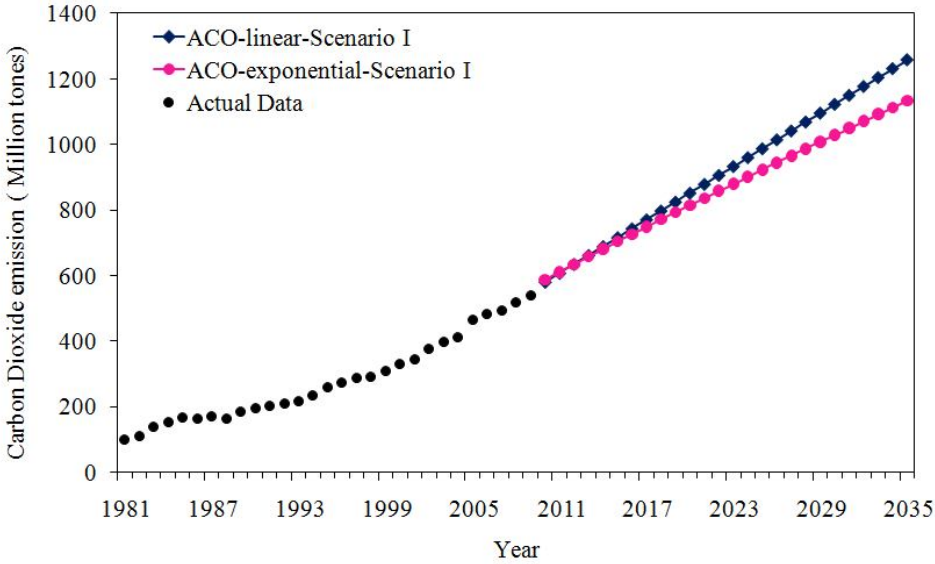

Figure 1. Comparison between different projections for CO2 emission based on Scenario I.

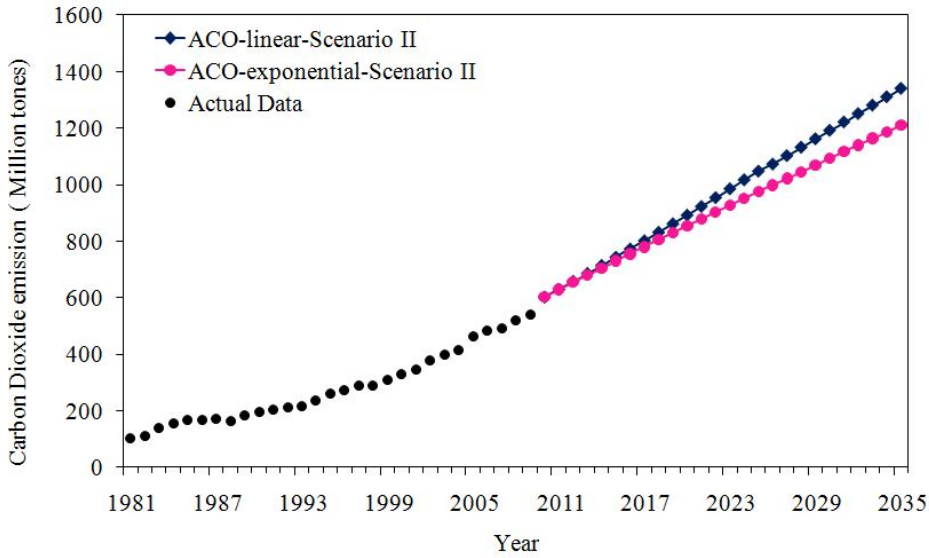

Figure 2. Comparison between different projections for CO2 emission based on Scenario II.

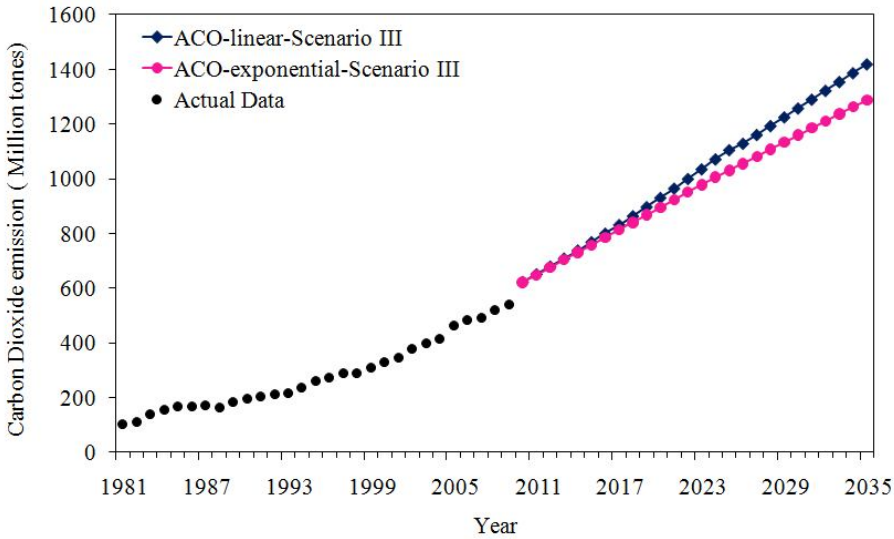

Figure 3. Comparison between different projections for CO2 emission based on Scenario III.

CONCLUSION

This paper investigates the causal relationships among carbon emission and energy consumption, using ACO. 30 years data (1981–2009) were used for developing both forms (linear and exponential) of ACO estimation models. Validations of models show that the estimation models are in good agreement with the observed data but ACO_{linear} outperformed another developed model 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 Particle Swarm Optimization, Artificial Bee Colony, Genetic Algorithm (GA), or other metaheuristic algorithms. The results of the different methods can be compared with the ACO 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). Application of Ant Colony Optimization (ACO) to forecast CO_2 Emission in Iran. *Bull. Env. Pharmacol. Life Sci.,* Vol 2 (6): 95-99.