World Applied Sciences Journal 28 (12): 1996-2002, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.28.12.1155

Comparison Between Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) Techniques for NO_x Emission Forecasting in Iran

Reza Samsami

Department of Chemistry, Dezful Branch, Islamic Azad University, Dezful, Iran

Abstract: Urbanization, industrialization, rapid traffic growth and increasing levels of anthropogenic emissions have resulted in a substantial deterioration of air quality over the globe. Global climate change due to Greenhouse gas (GHGs) emissions is an issue of international concern that primarily attributed to fossil fuels. In this study, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) techniques are applied for analyzing NO_x emission in Iran based on the values of oil, natural gas, coal andprimary energy consumptions, as the energy indicators. Linear and non-linear forms of equations are developed to forecast NO_x emission using GA, PSO and ACO. 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 2025.

Key words: Genetic Algorithm (GA) · Particle Swarm Optimization (PSO) · Ant Colony Optimization (ACO) · Fossil fuels · Primary Energy · Carbon Dioxide Emission · Forecasting

INTRODUCTION

No_x indirectly influences the radiation budget of the atmosphere through O_3, which possibly represents 10-15% of the total anthropogenic greenhouse radiative forcing in the atmosphere [1].

No_x also influences the oxidation capacity of the atmosphere through OH and nitrate. O_3 production in the troposphere is mainly due to the oxidation of CH4, CO and hydrocarbons in the presence of NOx [2]. 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 [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 No_x emissions reaching 1,836 thousand tons [4].

Many studies are presented to propose some models to forecast future scenarios for energy demand and GHGs emission [5-16].

This study employs GA, ACO and PSO techniques to forecast NO_x emission due to energy consumption in Iran.

Genetic Algorithm (GA): GAs encode candidate solutions as binary strings. Each string (chromosome) is built by chaining a number of sub-strings, each sub-string 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 [17] 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, non-binary representations may be more

Corresponding Author: Reza Samsami, Department of Chemistry, Dezful Branch, Islamic Azad University, Dezful, Iran.
Tel: +98 916 6421738; Fax: +98 641 6265024.

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 [18].

Similarly to the other Evolutionary Algorithms (EAs), canonical GAs use generational replacement. Popular alternatives are elitism and steady-state replacement [19]. 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 [20].

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 [21]. Other popular selection schemes are fitness ranking [22] and tournament selection [23]. For a comparison of selection procedure, the reader is referred to Goldberg and Deb [23].

Crossover is the main search operator in GAs, creating offsprings 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 [19]. In canonical Gas, a crossover probability is set for each couple. Couples not selected for recombination will generate two offsprings identical to the parents.

A small fraction of the offsprings 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 andto 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 [24, 25]. 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 [26] 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 an increase in the search power of the algorithm but a loss of general applicability. This issue is analyzed in [27].

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 [28]. 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 [29]. As shown by [30], 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 [29, 30], 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 [29]. 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 andcan 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 [28- 30].

Particle Swarm Optimization (PSO): The Particle Swarm Optimization algorithm was first proposed by Eberhart and Kennedy [31], 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 andadjusts its trajectory according to two pieces of information, the best position that it has so far visited andthe 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 andthe 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 andthe 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 [32]. 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 [32]. The PSO algorithm is composed of 5 main steps:

- 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.
- 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.
- 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.
- Change velocities and positions by using Eqs.1 and 2.
- 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 GA, ACO and PSO. For this purpose, following forms of equations (Linear and exponential) are developed:

$$NO_{x_{linear}} = w_1\,OIL + w_2\,NG + w_3\,COAL + w_4\,PE + w_5 \quad (3)$$

$$NO_{x_{exponential}} = w_1\,OIL^{w2} + w_3\,NG^{w4} + w_5\,COAL^{w6} + w_7\,PE^{w8} + w_9 \quad (4)$$

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:

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

Table 1: The values of oil, natural gas, coal andprimary energy consumption and related NO_x emission [4].

Year	NO_x emission (Tt)	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](Tt): Thousand tone

[b](Mboe): Million barrels oil equivalent

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of NO_x emission respectively andm 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 [4] and shown in Table 1.

RESULTS AND DISCUSSION

Estimating Weighting Factors Values by PSO: In this section for each algorithm (i.e. GA, ACO and PSO) a code was developed 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:

- All input and output variables in Eqs.3 and 4 were normalized in the (0, 1) range.
- 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.
- 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.
- Forecasting models were proposed using the optimal values of weighting parameters. The best obtained weighting factors for GA, ACO 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 NO_x emission on testing period. 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 the other presented models.

Table 2: The best obtained weighting factors by GA, ACO, 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
GA-$No_{x\ linear}$	0.1801	0.7716	0.0314	-0.0092	0.0921	-	-	-	-
GA-$No_{x\ exponential}$	0.1701	0.2922	0.8273	1.001	0.4995	0.9887	-0.5466	0.5272	0.1388
ACO-$No_{x\ linear}$	0.0399	0.9946	0.1056	-0.3671	0.2282	-	-	-	-
ACO-$No_{x\ exponential}$	0.9081	0.2118	0.7089	1.0624	0.2565	0.1437	-1.3138	0.128	0.4503
PSO-$No_{x\ linear}$	0.7685	1.0095	0.5929	-1.5834	0.3838	-	-	-	-
PSO-$No_{x\ exponential}$	-0.1657	0.924	0.659	1.2807	-0.0244	0.6809	0.3828	0.2135	0.0999

Table 3: 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] (Tt)	1111.2	1168.4	1256.2	1346.6	1379	1808.6	1836.3	_
GA $_{exponential}$	1133.4	1240.5	1308.4	1458.6	1626.2	1653.4	1771.9	_
Relative error (%)	1.99	6.18	4.15	8.32	17.93	-8.58	-3.51	7.24
GA $_{linear}$	1168.4	1281.3	1358.3	1512.3	1698.4	1719.7	1831.2	_
Relative error (%)	5.14	9.67	8.13	12.31	23.16	-4.91	-0.28	9.08
ACO $_{exponential}$	1107.3	1212	1281.1	1426.9	1604.7	1623.9	1734.3	_
Relative error (%)	-0.35	3.73	1.98	5.97	16.37	-10.21	-5.56	6.31
ACO $_{linear}$	1085.9	1204.1	1267.2	1430.2	1632.4	1650.6	1784	_
Relative error (%)	-2.28	3.06	0.87	6.21	18.38	-8.73	-2.85	6.06
PSO $_{exponential}$	1090.5	1205.9	1262.1	1412.6	1631.6	1636.6	1779.7	_
Relative error (%)	-1.87	3.21	0.46	4.9	18.32	-9.51	-3.08	5.91
PSO $_{linear}$	1071.1	1170.6	1261.5	1463.1	1628.8	1700.3	1826.9	_
Relative error (%)	-3.61	0.19	0.42	8.65	18.11	-5.99	-0.51	5.35

[a] (Energy balance, 2010)

Table 4: Predicted values of oil, natural gas, coal andprimary energy consumptions between 2010 and 2035 based on *Scenario I* designed by [5].

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

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 [5]. Tables 4 and 5 show the values of oil, natural gas, coal andprimary energy consumptions between 2010 and 2035 based on the designed scenarios by [5].

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

Table 5: Predicted values of oil, natural gas, coal andprimary energy consumptions between 2010 and 2035 based on *Scenario II* designed by [5].

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

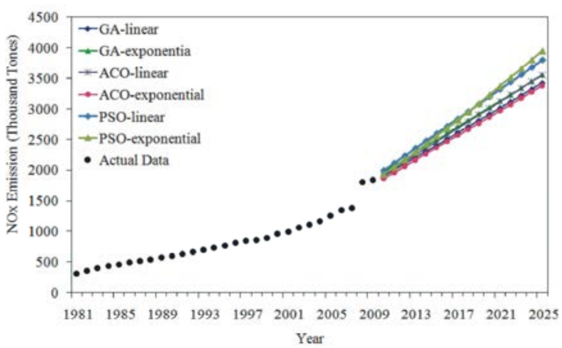

Fig. 1: Comparison between different projections for NOx emission based on Scenario I.

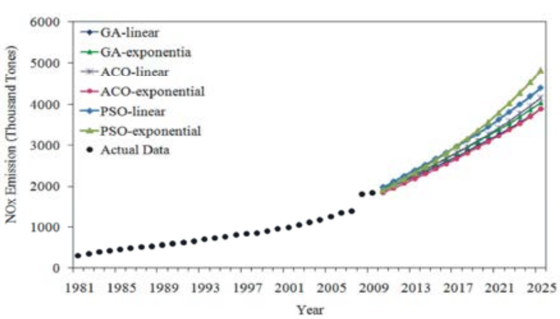

Fig. 2: Comparison between different projections for NOx emission based on Scenario II.

CONCLUSION

This paper investigates the causal relationships among No_x emission and energy consumption, using GA, ACO 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 PSO- $NO_{x\ linear}$ outperformed other developed models 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, Bees Algorithm, or other metaheuristic algorithms. The results of the different methods can be compared with the presented techniques in this study.

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

REFERENCES

1. Wild, O. M.J. Prather and H. Akimoto, 2001. Indirect long-term global radiative cooling from NOx emissions. Geophys. Res. Lett. 28: 1719-1722.
2. Chameides, W.L. and J.C.G. Walker, 1973. A photochemical theory of tropospheric ozone. J. Geophys. Res. 78: 8751- 8760.
3. Davoudpour, H. and M. Sadegh Ahadi, 2006. The potential for greenhouse gases mitigation in household sector of Iran: cases of price reform/efficiency improvement and scenario for 2000-2010. Energy Policy, 34: 40-49.
4. Energy Balance. 2010. Tehran: Ministry of Energy.
5. Behrang, M.A., E. Assareh, M.R. Assari and A. Ghanbarzadeh, 2013. Using ITOs and ANNs to Forecast Iran's GHGs Emission. Energy. submitted.

6. Ghosh, S., 2010. Examining carbon emissions economic growth nexus for India: a multivariate cointegration approach. Energy Policy, 38: 3008-14.
7. Behrang, M.A., E. Assareh, M.R. Assari and A. Ghanbarzadeh, 2011a. Using Bees Algorithm and Artificial Neural Network to Forecast World Carbon Dioxide Emission. Energy Sources, Part A, 33: 1747-1759.
8. Behrang, M.A., E. Assareh, M.R. Assari and A. Ghanbarzadeh, 2011b. Total energy demand estimation in Iran using bees algorithm. Energy Sources, Part B: Economics, Planning and Policy, 6(3): 294-303.
9. Behrang, M.A., E. Assareh, M.R. Assari and A. Ghanbarzadeh, 2011c. Assessment of electricity demand in Iran's industrial sector using different intelligent optimization techniques. Applied Artificial Intelligence, 25: 292-304.
10. Behrang, M.A., E. Assareh, M. Ghalambaz, M.R. Assari and A.R. Noghrehabadi, 2011d. Forecasting future oil demand in Iran using GSA (Gravitational Search Algorithm). Energy, 36: 5649-5654.
11. Fallahi, F., 2011. Causal relationship between energy consumption (EC) and GDP: A Markov-switching (MS) causality. Energy, 36: 4165-4170.
12. Pi, D., J. Liu and X. Qin, 2010. A Grey Prediction Approach to Forecasting Energy Demand in China. Energy Sources, Part A, 32(16): 1517-1528.
13. Meng, M. and D. Niu, 2011. Modeling CO2 emissions from fossil fuel combustion using the logistic equation. Energy, 36: 3355-3359.
14. Soytas, U. and R. Sari, 2009. Energy consumption, economic growth andcarbon emissions: challenges faced by an EU candidate member. Ecol. Econ., 68: 1667-75.
15. Sozen, A., Z. Gulseven and E. Arcaklioglu, 2009. Estimation of GHG Emissions in Turkey Using Energy and Economic Indicators. Energy Sources, Part A, 31(13): 1141-1159.
16. Toksari, M., 2010. Predicting the Natural Gas Demand Based on Economic Indicators: Case of Turkey. Energy Sources, Part A, 32(6): 559-566.
17. Holland, J.H., 1975. Adaptations in Natural Artificial Systems. Ann Arbor, MI: University of Michigan Press.
18. Michalewicz, Z., 1999. Genetic Algorithms C Data Structures D Evolution Programs. Berlin: Springer-Verlag.
19. Davis, L., 1991. Handbook of Genetic Algorithms. New York: Van Nostrand Reinhold.
20. Syswerda, G., 1991. Reproduction in generational and steady state genetic algorithm. In: Foundations of Genetic Algorithms, Ratlines, G. (Ed.). Los Altos, CA: Morgan Kaufmann, pp: 94-101.
21. Goldberg, D.E., 1989. Genetic Algorithms in Search,Optimization and Machine Learning. Reading, MA: Addison-Wesley Longman.
22. Baker, J.E., 1985. Adaptive selection methods for genetic algorithms. Proceedings of Int. Conference on Genetic Algorithms and Their Applications, Hillsdale, NJ: Lawrence Erlbaum Associates, pp: 101-111.
23. Goldberg, D.E. and K. Deb, 1991. A comparison of selection schemes used in genetic algorithms. In: Foundations of Genetic Algorithms, Rawlins, G. J. (Ed.). pp: 69-93.
24. Grefenstette, J.J., 1986. Optimization of control parameters for genetic algorithms. Systems, man and cybernetics. IEEE Transactions on Systems, Man and Cybernetics, 16: 122-128.
25. Schaffer, J.D., R.A. Caruana, L.J. Eshelman and R. Das, 1989. A study of control parameters affecting online performance of genetic algorithms for function optimization. In: Proceedings of the Third International Conference on Genetic Algorithms, San Francisco, CA: Morgan Kaufmann, pp: 51-60.
26. Hinterding, R., Z. Michalewicz and A.E. Eiben, 1997. Adaptation in evolutionary computation: A survey. Proceedings of IEEE International Conference on Evolutionary Computation, Indianapolis, IN, pp: 65-69.
27. Michalewicz, Z., 1993. A hierarchy of evolution programs: An experimental study. Evol. Comput., 1: 51-76.
28. Dorigo, M., V. Maniezzo and A. Colorni, 1996. Ant system: optimization by a colony of cooperating agents. Systems, Man andCybernetics, Part B, IEEE Transactions on 26(1): 29-41.
29. Dorigo, M. and T. Stützle, 2004. Ant Colony Optimization. MIT Press, Cambridge.
30. Deneubourg, J.L., S. Aron, S. Goss and J.M. Pasteels, 1990. The self-organizing exploratory pattern of the argentine ant. Journal of Insect Behavior, 3:159-168.
31. Kennedy, J. and R. Eberhart, 1995. Particle swarm optimization. Proc Neural Networks. Proceedings, vol. 1 944. IEEE International Conference on. pp: 1942-1948.
32. Engelbrecht, A.P., 2005. Fundamentals of computational swarm intelligence. Hoboken, N.J.: Wiley.