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ORIGINAL ARTICLE

Comparative Analyzes of Genetic Algorithm (GA) and Simulated Annealing (SA) for forecasting global CO_2 Emission

H. Kavoosi[*,a], M. Kavoosi[b]
[a] Department of Mechanical Engineering, Izeh Branch, Islamic Azad University, Izeh, Iran
[b] Department of Computer Engineering, Izeh Branch, Islamic Azad University, Izeh, Iran
[*]Corresponding author. Tel.: +98 916 6917126; fax: +98 692 5231068.

ABSTRACT
Global climate change due to CO2 emissions is an issue of international concern that primarily attributed to fossil fuels. In this study, Genetic Algorithm (GA) and Simulated Annealing (SA) are applied for analyzing global CO_2 emission based on the global energy consumption. Linear and non-linear forms of equations were developed to forecast CO_2 emission based on the global oil, natural gas, coal, and primary energy consumption. The related data between 1980 and 2010 were used, partly for installing the models (finding candidates of best weighting factors for each model (1980-2003)) and partly for testing the models (2004–2010). Global CO_2 emission is forecasted up to year 2030.
Keywords: *Genetic Algorithm (GA); Simulated Annealing (SA); Fossil fuels; Primary Energy; Carbon Dioxide Emission; Forecasting.*

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INTRODUCTION

Amongst several environmental pollutants causing climate change, carbon dioxide (CO2) is held responsible for 58.8% of GHGs [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]. Global energy consumption and carbon dioxide (CO2) emissions have increased rapidly in the past few years. In 2010, the global primary energy consumption reached 12.002 billion tons oil equivalent (toe), with the total CO2 emissions reaching 33.158 billion tons [3].

Many studies are presented to propose some models to forecast future scenarios for global CO2 emissions (see [4- 7]).

This study employs Genetic Algorithm (GA) and Simulated Annealing (SA) techniques to forecast global CO_2 emission due to energy consumption.

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 [8] 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 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 [9].
Similarly to the other Evolutionary Algorithms (EAs), canonical GAs use generational replacement. Popular alternatives are elitism and steady-state replacement [10]. 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 [11].
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 [12]. Other popular selection schemes are fitness ranking [13] and tournament selection [14]. For a comparison of selection procedure, the reader is referred to [14].
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 [10]. 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, and to 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 [15]. 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 [13- 15] 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.

SIMULATED ANNEALING (SA)

Simulated Annealing (SA) comes from the Metropolis algorithm [16], a simulation of the recrystallization of atoms in metal during its annealing (the process of slow cooling is known as annealing process). In the physical annealing of metals, as the temperature is reduced, the atoms start to get arranged and finally form crystals having the minimum possible energy. It is the basic concept of SA to search the optimal solution in an optimization problem [17]. SA has been successfully applied to solve a variety of optimization problems. For more details about SA the readers are referred to [16, 17].

PROBLEM DEFINITION

In this study, global CO_2 emission was projected based on the global oil, natural gas, coal and primary energy consumption using GA and SA techniques.
Following the empirical literature in energy economics, it is plausible to form a long-run relationship between CO2 emissions and energy consumption as follow:

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

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

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

The related data from 1980 to 2010 were used, partly for installing the models (finding candidates of best weighting factors for each model (1980-2003)) and partly for testing the models (2004–2010).

The values of global CO_2 emission, and oil, natural gas, coal, and primary energy consumption are obtained from [4] and shown in Table 1.

RESULTS AND DISCUSSION

Estimating Weighting Factors Values by GA and SA

In this section, for each algorithm (i.e. GA and SA), a code was developed in MATLAB 2008 (Math Works, Natick, MA) and applied for finding optimal values of weighting factors regarding actual data (1980-2010). For this purpose, following steps were done:

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

(b): Installation data series (i.e. the related data from 1980 to 2003) are used in the proposed algorithms to find candidates of the best weighting factors (w_i) for each model. The criteria to select optimal coefficients is the minimum fitness function defined by

$$\text{Min } F(x) = \sum_{j=1}^{m} (E_{actual} - E_{predicted})^2 \quad (3)$$

Where E_{actual} and $E_{predicted}$ are the actual and predicted values of global CO_2 emission respectively, m is the number of observations.

Table 1. The values of global oil, natural gas, coal, and primary energy consumption and CO_2 emission (Workbook; 2011).

Year	Oil consumption (Mtoe)[a]	NG consumption (Mtoe)	Coal consumption (Mtoe)	PE consumption (Mtoe)	CO_2 emission (Mt)[b]
1980	2972.2	1296.9	1806.4	6624.0	19322.4
1981	2863.0	1309.5	1820.6	6577.5	19073.2
1982	2770.7	1312.5	1846.9	6548.4	18900.7
1983	2748.3	1329.0	1897.7	6638.2	19072.1
1984	2810.1	1440.0	1983.2	6960.2	19861.0
1985	2804.7	1488.3	2056.0	7137.5	20246.7
1986	2894.1	1503.6	2089.2	7307.5	20688.3
1987	2946.8	1579.6	2169.0	7555.7	21344.5
1988	3038.8	1654.9	2231.7	7833.5	22052.2
1989	3093.0	1729.2	2251.2	8001.7	22470.2
1990	3148.6	1769.5	2220.3	8108.7	22613.2
1991	3148.2	1807.5	2196.4	8156.0	22606.5
1992	3184.8	1817.9	2174.6	8187.6	22656.7
1993	3158.0	1853.9	2187.6	8257.5	22710.6
1994	3218.7	1865.4	2201.9	8357.6	22980.3
1995	3271.3	1927.0	2256.2	8577.9	23501.7
1996	3344.9	2020.5	2292.2	8809.5	24089.8
1997	3432.2	2016.8	2301.8	8911.6	24387.1
1998	3455.4	2050.3	2300.2	8986.6	24530.5
1999	3526.0	2098.4	2316.0	9151.4	24922.7
2000	3571.6	2176.2	2399.7	9382.4	25576.9
2001	3597.2	2216.6	2412.4	9465.6	25800.8
2002	3632.3	2275.6	2476.7	9651.8	26301.3
2003	3707.4	2353.1	2677.3	9997.8	27508.7
2004	3858.7	2431.8	2858.4	10482.0	28875.2
2005	3908.5	2511.2	3012.9	10800.9	29826.1
2006	3945.3	2565.6	3164.5	11087.8	30667.6
2007	4007.3	2661.3	3305.6	11398.4	31641.2
2008	3996.5	2731.4	3341.7	11535.8	31915.9
2009	3908.7	2661.4	3305.6	11363.2	31338.8
2010	4028.1	2858.1	3555.8	12002.4	33158.4

[a](Mtoe): Million tone oil equivalent

[b](Mt): Million tone

(c): Outputs of each algorithm (candidates of the best weighting factors (w_i)) after each run are validated using a different series of data called herein the testing data series (i.e. the related data from 2004 to 2010).
(d): Demand estimation models were developed using the optimal values of weighting parameters.
The GA and SA models were performed using the following user-specified parameters:

GA:
Population size: 50
Crossover rate: 0.85
Mutation rate: 0.01
Maximum Generation: 200

SA:
Maximum Iteration number: 5000.
Initial temperature: 100.
Annealing function: Fast Annealing.
Temperature update function: Exponential.

In the linear forms of developed models, coefficients obtained are given below:

$$GA_{linear} = 0.9219OIL - 0.2113NG + 0.3224COAL + 0.0435PE - 0.0777 \quad (4)$$

$$SA_{linear} = 0.1173OIL + 0.4612NG + 0.4553COAL + 0.0071PE - 0.0191 \quad (5)$$

In the exponential forms of developed models, coefficients obtained are given below:

$$GA_{exponential} = 0.8166\ OIL^{1.3723} - 0.3251\ NG^{0.`29} + 0.868\ COAL^{0.6649} - 1.0574\ PE^{0.4807} + 0.6505 \quad (6)$$

$$SA_{exponential} = 0.8507\ OIL^{0.8448} - 0.1557\ NG^{0.1928} + 0.9191\ COAL^{0.4788} - 0.3402\ PE^{0.5284} - 0.2227 \quad (7)$$

Table 2 shows comparison between the actual data and estimated values of global CO_2 emission using GA and SA models on testing period.

Table 2. Comparison between the Actual and estimated values of global CO2 emission on testing period (2004-2010).

Years	2004	2005	2006	2007	2008	2009	2010	Average
Actual Data[a]	28875.2	29826.1	30667.6	31641.2	31915.9	31338.8	33158.4	-
$GA_{exponential}$	29046.5	29992.0	30815.3	31817.5	31705.0	30773.5	32535.4	-
Relative error (%)	0.59	0.56	0.48	0.56	0.66	1.80	1.88	0.94
GA_{linear}	29244.3	30046.0	30771.6	31602.7	31522.7	30782.6	32298.7	-
Relative error (%)	1.28	0.74	0.34	0.12	1.23	1.77	2.59	0.91
$SA_{exponential}$	29433.9	30183.7	30826.9	31545.6	31530.7	30945.3	32199.7	-
Relative error (%)	1.93	1.20	0.52	0.30	1.21	1.26	2.89	1.33
SA_{linear}	28975.1	30026.6	30957.4	32022.7	32439.9	31918.7	33921.2	-
Relative error (%)	0.35	0.67	0.95	1.21	1.64	1.85	2.30	1.11

[a] (Workbook, 2011)

For the best results of GA, the average relative errors on testing data were 0.95% and 0.91% for $GA_{exponential}$ and GA_{linear}, respectively. The corresponding value
for SA were 1.33% and 1.11% for $SA_{exponential}$ and SA_{linear}, respectively.
As it can be seen in this table, all estimation models are in good agreement with the actual data but GA_{linear} outperformed another models presented here.

Future Projection

In order to use Eqs. (4) to (7) 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 (2011–2030). In this study, the future projection scenarios for each input variable remained the same as the ones developed by Behrang et al. The values of oil, natural gas, coal, and

primary energy consumptions between 2011 and 2030 based on the designed scenarios by Behrang et al. [18] are shown in Table 3.
Figure 1 shows the comparison between different projections for global CO2 emission.
According to the best model (i.e. GA_{linear}) CO_2 emission by 2030 is about 46897.3 million tones.
Table 4 shows the comparison of different projections for global CO_2 emission.
As it can be seen in Table 5, forecasting of global CO_2 emissions using the $CO_{2\ linear}$ model is underestimated when the results are compared with Behrang et al., [18].

Table 3. The values of designed scenarios by Behrang et al. (2011a) for oil, natural gas, coal, and primary energy consumptions between 2011 and 2030.

Year	Oil consumption (Mtoe)	NG consumption (Mtoe)	Coal consumption (Mtoe)	PE consumption (Mtoe)
2011	4071.1	2888.1	3662.3	12206.0
2012	4104.7	2952.9	3775.6	12455.5
2013	4138.3	3017.6	3888.8	12704.9
2014	4171.9	3082.4	4002.1	12954.4
2015	4205.4	3147.2	4115.3	13203.8
2016	4239.0	3211.9	4228.5	13453.2
2017	4272.6	3276.7	4341.8	13702.7
2018	4306.2	3341.4	4455.0	13952.1
2019	4339.7	3406.2	4568.3	14201.6
2020	4373.3	3470.9	4681.5	14451.0
2021	4406.9	3535.7	4794.8	14700.5
2022	4440.5	3600.5	4908.0	14949.9
2023	4474.0	3665.2	5021.3	15199.3
2024	4507.6	3730.0	5134.5	15448.8
2025	4541.2	3794.7	5247.8	15698.2
2026	4574.7	3859.5	5361.0	15947.7
2027	4608.3	3924.3	5474.3	16197.1
2028	4641.9	3989.0	5587.5	16446.6
2029	4675.5	4053.8	5700.8	16696.0
2030	4709.0	4118.5	5814.0	16945.4

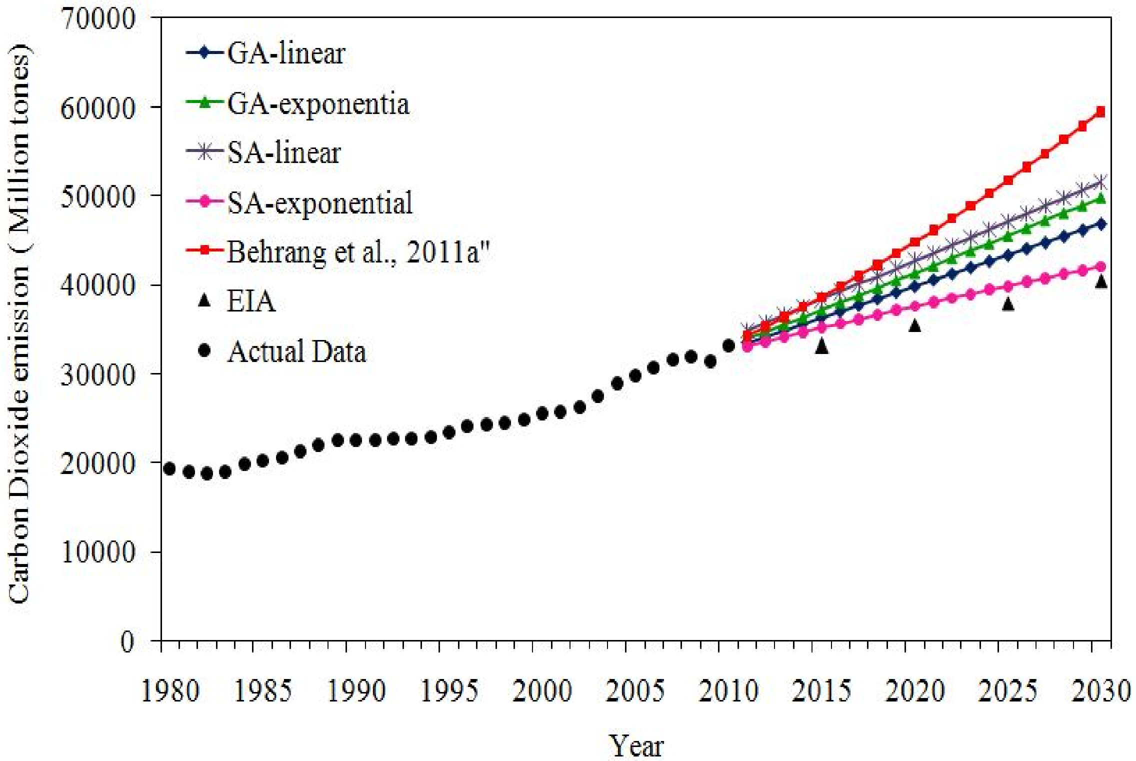

Figure 1. Comparison between different projections for global CO2 emission.

Table 4. Comparison between different projections for global CO2 emission (in million tons) up to 2030.

Projection	Year			
	2015	2020	2025	2030
Present Study- GA_{linear}	36308.3	39838.0	43367.6	46897.3
Present Study- $GA_{exponential}$	37181.3	41319.0	45540.3	49849.6
Present Study- SA_{linear}	38361.2	42749.1	47137.1	51525.0
Present Study- $SA_{exponential}$	35177.5	37611.7	39898.2	42072.7
Behrang et al (2011a)- BA_{linear}	38637.1	44812.5	51765.3	59469.7
Behrang et al (2011a)- $BA_{exponential}$	37820.2	44271.2	51995.1	61123.4
EIA (2009)	33111	35428	37879	40385

CONCLUSION

This paper investigates the causal relationships among global carbon emission and energy consumption, using GA and SA techniques. 31 years data (1980–2010) were used for developing both forms (linear and exponential) of GA and SA estimation models. Validations of models show that the estimation models are in good agreement with the observed data but GA_{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 Gravitational Search Algorithm, Particle Swarm Optimization, Artificial Bee Colony, Ant Colony, or other metaheuristic algorithm. The results of the different methods can be compared with the GA technique.

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