Forecast Global Carbon Dioxide Emission

By Use of Genetic Algorithm (GA)

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Abstract

Global climate change due to CO_2 emissions is an issue of international concern that primarily attributed to fossil fuels. In this study, Genetic Algorithm (GA) is used for analyzing world CO_2 emission based on the global energy consumption. Linear and non-linear forms of equations were developed to forecast CO_2 emission using Genetic Algorithm (GA) based on the global oil, natural gas, coal, and primary energy consumption figures. 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); Fossil fuels; Primary Energy; Carbon Dioxide Emission; Forecasting.

1. Introduction

The combustion of fossil fuels is the largest contributor to CO_2 emissions. Research on emission trends and further forecasting their further values is important for adjusting energy policies, particularly those relative to low carbon (Lotfalipour et al., 2010).

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 (Davoudpour and Sadegh Ahadi, 2006). 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 (Behrang et al., 2011a; Pao, H.T. Tsai, 2011; Lotfalipour et al., 2010)

This study presents a Genetic Algorithm (GA) approach to forecast global CO_2 emission due to energy consumption.

2. 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

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procedures have been explored leading to a de bate on the most appropriate choice. Holland (1975) 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 m ore natural for some problem domains and may reduce t he computational burden of the search. The canonical binary-coded GA as described here is now rarely used for continuous function optimization as it h as been shown that solutions are too easily disrupted (the Hamming cliff issue). Therefore researchers tend to use less disruptive c oding such as Gray coding (Michalewicz, 1999).

Similarly to the other Evolutionary Algorithms (EAs), canonical GAs use generational replacement. Popular alternatives are elitis m and steady-state replacem ent (Davis,1991). In the first ca se, the best solution(s) a re directly copied into the new population while in th e second case only a fraction of the population is replaced at each generation. Bot h variants aim to improve the preservation of good genetic material at the expense of a reduced search space e xploration. A com parison between the behavior of ge nerational and steady-state replacement is given in Syswerda (1991).

Individuals are selected for reproduction with a probability depending on their fitness. Canonical GAs allocate the mating probability of each indi vidual proportionally to its fitn ess (proportional selection) and draw the parents set (mating pool) through the roulette wheel selection procedure (Goldberg, 1989). Other popular selection schemes are fitness ranking (Baker,1985) and tournament selection(Goldberg and Deb, 1991). For a comparison of selection procedure, the reader is referred to Goldberg and Deb (1991).

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 im plementation. The most common crossover procedures are one-point crossover, two-point crossover and uniform crossover (Davis, 1991). In canonical GAs, a cro ssover probability is set for each couple. Couples not selected for reco mbination will generate two offsprings identical to the parents.

A small fraction of the offsprings are randomly selected to undergo genetic mutation. The m utation operator randomly picks a location from a bi t-string and fl ips 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 t he population.

GAs require the tuning of some parameters such as t he mutation rate, crossover rate and replacement rate in the case of steady-state replacement. This task is o ften not trivial as th e chosen values may strongly influence the search process (Grefenstette,1986; Schaffer et al.,1989). Moreover, the optimal value for the GA parameters may vary according to the evoluti on of the search process. For all these reasons, several adaptive schemes have been investigated. A surv ey of adaptation in GAs is given in (Hinterding et al.,19 97; Back,1993) 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 su ch operators results an increase in th e search power of t he algorithm but a l oss of ge neral applicability. This issue is an alyzed in Michalewicz (1993). For more details about intelligent optimization techniques the readers are referred to (Assareh et al., 2012a; Assareh et al., 2 012b; A ssareh et al., 2 010; Behrang et al ., 2010; 2011a; 2011b; 2011c; 2011d; 2011e).

3. 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.

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

$$CO_{2_{linear}} = w_1\,OIL + w_2\,NG + w_3\,COAL$$
$$+ w_4\,PE + w_5 \qquad\qquad (1)$$

$$CO_{2_{exponential}} = w_1\,OIL^{w2} + w_3\,NG^{w4} +$$

$$w_5\,COAL^{w6} + w_7\,PE^{w8} + w_9 \qquad\qquad (2)$$

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

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

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

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 oil, natural gas,   coal, and primary energy consumption are obtained from Workbook (2011) and shown in Table 1.

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

4. Results and discussion

4.1 Estimating Weighting Factors Values by GA

In this section a code was developed in MATLAB 2008 (Math Works, Natick, MA) based on the GA and applied for finding optimal values of weighting factors regarding actual data (1980-2010). 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 (GA) was applied in order to determine corresponding weighting factors (w_i) for each model. The related data from 1980 to 2003 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 2004 to 2010 were used in this stage.

(d): Demand estimation models were proposed using the optimal values of weighting parameters. The GA models were performed using the following user-specified parameters:

Population size: 50

Crossover rate: 0.85

Mutation rate: 0.01

Maximum Generation: 200

In the linear and exponential forms of GA models, coefficients obtained are given below:

$$GA - CO_{2_{linear}} = 0.2763\,OIL + 0.0264\,NG + 0.4218\,COAL$$

$$+ 0.1973\,PE + 0.0326 \qquad\qquad (4)$$

$$GA - CO_{2_{exponential}} = 0.3427\,OIL^{2.0509} + 0.9188\,NG^{0.9115}$$

$$+ 0.0092\,COAL^{0.9096} - 0.25644\,PE^{0.2827} + 0.3597 \qquad (5)$$

Table 2 shows the comparison between the Actual and estimated values of global CO_2 emission on testing period.

<< Table 2. Comparison between the Actual and estimated values of global CO_2 emission on testing period (2004-2010) >>

As it can be seen in this table, the estimation models are in good agreement with the actual data but $GA - CO_{2_{linear}}$ outperformed another presented model.

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4.2. 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 (2011–2030). To achieve this, the designed scenarios for future projection of each input variable remained the same which were developed by Behrang et al. (2011a). The values of oil, natural gas, coal, and primary energy consumptions between 2011 and 2030 based on the designed scenario by Behrang et al., (2011a) are shown in Table 3.

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

Figure 1 shows the comparison between different projections for global CO2 emission.

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

Table 4 shows the comparison of different projections for global CO_2 emission.

<<Table 4. Comparison of different projections for global CO_2 emission (in million tones) up to 2030. >>

5. Conclusion

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

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Figure Captions:

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

Table Captions:

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

Table 2. Comparison between the Actual and estimated values of global CO_2 emission on testing period (2004-2010) .

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

Table 4. Comparison of different projections for global CO_2 emission (in million tones) up to 2030.

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 tonne oil equivalent
[b](Mt): Million tonne

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-CO2$_{exponential}$	28033.8	29481.9	30217.8	30859.0	31630.7	31728.3	31080.5	-
Relative error (%)	4.46	0.68	0.45	1.00	1.00	2.66	5.55	2.26
GA-CO2$_{linear}$	27586.2	29624.2	30530.8	31324.7	32233.9	32171.0	31317.7	-
Relative error (%)	1.91	2.10	1.31	0.62	0.03	0.59	0.82	1.06

[a] (Workbook, 2011)

Table 3. The values of designed scenario 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

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

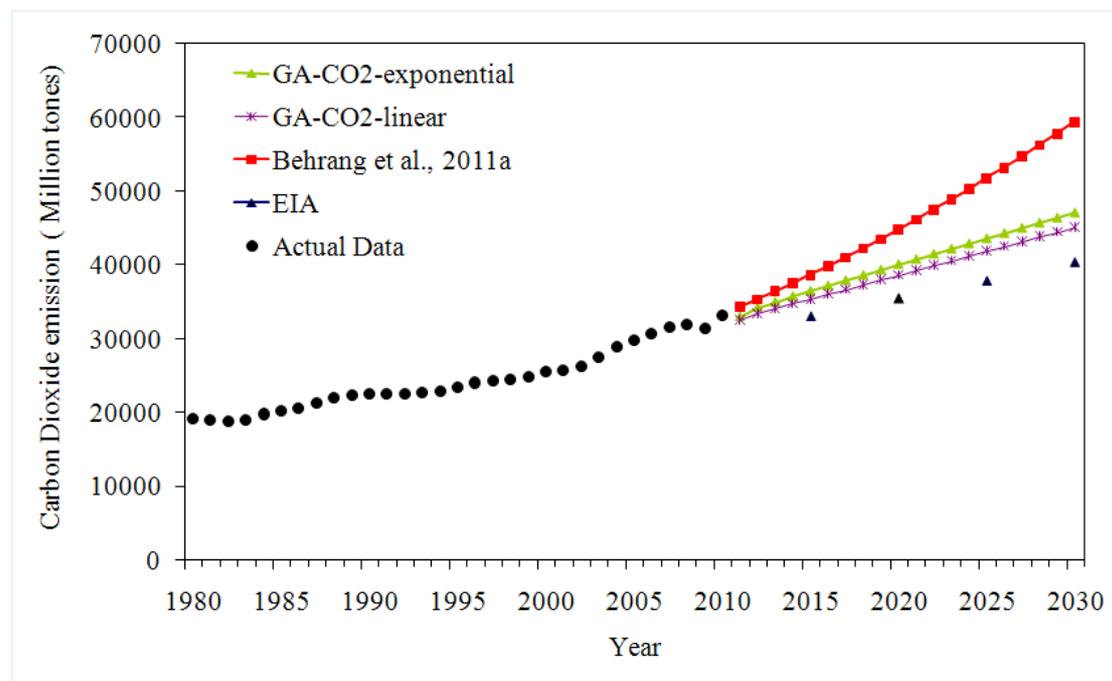| Projection	Year			
	2015	2020	2025	2030
Present Study ($Co_{2\ linear}$)	35436.8	38674.4	41912.0	45149.6
Behrang et al (2011a)	38637.1	44812.5	51765.3	59469.7
EIA (2009)	33111	35428	37879	40385

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

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