Forecasting Carbon Dioxide Emissions in China Using Optimization Grey Model

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***Abstract*—Carbon dioxide (CO_2) is one of the most important anthropogenic greenhouse gases (GHG) that caused global environmental degradation and climate change. China has been the top carbon dioxide emitter since 2007, surpassing the USA by an estimated 8%. So, forecasting future CO_2 emissions trend in China provides the basis for policy makers to draft scientific and rational energy and economic development policies. This paper presents an optimization GM (1, 1) model to forecast the carbon dioxide emissions in China. In traditional GM (1, 1) model, the background value usually chooses the constant 0.5. But taking the same background parameter values for each time with different trend will result in degrading the forecasting accuracy. And it is also the main reason why the accuracy is lower with non-smooth sequence forecasting. So, the rational background value should be selected during parameter identification process. Considering the limitation of traditional GM (1, 1), the background value vector α is introduced to assign different parameters for different times instead of choosing constant value 0.5 to compute background value array. And the Harmony Search (HS) algorithm is adopted to determine the value of α through optimizing the Mean Absolute Percentage Error (MAPE) function. The proposed HS optimization GM (1, 1) is applied to carbon dioxide emissions forecast in China. And the simulation results show that the HS optimization GM (1, 1) model gives better accuracy.**

***Index Terms*—Carbon dioxide emissions forecasting, greenhouse gases, Harmony Search algorithm, optimization GM (1, 1) model**

I. INTRODUCTION

Carbon dioxide (CO_2) is the most important anthropogenic GHG that caused global environmental degradation and climate change. Its annual emissions have grown between 1970 and 2004 by about 80%, from 21 to 38 gigatonnes (Gt) [1]. Especially between 2007 and 2008, global CO_2 emissions increased by 0.4 Gt, which represented a growth rate of 1.5% [2]. China, the most important developing country, emitted about 6 billion tones of CO_2 in 2007 (accounting for 21% of global emissions) [3]. Correspondingly, China topped the list of CO_2 emitting countries, surpassing the USA by an estimated 8% [4]. Moreover, the total amount of CO_2 emission will keep at high speed for decades since China is just in the process of industrialization and urbanization [5, 6]. Responding climate change and reducing CO_2 emission has become a hot discussion topic and the most important target for china's sustainable development. Chinese Government made a commitment to reduce CO_2 emission intensity to 40-45% of the 2005's level by 2020 just before the 2009 U.N. Climate Change Conference in Copenhagen. Therefore, modeling and forecasting future CO_2 emission trend in China provides the basis for policy makers to draft scientific and rational energy and economic development policies.

There are certain representative literatures on forecasting energy or carbon dioxide emissions for China. Meng adopted logistic function to simulate emission form fossil fuel combustion, and applied this model to China [6]. Pi used improved grey forecasting model to forecast China's electricity demand and energy production [7]. He estimates China's future energy requirements and projects its CO_2 emission from 2010 to 2020 based on the scenario analysis approach [8]. Yu proposed particle swarm optimization and genetic algorithm optimal energy demand estimating (PSO–GA EDE) model for China's Energy demand projection [9].

Grey (1, 1) model (GM (1, 1)), based on grey system theory proposed by Deng in 1982[10], has the ability to deal with the system with incomplete information. It requires only a limited amount of data to estimate the behavior of unknown system. So, GM (1, 1) has the advantages of not needing a large number of sample data, small amount of calculation and without assuming the distribution of data series. GM (1, 1) has been widely used in many fields [11-15], such as energy-related

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indicator forecasting, engineering, social issues, financial, etc. Although the grey model has been widely adopted, its forecasting performance still can be improved. Some studies have proposed the improved grey model for better forecasting accuracy [15-17]. To increase the accuracy of the grey model, this study proposed a novel Harmony Search optimization GM (1, 1) forecasting model (HS GM (1, 1)).

For building low-carbon energy and economy system, it is necessary for policy makers to establish CO_2 emissions model and formulate reasonable polices for country's sustainable development, which is also the most important motivation of this study. Therefore, this study presents Harmony Search based optimization grey forecasting model to forecast CO_2 emissions in China. This model could guide the formulation of low-carbon development policy and sustainable development of economy and energy system.

II. Traditional GM (1, 1) model

GM (1, 1) is one of the most frequently used models for forecasting model dealing with small data.

Suppose $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\}$ is original data series of real numbers with irregular distribution. Generate the first-order accumulated generating operation (AGO) sequence $x^{(1)}$ based on the original data sequence $x^{(0)}$.

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \cdots, x^{(1)}(n)\}$$

Where $x^{(1)}(i) = \sum_{k=1}^{i} x^{(0)}(k), i = 1,2,\cdots n$

Then GM (1, 1) first order differential equation is written as Eq. (1)

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{1}$$

where the background value $x^{(1)}$ is replaced by the equal weight moving average of before and after the two time point, shown as Eq. (2).

$$x^{(1)} = \left(x^{(1)}(k+1) + x^{(1)}(k)\right)/2 \tag{2}$$

The coefficients *a* and *b* are the interim parameters that can be obtain by using the OLS method, shown in Eq. (3).

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{3}$$

where

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix}$$

The time response function of the whitening equation (Eq. (1)) is

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a} \tag{4}$$

Finally, the inverse accumulated generating operation (IAGO) process is employed to obtain the grey forecasting mode for original sequence $x^{(0)}$.

$$\begin{aligned} \hat{x}^{(0)}(k) &= \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \\ &= \left(1 - e^{a)}\right)\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} \end{aligned} \tag{5}$$

III. Harmony Search optimization GM (1, 1) model

In reference [18], Zhuang pointed that the accurate calculation formula for the background value $x^{(1)}$ should be written as Eq. (6) instead of equal weight form in Eq. (2).

$$x^{(1)} = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k+1) \tag{6}$$

where $\alpha = 1/\beta - 1/\left(e^{\beta} - 1\right)$. When $\beta \to 0$, $\alpha \to 0.5$; when $|\beta|$ is smaller, α is close to 0.5; when $|\beta|$ is larger, α deviates 0.5. So it is not suitable to take α a constant value 0.5, and that is the reason why the forecasting accuracy is not satisfactory when $|\beta|$ is a large value. In this paper, the background value vector $\alpha = (\alpha_2, \alpha_3, \cdots, \alpha_k, \cdots, \alpha_n)$ is introduced in order to adopt adaptive value instead of 0.5. Then matrix *B* is written as follows:

$$B = \begin{bmatrix} -\left[\alpha_2 x^{(1)}(k) + (1-\alpha_2)x^{(1)}(k+1)\right] & 1 \\ -\left[\alpha_3 x^{(1)}(k) + (1-\alpha_3)x^{(1)}(k+1)\right] & 1 \\ \vdots & \vdots \\ -\left[\alpha_n x^{(1)}(k) + (1-\alpha_n)x^{(1)}(k+1)\right] & 1 \end{bmatrix} \tag{7}$$

Combined Eq. (3) and (7), the coefficients *a* and *b* of optimization GM (1, 1) can be determined. Thus we can conclude that the key of optimization GM (1, 1) is how to determine vector $\alpha = (\alpha_2, \alpha_3, \cdots, \alpha_k, \cdots, \alpha_n)$. Seeing from time response function, the optimal vector α cannot be got through traditional method. So Harmony Search optimization technique is adopted in this paper to determine the adaptive α vector.

Harmony Search (HS) is a new meta-heuristic optimization algorithm named proposed by Geem et al [19]. It mimics the improvisation process of music players for a perfect state of harmony. The HS algorithm behaves excellent effectiveness and robustness when applied to several optimization problems and presents lots of advantages when compared to other heuristic optimization algorithms [20, 21]. Figure 1 shows the HS optimization procedures which consists of Steps 1-5 shown as follows.

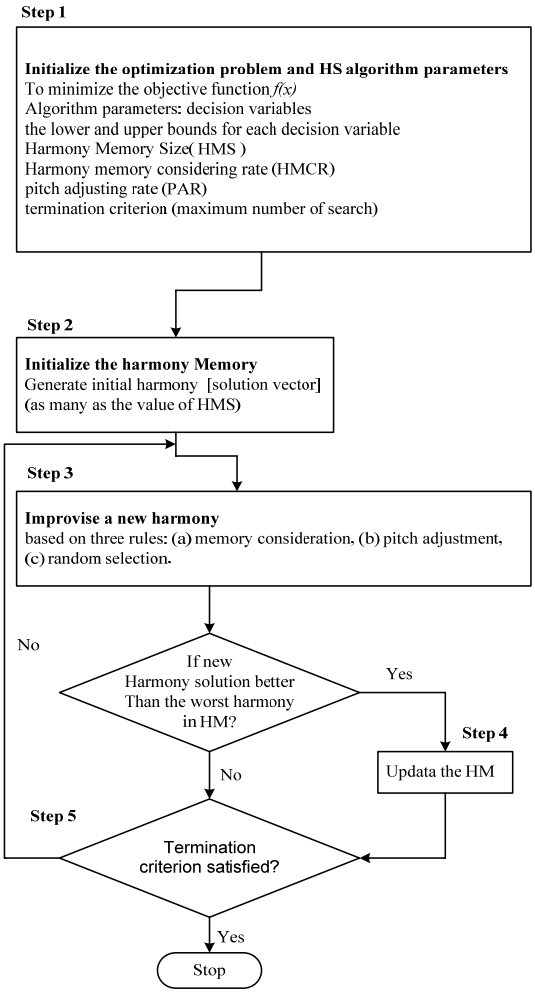

Figure 1. Harmony Search optimization procedure.

Step 1. Initialize the optimization problem and algorithm parameters.

Minimize $f(x)$

s.t. $x_i \in X_i \qquad i = 1,2,\cdots,N$

where $f(x)$ is the objective function; x is the set of each design variable (x_i); X_i is the set of the possible range of values for each design variable; N is the number of design variables.

In addition, the HS algorithm parameters including harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR), and termination criterion should also be specified in this step.

Step 2. Initialize the Harmony Memory (HM).

The HM is a memory location where all the solution vectors (sets of decision variables) are stored. In this step, the HM matrix is filled with as many randomly generated solution vectors as the HMS and sorted by the values of the objective function $f(x)$.

Step 3. Improvise a new harmony from the HM.

A new harmony vector is generated based on three rules: memory consideration, pitch adjustment and random selection.

Step 4. Update the HM.

On condition that the new harmony vector showed better fitness function than the worst harmony in the HM, the new harmony is included in the HM and the existing worst harmony is excluded from the HM.

Step 5. Repeat steps 3 and 4 until the termination criterion is satisfied.

IV. Simulation and Results

A. Training Data

To demonstrate the applicability and effectiveness of HS optimization GM (1, 1) model, the proposed model is applied to China for carbon dioxide emissions forecasting. The data of CO_2 emissions from fossil fuel consumption were collected from BP (British Petroleum) Statistical Review of World Energy (BP2010) [22].

China has experienced a rapidly increasing economy and fossil fuel energy consumption accompanied by large amounts of carbon dioxide. China is the top one carbon dioxide emitter of the world. In 2009, China contributed a comparable share of world emissions (24%) while accounting for 20% of the world population. Currently, coal is filling much of the growing energy demand in China, where energy-intensive industrial production is growing rapidly and large coal reserves exist with limited reserves of other energy sources. The future trend in China's CO_2 emissions will be growing continuously which is similar with growth trends of exponential function. So China is selected as a sample to confirm the effect of proposed model.

B. Simulation and Results

The selection of HS algorithm parameters is as follows.

HMS=5, PAR=0.6, HMCR=0.99, lb=0, ub=1.

HMS: harmony memory size;

HMCR: harmony memory considering rate;

PAR: pitch adjusting rate;

Max: max iteration number

lb: the lower bound for variables;

ub: the upper bound for variables.

In the HS algorithm, bandwidth (short for BW) is fixed which doesn't consider different phase of the algorithm needs different BW value to gain better searching performance. In order to make full use of new vector information and reduce parameters initialized, new vector is added to calculate BW value shown as Eq. (8).

$$\begin{aligned} x'_{ijnew} &= x_{ijnew} + (UB_j - x_{ijnew}) \times Rand(0,1) \\ &\qquad Rand(0,1) > 0.618 \\ x'_{ijnew} &= x_{ijnew} - (x_{ijnew} - LB_j) \times Rand(0,1) \\ &\qquad Rand(0,1) \le 0.618 \end{aligned} \tag{8}$$

where x'_{ijnew} is the new vector after pitch adjusting; x_{ijnew} is the new vector before pitch adjusting; UB_j is the upper limit of variable x_{ij} ; LB_j is the lower; $i \in [1, HMS]$; $j \in [1, N]$, N is the number of design

variables. Eq. (8) shows x'_{ijnew} following such pitch adjusting strategy is bounded in the possible range of x_{ij}, then sloping over estimation is eliminated.

All the programs were run on a 2.27GHz Intel Core Double CPU with 1 GB of random access memory. In each case study, 30 independent runs were made for the HS optimization method in MATLAB 7.6.0 (R2008a) on Windows 7 with 32-bit operating systems.

Table I represents the different background value for different time point determined by HS optimization technique. Figure 2 shows the actual data curve and the forecast data curve for China's CO_2 emissions. Table II shows the actual data and forecasting data using traditional GM (1, 1) model and HS optimization GM (1, 1) model for the same period. To evaluate the forecast accuracy of the presented model's performance, the mean absolute percentage error (MAPE) was calculated for the traditional GM (1, 1) model and the Harmony Search optimization GM (1, 1) model respectively. The MAPE of Harmony Search optimization GM (1, 1) is 3.934%, while the MAPE for traditional GM (1, 1) model is 4.35%. It means that the optimization GM (1, 1) model can increase the forecasting accuracy compared with traditional GM (1, 1) model.

TABLE I.
THE BACKGROUND VALUE DETERMINED BY HS

i	2	3	4	5	6
α_i	0.379940	0.861508	0.009486	0.714895	0.028128
i	7	8	9	10	11
α_i	0.004408	0.061254	0.911770	0.688860	0.825733

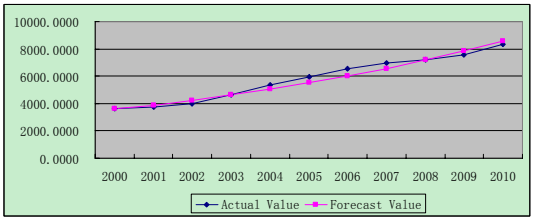

Figure 2. Actual Curve and Forecasting Curve

In addition, we also carried out the posterior-variance test and small error probability test for HS optimization GM (1, 1) model. The posterior-variance test is a technique according to the statistical state between forecasting data and actual data, which is transplanted from probability prediction method. The posterior-variance test is the ratio between root mean square of the variance for residuals and root mean square of the variance for actual data, shows as Eq. (9).

TABLE II.
FORECAST VALUE AND MAPE FOR TWO MODELS(MILLION TONNES)

	Actual Value	GM(1,1) Forecast Data	GM(1,1) Error (%)	HS GM(1,1) Forecast Data	HS GM(1,1) Error (%)
2000	3659.3483	3659.3483	0.00	3659.3483	0.00
2001	3736.9794	4030.3437	7.85	3864.8351	3.42
2002	3969.8231	4380.2836	10.34	4222.8001	6.37
2003	4613.9200	4760.6075	3.18	4613.9202	0.00
2004	5357.1651	5173.9535	-3.42	5041.2662	-5.90
2005	5931.9713	5623.1889	-5.21	5508.1934	-7.14
2006	6519.5965	6111.4297	-6.26	6018.368	-7.69
2007	6979.4653	6642.0626	-4.83	6575.7954	-5.78
2008	7184.8542	7218.7685	0.47	7184.8523	0.00
2009	7546.6829	7845.5476	3.96	7850.3206	4.02
2010	8332.5158	8526.7477	2.33	8577.4254	2.94
MAPE		4.3502245		3.9335443	

$$C = \frac{S_2}{S_1} = \frac{\sqrt{\frac{1}{m}\sum_{k=1}^{m}\left(\varepsilon(k)-\bar{\varepsilon}\right)^2}}{\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(x^{(0)}(k)-\bar{x}\right)^2}} \tag{9}$$

where S_1 is the root mean square of the variance for actual data. S_2 is the root mean square of the variance for residuals; $\varepsilon(k)$ is the difference between the actual and forecasted value for the time period k (*i.e.* the residual for the kth period). $\bar{\varepsilon}$ is the mean of the residuals. $x^{(0)}(k)$ is the actual data for the kth period. $\bar{x}$ is the mean for original sequence.

The small error probability value is defined as Eq. (10).

$$P = P\left\{\left|\varepsilon(k)-\bar{\varepsilon}\right|\right\} < 0.6745 S_1 \tag{10}$$

Base on Eq. (9), the ratio of posterior-variance test for proposed model is 0.02996<0.35.

Another,

$$P = P\left\{\left|\varepsilon(k)-\bar{\varepsilon}\right|\right\} < 0.6745 \times \sqrt{1569.5835} = 1 > 0.95$$

TABLE III.
POSTERIOR VARIANCE RATIO (C) AND SMALL ERROR PROBABILITY (P)

Forecast accuracy class	P	C
Good (Class A)	>0.95	<0.35
Qualified(Class B)	>0.8	0.35=< C <0.5
Unconvinced (Class C)	>0.7	0.5=< C <0.65
Unqualified(Class D)	>=0.7	>=0.65

According to Table III, the proposed HS optimization GM (1, 1) model belongs to "Good" (Class A). The proposed model has good forecasting performance.

V. CONCLUSION

In this paper, we proposed a Harmony Search optimization GM (1, 1) model for CO_2 emissions forecasting in China. In this model, the adaptive vector α is introduced instead of choosing constant value 0.5 to compute background value array. The Harmony Search (HS) algorithm is used to determine the value of α through optimizing the Mean Absolute Percentage Error (MAPE) function. The proposed HS optimization grey GM (1, 1) is applied to carbon dioxide emissions forecast for China since China is now the top CO_2 emitter. The MAPE of presented model is compared with that of traditional GM (1, 1) model. And the previous one shows better prediction accuracy. The advantage of the HS GM (1, 1) model is to assign different background parameters for different times, which can treat the non-smooth sequence forecasting issue with better prediction performance. Each background value could be determined through optimization technique on the condition of minimal Mean Absolute Percentage Error. In all, the proposed HS GM (1, 1) forecasting model shows better practical performance and accuracy in CO_2 prediction field.

REFERENCES

[1] IPCC, 2007. Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K and Reisinger, A. (Eds.)]. IPCC, Geneva, Switzerland.

[2] IEA, CO_2 emissions from Fuel Combustion. OECE/IEA, Paris, 2010.

[3] IEA. CO_2 emissions from Fuel Combustion. OECE/IEA, Paris, 2009.

[4] PBL. Chinese CO_2 emissions in perspective-Country intercomparison of CO_2 emissions, 2007, Available from: http://www.pbl.nl/en/news/newsitems/2007/20070622ChineseCO$_2$emissionsinperspective.

[5] B. Jiang, Z. Sun, M. Liu, "China's energy development strategy under the low-carbon economy," *Energy*, vol. 35, pp. 4257-4264, November 2010.

[6] M. Meng, D.Niu "Modeling CO2 emissions from fossil fuel combustion using the logistic equation," *Energy*, vol. 36, pp. 3355-3359, May 2011.

[7] D. Pi, J. Liu, X. Qin, "A Grey Prediction Approach to Forecasting Energy Demand in China," *Energy Sources, Part A*, vol.32, pp. 1517-1528, June 2010.

[8] J. He, J. Deng, M. Su, "CO_2 emission from China's energy sector and strategy for its control," *Energy*, vol. 35, pp. 4494-4498, November 2010.

[9] S. Yu, K. Zhu, X. Zhang, "Energy demand projection of China using a path-coefficient analysis and PSO–GA approach," *Energy Convers Manage*, vol. 53, pp. 142-153, January 2012.

[10] J. Deng, Control problems of grey system. *Syst Control Lett.*, vol.1, pp.288–294, March 1982.

[11] C. C. Hsu, C. Y. Chen, "Applications of improved grey prediction model for power demand forecasting," *Energy Convers Manage*, vol. 44, pp. 2241–2249, August, 2003.

[12] L. Hsu, "Applying the Grey prediction model to the global integrated circuit industry," *Technol Forecast Soc Change*, vol. 70, pp. 177–186, July 2003.

[13] P. S. Yu, C. J. Chen, "Application of gray and fuzzy methods for rainfall forecasting," *J Hydrol Eng*, vol. 5, pp. 339–345, May 2000.

[14] Y. F. Wang, "Predicting stock price using fuzzy grey prediction system," *Expert Syst Appl*, vol. 22, pp. 33–39, January 2002.

[15] W. L.Yao, S. C.Chi, J. H. Chen, "An improved Grey-based approach for electricity demand forecasting," *Electr Pow Syst Res*, vol. 67, pp. 217–224, December 2003.

[16] G. D. Li, C. H. Wang, S. Masuda, M. Nagai, "A research on short term load forecasting problem applying improved grey dynamic model," *Elec Pow Energy Syst*, vol. 33, pp. 809–816, May 2011.

[17] Y. S. Lee, L. I. Tong, "Forecasting energy consumption using a grey model improved by incorporating genetic programming," *Energy Convers Manage*, vol. 52, pp. 147–152, January 2011.

[18] H. Zhuang, "Modeling Mechanism and Prerequisites for GM (1, 1) and the Revised Methods," *Syst Engrg Theory Pr,* vol. 2, pp. 56-62, March 1993.

[19] Z.W. Geem, J.H. Kim, G.V. Loganathan, "A new heuristic optimization algorithm: Harmony search," *Simulat*, vol. 76, pp. 60-68, February 2001.

[20] K.S. Lee, Z.W. Geem, "A new meta-heuristic algorithm for continues engineering optimization: harmony search theory and practice," *Comput Methods Appl Mech Engrg,* vol. 194, pp. 3902-3933, September 2005.

[21] K.S. Lee, Z.W. Geem, "A new structural optimization method based on the harmony search algorithm," *Comput. Struct.* vol. 82, pp. 781-798, April 2004.

[22] BP. 2010. BP Statistical Review of World Energy. London: BP. http://bp.com/statisticalreview.

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