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Research Article

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Integrated forecasting model with adaptive parameters optimization using a harmony search algorithm for carbon dioxide emissions

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ABSTRACT

With the significant increase of greenhouse gases and environmental deterioration, it is essential to understand trends of CO2 emissions form fossil fuel so as to establish effective energy policies and environmental strategy decision. In this study, a novel integrated forecasting model with adaptive parameters optimization by using Harmony Search (HS) algorithm for carbon dioxide emissions is established. In this proposed model, the integrated weights and nonlinear exponential parameters for single models are determined by HS. This novel integrated model is applied to CO2 emissions from 2000 to 2010 for China and United States in order to test the applicability and forecasting accuracy. Through the comparison with other integrated methods (EW, VACO, R, DMFSE), our model showed better forecasting performance with the smaller MAPE.

Key words: Carbon Dioxide Forecasting; integrated model; Harmony Search; adaptive parameter optimization

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INTRODUCTION

It is widely considered that the greenhouse gas (GHG) causes the global climate change and environmental degradation. The real increase in GHG began around the time of the Industrial Revolution. This is when we began to burn fossil fuels in large quantities to power our steam engines for industry, generate electricity, and heat our homes. About three quarters of the human-caused carbon emissions of the past 20 years are due to fossil fuel burning. Furthermore, the global CO2 emissions from fossil fuel consumption will also have grown strongly in the future. It is projected by EIA that the energy-related CO2 emissions in 2035 are 5864 million metric tons and 6795 million metric tons, respectively [1]. To establish effective energy policies and environmental strategy decision requires understanding of trends of CO2 emissions form fossil fuel. Therefore, accurate forecasting of emissions is important.

In CO2 forecasting modeling, a large number of literatures using various estimation methods have been published. Bulent [2], and Raghuvanshi [3] employed trend analysis approach for modeling world total carbon dioxide emissions and CO2 emissions from power generation in India. Liang [4] established a multi-regional input-output model for energy requirements and CO2 emissions for eight economic regions in China and performed scenario in year 2010 and 2020. Chen [5] proposed a hybrid fuzzy linear regression (FLR) and back propagation network (BPN) approach for global CO2 concentration forecasting. Sun [6] provided a GDP based alternative viewpoint on the forecasting of energy-related CO2 emissions in OECD countries. Pao [7] and Lin [8] applied Grey prediction model (GM) to predict CO2 emissions in Brazil and Taiwan. Ramanathan [9] used Data Envelopment Analysis (DEA) method for the prediction of energy consumption and carbon dioxide emissions from 17 countries of the Middle East and North Africa. He (2010) [10] estimated China's future energy requirements and projected its CO2 emission from 2010 to 2020 based on the scenario analysis approach.

No matter what single forecasting models for energy or CO2 emissions prediction, a certain number of undetermined parameter exist in forecasting models. The way selecting the parameters will affect the forecasting accuracy. The adaptive optimization for parameters is the key to solve this kind of problems. Furthermore, there is significant uncertainty associated with future CO2 emissions trend, so single forecasting model may not describe the trend accurately in all situations. The integrated forecasting model can synthesize the information of each individual forecast into a composite forecast so as to face less risk in choosing an individual method out of a set of available methods [11-13].

The purpose of this study is to develop an integrated model with adaptive parameters optimization, which is an effective way to improve the accuracy of the forecasting problem. Through using Harmony Search (HS) algorithm, the integrated weights and nonlinear exponential parameters for single model can be determined by adaptive optimization.

METHODOLOGIES

Adaptive optimization for combined weights

The method of combination forecasting with adaptive optimization is described in this part. Firstly, the optimization objective function is specified as the mean absolute percentage error (MAPE). The MAPE is measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage, eliminating the interaction between negative and positive values by taking absolute operation [14], shown in Eq. (1).

$$\min(MAPE) = \min\left\{\frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t-\hat{y}_t}{y_t}\right|\right\} \tag{1}$$

where y_t is the actual value for tth period; $\hat{y}_t$ denotes the integrated forecasting value for the same period. $\hat{y}_t$ can be calculated through Eq. (2).

$$\hat{y}_t = \sum_{i=1}^{k}\omega_i\left[\hat{y}_t^{(i)}\right]^{n_i} \tag{2}$$

where $\hat{y}_t^{(i)}$ is the ith forecasting in time period t; k is the number of forecasts to be combined. A novel nonlinear integrated model is adopted to obtain better fitting performance. Then the optimization objective function is expressed as follows.

$$\min(MAPE) = \min\left\{\frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t-\hat{y}_t}{y_t}\right|\right\} = \min\left\{\frac{1}{T}\sum_{t=1}^{T}\left|\left.y_t-\sum_{i=1}^{k}\omega_i\left[\hat{y}_t^{(i)}\right]^{n_i}\right/ y_t\right|\right\} \tag{3}$$

Secondly, determine the parameters through using Harmony Search (HS) algorithm. In Eq. (3), the optimal value of the integrated weights ω_i and exponential parameter n_i for the ith separate can be found by using HS. Next section shows the procedures of HS algorithm.

Harmony Search Algorithm (HS)

Recently, a new meta-heuristic optimization algorithm named Harmony Search (HS) is proposed by Geem *et al* [15]. 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 [16-17]. Fig. 1 shows the HS optimization procedures which consists of Steps 1-5 shown as follows. HS optimization procedures consisting of Steps 1-5 are shown as follows.

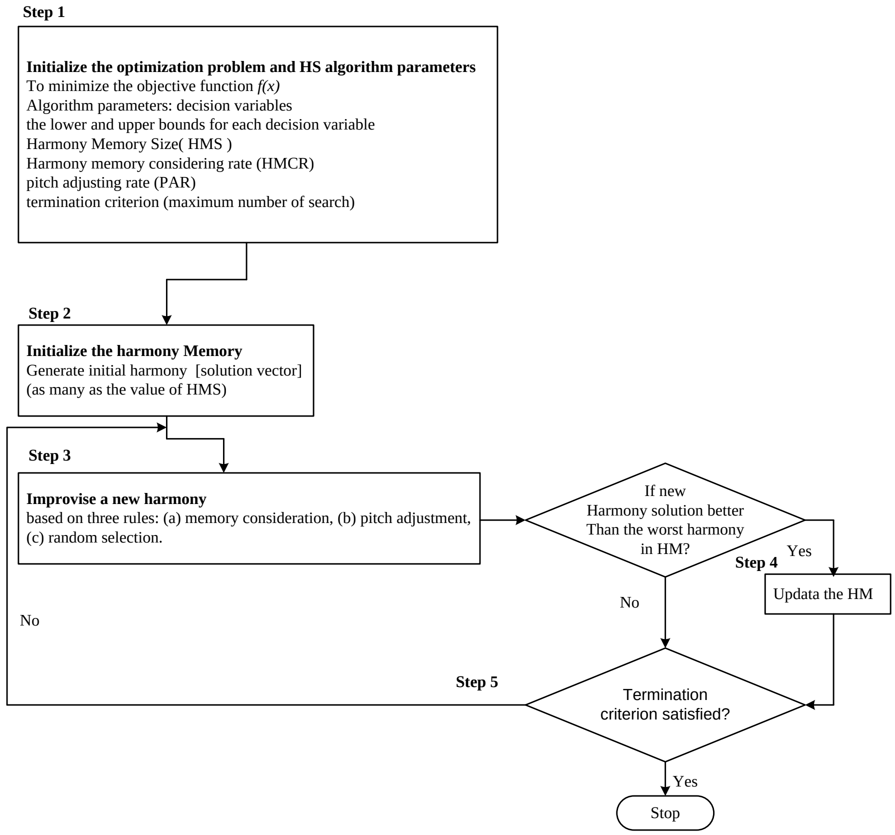

Fig. 1. The flowchart for Harmony Search algorithm

Step 1. Initialize the optimization problem and algorithm parameters.
In this step, the objective function and the design variable set are determined first. Then, the harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR), the lower and upper bounds for each decision variable are also specified in this step.

Step 2. Initialize the Harmony Memory (HM).
HM is a memory location that stored all the solution for decision variables. And the HM matrix is filled with as many randomly generated solution vectors as the HMS and sorted by the objective function values.

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.
If the new harmony vector is better than the worst harmony in the HM, judged in terms of the objective function value, the new harmony is included in the HM and the previous worst harmony is excluded from the HM. The HM is then sorted by the objective function value.

Step 5. Repeat steps 3 and 4 until the termination criterion is satisfied.
The computations are terminated when the termination criterion is satisfied. If not, Steps 3 and 4 are repeated.

EMPIRICAL SIMULATION AND RESULTS

This section describes how to apply the HS algorithm to integrated forecasting model with adaptive parameters optimization model. To test the applicability and efficiency of the proposed method, the proposed method is applied to China and United States. The annual CO2 emissions data of China and United States for the period from 2000 until 2010 are collected from BP [18]. Combined China and Unites States, these two countries alone produced 14.48 Gt CO2, about 43.6% of world CO2 emissions. China, the world's largest emitter of CO2 emissions from fuel combustion, generated

8.33 Gt CO2, which accounts 25.1% of the world total. Due to the energy-intensive industrial production, large coal reserves exist and intensified use of coal, the CO2 emissions would increase substantially for a certain period. The United States generated 18.5% of world CO2 emissions, despite a population of less than 5% of the global total. In the United States, the large share of global emissions is associated with a commensurate share of economic output.

Firstly, choose individual forecasting model and calculate separate forecasting result before we establish the integrated model. In our work, we adopted linear regression, time series, Grey (1, 1) and Grey Verhulst model [19].

Secondly, establish integrated model with adaptive parameters optimization by using HS algorithm. In simulation, the selection of HS algorithm parameters is as follows.

HMS=20, PAR=0.5, HMCR=0.5, BW=1, lb=-100, ub=100.
HMS: harmony memory size；
HMCR: harmony memory considering rate；
PAR: pitch adjusting rate;
BW: population variance (bandwidth);
lb: the lower bound for variables;
ub: the upper bound for variables.

All the programs were run on a 2.27GHz Intel Core Double CPU with 1 GB of random access memory. The optimal values of integrated weights ω_i and exponential parameter n_i for the ith separate model searched by HS are shown in Table 1. Table 2 shows the original CO_2 data and forecasting results for China and US through using presented integrated model with adaptive parameters optimization. Fig. 2 displays the fitting curve using our integrated model with adaptive parameters optimization model for China and US.

Table 1. Parameters determine by HS

Parameters	Countries	1	2	3	4
ω	China	1.0765	-95.7937	87.0434	6.8516
	US	6.4290	83.2769	56.7556	-55.1495
n	China	0.9698	-2.4801	-2.4435	-69.1194
	US	-81.0547	-3.6783	-0.7636	-1.0779

Table 2. Original and Forecasting results for China and US

	China		US	
Year	Original	Forecast	Original	Forecast
2000	3659.3483	3642.9790	6377.0493	6408.1152
2001	3736.9794	3748.8364	6248.3608	6321.3989
2002	3969.8231	3965.2189	6296.2248	6331.9540
2003	4613.9200	4429.5809	6343.4769	6339.9834
2004	5357.1651	5300.0054	6472.4463	6345.2326
2005	5931.9713	6002.6140	6493.7341	6347.4229
2006	6519.5965	6506.2892	6411.9503	6346.2487
2007	6979.4653	6991.2216	6523.7987	6341.3745
2008	7184.8542	7436.0752	6332.6004	6332.4326
2009	7546.6829	7838.4159	5904.0382	6319.0198
2010	8332.5158	8287.4665	6144.8510	6300.6933

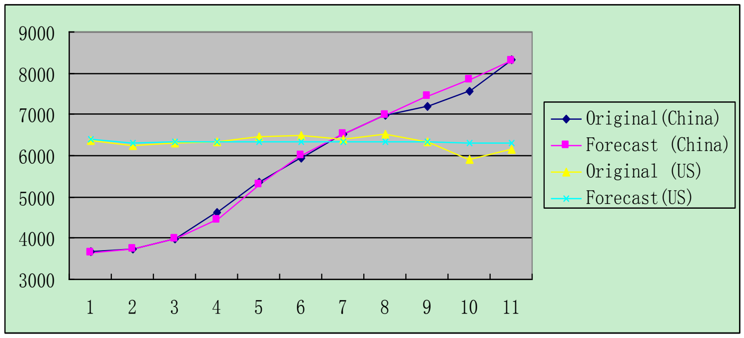

Fig. 2: Original and forecasting curve for China and US

To evaluate the forecasting accuracy of the presented model's performance, the mean absolute percentage error (MAPE) was calculated for China and US. The performance of the presented mode is also compared with Equivalent Weight (EW) method, Variance-Covariance (VACO) Method, Regression combination (R) method, Discounted Mean Square Forecast Error (DMSFE) method. From Table 3, we can see that the MAPE of integrated model with adaptive parameters optimization is much smaller that other integrated method. For China, the MAPE for EW, VACO, R and DMFSE are 3.92206%, 3.0601%, 2.6447% and 3.2069% respectively, while the MAPE for the integrated model with adaptive parameters optimization is 1.4008%. For US, the corresponding MAPE values are 2.4754%, 2.0494%, 8.3801%, 2.3788% and 1.8078% respectively.

Taking the MAPE of the integrated model with adaptive parameters optimization as a benchmark, the improvement rate with respect to other four combination models is also calculated. The improvement rates of EW, VACO, R and DMFSE are 129.92%, 118.45%, 88.80%, 128.93% respectively, for China; 36.93%, 13.36%, 363.55%, 31.59% respectively, for United States. Therefore, it can be conclude that the integrated model with adaptive parameters optimization can increase the forecasting accuracy compared with other traditional combination models.

Since the combination weights for EW, VACO, R and DMSFE integrated method can be definitely calculated through certain equations, these fixed weights can not be changed in future forecasting. Due to the uncertainty of future data trend, the fixed weights may not the best fitting performance for future use. In our proposed adaptive parameters optimization, the weights and the exponential parameter would change along with the input and output information in order to obtain the best performance.

Table 3. MAPE for China and US

MAPE(%)	EW	VACO	R	DMFSE	Proposed method
China	3.2206	3.0601	2.6447	3.2069	1.4008
US	2.4754	2.0494	8.3801	2.3788	1.8078

CONCLUSION

This paper presented a novel integrated forecasting model with adaptive parameters optimization through using Harmony Search (HS) algorithm. The integrated model can synthesize the information of each individual forecast to reduce the risk of a single forecasting model. All the integrated weights and exponential index can be determined by HS, which would change along with the input and output information. Compared with fixed weight, the adaptive parameters can simulate the future carbon dioxide trend. The empirical results reveal that this proposed model showed better forecasting performance with smaller mean absolute percentage error.

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