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Article

Forecasting Energy CO_2 Emissions Using a Quantum Harmony Search Algorithm-Based DMSFE Combination Model

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Abstract: The accurate forecasting of carbon dioxide (CO_2) emissions from fossil fuel energy consumption is a key requirement for making energy policy and environmental strategy. In this paper, a novel quantum harmony search (QHS) algorithm-based discounted mean square forecast error (DMSFE) combination model is proposed. In the DMSFE combination forecasting model, almost all investigations assign the discounting factor (β) arbitrarily since β varies between 0 and 1 and adopt one value for all individual models and forecasting periods. The original method doesn't consider the influences of the individual model and the forecasting period. This work contributes by changing β from one value to a matrix taking the different model and the forecasting period into consideration and presenting a way of searching for the optimal β values by using the QHS algorithm through optimizing the mean absolute percent error (MAPE) objective function. The QHS algorithm-based optimization DMSFE combination forecasting model is established and tested by forecasting CO_2 emission of the World top–5 CO_2 emitters. The evaluation indexes such as MAPE, root mean squared error (RMSE) and mean absolute error (MAE) are employed to test the performance of the presented approach. The empirical analyses confirm the validity of the presented method and the forecasting accuracy can be increased in a certain degree.

Keywords: fossil fuel energy; CO_2 emissions; quantum harmony search algorithm; discounting factor; combination forecasting method

1. Introduction

With the advent of industrialization and globalization, World energy consumption has increased exponentially by about 30% in the last 25 years [1]. Fossil fuel consumption, attributed to economic growth in a large part, comprises 80% of the World's energy use [2]. It is scientifically understood that the detrimental impacts of GHG emissions, especially carbon dioxide (CO_2) emissions, on the living environment such as global warming, greenhouse effect, and climate change are mainly the result of fossil fuel combustion for heat supply, electricity generation and transportation purposes [3]. About three quarters of the human-caused carbon emissions of the past 20 years derived from fossil fuel burning. CO_2 is considered as the single most important greenhouse gas and is held responsible for approximately 60% of the greenhouse effect resulting in increasing global warming and climatic instability [4]. The Kyoto Protocol, a legally binding agreement linked to the United Nations Framework Convention on Climate Change (UNFCCC), is the first international commitment that sets binding targets for participating countries for reducing collective emissions of greenhouse gases by 5.2% below the emission levels of 1990 by 2012. Forecasting CO_2 emissions from fossil fuel consumption could provide an important reference for energy planning and environmental strategy decisions.

In CO_2 forecasting modeling, a large amount of literature using various estimation methods has been published. Meng [5] adopted a logistic function to simulate emissions from fossil fuel combustion. Bulent [6], Köne [7] and Raghuvanshi [8] employed trend analysis approaches for modeling World total CO_2 emissions and CO_2 emissions from power generation in India. Liang [9] established a multi-regional input-output model for energy requirements and CO_2 emissions for eight economic regions in China and performed scenario studies for the years 2010 and 2020. Chen [10] proposed a hybrid fuzzy linear regression (FLR) and back propagation network (BPN) approach for global CO_2 concentration forecasting. Sun [11] provided a GDP based alternative viewpoint on the forecasting of energy-related CO_2 emissions in OECD countries. Pao [12] and Lin [13] applied a Grey prediction model (GM) to predict CO_2 emissions in Brazil and Taiwan. Ramanathan [14] used the Data Envelopment Analysis (DEA) method for the prediction of energy consumption and CO_2 emissions from 17 countries of the Middle East and North Africa. Ullash [15] developed a long term forecast of energy demands and related CO_2 emissions for China using an approach based on key energy indicators in conjunction with the TIMES G5 model. He [16] estimated China's future energy requirements and projected its CO_2 emissions from 2010 to 2020 based on the scenario analysis approach.

Although many quantitative methods have been applied to CO_2 emissions forecasting, no single forecasting method has been found to outperform all others in all situations since each method has its own particular advantages or disadvantages. The combination forecasting method, introduced by Bates and Granger [17] is often regarded as a successful alternative to using just an individual method. The rationale of combination forecasting is to synthesize the information of each individual forecasting into a composite one. Another advantage is that it is less risky in practice to combine forecasts than to

select an individual forecasting method [18]. By combining different methods, the problem of model selection can be eased with a little extra effort [19]. Choosing an individual method out of a set of available methods is more risky than choosing a combination because there is significant uncertainty associated with CO_2 emissions forecasting. In a combination forecasting model, how to determine the combination weights plays an important role since it affects the final forecast results. The combination weights methods encompass simple average combination, variance covariance combination, Granger and Ramanthan Regression method, discounted mean square forecast error (DMSFE) combination, *etc*. The combination weights can be definitely calculated or distributed by certain algorithms, except that the combination weights of the DMSFE method rely on the selection of the discounting factor (β). It is vital to select the β value in order to achieve an optimal combination result with minimum error.

The purpose of this investigation is to develop an effective way to search for the optimal β values for each single model in the combination model by using a quantum harmony search (QHS) algorithm and to establish the QHS algorithm-based optimization DMSFE combination forecasting method. Through the QHS algorithm, the optimal values of β can be found on the condition of minimizing mean absolute percent error (MAPE). The innovative combination forecasting model can also achieve a pretty good forecasting performance.

The rest of the paper is organized as follows: in Section 2, the DMSFE combination method, QHS algorithm and QHS algorithm based DMSFE combination model are described. Section 3 presents the empirical simulation and analysis on CO_2 emissions of the World–top 5 emitters to test the validity of the model introduced above. Apart from the QHS algorithm-based DMSFE combination model, other cases with different given β values (β = 0.1, 0.5 and 1 respectively) are designed to compare with the proposed model to test the performance through forecasting error indicators. The forecasting results and scenario analysis of applying the same optimal β value to all individual models of DMSFE combination forecasting model basing on QHS algorithm are given for the same purpose. Finally, main conclusions are given in Section 4.

2. Methodologies

2.1. Discounted Mean Square Forecast Error (DMSFE) Method

The general form of combination forecasting model can be written as follows:

$$\hat{y}_t = \sum_{i=1}^{k} \omega_i \hat{y}_t^{(i)} \tag{1}$$

where $\hat{y}_t^{(i)}$ is the forecasting value for period *t* from forecasting model *i*; ω_i is the combination weight assigned to the *i*th participating model through using DMSFE method; $\hat{y}_t$ denotes the combined forecasting value for the *t*th period; *k* is the number of forecasts to be combined. The DMSFE method, first proposed by Bates and Granger in 1969, uses the mean square error to calculate the optimal weights. It weighs recent forecasts more heavily than distant ones through using a discounting factor [20]. The weight for the *i*th participating model can be defined as Equation (2):

$$\omega_i = \frac{\left[\sum_{t=1}^{T} \beta^{T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}}{\sum_{i=1}^{k}\left[\sum_{t=1}^{T} \beta^{T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}} \tag{2}$$

where y_t is the actual value for the *t*th period; β is the discounting factor with $0 < \beta < 1$; *T* denotes the observation lengths used to obtain the weights.

Combine Equations (1) and (2), the DMSFE combination model can be written as Equation (3):

$$\hat{y}_t = \sum_{i=1}^{k} \omega_i \hat{y}_t^{(i)} = \sum_{i=1}^{k} \frac{\left[\sum_{t=1}^{T} \beta^{T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}}{\sum_{i=1}^{k}\left[\sum_{t=1}^{T} \beta^{T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}} \hat{y}_t^{(i)} \tag{3}$$

2.2. Quantum Harmony Search (QHS) Algorithm

The harmony search (HS) algorithm pioneered by Geem *et al*. [21] in 2001 is a new meta-heuristic algorithm which mimics the improvisation process of music players for a perfect state of harmony [22]. A new harmony is selected randomly from the harmony memory (HM) based on the harmony memory considering rate (HMCR). Then, the new harmony is adjusted with the probability of the pitch adjusting rate (PAR). Due to its advantages of a simple concept, fewer parameters, excellent effectiveness, strong robustness and easy implementation, the HS algorithm has been successfully applied to many optimization problems in the computation and engineering fields [23,24]. However, the parameter setting and new vector creation manner influence the performance of the HS algorithm awfully. When applied to numerical optimization problems, it tends to perform badly in local searching. Lots of improved HS algorithms have been presented to enhance the performance of the HS algorithm [23,25,26]. Inspired by quantum computing, a new variation of the HS algorithm called quantum harmony search algorithm (QHS) is proposed in this paper. The new approach applies concepts and principles of the quantum mechanism to the HS algorithm, such as quantum bit (qbit), superposition and collapse of states.

2.2.1. Quantum Encoding and Observation of Harmony

The QHS algorithm employs qbits to express the harmonies in HM as shown in Equation (4), inspired by the concept of states superposition in quantum computing. The strength of quantum harmony comes from the fact that it can represent a linear superposition of solutions based on the probabilistic representation. Hence, the individual harmony could bring more information. Then, the convergence speed of the algorithm increases:

$$q^t{}_i = \begin{bmatrix} q_{i1}^t & q_{i2}^t \cdots & q_{in}^t \end{bmatrix} = \begin{bmatrix} \alpha_{i1}^t & \alpha_{i2}^t \cdots & \alpha_{in}^t \\ \beta_{i1}^t & \beta_{i2}^t \cdots & \beta_{in}^t \end{bmatrix} \quad i = 1,2,\cdots,m \tag{4}$$

where $q^t{}_i$ is the *i*th quantum harmony at generation *t* in HM denoting a potential solution vector; *m* is the size of HM (HMS); *n* is the dimension of the problem concerned; $|\alpha|^2$ and $|\beta|^2$ is the probabilities that the qbit exists in state "0"and state "1", respectively.

When observed as Equation (5), the quantum harmony collapses to a single state:

$$\begin{aligned} &q^t{}_{ij} \to |1\rangle \quad , when \quad rand(0,1) > |\alpha_{ij}|^2 \quad i = 1,2,\cdots,m \\ &q^t{}_{ij} \to |0\rangle \quad , others \qquad\qquad\qquad\quad j = 1,2,\cdots,n \end{aligned} \tag{5}$$

where *rand*(0,1) is a random number from the uniform distribution [0,1]. For more details for quantum computing readers are referred to other references [27].

2.2.2. Adjusting Bandwidth Dynamically

Bandwidth (BW) is an important parameter in the HS algorithm in solution vectors fine-tuning. Small BW values bring small adjustments in the process of pitch adjustment, which means a relatively better local search capability. On the contrary, a large BW is good to enhance the exploration of the method [28]. BW is fixed and chosen based on the investigators experience in the HS algorithm. How to select appropriate parameters is an interesting problem, investigated by many researchers [23,28]. In order to use the new harmony information, we adjust BW dynamically and decrease the number of parameters chosen in the initialization process, and the new harmony is adopted to calculate BW as in Equation (6):

$$\begin{aligned} q'_{ijnew} &= q_{ijnew} + Rand(0,1) \times (\frac{\pi}{2} - q_{ijnew}), Rand(0,1) > 0.618 \\ q'_{ijnew} &= q_{ijnew} - Rand(0,1) \times q_{ijnew}, others \end{aligned} \quad (6)$$

where q'_{ijnew} is the new vector after pitch adjusting, q_{ijnew} is the new vector before pitch adjusting. The pitch adjusting procedure employs the golden selection mechanism shown in Equation (6) [29].

2.2.3. QHS Optimization Procedure

Figure 1 shows the QHS optimization procedure consisting of Steps 1–5, as follows, based on the discussion above:

Step 1. Initialize the optimization problem and algorithm parameters.
Minimize $f(x)$ $s.t.$ $x_i \in X_i$ $i = 1,2,\cdots,n$
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 QHS algorithm parameters including HMS, HMCR, PAR and termination criterion should also be specified in this step.

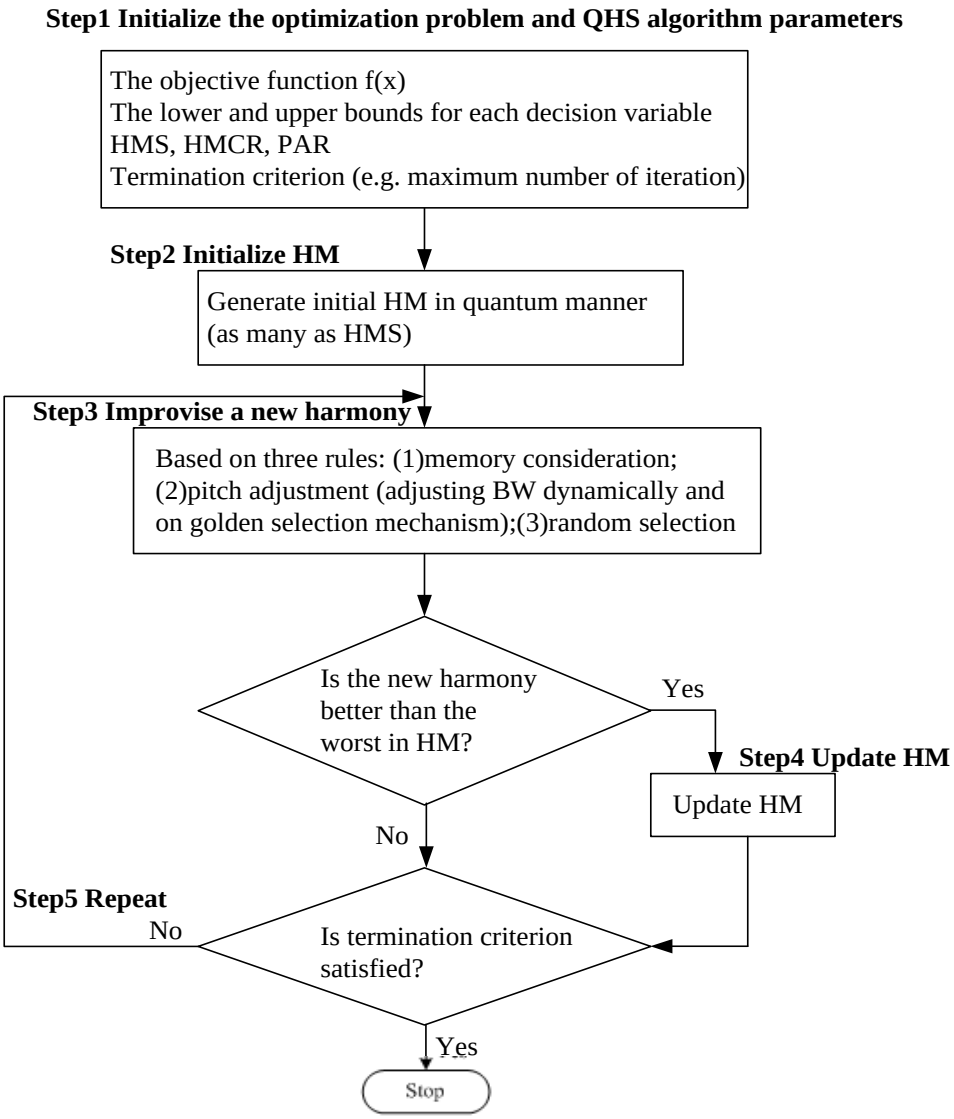
Step 2. Initialize HM.
HM is a memory location where all the solution vectors (sets of decision variables) are stored. In this step, quantum HM matrix is filled with as many randomly generated solution vectors as the HMS.

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 shows better fitness 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.
The computations are terminated when the termination criterion is satisfied such as when no manifest improvement in the best found solution is seen after a predetermined number of iterations or the maximum number of iterations is reached.

Figure 1. QHS optimization procedure.



2.3. Design of QHS Algorithm Based DMFSE Combination Model

In Equation (1), the different individual models have different combination weights to display the proportion of the corresponding individual model forecasting result in the combination model forecasting results. Equation (2) denotes that ω is influenced by two parts: β and the error between the actual value and the forecasting value. Equation (2) shows that the combination weight ω is influenced by the discounting factor β badly. In other words, the discounting factor β also influences this proportion because β influences ω. Different individual forecasting models have different applicability to different kinds of forecasting cases, according to the growth pattern. Such as, the GM(1,1) model is effective in those with a power growth pattern, whereas, a linear model is appropriate for a linearly increasing situation. The proportion of the same individual model forecasting results in the combination forecasting result is probably different according to different application cases, even when the same individual models are selected, so it seems more reasonable to adopt different β values for different individual models than to employ the same β value for all individual models. According to the same reasoning, the error of different periods employing different β values is more reasonable than

applying the same β value to all different period errors. Thus, the β value in Equation (2) is changed from one parameter to a matrix $\beta_{k\times T}$. Then, Equation (2) changes to Equation (7) and Equation (3) changes to Equation (8) where β_{it} is the discounting factor for the *t*th period from the *i*th forecasting model. In Equation (7) a different β value is employed for different period errors of different individual models, which implies a discrepancy between models and periods considered:

$$\omega_i = \frac{\left[\sum_{t=1}^{T} \beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}}{\sum_{i=1}^{k}\left[\sum_{t=1}^{T} \beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}} \tag{7}$$

$$\hat{y}_t = \sum_{i=1}^{k} \omega_i \hat{y}_t^{(i)} = \sum_{i=1}^{k} \frac{\left[\sum_{t=1}^{T} \beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}}{\sum_{i=1}^{k}\left[\sum_{t=1}^{T} \beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}} \hat{y}_t^{(i)} \tag{8}$$

The discounting factor β varies between 0 and 1, so different β selection leads to different combination weights and different combination forecasting results. How to determine the suitable β value with least forecasting error becomes an important issue. In most investigations, choosing β relies only on discretionary selection. This manner would not necessarily guarantee the best forecasting performance (*i.e.*, minimal forecasting error) because it is almost impossible to select the optimal β value. On the other hand it is difficult to find the optimal $\beta_{k\times T}$ just by traditional mathematic methods since $\beta_{k\times T}$ is a matrix and there are $k \times T$ numbers to be obtained. It will be a high dimension problem when *k* and *T* are big. An artificial intelligence optimization method is a good technique to resolve this problem by taking the problem as an optimal question. In this proposed work, the novel intelligence optimization method—QHS algorithm is adopted to determine the optimal β values for each individual model and each forecasting period with steps as follows:

Step 1. Choose individual forecasting model and calculate separate forecasting result. Before the combination forecasting model is set up, the individual forecasting model should be first selected according to practical problem. Then individual model forecasting results are obtained.

Step 2. Establish DMSFE combination model. Based on the individual forecasting results, the DMSFE combination model can be built up according to Equation (1).

Step 3. Determine the values of discounting factor β by using QHS algorithm. Due to the blindness and arbitrary in picking β, no theoretical guidance is provided to determine the β value in order to get the best combination forecasting performance (*i.e.*, least forecasting error). So in this step, the QHS algorithm is adopted for determining optimal β values for every individual model and every forecasting period based on the least mean absolute percent error (MAPE).

Step 4. Calculate combination forecasting results. The forecasting results of the combination model could be achieved according to Equation (8) with different optimal β values obtained in Step 3.

3. Experimental Simulation and Analysis

3.1. CO_2 Emissions Data Sources

This section describes how to apply the QHS algorithm to searching for the optimal β values for the DMSFE method and then establish the QHS-based optimization DMSFE combination forecast model.

To examine the applicability and efficiency of the proposed method, the proposed method is applied to the top-5 CO_2 emitters.

British Petroleum (BP) provides high-quality, objective and globally consistent data on World energy markets, covering data on petroleum, coal, natural gas, nuclear and power. The data of CO_2 emissions from fossil fuel consumption were adopted from the *BP Statistical Review of World Energy* (Excel data, 2011) [30]. BP presents in detail main 68 countries for the period from 1965 until 2010. In 2010, China, the United States, the Russian Federation, India and Japan, the largest five emitters, produced together 57.8% of the World's CO_2 emissions, with the shares of China and the United States far surpassing those of all others. Combined, these two countries alone produced 14.48 Gt CO_2, about 43.6% of World CO_2 emissions. China has experienced an approximate 10 percent average annual GDP growth over the last two decades and caused a large amount of resource and energy consumption and associated emissions creating serious environmental problems [31]. China, now the World's largest emitter of CO_2 emissions from fuel combustion, generated 8.33 Gt CO_2, which accounts 25.1% of the World total. Due to the energy-intensive industrial production, large coal reserves exist and with intensified use of coal, the CO_2 emissions would increase substantially for a certain period. The United States alone generated 18.5% of World CO_2 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. The Russian Federation and India are the two BRICS countries representing over one-fourth of World GDP, 30% of global energy use and 33% of CO_2 emissions from fuel combustion. With their ongoing strong economic performance, the share of global emissions for the Russian Federation and India are likely to rise further in coming years. India now emits over 5% of global CO_2 emissions, and emissions will continue to grow. The World Energy Outlook projects that CO_2 emissions in India will more than double between 2007 and 2030. Japan, one of the world's leading industrial economies, is the fifth emitter, with 1.31 Gt CO_2 in 2010, contributing a significant share of global CO_2 emissions (3.9%).

In this study, the annual CO_2 emissions data of the top-5 countries for the period from 2000 to 2010 were collected. Table 1 shows the data for CO_2 emissions from fossil fuel consumption from 2000 to 2010 and Table 2 shows the share of the World total amount for these countries in 2010.

Table 1. CO_2 emissions data from 2000 to 2010 for top-5 countries (Mtonnes).

Country	2000	2001	2002	2003	2004	2005
China	3659.3483	3736.9794	3969.8231	4613.9200	5357.1651	5931.9713
USA	6377.0493	6248.3608	6296.2248	6343.4769	6472.4463	6493.7341
Russia	1562.9791	1574.4929	1583.9895	1624.7682	1628.0350	1618.0046
India	952.7665	959.1636	1001.2000	1030.4714	1118.3646	1172.8631
Japan	1327.1324	1324.4486	1322.9523	1376.2507	1380.7913	1397.7016
Country	**2006**	**2007**	**2008**	**2009**	**2010**	
China	6519.5965	6979.4653	7184.8542	7546.6829	8332.5158	
USA	6411.9503	6523.7987	6332.6004	5904.0382	6144.8510	
Russia	1663.3323	1678.7276	1711.0866	1602.5212	1700.1992	
India	1222.4088	1327.0771	1442.1529	1563.9172	1707.4594	
Japan	1379.2997	1392.1297	1389.3573	1225.4810	1308.3958	

Table 2. Share of the World total in 2010.

Rank	Country	CO_2 emission	Total (%)
1	China	8332.5	25.1%
2	US	6144.9	18.5%
3	Russian Federation	1700.2	5.1%
4	India	1707.5	5.1%
5	Japan	1308.4	3.9%

3.2. Experimental Simulation

(1) The combination forecasting procedures

Since the CO_2 emission curves of different industries have different characteristics and the future trend is full of uncertainties, it is more risky to select a certain forecasting model. To establish a combination model for CO_2 emissions becomes a better solution.

Firstly, choose individual forecasting model and calculate individual forecasting results. Linear regression model [7], time series model [32], Grey (1,1) forecasting model [33] and Grey Verhulst model [34] are selected to generate the individual forecasting results. The reason why we choose these models is that they have been widely and successfully used in forecasting CO_2 emissions. Considering the time series method may lead to the loss of data, more original data were chosen in order for the consistent comparison period. The participating model forecasting results are shown in Appendix from Tables A1–A5.

Secondly, establish DMSFE combination forecasting model. According to Equation (3), the DMSFE combination forecasting model could be established based on the individual forecasting model.

Thirdly, determine the optimal β_{it} values for every separate forecasting model and period by using QHS algorithm. The β matrix is 4 × 11 in this simulation since four individual models and 11 periods are adopted. In other words, there are 44 parameters to be optimized. It is a relatively high dimension problem. Finally, achieve the combination forecasting results according to Equation (8).

(2) The β optimization process based on the QHS algorithm

The optimization objective function $f(x)$ of QHS algorithm is specified as the Mean Absolute Percentage Error (MAPE) in this proposed investigation. The MAPE is the 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 [10], shown in Equation (9):

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{9}$$

Minimize:

$$f(x) = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right| = \frac{1}{T}\sum_{t=1}^{T}\left\{\left|y_t - \sum_{i=1}^{k}\frac{\left[\sum_{t=1}^{T}\beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}\hat{y}_t^{(i)}}{\sum_{i=1}^{k}\left[\sum_{t=1}^{T}\beta_{it}^{\,T-t+1}\left(y_t - \hat{y}_t^{(i)}\right)^2\right]^{-1}}\right| \Big/ |y_t|\right\} \tag{10}$$

$$s.t.\quad 0 \le \beta_{it} \le 1$$

The QHS optimization DMSFE approach has been employed to determine optimal β_{it} values for the top-5 CO_2 emitting countries. The QHS algorithm parameters are selected by uniform design [35] as follows: HMS = 35, HMCR = 0.99, PAR = 0.6, lb = 0, ub = 1, where lb is the lower bound for decision variable β_{it}, ub is the upper bound for decision variable β_{it}.

All the programs were run on a 2.27 GHz Intel Core Duo CPU with 1 GB of random access memory. In each case study, 30 independent runs were made for the QHS optimization procedure in MATLAB 7.6.0 (R2008a) on Windows 7 with 32-bit operating systems. Then, the best key was assigned as the optimal β_{it} values for the corresponding individual model and period shown as follows:

$$\beta_1 = \begin{bmatrix} 3.0537\times10^{-1} & 7.2000\times10^{-1} & 9.4362\times10^{-1} & 2.9229\times10^{-1} \\ 8.3754\times10^{-1} & 3.8874\times10^{-1} & 9.9363\times10^{-1} & 5.7866\times10^{-1} \\ 5.0000\times10^{-1} & 6.4622\times10^{-1} & 9.9977\times10^{-1} & 4.9153\times10^{-1} \\ 7.5580\times10^{-1} & 6.0927\times10^{-1} & 7.9302\times10^{-1} & 5.6514\times10^{-1} \\ 8.5425\times10^{-1} & 6.0933\times10^{-1} & 9.9864\times10^{-1} & 6.6901\times10^{-1} \\ 1.6120\times10^{-1} & 5.8412\times10^{-1} & 9.9995\times10^{-1} & 5.0000\times10^{-1} \\ 2.4265\times10^{-1} & 8.7951\times10^{-1} & 9.9999\times10^{-1} & 5.0000\times10^{-1} \\ 9.9417\times10^{-1} & 5.0000\times10^{-1} & 9.4228\times10^{-1} & 6.5848\times10^{-1} \\ 7.7294\times10^{-1} & 1.5657\times10^{-3} & 1.0506\times10^{-1} & 6.9660\times10^{-1} \\ 1.2785\times10^{-1} & 2.1846\times10^{-1} & 9.5525\times10^{-1} & 6.4635\times10^{-1} \\ 6.4795\times10^{-1} & 4.8761\times10^{-1} & 9.5044\times10^{-1} & 5.0000\times10^{-1} \end{bmatrix}^T$$

$$\beta_2 = \begin{bmatrix} 9.9988\times10^{-1} & 8.3856\times10^{-1} & 9.8044\times10^{-1} & 6.3427\times10^{-1} \\ 1.0000 & 9.9652\times10^{-1} & 5.8076\times10^{-1} & 7.7253\times10^{-1} \\ 9.8022\times10^{-1} & 9.9697\times10^{-1} & 9.0721\times10^{-1} & 7.4681\times10^{-1} \\ 9.1888\times10^{-1} & 7.8330\times10^{-1} & 8.3612\times10^{-1} & 8.6807\times10^{-1} \\ 9.9997\times10^{-1} & 9.9932\times10^{-1} & 3.0525\times10^{-1} & 1.9819\times10^{-1} \\ 9.9924\times10^{-1} & 9.9957\times10^{-1} & 8.5354\times10^{-1} & 1.9655\times10^{-1} \\ 9.9930\times10^{-1} & 1.0000 & 3.5637\times10^{-1} & 7.3147\times10^{-1} \\ 9.8933\times10^{-1} & 1.0000 & 2.1782\times10^{-1} & 3.3123\times10^{-1} \\ 9.9778\times10^{-1} & 1.0000 & 9.8847\times10^{-1} & 7.2151\times10^{-1} \\ 1.0000 & 9.9967\times10^{-1} & 2.5472\times10^{-1} & 6.8253\times10^{-1} \\ 5.3405\times10^{-1} & 1.0000 & 9.9984\times10^{-1} & 5.3690\times10^{-1} \end{bmatrix}^T$$

$$\beta_3 = \begin{bmatrix} 9.9900\times10^{-1} & 1.0000 & 9.9901\times10^{-1} & 7.7889\times10^{-1} \\ 1.2562\times10^{-1} & 5.0620\times10^{-1} & 7.3263\times10^{-1} & 9.7903\times10^{-1} \\ 3.3333\times10^{-1} & 9.9053\times10^{-1} & 9.9918\times10^{-1} & 6.2317\times10^{-1} \\ 9.9193\times10^{-1} & 8.7692\times10^{-1} & 9.3247\times10^{-1} & 5.3028\times10^{-1} \\ 9.9877\times10^{-1} & 9.3810\times10^{-1} & 9.8234\times10^{-1} & 2.4884\times10^{-1} \\ 1.0000 & 8.1265\times10^{-1} & 9.3706\times10^{-1} & 6.9827\times10^{-1} \\ 2.6092\times10^{-1} & 9.8815\times10^{-1} & 4.9718\times10^{-1} & 3.2615\times10^{-1} \\ 9.9000\times10^{-1} & 9.9444\times10^{-1} & 9.9838\times10^{-1} & 4.7104\times10^{-1} \\ 8.0638\times10^{-1} & 1.0000 & 9.9999\times10^{-1} & 5.5961\times10^{-2} \\ 9.9863\times10^{-1} & 1.9856\times10^{-1} & 1.0000 & 2.9490\times10^{-2} \\ 4.5254\times10^{-1} & 9.1639\times10^{-1} & 9.9479\times10^{-1} & 9.6163\times10^{-1} \end{bmatrix}^T$$

$$\beta_4 = \begin{bmatrix} 1.0000 & 6.1020\times10^{-1} & 8.2721\times10^{-1} & 4.4806\times10^{-1} \\ 4.3893\times10^{-1} & 8.1632\times10^{-1} & 7.8088\times10^{-1} & 5.6974\times10^{-1} \\ 8.1888\times10^{-1} & 2.7395\times10^{-1} & 7.4244\times10^{-1} & 6.1378\times10^{-1} \\ 9.9521\times10^{-1} & 9.9430\times10^{-1} & 9.1750\times10^{-1} & 6.9563\times10^{-1} \\ 1.0000 & 5.0596\times10^{-2} & 1.0000 & 2.6973\times10^{-1} \\ 9.8277\times10^{-1} & 9.1807\times10^{-1} & 7.6791\times10^{-1} & 7.8573\times10^{-1} \\ 1.0000 & 5.0589\times10^{-1} & 9.5817\times10^{-1} & 3.6899\times10^{-1} \\ 9.9871\times10^{-1} & 6.5940\times10^{-1} & 5.9211\times10^{-1} & 8.2182\times10^{-1} \\ 9.3071\times10^{-1} & 5.5626\times10^{-1} & 1.4716\times10^{-1} & 6.1601\times10^{-1} \\ 9.8508\times10^{-1} & 3.8165\times10^{-1} & 4.5431\times10^{-1} & 1.3320\times10^{-1} \\ 9.9991\times10^{-1} & 2.2622\times10^{-1} & 8.7349\times10^{-1} & 8.3105\times10^{-1} \end{bmatrix}^T$$

$$\beta_5 = \begin{bmatrix} 9.9998\times10^{-1} & 2.2472\times10^{-1} & 9.7696\times10^{-1} & 9.9998\times10^{-1} \\ 1.0000 & 9.4249\times10^{-1} & 6.8640\times10^{-1} & 6.2069\times10^{-1} \\ 9.2596\times10^{-1} & 8.2604\times10^{-1} & 2.4110\times10^{-1} & 8.4266\times10^{-1} \\ 8.0391\times10^{-1} & 9.9758\times10^{-1} & 8.5322\times10^{-1} & 9.0891\times10^{-1} \\ 6.6755\times10^{-1} & 8.3244\times10^{-1} & 3.9699\times10^{-1} & 4.2721\times10^{-1} \\ 8.8024\times10^{-1} & 1.0666\times10^{-1} & 3.1147\times10^{-1} & 9.9761\times10^{-1} \\ 9.3537\times10^{-1} & 9.9998\times10^{-1} & 5.0190\times10^{-1} & 9.9998\times10^{-1} \\ 7.2457\times10^{-1} & 9.9982\times10^{-1} & 2.6831\times10^{-1} & 9.9999\times10^{-1} \\ 1.0000 & 1.0000 & 2.8461\times10^{-1} & 8.0354\times10^{-1} \\ 9.9997\times10^{-1} & 7.2360\times10^{-1} & 1.5597\times10^{-2} & 7.4259\times10^{-1} \\ 9.4032\times10^{-1} & 8.4071\times10^{-1} & 4.9635\times10^{-1} & 5.1870\times10^{-1} \end{bmatrix}^T$$

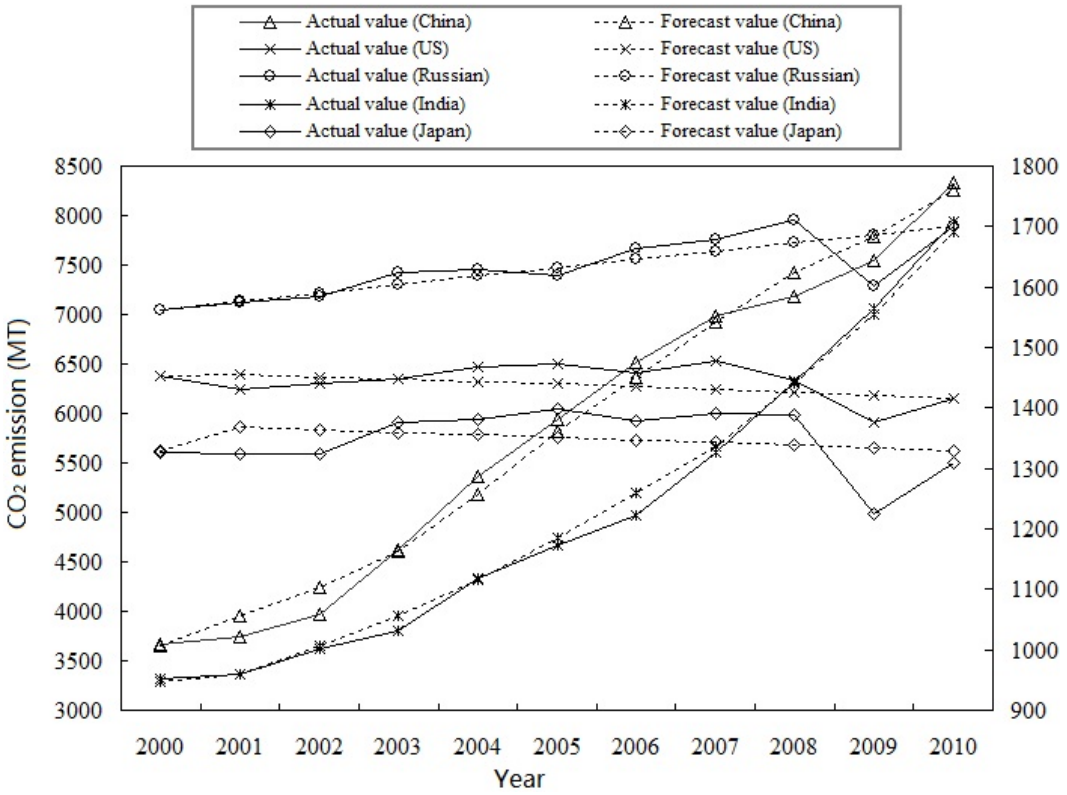
where β_1 is the optimal β matrix for China, β_2 for US, β_3 for Russia, β_4 for India and β_5 for Japan. It could be found that the optimal β_{it} values vary quite a lot from each other even for the same county. The data differ from each other heavily in the case of China. The situations of Russia and Japan are similar to it of China. In the first column of matrix, all data, with uniform magnitude, are very close or equal to 1.0000 except one in the case of USA. The situation of India is similar to that of the USA. From the final optimal β values, we can draw two conclusions: (1) the best β values may be different for different counties; (2) the best β values may be different for different individual models and forecasting periods, even in the same country, since β ranges from 0 to 1, therefore, the arbitrary selection of β may not result in the best combination forecast effect, *i.e.*, not the minimal MAPE. Taking the same β for all individual models and forecasting period may bring the same drawback as the one above. It is vital to select suitable β values for the combination model. Through an optimization process, the best β values could be found with the minimal MAPE for combination forecast based on QHS algorithm. With these optimal β values the forecasting results and evaluating indexes could be obtained and presented in next sections.

(3) The forecasting results

Figure 2 shows the curves of actual data and forecasting results achieved by the presented approach for the top-5 emitters from 2000 to 2010 respectively. Dual coordinates are employed in Figure 2: the curves of actual data and forecasting results for China and US correspond to the left y-axis coordinate; the curves of actual data and forecasting results for the other three countries correspond to the right y-axis coordinate. These five counties could be divided into two kinds according to the growth

direction: (1) ascending cases such as China, India and Russia; (2) fluctuating cases such as the US and Japan. From Figure 2 we find that the forecasting results of China, Russia, India and US are relatively close to the original values at every point. For Japan, the proposed approach behaves well at some points and relatively poor at others. But, analyzing the MAPE in next section, the forecasting errors are acceptable, even in those poor situations. There is a sudden drop in the actual values of Russia, US and Japan between 2008 and 2010 because an abrupt economy crisis broke out around the World and resulted in lowered CO_2 emissions in these countries. The forecasting results are relatively inaccurate in those years because of the abruptness. It is natural since there is no one method works well for all situations. Every method has its own application circumstance. The presented method forecasting results are satisfied for different growth pattern that means the flexibility of the QHS algorithm based DMFSE combination model is excellent.

Figure 2. Actual and forecast values for the World top-5 emitters.



3.3. Case Comparison

In order to testify the validity of the QHS algorithm-based DMFSE combination forecasting method, five cases were considered in this section: Case 1, $\beta = 0.1$; Case 2, $\beta = 0.5$; Case 3, $\beta = 1$; Case 4, β^* (adopting the same optimal β value for all individual models and all forecasting periods obtained by QHS algorithm shown in Table 3; the parameters of QHS algorithm achieved by uniform design); Case 5, $D\beta^*$ (adopting the different optimal β values for different individual model and period obtained by QHS algorithm). We selected three cases near the beginning, middle and end of β span as examples since β varies from 0 to 1. Tables 4–8 show the combination forecasting results of different cases for China, US, Russian Federation, India and Japan respectively. From these tables we could find

that the forecasting results obtained by the presented approach are the best in most situations for all the five counties.

Furthermore, the fitting effect is evaluated through some common evaluating indicators *i.e.*, MAPE, RMSE and MAE shown in Equations (9), (11) and (12). The evaluating results are exhibited in Tables 9–11:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{11}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - \hat{y}_t\right| \tag{12}$$

Table 3. The optimal β values in case 4 for top-5 countries.

	China	United States	Russian Federation	India	Japan
β*	1.0000	2.2195×10^{-5}	2.9628×10^{-5}	2.7599×10^{-5}	1.0000

Table 4. Forecasting values with different cases for China (Mtonnes).

Year	t	Original data	β = 0.1	β = 0.5	β = 1	β*	Dβ*
2000	1	3659.3483	3530.3572	3558.3733	3606.6073	3606.6073	3658.8771
2001	2	3736.9794	3932.1966	3942.4741	3959.6479	3959.6479	3959.8116
2002	3	3969.8231	4332.1111	4320.5721	4302.4815	4302.4815	4243.2317
2003	4	4613.9200	4761.4967	4734.9856	4693.8221	4693.8221	4599.3799
2004	5	5357.1651	5267.1257	5247.2098	5222.9176	5222.9176	5186.9109
2005	6	5931.9713	5795.6774	5787.7327	5788.9735	5788.9735	5825.7973
2006	7	6519.5965	6303.2887	6299.5006	6309.3182	6309.3182	6368.3617
2007	8	6979.4653	6823.7005	6827.1577	6848.8813	6848.8813	6930.0485
2008	9	7184.8542	7807.4174	7339.7023	7808.0081	7362.8626	7430.7278
2009	10	7546.6829	8316.2067	7807.1845	8316.1072	7808.0081	7793.0080
2010	11	8332.5158	8348.3939	8320.2893	8348. 5952	8316.1072	8251.4506

Table 5. Forecasting values with different cases for the United States (Mtonnes).

Year	t	Original data	β = 0.1	β = 0.5	β = 1	β*	Dβ*
2000	1	6377.0493	6381.0250	6373.7812	6380.1481	6386.2180	6377.5702
2001	2	6248.3608	6375.7827	6368.4882	6378.6697	6385.2835	6388.6531
2002	3	6296.2248	6353.7094	6345.6626	6356.3869	6363.6782	6366.5027
2003	4	6343.4769	6330.7889	6322.1567	6333.6167	6341.3799	6343.6542
2004	5	6472.4463	6306.9531	6297.9141	6310.3176	6318.3324	6320.0496
2005	6	6493.7341	6282.1296	6272.8750	6286.4460	6294.4762	6295.6276
2006	7	6411.9503	6256.2428	6246.9770	6261.9561	6269.7488	6270.3240
2007	8	6523.7987	6229.2130	6220.1543	6236.7998	6244.0848	6244.0715
2008	9	6332.6004	6200.9574	6192.3385	6210.9268	6217.4158	6216.7998
2009	10	5904.0382	6171.3898	6163.4585	6184.2853	6189.6709	6188.4359
2010	11	6144.8510	6140.4217	6133.4411	6156.8215	6160.7771	6158.9047

Table 6. Forecasting values with different cases for the Russian Federation (Mtonnes).

Year	t	Original data	β = 0.1	β = 0.5	β = 1	β*	Dβ*
2000	1	1562.9791	1567.4618	1570.7326	1570.5784	1563.0058	1563.1559
2001	2	1574.4929	1583. 8675	1586.3849	1586.1943	1576.6864	1576.8574
2002	3	1583.9895	1595.8494	1597.7964	1597.6500	1590.3556	1590.4870
2003	4	1624.7682	1607.7865	1609.0065	1608.9094	1604.0405	1604.1273
2004	5	1628.0350	1619.6925	1620.0589	1620.0154	1617.7395	1617.7777
2005	6	1618.0046	1631.5788	1630.9891	1631.0024	1631.4507	1631.4374
2006	7	1663.3323	1643.4545	1641.8253	1641.8980	1645.1725	1645.1050
2007	8	1678.7276	1655.3266	1652.5904	1652.7245	1658.9030	1658.7795
2008	9	1711.0866	1667.2010	1663.3029	1663.4998	1672.6407	1672.4596
2009	10	1602.5212	1679.0820	1673.9774	1674.2383	1686.3835	1686.1438
2010	11	1700.1992	1690.9734	1684.6257	1684. 9515	1700.1300	1699.8306

Table 7. Forecasting values with different cases for India (Mtonnes).

Year	t	Original data	β = 0.1	β = 0.5	β = 1	β*	Dβ*
2000	1	952.7665	942.7369	942.0609	940.7183	942.7948	946.7714
2001	2	959.1636	946.7968	944.4024	945.9440	947.4891	959.1655
2002	3	1001.2000	999.7583	998.5021	998.9527	1000.1231	1005.5160
2003	4	1030.4714	1056.8241	1056.7104	1055.8411	1056.8488	1055.8330
2004	5	1118.3646	1120.3921	1121.0592	1119.4426	1120.1885	1114.9742
2005	6	1172.8631	1191.5319	1192.5314	1190.8567	1191.2380	1184.5290
2006	7	1222.4088	1269.0237	1270.2957	1268.2112	1268.6389	1260.5112
2007	8	1327.0771	1351.2171	1353.3176	1348.9823	1350.5562	1337.5920
2008	9	1442.1529	1449.8665	1451.0315	1447.4499	1449.4336	1441.1711
2009	10	1563.9172	1558.7055	1559.0465	1554.8412	1558.4475	1553.8716
2010	11	1707.4594	1685.9968	1684.4426	1680.3683	1686.2154	1690.9122

Table 8. Forecasting values with different cases for Japan (Mtonnes).

Year	t	Original data	β = 0.1	β = 0.5	β = 1	β*	Dβ*
2000	1	1327.1324	1335.7870	1337.9497	1340.2127	1340.2127	1328.2275
2001	2	1324.4486	1345.3518	1348.5590	1352.5496	1352.5496	1368.1131
2002	3	1322.9523	1342.5741	1346.1892	1350.6658	1350.6658	1363.8899
2003	4	1376.2507	1339.5890	1343.5568	1348.4494	1348.4494	1359.6458
2004	5	1380.7913	1336.4605	1340.7632	1346.0493	1346.0493	1355.3961
2005	6	1397.7016	1333.2195	1337.8593	1343.5409	1343.5409	1351.1491
2006	7	1379.2997	1329.8798	1334. 8695	1340.9617	1340.9617	1346.9085
2007	8	1392.1297	1326.4468	1331.8050	1338.3305	1338.3305	1342.6762
2008	9	1389.3573	1322.9214	1328.6703	1335.6560	1335.6560	1338.4531
2009	10	1225.4810	1319.3021	1325.4661	1332.9418	1332.9418	1334.2398
2010	11	1308.3958	1315.5861	1322.1915	1330.1890	1330.1891	1330.0362

Table 9. MAPE values with different case for top-5 countries (%).

Country	β = 0.1	β = 0.5	β = 1	β*	Dβ*
China	3.3011	3.2285	3.0601	3.0601	2.6211
United States	2.0594	2.1104	2.0494	2.0282	2.0135
Russian Federation	1.3183	1.4003	1.3959	1.1854	1.1894
India	1.3249	1.4144	1.3537	1.3010	0.9462
Japan	3.2263	3.1894	3.1415	3.1415	2.9949

Table 10. MAE values with different case for top-5 countries (Mtonnes).

Country	β = 0.1	β = 0.5	β = 1	β*	Dβ*
China	1.6886×10^2	1.6659×10^2	1.6017×10^2	1.6017×10^2	1.4196×10^2
United States	1.3022×10^2	1.3357×10^2	1.2943×10^2	1.2797×10^2	1.2703×10^2
Russian Federation	2.1597×10	2.2967×10	2.2893×10	1.9402×10	1.9469×10
India	1.6003×10	1.7051×10	1.6466×10	1.5728×10	1.1539×10
Japan	4.3382×10	4.2723×10	4.1881×10	4.1881×10	3.9763×10

Table 9 shows the MAPE values of different β values for these five countries. The MAE values for all situations for all the five countries are shown in Table 10. The MAPE and MAE values of Dβ* are the least in five situations for China, USA, India and Japan. The MAPE and MAE values of Dβ* are better than those of βs obtained arbitrarily, but worse a little than β* for Russia. Actually, they are very close to those of β* for Russia. Comparing the MAPE and MAE results of β* and Dβ* with those of the other three βs shown in Tables 9 and 10 it could be found: (1) the MAPE and MAE values of the first three βs are close to each other; (2) the MAPE and MAE values of β* increase to a certain extent for USA and India; (3) the MAPE and MAE values of β* are the same as those of β = 1 and better than those of β = 0.1 and β = 0.5 for China and Japan; (4) the MAPE and MAE values of β* are the best among the five cases for Russia; (5) the MAPE and MAE values of Dβ* are improved relatively remarkably for all five countries, especially in the case of India compared with those of βs obtained arbitrarily; (6) the MAPE and MAE values of Dβ* are the best among all five cases for all countries except Russia; (7) the MAPE and MAE values of Dβ* are better than those of βs obtained arbitrarily and close to those of β* for Russia. The results of β* for China and Japan are the same as those of β = 1 because the optimal β values found are 1. The results of β* show that adopting an optimization method to choose an optimal β value is better than the method of assigning β values arbitrarily. The results of Dβ* indicate that considering different individual models and periods is better than applying one β value to all separate models and periods. The empirical results suggest that QHS algorithm-based combination forecasting method enhances the MAPE and MAE to a certain degree for every country, especially for India. Namely, the proposed method outperforms all the other methods concerned. For India, the MAPE increases from over 1.3249% to 0.9462% and the MAE increases from over 16.003 Mtonnes to 11.539 Mtonnes. It means over 28% performance enhancement compared with the original method. It enhances over 14% in the case of China. For Russian it improves by over 10%. It increases relatively indistinctively only in the case of Japan and US, near 5% and 2%, respectively.

The RMSE values of all situations for five countries are shown in Table 11. The results of Dβ* are the best among all five situations for all countries, except Russia. The RMSE results for Russia presents an opposite situation compared with the status when considering the MAPE values *viz*. the results of β* and Dβ* are worse than those of β = 0.1, β = 0.5 and β = 1. The RMSE value of Dβ* is better than that of β* for Russia. The RMSE value for India of Dβ* is improved over 22.3% compared with the original method. It increases over 6.7% for China, 1.5% for USA and 1.7% for Japan. The RMSE values of β* for USA and India are enhanced too compared with those of β = 0.1, β = 0.5 and β = 1. China and Japan share the same RMSE value of β = 1 and β* for the reason mentioned last paragraph. And the values of β* are better than those of β = 0.1, β = 0.5. All these again show that adopting the optimization method to choose an optimal β value is better than the method of assigning β value arbitrarily. The method taking different individual models and periods into consideration is the best among all the methods. The conclusion is the same as the one drawn when discussing the MAPE index.

Table 11. RMSE values with different case for top-5 countries (Mtonnes).

Country	β = 0.1	β = 0.5	β = 1	β*	Dβ*
China	1.8966×10^2	1.8748×10^2	1.8325×10^2	1.8325×10^2	1.7000×10^2
United States	1.6285×10^2	1.6600×10^2	1.6190×10^2	1.5966×10^2	1.5951×10^2
Russian Federation	2.9552×10	2.9619×10	2.9606×10	3.0144×10	3.0113×10
India	2.0462×10	2.1386×10	2.0705×10	2.0218×10	1.5907×10
Japan	5.0801×10	4.9519×10	4.8536×10	4.8536×10	4.7725×10

According to the discussions above, the presented method shows the best MAPE, RMSE and MAE performance among the five situations for all countries, except Russia. For Russia the proposed method shows a better RMSE performance than the method of applying the same optimal β value for all individual models and forecasting periods. A better MAPE and MAE performance are obtained by the presented method compared with those of the original method. All in all the presented approach could provide a relatively better forecasting performance in comparison with the methods of choosing β values arbitrarily and assigning the same optimal β value to all individual models synthesizing the MAPE, RMSE and MAE indexes discussed above. The analysis based on MAPE, RMSE and MAE indicates that the proposed method has a good robustness to the choice of index for forecasting accuracy.

3.4. Analysis of Future Projections

In order to evaluate the out-of-sample forecasting performance of the proposed approach, the forecasting values calculated with the optimal β values obtained in Section 3.2 and the relative errors between the forecasting values and the actual values of the year 2011 are shown in Table 12. The forecasting performance is relatively nice for all the five countries, especially for China.

The forecasting values of the year 2012–2015 are shown in Table 13. We could find that the trend of the CO_2 emissions for China and India is increasing and it is fluctuating for USA, Russia and Japan based on the analysis of the forecasting values. These trends are consistent with the expectations. The situation is very critical since CO_2 has so many detrimental impacts on our living environment. The technical improvements and energy policies of the government should be made to reduce the emissions.

Table 12. Forecasting values and relative errors of 2011 for top-5 countries.

	China	USA	Russia	India	Japan
Original data (Mtonnes)	8979.1411	6016.6127	1675.0355	1797.9879	1307.4005
Forecasting data (Mtonnes)	8947.8374	6134.1258	1712.9565	1855.5183	1324.2965
Relative error (%)	0.3486	1.9531	2.2639	3.1997	1.2923

Table 13. Forecasting values of 2012–2015 for top-5 countries (Mtonnes).

Country	2012	2013	2014	2015
China	9268.5600	9821.0476	10391.8123	10981.5386
USA	6102.2810	6068.9120	6034.0906	5997.7174
Russia	1727.0771	1740.7605	1754.4431	1768.1233
India	2039.1502	2291.2737	2641.2330	3182.6860
Japan	1321.4904	1317.3657	1313.2513	1309.1472

4. Conclusions

As Hibon pointed out, no one forecasting model can outperform others in all circumstances [18]. Choosing a combination method could lead to less risk than choosing one single method. The DMSFE combination method was applied in this work to forecast CO_2 emissions. The individual forecasting method was first selected to establish the combination model. Then, the QHS algorithm was introduced to search for the optimal discounting factor β values for each individual model and forecasting period. Finally, the combination forecasting results were obtained. In the DMSFE combination forecasting method, how to select the β value is a key problem since it varies between 0 and 1 and influences the forecasting results directly. However, it is hard to choose the appropriate β values for decision-makers only by arbitrary attempts, and this manner often leads an unsatisfactory forecasting performance. Assigning the same β value for all separate models and forecasting period in all application cases is somewhat unreasonable since it affects the proportion of each individual model forecasting results in the combination model forecasting results. Applying different β values to different individual models and forecasting periods sounds more suitable. Thus, β was changed from one value to a matrix to express the influences of the individual models and forecasting periods. It is difficult to seek the optimal matrix by traditional mathematical methods since there are so many parameters to be optimized. The optimization algorithm provides a valid way to solve these problems through optimizing objective function (MAPE in this work) to find the optimal β values. A novel and effective intelligence optimization method called QHS algorithm was applied in this investigation to find the optimal β values for every individual forecasting model and forecasting period in the combination model. The empirical analysis applied to the World's top-5 emitters shows that the QHS- based optimization DMSFE combination method performs much better than the original method with an arbitrarily chosen parameter β value. The contributions of this work are as follows: (1) The optimal discounting factor β can be determined by using an optimization technique; (2) Applying different β values to different individual models and forecasting periods is more reasonable than the manner where the same value is applied to all separate models; (3) The QHS-based combination forecasting model can increase forecasting accuracy in a certain degree.

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Appendix

Table A1. Actual and forecasted value of China's CO_2 emissions (Mtonnes).

Year	t	Original data	Linear	Time series	GM(1,1)	Grey Verhulst
2000	1	3659.3483	3341.8808	3805.3326	3659.3483	3659.3483
2001	2	3736.9794	3834.0923	3986.7985	4030.3437	4041.8571
2002	3	3969.8231	4326.3038	4127.3788	4380.2836	4450.4295
2003	4	4613.9200	4818.5153	4392.4903	4760.6075	4884.0364
2004	5	5357.1651	5310.7268	5075.6312	5173.9535	5341.0744
2005	6	5931.9713	5802.9384	5844.9986	5623.1889	5819.3488
2006	7	6519.5965	6295.1499	6428.7331	6111.4297	6316.0849
2007	8	6979.4653	6787.3614	7041.1086	6642.0626	6827.9699
2008	9	7184.8542	7279.5729	7535.3537	7218.7685	7351.2249
2009	10	7546.6829	7771.7844	7769.8726	7845.5476	7881.7080
2010	11	8332.5158	8263.9959	8179.2798	8526.7477	8415.0396
2011	12	8979.1411	8756.2075	9015.3020	9267.0938	8946.7454
2012	13		9248.4190	9133.1506	10071.7214	9472.4053
2013	14		9740.6305	9704.6868	10946.2120	9987.7987
2014	15		10232.8420	10311.9889	11896.6313	10489.0362
2015	16		10725.0535	10957.2947	12929.5720	10972.6686

Table A2. Actual and forecasted value of the United States' CO_2 emissions (Mtonnes).

Year	t	Original data	Linear	Time series	GM(1,1)	Grey Verhulst
2000	1	6377.0493	6419.3668	6185.1970	6377.0493	6377.0493
2001	2	6248.3608	6400.0122	6143.7445	6415.6747	6356.7048
2002	3	6296.2248	6380.6575	6102.5698	6393.5792	6334.5820
2003	4	6343.4769	6361.3029	6061.6711	6371.5598	6310.5402
2004	5	6472.4463	6341.9483	6021.0465	6349.6163	6284.4300
2005	6	6493.7341	6322.5937	5980.6942	6327.7483	6256.0938
2006	7	6411.9503	6303.2391	5940.6123	6305.9556	6225.3658
2007	8	6523.7987	6283.8845	5900.7990	6284.2380	6192.0722
2008	9	6332.6004	6264.5299	5861.2525	6262.5952	6156.0317
2009	10	5904.0382	6245.1753	5821.9711	6241.0269	6117.0562
2010	11	6144.8510	6225.8206	5782.9529	6219.5329	6074.9517
2011	12	6016.6127	6206.4660	6053.4690	6198.1130	6029.5197
2012	13		6187.1114	6180.4805	6176.7668	5980.5582
2013	14		6167.7568	6146.2823	6155.4941	5927.8637
2014	15		6148.4022	6112.2734	6134.2947	5871.2337
2015	16		6129.0476	6078.4527	6113.1683	5810.4687

Table A3. Actual and forecasted value of the Russian Federation's CO_2 emissions (Mtonnes).

Year	t	Original data	Linear	Time series	GM(1,1)	Grey Verhulst
2000	1	1562.9791	1571.5251	1595.7145	1562.9791	1562.9791
2001	2	1574.4929	1583.5498	1604.7234	1587.7206	1576.6415
2002	3	1583.9895	1595.5745	1611.9879	1598.7991	1590.3213
2003	4	1624.7682	1607.5993	1617.8458	1609.9548	1604.0169
2004	5	1628.0350	1619.6240	1622.5694	1621.1884	1617.7264
2005	6	1618.0046	1631.6487	1626.3785	1632.5003	1631.4482
2006	7	1663.3323	1643.6735	1629.4500	1643.8912	1645.1804
2007	8	1678.7276	1655.6982	1631.9267	1655.3616	1658.9213
2008	9	1711.0866	1667.7230	1633.9240	1666.9120	1672.6692
2009	10	1602.5212	1679.7477	1635.5344	1678.5430	1686.4222
2010	11	1700.1992	1691.7724	1636.8331	1690.2551	1700.1786
2011	12	1675.0355	1703.7972	1664.2550	1702.0490	1713.9367
2012	13		1715.8219	1717.9585	1713.9252	1727.6946
2013	14		1727.8466	1731.5470	1725.8842	1741.4505
2014	15		1739.8714	1745.2431	1737.9267	1755.2028
2015	16		1751.8961	1759.0474	1750.0532	1768.9495

Table A4. Actual and forecasted value of India's CO_2 emissions (Mtonnes).

Year	t	Original data	Linear	Time series	GM(1,1)	Grey Verhulst
2000	1	952.7665	853.7771	941.3825	952.7665	952.7665
2001	2	959.1636	928.4370	974.8739	911.6569	989.5973
2002	3	1001.2000	1003.0970	998.0749	974.3971	1031.2846
2003	4	1030.4714	1077.7569	1020.9715	1041.4550	1078.8060
2004	5	1118.3646	1152.4168	1066.0052	1113.1279	1133.4199
2005	6	1172.8631	1227.0768	1137.1655	1189.7333	1196.7737
2006	7	1222.4088	1301.7367	1207.2558	1271.6107	1271.0674
2007	8	1327.0771	1376.3967	1239.9065	1359.1229	1359.3059
2008	9	1442.1529	1451.0566	1360.1818	1452.6576	1465.7047
2009	10	1563.9172	1525.7165	1459.7331	1552.6295	1596.3681
2010	11	1707.4594	1600.3765	1597.1158	1659.4813	1760.4798
2011	12	1797.9879	1675.0364	1748.0260	1773.6868	1972.5260
2012	13		1749.6964	1814.7520	1895.7518	2256.7673
2013	14		1824.3563	1951.5173	2026.2173	2657.1569
2014	15		1899.0162	2098.5896	2165.6615	3262.4076
2015	16		1973.6762	2256.7456	2314.7022	4282.4294

Table A5. Actual and forecasted value of Japan's CO_2 emissions (Mtonnes).

Year	t	Original data	Linear	Time series	GM(1,1)	Grey Verhulst
2000	1	1327.1324	1359.4524	1342.8458	1327.1324	1327.1324
2001	2	1324.4486	1357.0881	1347.3844	1369.6358	1323.8707
2002	3	1322.9523	1354.7238	1349.7048	1365.1630	1320.4393
2003	4	1376.2507	1352.3595	1350.8911	1360.7048	1316.8304
2004	5	1380.7913	1349.9952	1351.4976	1356.2611	1313.0358
2005	6	1397.7016	1347.6309	1351.8077	1351.8320	1309.0473
2006	7	1379.2997	1345.2667	1351.9662	1347.4173	1304.8563
2007	8	1392.1297	1342.9024	1352.0473	1343.0170	1300.4539
2008	9	1389.3573	1340.5381	1352.0887	1338.6311	1295.8312
2009	10	1225.4810	1338.1738	1352.1099	1334.2595	1290.9789
2010	11	1308.3958	1335.8095	1352.1207	1329.9022	1285.8877
2011	12	1307.4005	1333.4452	1294.8801	1325.5592	1280.5479
2012	13		1331.0809	1337.9647	1321.2303	1274.9498
2013	14		1328.7166	1338.8713	1316.9155	1269.0835
2014	15		1326.3523	1339.7786	1312.6149	1262.9392
2015	16		1323.9880	1340.6865	1308.3283	1256.5068