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Article

Forecasting Annual Power Generation Using a Harmony Search Algorithm-Based Joint Parameters Optimization Combination Model

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Abstract: Accurate power generation forecasting provides the basis of decision making for electric power industry development plans, energy conservation and environmental protection. Since the power generation time series are rarely purely linear or nonlinear, no single forecasting model can identify the true data trends exactly in all situations. To combine forecasts from different models can reduce the model selection risk and effectively improve accuracy. In this paper, we propose a novel technique called the Harmony Search (HS) algorithm-based joint parameters optimization combination model. In this model, the single forecasting model adopts power function form with unfixed exponential parameters. The exponential parameters of the single model and the combination weights are called joint parameters which are optimized by the HS algorithm by optimizing the objective function. Real power generation time series data sets of China, Japan, Russian Federation and India were used as samples to examine the forecasting accuracy of the presented model. The forecasting performance was compared with four single models and four combination models, respectively. The MAPE of our presented model is the lowest, which shows that the proposed model outperforms other comparative ones. Especially, the proposed combination model could better fit significant turning points of power generation time series. We can conclude that the proposed model can obviously improve forecasting

accuracy and it can treat nonlinear time series with fluctuations better than other single models or combination models.

Keywords: power generation; joint parameter optimization; Harmony Search algorithm; combination forecasting method

1. Introduction

The electric power industry is the basic industry for both national economy and social development. Electrification is an important index for assessing a country's level of modernization. The rapid development of the power industry means the rapid growth of installed capacity and generation capacity. Power generation forecasting plays an important role in national and international electric power planning, which also provides the basis of decision making for the government and the power industry development plan.

First, due to the increase in continuous sustainable positive economic growth rate and large scale industrialization, worldwide electricity consumption is quickly rising [1]. In order to meet growing electricity demand, more accurate power generation forecasting is needed for future power planning.

Second, the power generation sector, mainly based on fossil-fueled generation forms, is a typical high energy consumption section. The accelerating economic development leads to increasing energy demand for power generation which results in a series of adverse effects such as air pollution and greenhouse gas (GHG) emission [2]. A particularly large fraction of CO_2 emissions, the most important anthropogenic GHG, comes from combustion of fossil fuels at power plants [3]. The contribution of power generation systems to global energy-related CO_2 emissions increased from 32.67% (7.41 Gt CO_2) in 1997 to 41% (11.9 Gt CO_2) in 2007 [4]. The effect of power generation on climate change has become a key current issue for researchers and policymakers, so for the national energy conservation and environmental protection, accurate power generation is also required.

Third, to respond to global climate change and GHG emissions, measures to realize low carbon electric power sector have been taken, including fuel switching, improving energy efficiency, renewable energy development and deployment and demand side management (DSM) programs, *etc.* [5]. On the power generation side, many countries have enacted decrees to raise the renewable energy generation share in their power generation systems. The characteristics of renewable energy sources, such as unstability and intermittence cause many difficulties for power generation forecasting. It is meaningful and challenging to obtain more accurate power generation predictions under the circumstance of mixed existence of traditional generation forms and various renewable energy generation forms.

In the last few decades, abundant literature [6–8] has focused on power generation forecasting using different classical methods so as to avoid electricity shortages and guarantee adequate infrastructures. The major shortcoming of traditional methods such as regression and time series is their limited accuracy, partially resulting from the use of linear model structures or the predominant use of static nonlinear function relationships. Due to the development of artificial intelligence techniques, artificial neural network (ANN) forecasting models and ANNs combining wavelet, optimization and fuzzy techniques are developed for power generation forecasting [9–14]. The ANN technique, which is

inspired on the biological neural system, represents higher nonlinearity between independent and dependent variables [15]. The ANN models can treat nonlinear issues with capability to learn, store and recall information based on a given training dataset [16]. However, the accuracy of ANN models is limited because the forecasting accuracy depends on the scale of the training data sets and the inadequacy of these data sets will reflect over the entire problem. Moreover, the hidden layers in ANNs are difficult to explain and they easily achieve local optimal solutions due to the random selection of initial weights [17].

No single forecasting method has been found to outperform other models in all situations since each single model with its own particular advantages and disadvantages cannot identify the true process exactly [18]. The purpose of combining forecasts from different models is that this can synthesize the information of each individual forecast into a composite one, which is often regarded as a successful alternative to just using an individual method [19]. The combination technique was pioneered by Bates and Granger [20], and applications of combination forecasting can be found in many fields. It is less risky in practice to combine forecasts than to select an individual forecasting method. Moreover, it is proved that the combination forecasting model outperforms the poorest individual forecast, and sometimes even performs better than the best individual model [21].

In electric power systems, power generation time series are rarely pure linear or nonlinear, as they often contain both linear and nonlinear patterns, so no single model is best to treat these uncertain data sequences. That is the main purpose to propose a power generation combination forecasting model. In the existing combination forecasting field, much of the literature has focused on how to determine the combination forecasting weights. The common combination weights determination methods include simple average combination, variance covariance combination, Granger and Ramanthan regression method, and the Discounted Mean Square Forecast Error (DMSFE) combination. No researcher has yet paid attention to the form of a single model in combination forecasting methods, *i.e.*, the single forecast model often adopts a fixed form. In other words, the combination forecasting weights and the form of the single forecasting model are not combined to adjust and adapt to different forecasting issues. In this paper, we proposed a novel Harmony Search (HS) algorithm-based joint parameters optimization combination model. The motivation of the combination model comes from the following aspects: first, the single forecasting model adopts a power function form instead of the traditional fixed form, and the exponential parameter in power functions can be adjusted under certain criteria. Second, the exponential parameter and the combination weights, called joint parameters, are adjusted simultaneously. Through adjusting these joint parameters, the combination forecasting model can reach the best results. Third, the optimal values of joint parameters are determined by using the HS algorithm.

The Harmony Search (HS) algorithm, as a recently emerging metaheuristic technique mimicking the improvisation behavior of musicians [22], is considered a novel successful evolutionary algorithm. The HS algorithm has been successfully applied to many optimization problems in the computation and engineering fields [23–25]. One of key successful factors of the algorithm is the use of a novel stochastic derivative which can be used even for discrete variables. Instead of a traditional calculus-based gradient, the HS algorithm utilizes a musician's experience as a derivative in searching for an optimal solution. The advantages of the HS algorithm are that it may escape local optima and overcome the drawback of GA's building block theory which works well only if the relationship among variables in

a chromosome is carefully considered. Therefore, this paper attempts to use a HS algorithm to optimize the joint parameters in a combination forecasting model in order to improve the forecasting accuracy. Cases are then employed to test the performance of the proposed model. The rest of the paper is organized as follows: Section 2 introduces the joint parameters optimization combination model, Harmony Search algorithm and the HS based joint parameters optimization combination model. The empirical simulation and results analysis are presented in Section 3. Finally, Section 4 gives our conclusions.

2. HS-Based Joint Parameters Optimization Combination Model

2.1. Joint Parameters Optimization Combination Model (JPOC)

From the point of view of system identification and modeling, the objective of modeling of a certain system is to determine a model similar to the measured system from a given set of model classes on the basis of the input and output data [26]. In other words, the task of system modeling is to find a model which can describe the system characteristics and fit future development trends as accurately as possible. For a practical forecasting issue, it is not easy to exactly identify the future trends of the time series sequence, so a single forecast model cannot always fit the series data better for all situations [18].

Inspired by the system identification and modeling theory, a nonlinear combination model is proposed in our work to forecast the power generation sequence. Adopting a nonlinear model to describe the power generation forecasting model is more appropriate than a linear one since in essence the power generation growth trend is nonlinear. In the nonlinear combination model, the single model adopts a power function form. It is very hard to solve a nonlinear model using the traditional analytical methods. The process of finding the coefficients and exponents of the nonlinear model could be regarded as an optimization problem. Artificial intelligence methods provide an effective approach to solve such optimization problems. A novel intelligence optimization method—Harmony Search algorithm—is introduced to access the optimal exponential parameters of the single power function model and the combination forecasting weights simultaneously.

In this section, the joint parameters optimization combination model is described. The joint parameters optimization combination model includes single model parameter optimization and combination weight optimization.

The form of joint parameters optimization combination model is written as follows:

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

where $\hat{y}_t$ denotes the combined forecasting value for the time period t, $\hat{y}_t^{(i)}$ is the ith forecasting value for the same period, k is the number of forecasts to be combined, $\grave{u}_i$ is the combination forecasting weight assigned to the ith participating model, n_i is the exponent of the ith single model. The optimal value of $\grave{u}_i$ and n_i can be determined by the Harmony Search algorithm optimization technique.

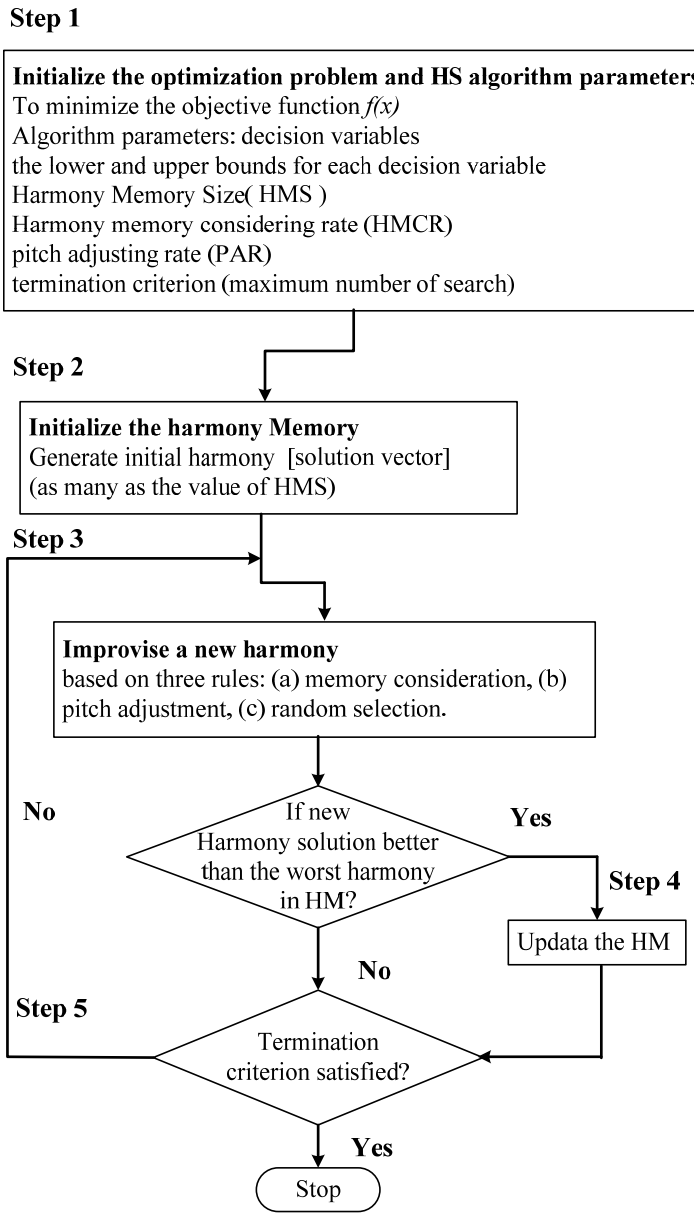
In all, the advantages of the proposed HS algorithm-based joint parameters optimization combination model are as follows: first, it is presented based on nonlinear theory which reflects the nonlinear essence of the power generation sequence. Second, the joint optimal parameters, including exponent coefficient and combination weights, could only be determined simultaneously through

artificial intelligence techniques and cannot be solved through traditional analytical methods. Third, the HS algorithm imitates the musical improvisation process in which seeking a perfect state of harmony between different instruments according to aesthetic standard is analogous to seeking a global optimum between different variables according to an objective function in optimization techniques. This means the HS algorithm is easily understood compared with other optimization algorithms.

2.2. Harmony Search (HS) Algorithm

The Harmony Search (HS) algorithm, proposed by Geem *et al*., is a phenomenon-mimicking algorithm inspired by the improvisation process of musicians [22]. Compared with other heuristic optimization algorithms, it behaves with excellent effectiveness and robustness and presents lots of advantages when applied to optimization problems [27,28]. Scheme 1 shows the HS algorithm optimization procedures consisting of Steps 1–5.

Scheme 1. Harmony Search (HS) optimization procedures.



Step 1. Initialize the optimization problem and algorithm parameters:

$$\text{Minimize } f(x)$$
$$s.t.\ \ x_i \in X_i \qquad i = 1,2,\cdots,N$$

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), the lower bounds (lb) and upper bounds (ub) for each decision variable and termination criterion should also be specified in this step.

Step 2. Initialize the Harmony Memory (HM).

The HM is a location storing all the solution vectors. In this step, the HM matrix is filled with randomly generated solution vectors 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.

2.3. HS Based Joint Parameters Optimization Combination Model (HS Based JPOC Model)

The HS-based joint parameters optimization combination model (HS-based JPOC model) is described in this section. 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 [29], shown in Equation (2):

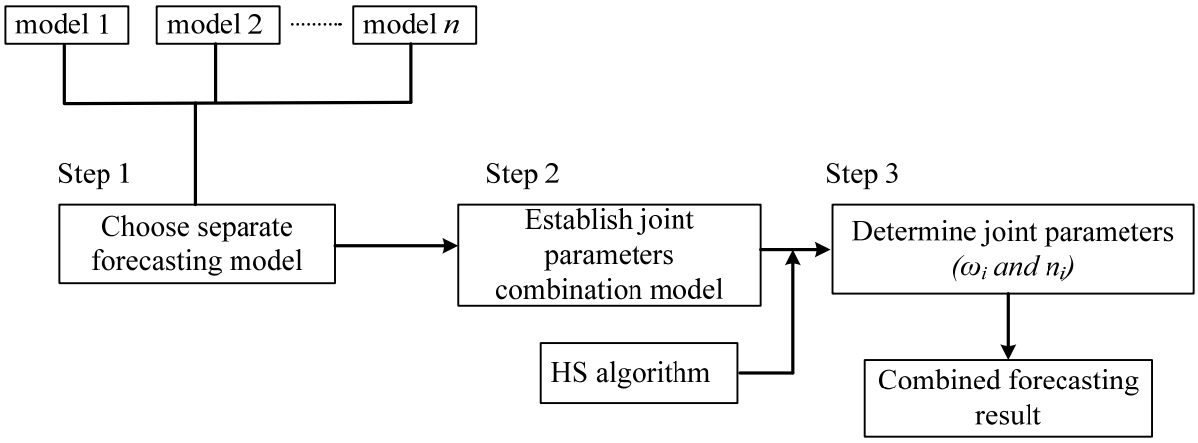
$$\min(MAPE) = \min\left\{\frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right|\right\} \tag{2}$$

where y_t is the actual value for tth period; $\hat{y}_t$ represents its forecasting result which can be calculated through Equation (1); and T is the number of data used for the MAPE calculation. Then the optimization objective function is expressed as follows:

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

The optimal values of the joint parameters $\grave{u}_i$ and n_i for the ith separate model are obtained by using HS algorithm. The modeling design procedures are shown in Scheme 2.

Scheme 2. Harmony Search Based JPOC model design procedures.



Step 1. Choose single forecasting model and calculate separate forecasting results. Before the HS-based JPOC model is set up, the single forecasting model should be first selected according to the practical problem. For each model, the corresponding separate forecasting results can be calculated.

Step 2. Establish the joint parameters optimization combination (JPOC) model. Based on the single forecast, the JPOC combination model can be built up according to Equation (1).

Step 3. Determine the optimal values of the joint parameters $\grave{u}_i$ and n_i by using the HS algorithm.

Step 4. Obtain the combination forecasting results from the HS-based JPOC model.

3. Empirical Simulation and Results Analysis

3.1. Data Sources

This section describes how to apply the HS algorithm to searching for the optimal values of exponential parameters and the combination forecasting weights and then establish the HS-based JPOC forecasting model. The yearly power generation data (Terawatt-hours, TWh for short) for China, Japan, Russian Federation and India from 2000 to 2010 obtained from the website of British Petroleum (BP) [30] were collected to validate the aforementioned method. The *BP Statistical Review of World Energy* which is one of the most widely respected and authoritative publications in the field of energy economics, provides high-quality, objective and globally consistent data on world energy markets. In 2010, the power generation for China, Japan and India accounted for 19.7%, 5.4% and 4.3% of the total power generation in the World, respectively. Combined, these top three countries constitute 29.4% of the global power generation and 76.36% of Asian power generation. The power generation in the Russian Federation accounts for 4.9% of the World total and nearly one fifth in the total of Europe and Eurasia in 2010.

Since China's reform and opening-up policy in 1980s, the average annual growth rate of GDP has been about 10%. Rapid and sustainable development of the economy has led to increased power generation, thus the power generation has grown rapidly from 300 TWh in 1980 to 4604 TWh in 2011. Now, the installed capacity ranks second in the World and the power generation ranks the first. Furthermore, the power generation in China will remain at high speed for decades since China is just in the process of industrialization and urbanization.

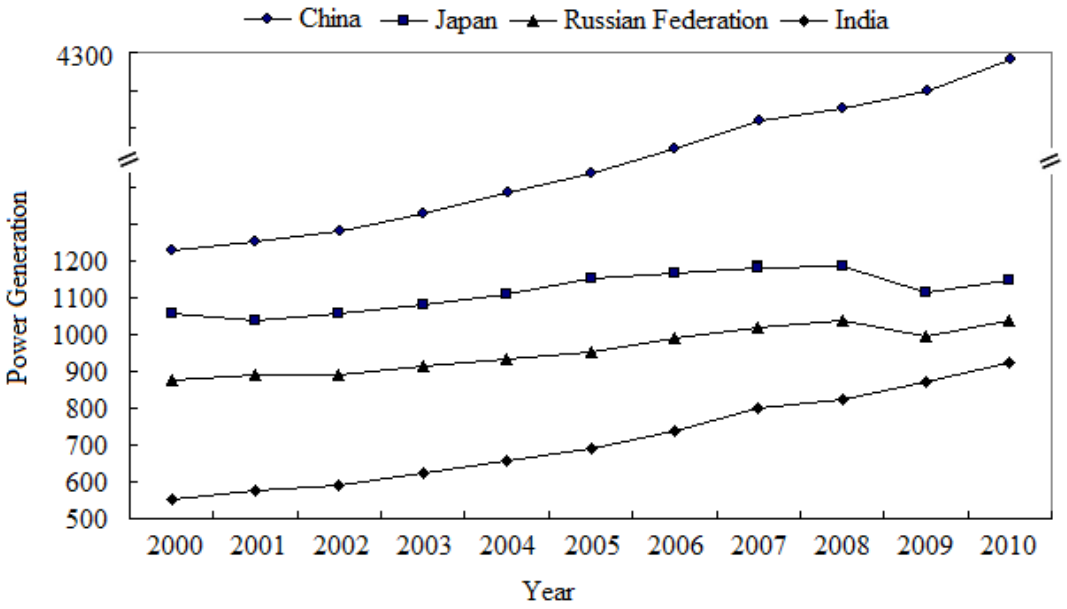
Japan is a country with rapid economic development. The Japanese economy has experienced a period of post-war economic recovery and rapid economic development in nineteenth century. And Japan has also experienced an atrophy period since the first 10 years of the 21st century. The power generation in Japan also shows fluctuating trends in typical years. How to accurately forecast power generation is difficult due to this fluctuating-type growth.

For a long time, India's power generation has found it difficult to meet the lighting needs of the residents and industrial electricity consumption due to the rapid economic development in the nation. Especially, blackouts have affected northern India, eastern and northeastern regions since 30 July, 2012. After years of rapid economic growth, electricity supply has become the bottleneck constraining growth. It is reported that during the 12th Five-Year Plan, India will make efforts to develop its power industry since 2012. The increase of India's power generation will accelerate in the future. To forecast future power generation in India has important theoretical and practical guiding significance.

Since the first eight years of the 21st century, the Russian Federation has experienced rapid economic growth. During the same period, the power generation also showed significant growth trends. Since September 2008, with the rapid spread of the international financial crisis and the global real economy downturn, Russia's economy fell into a severe recession. Therefore, the corresponding power generation decreased in 2009, so the power generation sequence of the Russian Federation shows a rising trend with typical fluctuations in certain years.

The yearly power generation curve (shown in Figure 1) exhibits different trends. The power generation curves of China and India show obvious rising trends, while the curves of Japan and Russian Federation show a basic rising trend with several waves. These four countries are selected as samples to test the applicability of the proposed HS-based JPOC forecasting model. Due to the different trends of the power generation curves, it is particularly meaningful to make accurate predictions. In next section, the performance data is presented to validate the aforementioned method.

Figure 1. Yearly power generation in China, Japan, Russian Federation and Indian from 2000 to 2010 (TWh).



3.2. Empirical Simulation

We conduct the experiments following the steps previously shown in Section 2.3. Firstly, we choose a separate forecasting model and calculate the single forecasting result. Linear regression model [31], time series model [32], Grey (1, 1) forecasting model (GM) [33] and Grey Verhulst model (GV) [34] are selected to generate the single forecasting result. Secondly, we establish the HS-based JPOC forecasting model according to Equation (1). Thirdly, determine the optimal value of the joint parameters using the HS algorithm.

A flowchart of the HS algorithm for parameter initialization is shown in Scheme 1. The details of the selection initial parameter model are as follows: HMS = 20, HMCR = 0.99, PAR = 0.5, BW = 1, lb = −100, ub = 100. All the programs were run on a 2.27 GHz Intel Core Duo CPU equipped 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) under the 32-bit Windows 7 operating system.

The proposed HS-based JPOC model was validated with the power generation data from 2000 to 2010 for China, Japan, Russian Federation and India. Table 1 shows the optimal values of exponential parameters for the separate model and the combination forecasting weights for the four countries. The combination forecasting weights have both positive and negative values, as can be seen from Table 1. In combination forecasting, different single models play different roles in the combination model. There may be positive or negative correlations between the individual forecasting result series and the original data sequence, so the case that combination forecasting weights have positive and negative values is consistent with the actual situation. The combination forecasting weights adopted in this paper not only have positive and negative values, but also have no restriction that the sum of weights equals to 1. This forecasting weights processing method can achieve more accurate results.

Table 1. The optimal value of $\grave{u}_i$ and n_i for four countries.

Optimal parameters	China	Japan	Russian Federation	India
ω_1	0.9077	72.6476	23.3226	4.7849
ω_2	−6.9740	−0.0157	−56.2980	−4.1747
ω_3	7.6333	2.3912	0.8225	0.9964
ω_4	0.2341	−58.4778	26.8964	0.9401
n_1	1.2236	−49.9990	32.0378	10.3544
n_2	−0.1259	−97.0534	29.3406	9.6253
n_3	−0.3048	−3.6961	−0.7928	19.8902
n_4	−4.4387	−40.8701	24.8709	0.8831

The forecasting values and the actual data for these countries are listed in Table 2. To test the forecasting performance, the HS-based JPOC model was compared with other four single models (linear regression model, time series model, GM model and GV model) and four combination models [Equivalent Weight (EW) model, Variance-Covariance (VACO) model, Granger and Ramanthan regression combination (R) model and Discounted MSFE model (DMSFE, â = 0.5)]. The comparison results are shown in the next section.

Table 2. Forecasting results of the HS-based JPOC model for four countries (TWh).

Year	China		Japan		Russian Federation		India	
	Actual	**Forecast**	**Actual**	**Forecast**	**Actual**	**Forecast**	**Actual**	**Forecast**
2000	1355.60	1355.60	1057.94	1057.94	877.80	891.56	554.74	553.94
2001	1480.80	1467.01	1039.72	1039.74	891.30	891.19	574.55	568.79
2002	1654.00	1667.22	1058.34	1053.38	891.27	893.10	592.19	596.02
2003	1910.58	1910.61	1082.61	1087.40	912.08	904.78	624.09	625.52
2004	2203.31	2201.42	1107.85	1123.63	931.90	925.74	657.72	657.74
2005	2500.26	2508.04	1153.06	1152.92	954.10	958.47	689.56	693.24
2006	2865.73	2817.67	1164.35	1170.92	992.10	986.86	738.71	732.62
2007	3281.55	3149.39	1180.11	1177.17	1018.70	1011.64	797.94	776.56
2008	3466.88	3493.64	1183.72	1173.00	1040.00	1034.05	824.45	825.24
2009	3714.65	3791.00	1114.00	1160.27	993.10	1009.53	869.80	869.17
2010	4206.54	4111.84	1145.27	1140.81	1036.78	1036.80	922.25	922.27

3.3. Results Analysis

3.3.1. Comparison with Four Other Single Models

This section focuses on the comparison between the HS-based JPOC model and the other four single models mentioned in this study. Table 3 and Figure 2 list the results of the HS-based JPOC model (HSC shown in figures), linear regression, time series, GM and GV forecasting models for China and the corresponding errors of these models. Due to the simple rising trend in China's power generation, the four separate models all capture the increasing trend better. The performance disparity for these five models can be identified from the errors in Table 3. For short range forecasting, the error range [−3%, +3%] is generally considered as a standard to measure forecasting result [35]. Next, this range is adopted to compare the five methods as follows: the proposed HS-based JPOC model has only one forecasting result point that exceeds the range in a total of 11 points −4.0274% in 2007). The maximum and minimum errors are 2.0554% and −4.0274% in 2009 and 2007, respectively. In the regression model, there are four result points larger than 3%, two smaller than −3%, and two points near −3%, so in total six points are not satisfactory. The regression model reaches the maximum error of 5.7904% in 2003 and the minimum error of −15.3452% in 2000. In the time series model, there are two result points larger than 3%, one point smaller than −3%, and two points near −3%. The maximum error is 6.3466% in 2008 and the minimum error is −3.1404% in 2003. In GM mode, there are four result points larger than 3%, and two smaller than −3%. The maximum error is 6.6759% in 2002 and the minimum error is −6.3135% in 2007. In GV mode, there are three result points larger than 3%, one smaller than −3%. The maximum error is 6.2340% in 2002 and the minimum error is −3.8098% in 2007. Compared with the four single models, the numbers that exceed the error range for the HS-based JPOC model are the least, and the maximum and minimum errors are smaller than other single models.

Table 3. Forecasting results of HS based JPOC model and other four single models for China (TWh).

Year	Actual	HS based JPOC model		Regression		Time series		GM		GV	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	1355.60	1355.60	0.0000	1147.58	−15.3452	1316.86	−2.8578	1355.60	0.0000	1355.60	0.0000
2001	1480.80	1467.01	−0.9313	1438.79	−2.8370	1504.08	1.5721	1578.96	6.6288	1545.61	4.3767
2002	1654.00	1667.22	0.7993	1730.00	4.5949	1651.65	−0.1421	1764.42	6.6759	1757.11	6.2340
2003	1910.58	1910.61	0.0016	2021.21	5.7904	1850.58	−3.1404	1971.66	3.1969	1991.06	4.2123
2004	2203.31	2201.42	0.0858	2312.42	4.9521	2141.59	−2.8012	2203.25	−0.0027	2248.10	2.0329
2005	2500.26	2508.04	0.3112	2603.63	4.1344	2472.39	−1.1147	2462.04	−1.5286	2528.38	1.1247
2006	2865.73	2817.67	−0.0168	2894.84	1.0158	2807.41	−2.0351	2751.22	−3.9958	2831.54	−1.1931
2007	3281.55	3149.39	−4.0274	3186.05	−2.9102	3219.00	−1.9061	3074.37	−6.3135	3156.53	−3.8098
2008	3466.88	3493.64	0.7719	3477.26	0.2994	3686.91	6.3466	3435.48	−0.9057	3501.65	1.0029
2009	3714.65	3791.00	2.0554	3768.47	1.4489	3895.65	4.8726	3839.00	3.3476	3864.49	4.0338
2010	4206.54	4111.84	−2.2513	4059.68	−3.4912	4174.39	−0.7643	4289.92	1.9822	4241.93	0.8413

Figure 2. Forecasting performance of HS based JPOC model and other four single models for China.

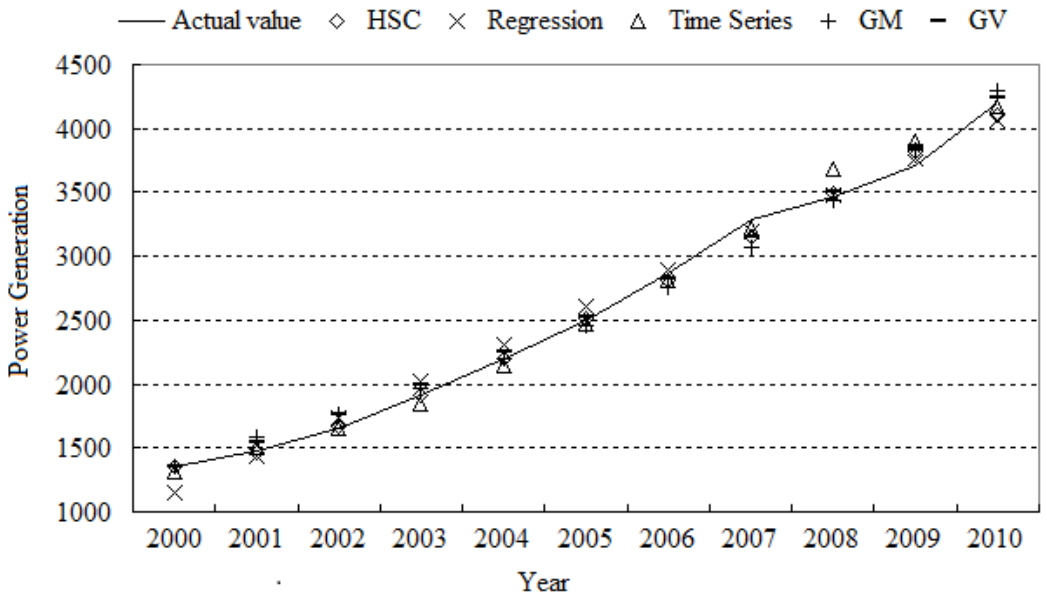


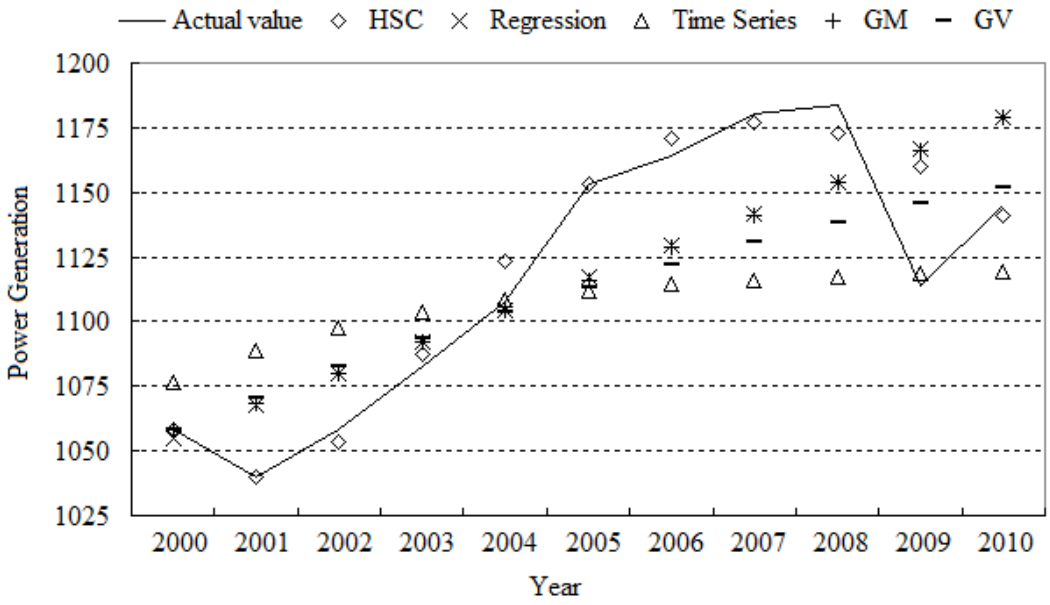
Table 4 lists the forecasting values and actual data of power generation for Japan and the corresponding errors. Figure 3 shows the curves of actual data and the forecasting results of the proposed model and the other four single models. The error analysis of Japan is as follows:

The proposed model has only one forecasting result point that exceeds the range (4.1535% in 2009). The minimum and maximum errors are −0.0121% and 4.1535% in 2005 and 2009. In the regression model, there is one result point larger than 3%, three smaller than −3%, one point near −3% and one point near +3%. Regression reaches the maximum error 4.7127% in 2009 and the minimum error −3.2505% in 2007.

Table 4. Forecasting results of HS based JPOC model and other four single models for Japan (TWh).

Year	Actual	HS based JPOC model		Regression		Time series		GM		GV	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	1057.94	1057.94	0.0000	1055.12	−0.2666	1076.88	1.7903	1057.94	0.0000	1057.94	0.0000
2001	1039.72	1039.74	0.0019	1067.49	2.6709	1088.67	4.7080	1068.34	2.7527	1070.54	2.9643
2002	1058.34	1053.38	−0.4687	1079.87	2.0343	1097.33	3.6841	1080.12	2.0579	1082.35	2.2686
2003	1082.61	1087.40	0.4424	1092.24	0.8895	1103.70	1.9481	1092.02	0.8692	1093.39	0.9957
2004	1107.85	1123.63	1.4244	1104.62	−0.2916	1108.37	0.0469	1104.06	−0.3421	1103.70	−0.3746
2005	1153.06	1152.92	−0.0121	1117.00	−3.1273	1111.80	−3.5783	1116.23	−3.1941	1113.32	−3.4465
2006	1164.35	1170.92	0.5643	1129.37	−3.0043	1114.32	−4.2968	1128.53	−3.0764	1122.27	−3.6140
2007	1180.11	1177.17	−0.2491	1141.75	−3.2505	1116.17	−5.4181	1140.96	−3.3175	1130.59	−4.1962
2008	1183.72	1173.00	−0.9056	1154.13	−2.4997	1117.53	−5.5917	1153.54	−2.5496	1138.32	−3.8354
2009	1114.00	1160.27	4.1535	1166.50	4.7127	1118.53	0.4066	1166.25	4.6903	1145.49	2.8268
2010	1145.27	1140.81	−0.3894	1178.88	2.9347	1119.27	−2.2702	1179.11	2.9548	1152.14	0.5999

Figure 3. Forecasting performance of the HS-based JPOC model and four other single models for Japan.



In time series model, there are two points larger than 3%, four points smaller than −3%. The maximum error is 4.7080% in 2001 and the minimum error is −5.5917% in 2008. In GM mode, there is one result point larger than 3%, three smaller than −3%, and two points near +3%. The maximum error is 4.6903% in 2009 and the minimum error is −3.3175% in 2007. In GV mode, there are three points smaller than −3% and two points near +3%. The maximum error is 2.9643% in 2001 and the minimum error is −4.1962% in 2007. From errors analysis, we also conclude that the proposed model has better forecasting performance. For Japan's power generation sequence, there are two turning points (in 2001 and 2009). The forecasting errors of the proposed model for these two points are smaller than that of other single forecasting models which can be seen from Table 4. We can conclude that the HS based JPOC model can obtain better predictive performances in obvious turning points.

For the Russian Federation, no error result point of the proposed model exceeds the error range [−3%, +3%] (Table 5, Figure 4). There is only one result point larger than +3% or smaller than −3% for the linear regression, time series, GM and GV models, respectively. For India, we can also see that the errors of the result points are all within the [−3%, +3%] error range for the proposed model, time series model, GM model and GV model (Table 6, Figure 5). In the linear regression model, there is one result point larger than 3% and one point smaller than −3%. It seems that the proposed HS-based JPOC model does not display any obvious advantage concerning forecasting error range compared with other four single models, but from another point of view, we can analyze the maximal absolute percentage error (MaxAPE) indicator for these models. The MaxAPE indicator is defined as follows:

$$MaxAPE = \max_{t}\left(\left|\frac{y_t - \hat{y}_t}{y_t}\right|\right)\times 100,\quad t = 1,2,\cdots,T \tag{4}$$

where y_t is the power generation value in the tth year; $\hat{y}_t$ represents its forecasting result for the same period; and T is the number of data used for the MaxAPE calculation.

Table 5. Forecasting results of the HS-based JPOC model and other four single models for Russian Federation (TWh).

Year	Actual	HS based JPOC model		Regression		Time series		GM		GV	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	877.80	891.56	1.5676	870.75	−0.8031	880.58	0.3167	877.80	0.0000	877.80	0.0000
2001	891.30	891.19	−0.0123	888.22	−0.3456	895.51	0.4723	887.95	−0.3759	894.35	0.3422
2002	891.27	893.10	0.2053	905.69	1.6179	910.60	2.1688	904.47	1.4810	910.80	2.1913
2003	912.08	904.78	−0.8004	923.16	1.2148	925.84	1.5086	921.31	1.0120	927.13	1.6501
2004	931.90	925.74	−0.6610	940.63	0.9368	941.24	1.0023	938.45	0.7029	943.33	1.2265
2005	954.10	958.47	0.4580	958.1	0.4192	956.79	0.2819	955.92	0.1908	959.39	0.5544
2006	992.10	986.86	−0.5282	975.57	−1.6662	972.51	−1.9746	973.71	−1.8536	975.29	−1.6944
2007	1018.70	1011.64	−0.6930	993.04	−2.5189	988.38	−2.9763	991.83	−2.6377	991.02	−2.7172
2008	1040.00	1034.05	−0.5721	1010.51	−2.8356	1004.40	−3.4231	1010.29	−2.8567	1006.57	−3.2144
2009	993.10	1009.53	1.6544	1027.98	3.5122	1020.59	2.7681	1029.09	3.6240	1021.92	2.9020
2010	1036.78	1036.80	0.0019	1045.45	0.8362	1036.93	0.0145	1048.24	1.1053	1037.08	0.0289

Figure 4. Forecasting performance of HS based JPOC model and other four single models for Russian Federation.

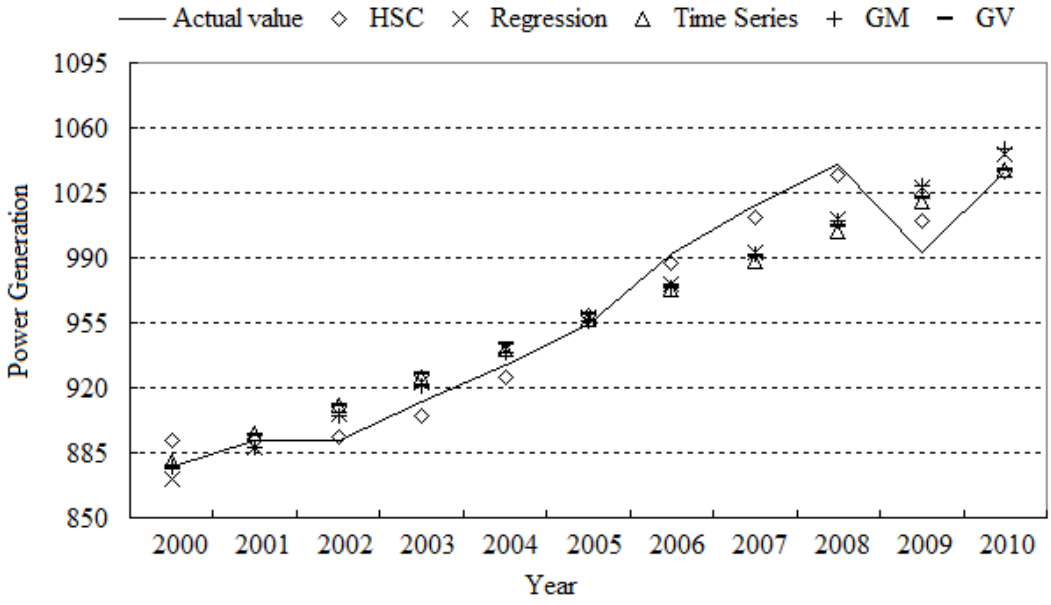
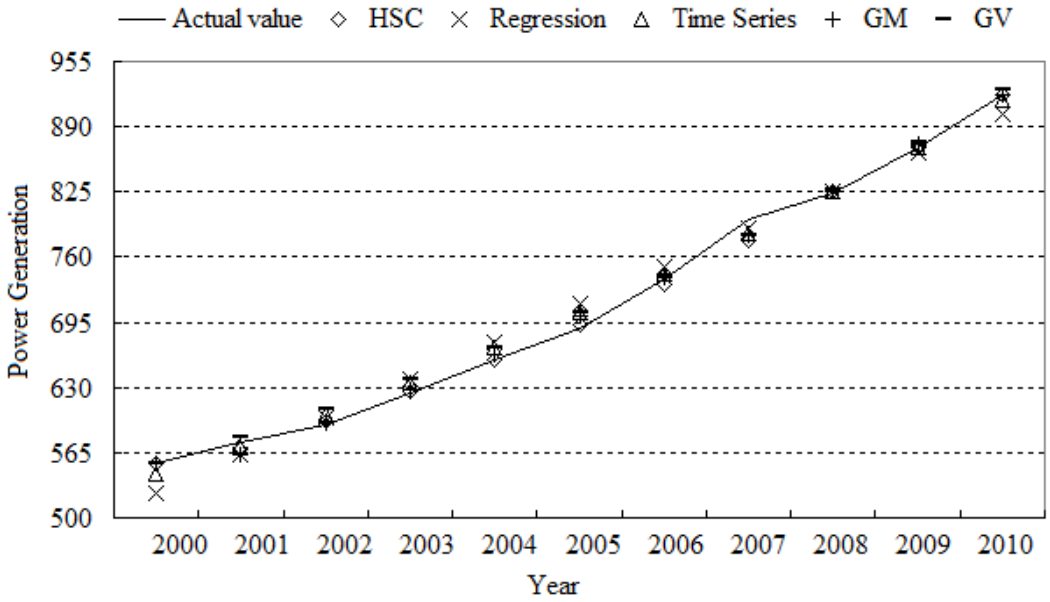


Table 6. Forecasting results of the HS-based JPOC model and the other four single models for India (TWh).

Year	Actual	HS based JPOC model		Regression		Time series		GM		GV	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	554.74	553.03	−0.1442	524.91	−5.3773	543.28	−2.0658	554.74	0.0000	554.74	0.0000
2001	574.55	574.65	−1.0025	562.58	−2.0834	572.42	−0.3707	562.53	−2.0921	580.62	1.0565
2002	592.19	598.29	0.6468	600.25	1.3610	603.12	1.8457	594.22	0.3428	608.34	2.7272
2003	624.09	624.76	0.2291	637.93	2.2176	635.46	1.8219	627.70	0.5784	638.09	2.2433
2004	657.72	655.13	0.0030	675.6	2.7185	669.53	1.7956	663.06	0.8119	670.11	1.8838
2005	689.56	690.47	0.5337	713.27	3.4384	705.42	2.3000	700.41	1.5735	704.63	2.1855
2006	738.71	731.39	−0.8244	750.95	1.6569	743.23	0.6119	739.87	0.1570	741.97	0.4413
2007	797.94	777.08	−2.6794	788.62	−1.1680	783.06	−1.8648	781.55	−2.0540	782.47	−1.9387
2008	824.45	824.57	0.0958	826.29	0.2232	825.02	0.0691	825.58	0.1371	826.54	0.2535
2009	869.80	870.19	−0.0724	863.96	−0.6714	869.22	−0.0667	872.09	0.2633	874.64	0.5564
2010	922.25	922.21	0.0022	901.64	−2.2348	915.78	−0.7015	921.22	-0.1117	927.37	0.5552

Figure 5. Forecasting performance of the HS-based JPOC model and the other four single models for India.



For the Russian Federation, the MaxAPE values are 1.6544%, 3.5122%, 3.4231%, 3.6240% and 3.2144% for the proposed HS-based JPOC model, linear regression model, time series model, GM model and GV model respectively. For India, the MaxAPE values are 2.6794%, 5.3773%, 2.3000%, 2.0921% and 2.7272% for the corresponding models. Compared with other four single models, the MaxAPE of the HS-based JPOC model is smaller, which means the proposed model has less forecasting risk. For the Russian Federation's power generation sequence, there is also a turning point in 2009, and forecasting error of the proposed model is also smaller than the other single models. It is also tested by this case that the HS-based JPOC model can treat the sudden turning points better than other models.

Next, the mean absolute percentage error (MAPE) is adopted as an indicator of forecasting precision listed in Table 7. The calculation of the MAPE indicator was mentioned above in Equation (2). Among these five forecasting models, the HS-based JPOC model is the most accurate forecasting model because of its smallest MAPE value. Taking the MAPE of the HS-based JPOC model as a benchmark, the improvement rate with respect to the other four single models is also reported in Table 7. The improvement rates of regression, time series, GM and GV are 262.5863%, 113.3657%, 167.7741% and 123.5114%, respectively, for China; 198.2371%, 291.8114%, 199.6679% and 191.7476% for Japan; 133.5178%, 136.3315%, 121.4022% and 130.9194% for the Russian Federation; 309.2960%, 138.8565%, 43.5823% and 144.7102% for India, respectively. Most MAPE improvements are over 100% for these four cases. The at least 43.5823% improvement reveals the superior forecasting performance of HS-based JPOC model. Therefore, it can be concluded that the proposed model is significantly more accurate than other four single forecasting models.

Table 7. The MAPE comparison of the HS based JPOC model and the other single models (%).

MAPE Comparison	China		Japan		Russian Federation		India	
	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)
HS-based JPOC model	1.1739	----	0.7828	----	0.6504	----	0.5142	----
Linear Regression	4.2564	262.5863	2.3346	198.2371	1.5188	133.5178	2.1046	309.2960
Time Series	2.5047	113.3657	3.0671	291.8114	1.5371	136.3315	1.2282	138.8565
GM	3.1434	167.7741	2.3458	199.6679	1.4400	121.4022	0.7383	43.58230
GV	2.6238	123.5114	2.2838	191.7476	1.5019	130.9194	1.2583	144.7102

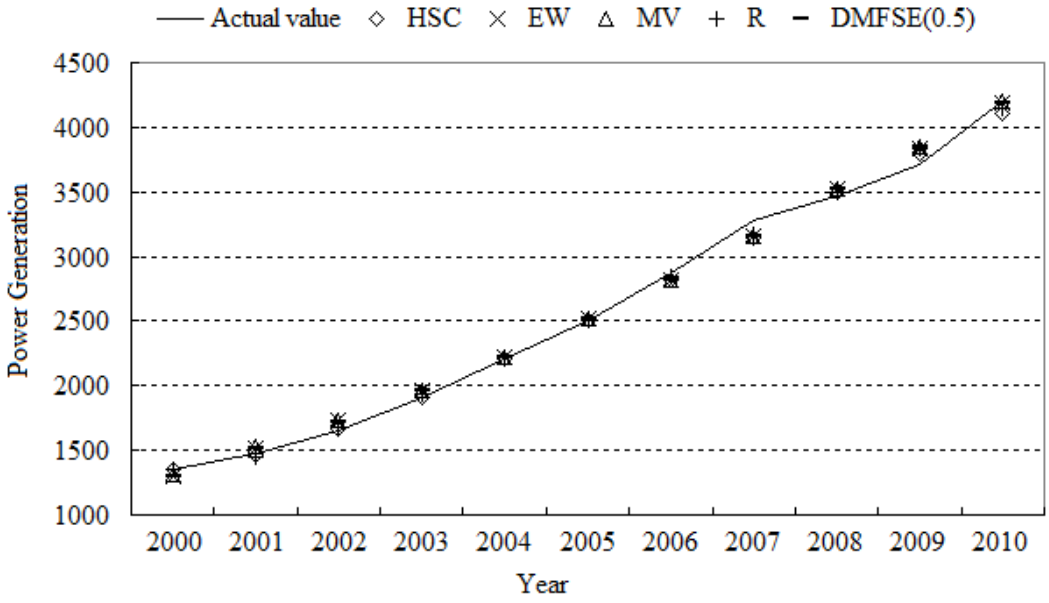
3.3.2. Compared with Other Combination Models

The forecasting performance of the HS-based JPOC model (HSC shown in figures) is compared with four other combination models (EW, VACO, R, and DMFSE). In the DMSFE combination forecast model, the discounting factor β is chosen as 0.5. Table 8 lists the combination forecasting values and actual data of China's power generation and the corresponding errors between the actual value and the forecasting results. Figure 6 shows the curves of actual data and the forecasting results of the proposed model and the other four combination models. We can hardly observe the advantages of our proposed model from Figure 4 since these combination forecasting results are all very close to the actual values, so we also adopt error analysis for the proposed model and the other combination models.

Table 8. Forecasting results of HS based JPOC model and other combination models for China (TWh).

Year	Actual	HS-based JPOC model		EW		VACO		R		DMFSE (0.5)	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	1355.60	1355.60	0.0000	1293.91	−4.5508	1306.24	−3.6412	1353.98	−0.1195	1295.39	−4.4416
2001	1480.80	1467.01	−0.9313	1516.86	2.4352	1522.51	2.8167	1451.09	−2.0063	1517.34	2.4676
2002	1654.00	1667.22	0.7993	1725.80	4.3410	1728.83	4.5242	1679.2	1.5236	1725.62	4.3301
2003	1910.58	1910.61	0.0016	1958.63	2.5149	1959.86	2.5793	1936.02	1.3315	1958.07	2.4856
2004	2203.31	2201.42	0.0858	2226.34	1.0452	2225.88	1.0244	2214.63	0.5138	2225.78	1.0198
2005	2500.26	2508.04	0.3112	2516.61	0.6539	2515.38	0.6047	2517.18	0.6767	2516.27	0.6403
2006	2865.73	2817.67	−0.0168	2821.25	−1.5521	2820.60	−1.5748	2841.72	−0.8378	2821.19	−1.5542
2007	3281.55	3149.39	−4.0274	3158.99	−3.7348	3158.86	−3.7388	3170.78	−3.3755	3159.47	−3.7202
2008	3466.88	3493.64	0.7719	3525.32	1.6857	3525.70	1.6966	3495.19	0.8166	3526.52	1.7203
2009	3714.65	3791.00	2.0554	3841.90	3.4256	3847.58	3.5785	3837.86	3.3169	3842.90	3.4525
2010	4206.54	4111.84	−2.2513	4191.48	-0.3580	4201.34	−0.1236	4142.26	−1.5281	4192.37	−0.3369

Figure 6. Forecasting performance of the HS-based JPOC model and the other combination models for China.



The proposed HS-based JPOC model has one forecasting result point that exceeds the range in the total of 11 points (−4.0274% in 2007). The maximum and minimum errors are 2.0554% and −4.0274% in 2009 and 2007, respectively. In the EW combination model, there are two result points larger than 3%, two smaller than −3%, and two points near 3%, so total of four points are not satisfactory. The EW model reaches the maximum error of 4.3410% in 2002 and the minimum error of −4.5508% in 2000. In the VACO combination model, there are two result points larger than 3%, two points smaller than −3%, and two points near 3%. The maximum error is 4.5242% in 2002 and the minimum error is −3.7388% in 2002. In the R combination model, there is one result point larger than 3%, and one smaller than −3%. The maximum error is 3.3169% in 2009 and the minimum error is −3.3755% in 2007. In the DMFSE model, there are two result points larger than 3%, two points smaller than −3% and two points near 3%. The maximum error is 4.3301% in 2002 and the minimum error is −4.4416% in 2000. In all, the numbers that exceed the error range for the HS-based JPOC model are the least, and the maximum and minimum errors are all smaller than those of the other combination models. The HS-based JPOC model showed better forecasting performance compared with the four other combination models for China.

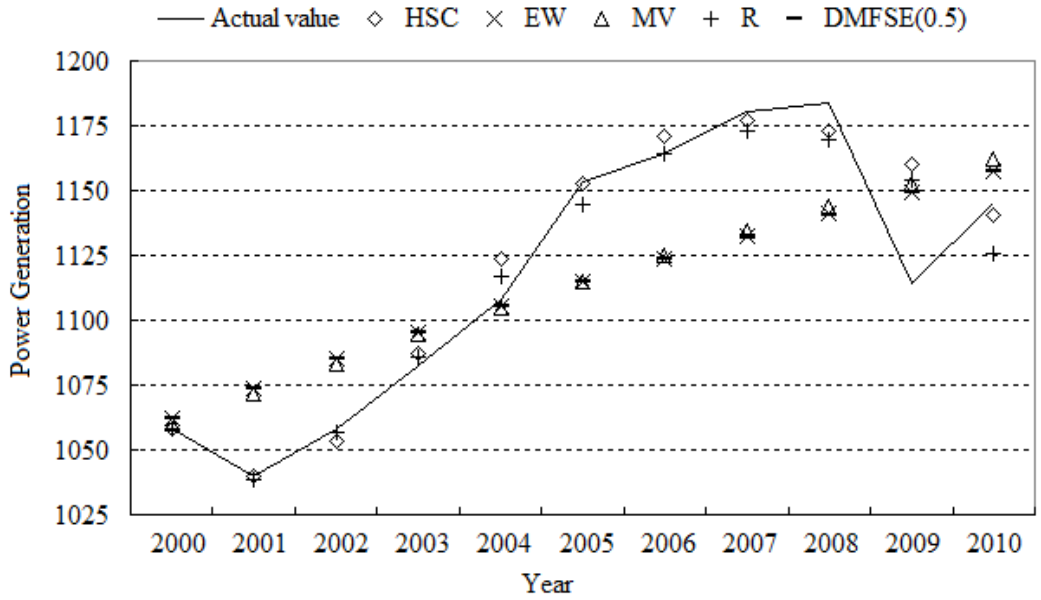
Table 9 lists the forecasting values and actual data of power generation for Japan and the forecasting errors. Figure 7 shows the curves of actual data and the forecasting results for the five models. The error analysis of Japan is as follows: the proposed model has only one forecasting result point that exceeds the range (4.1535% in 2009). The minimum and maximum errors are 50.0121% and 4.1535% in 2005 and 2009, respectively. In the EW combination model, there are two result points larger than 3%, and four smaller than −3%. The maximum error is 3.2740% in 2001 and the minimum error 54.0454% in 2007. In the VACO combination model, there are two result points larger than 3%, two points smaller than 53%. The maximum error is 3.5009% in 2009 and the minimum error is 53.8751% in 2007. In the R combination model, there is only one result point larger than 3%. The maximum error is 3.6221% in 2009 and the minimum error is −1.6965% in 2010. In the DMFSE

model, there are two result points larger than 3%, four points smaller than −3%. The maximum error is 3.2778% in 2001 and the minimum error is −4.0522% in 2007. The HS-based JPOC model also showed better performance compared with the four other combination models for Japan, from both the numbers exceeding forecasting error range [−3%, +3%] and the maximum and minimum errors.

Table 9. Forecasting results of HS-based JPOC model and the other combination models for Japan (TWh).

Year	Actual	HS based JPOC model		EW		VACO		R		DMFSE (0.5)	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	1057.94	1057.94	0.0000	1061.97	0.3809	1060.16	0.2098	1058.15	0.0198	1062.00	0.3838
2001	1039.72	1039.74	0.0019	1073.76	3.2740	1071.95	3.0999	1038.32	−0.1347	1073.80	3.2778
2002	1058.34	1053.38	−0.4687	1084.92	2.5115	1083.41	2.3688	1056.93	−0.1332	1084.95	2.5143
2003	1082.61	1087.40	0.4424	1095.34	1.1759	1094.33	1.0826	1085.91	0.3048	1095.36	1.1777
2004	1107.85	1123.63	1.4244	1105.19	−0.2401	1104.81	−0.2744	1116.91	0.8178	1105.19	−0.2401
2005	1153.06	1152.92	−0.0121	1114.59	−3.3363	1114.94	−3.3060	1144.29	−0.7606	1114.57	−3.3381
2006	1164.35	1170.92	0.5643	1123.62	−3.4981	1124.78	−3.3985	1163.88	−0.0404	1123.58	−3.5015
2007	1180.11	1177.17	−0.2491	1132.37	−4.0454	1134.38	−3.8751	1172.64	−0.6330	1132.29	−4.0522
2008	1183.72	1173.00	−0.9056	1140.88	−3.6191	1143.78	−3.3741	1169.76	−1.1793	1140.77	−3.6284
2009	1114.00	1160.27	4.1535	1149.19	3.1589	1153.00	3.5009	1154.35	3.6221	1149.04	3.1454
2010	1145.27	1140.81	−0.3894	1157.35	1.0548	1162.08	1.4678	1125.84	−1.6965	1157.16	1.0382

Figure 7. Forecasting performance of HS based JPOC model and other combination models for Japan.



The forecasting results and errors for the Russian Federation and India are listed in Table 10 and Table 11. The curves of actual data and the forecasting results for the two countries are drawn in Figure 8 and Figure 9.

Table 10. Forecasting results of the HS-based JPOC model and the other combination models for the Russian Federation (TWh).

Year	Actual	HS based JPOC model		EW		VACO		R		DMFSE (0.5)	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	877.80	891.56	1.5676	876.73	−0.1219	876.60	−0.1367	877.85	0.0057	876.74	−0.1208
2001	891.30	891.19	−0.0123	891.51	0.0236	891.38	0.0090	888.93	−0.2659	891.52	0.0247
2002	891.27	893.10	0.2053	907.89	1.8648	907.80	1.8547	895.16	0.4365	907.90	1.8659
2003	912.08	904.78	−0.8004	924.36	1.3464	924.30	1.3398	909.96	−0.2324	924.37	1.3475
2004	931.90	925.74	−0.6610	940.91	0.9668	940.89	0.9647	933.45	0.1663	940.92	0.9679
2005	954.10	958.47	0.4580	957.55	0.3616	957.56	0.3626	959.58	0.5744	957.55	0.3616
2006	992.10	986.86	−0.5282	974.27	−1.7972	974.31	−1.7932	988.48	−0.3649	974.27	−1.7972
2007	1018.70	1011.64	−0.6930	991.07	−2.7123	991.14	−2.7054	1011.15	−0.7411	991.06	−2.7133
2008	1040.00	1034.05	−0.5721	1007.94	−3.0827	1008.04	−3.0731	1024.59	−1.4817	1007.94	−3.0827
2009	993.10	1009.53	1.6544	1024.90	3.2021	1025.03	3.2152	1028.93	3.6079	1024.88	3.2001
2010	1036.78	1036.80	0.0019	1041.93	0.4967	1042.08	0.5112	1021.05	−1.5172	1041.91	0.4948

Figure 8. Forecasting performance of the HS-based JPOC model and the other combination models for the Russian Federation.

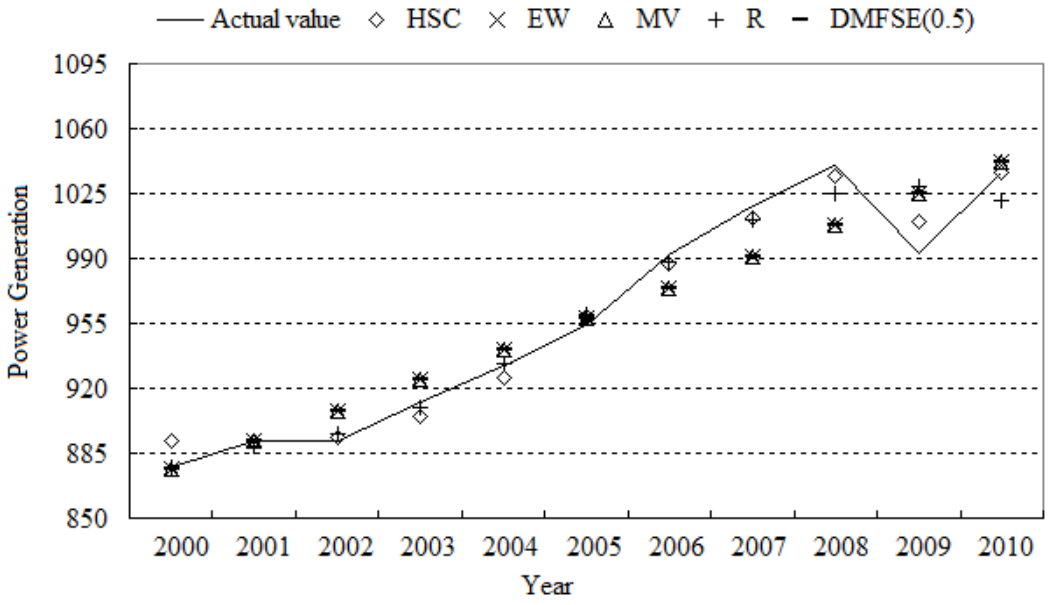
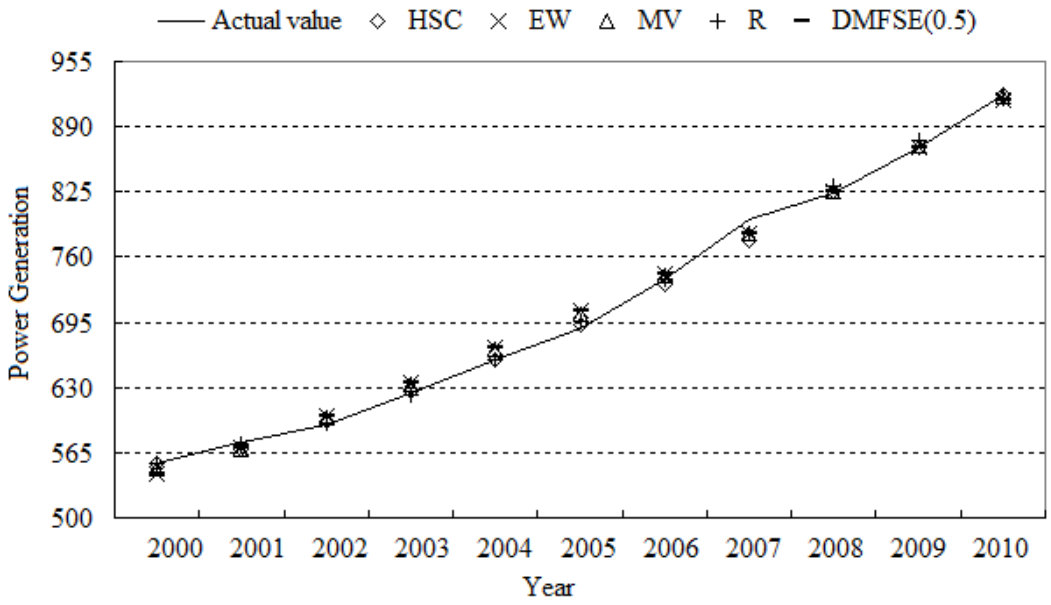


Table 11. Forecasting results of the HS-based JPOC model and the other combination models for India (TWh).

Year	Actual	HS based JPOC model		EW		VACO		R		DMFSE (0.5)	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
2000	554.74	553.03	−0.1442	544.42	−1.8603	549.23	−0.9933	554.79	0.0090	544.47	−1.8513
2001	574.55	574.65	−1.0025	569.54	−0.8720	568.95	−0.9747	572.73	−0.3168	569.55	−0.8702
2002	592.19	598.29	0.6468	601.48	1.5688	600.06	1.3290	594.83	0.4458	601.48	1.5688
2003	624.09	624.76	0.2291	634.79	1.7145	632.82	1.3988	623.06	−0.1650	634.78	1.7129
2004	657.72	655.13	0.0030	669.57	1.8017	667.34	1.4626	656.87	−0.1292	669.56	1.8002
2005	689.56	690.47	0.5337	705.93	2.3740	703.73	2.0549	695.72	0.8933	705.91	2.3711
2006	738.71	731.39	−0.8244	744.00	0.7161	742.16	0.4670	738.44	−0.0366	743.98	0.7134
2007	797.94	777.08	−2.6794	783.92	−1.7570	782.76	−1.9024	783.95	−1.7533	783.91	−1.7583
2008	824.45	824.57	0.0958	825.86	0.1710	825.72	0.1540	830.56	0.7411	825.86	0.1710
2009	869.80	870.19	−0.0724	869.98	0.0207	871.21	0.1621	876.37	0.7553	869.99	0.0218
2010	922.25	922.21	0.0022	916.50	−0.6235	919.47	−0.3014	918.44	−0.4131	916.54	−0.6191

Figure 9. Forecasting performance of the HS-based JPOC model and the other combination models for India.



No error point of the proposed model exceeds the range [−3%, +3%] for the Russian Federation. One result point is larger than +3% and one point is smaller than −3% for the EW model, the VACO model and the DMFSE model, respectively. Only one point is larger than +3% for the R model. For India, the errors of the four combination models are all within the error range. The HS-based JPOC model does not show any obvious advantage when dealing with the time series data trends of the Russian Federation and India. Next, we measure the forecasting risk by using the MaxAPE indicator. For the Russian Federation, the MaxAPE values for the five models are 1.6544%, 3.2021%, 3.2152%, 3.6079% and 3.2001%, respectively. The MaxAPE of the HS-based JPOC model is the smallest, which means that it will be less risky to choose the proposed model to forecast future trend. For India,

the MaxAPE values of the five models all fluctuate around 2% (2.6749%, 2.3840%, 2.05491%, 1.7533% and 1.8513%). The MaxAPE of the HS-based JPOC model is not the best in this case, but through analyzing the absolute value of errors, we can find that only in 2000 and 2009, the errors showed worse results (1.5676% in 2000 and 1.6544% in 2009). Only two error points are slightly larger for India. Since the overall error indicator MAPE is adopted for the objective function, there may be certain individual points with slightly larger errors during the HS optimizing training process, but in other year points, the errors of the HS-based JPOC model are much smaller than those of the other combination models. The errors of the HS-based JPOC model expressed smaller fluctuations, which in not the case for the other combination models. Furthermore, the overall MAPE indicator is the smallest, which explains the comprehensive performance of the proposed model shown in Table 12.

Table 12 shows the MAPE improvement rate of the HS-based JPOC model compared to the other four combination models. The improvement rates of EW, VACO, R, DMSFE ($\hat{a} = 0.5$) are 103.6545%, 100.5963%, 24.2695% and 102.6578%, respectively, for China; 205.3654%, 201.4563%, 8.4951% and 205.4037% for Japan; 123.3087%, 123.1550%, 31.3038% and 123.3087% for the Russian Federation; and 138.3119%, 98.0163%, 0.0389% and 137.9424% for India, respectively. We observe from Table 12 that the HS-based JPOC model outperforms all other combination forecast models since the proposed model has the lowest MAPE.

Table 12. The MAPE comparison of the HS-based JPOC model and the other combination models (%).

MAPE Comparison	China		Japan		Russian Federation		India	
	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)	MAPE	Improvement Rate (%)
HS based JPOC model	1.1739	-	0.7828	-	0.6504	-	0.5142	-
EW	2.3907	103.6545	2.3904	205.3654	1.4524	123.3087	1.2254	138.3119
VACO	2.3548	100.5963	2.3598	201.4563	1.4514	123.1550	1.0182	98.0163
R	1.4588	24.2695	0.8493	8.4951	0.8540	31.3038	0.5144	0.03890
DMFSE (β = 0.5)	2.3790	102.6578	2.3907	205.4037	1.4524	123.3087	1.2235	137.9424

4. Conclusions

It is well recognized that no single model consistently performs well in all situations. The combination model can always improve the accuracy of forecasting and is typically a reliable forecasting method for any practical forecasting issue. In this paper, the Harmony Search algorithm-based joint parameters optimization combination model is proposed for power generation forecasting. The single forecasting model adopts a power function form. The exponential parameters of the single power function model and the combination forecasting weights are then optimized simultaneously through using the HS algorithm to get the optimal parameter values. The combination forecasting results can be obtained finally. The yearly power generation data from 2000 to 2010 for typical countries with different trends are forecasted to test the effect and accuracy of the proposed method. Compared with four single models and four combination models for these four countries, the main conclusions drawn from the above study can be summarized as follows: first, the proposed combination model outperforms other

single models and combination models for China, Japan, the Russian Federation and India. The numbers that exceed the error range [+3%, −3%] for the proposed model are the least, and the maximum and minimum errors are all smaller than other single models and combination models. Second, in terms of prediction accuracy, the proposed model is superior to other single models and combination models because it has the minimum MAPE value. Third, the proposed combination model could achieve better predictive performances at obvious turning points of power generation time series which can be reflected in several special points of the Japan and Russian Federation data. Even if there may be certain fluctuations in the future trends for power generation sequences, the proposed model could show promising results. In summary, all of those results showed that the proposed combination model is superior to the single models and other combination models for the test countries in terms of forecasting accuracy and model selection risk.

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