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Monthly Load Forecasting Based on Economic Data by Decomposition Integration Theory

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Abstract: Accurate load forecasting can help alleviate the impact of renewable-energy access to the network, facilitate the power plants to arrange unit maintenance and encourage the power broker companies to develop a reasonable quotation plan. However, the traditional prediction methods are insufficient for the analysis of load sequence fluctuations. The economic variables are not introduced into the input variable selection and the redundant information interferes with the final prediction results. In this paper, a set of the ensemble empirical mode is used to decompose the electricity consumption sequence. Appropriate economic variables are as selected as model input for each decomposition sequence to model separately according to its characteristics. Then the models are constructed by selecting the optimal parameters in the random forest. Finally, the result of the component prediction is reconstituted. Compared with random forest, support vector machine and seasonal naïve method, the example results show that the prediction accuracy of the model is better than that of the contrast models. The validity and feasibility of the method in the monthly load forecasting is verified.

Keywords: ensemble empirical mode decomposition; random forest; support vector machine; monthly load forecasting; economic influence

1. Introduction

Power load forecasting plays a key role in the power system operation and electricity market activities. The forecasting is still more important because it is the base of schedule of power system operation [1,2]. Electricity comes from traditional coal-fired power generation, wind power generation [3,4], solar power generation [5,6], biomass power generation [7] and tidal power generation [8]. These directions also require accurate load forecasting. Many activities within the power system such as the maintenance scheduling of generators, renewable-energy integration and even the investment of power plants and power grids depend on the monthly load forecasting. In the electricity market the regulators monitor the activities based upon the forecasting load and power generators [9]. Customers and power brokers decide their action strategies.

Power load forecasting has been studied for decades [10]. Various models, novel algorithms, advanced techniques and ingenious tricks have been developed to improve forecasting accuracy [11,12]. It was based on SVR and fuzzy-rough with PSO algorithms to forecast the residential sector's electricity demand. And the method can identify relevant variables for developing the forecasting model [13]. It discussed the effects of various models in energy planning and forecasting, with emphasis on the application of ANN in the field of load forecasting [14,15]. It introduced different power load forecasting models and combined regression model with machine learning model to forecast the power load of commercial buildings [16].

The time-series models present good performance with historical data. Taking exogenous variables into account, the econometric models have better forecasting capability [16]. The model combined dynamic model and fuzzy time series. When considering the weather factors, the prediction accuracy of the model was better than that of the traditional model [17]. It based on a hybrid model of autoregressive integrated moving average (ARIMA) and support vector machines (SVMs). The ARIMA was used to predict the linear fundamental part of the load and the SVM predicted the nonlinearly sensitive part of the load [18]. It considered many long memories seasonal data sets and combined Fuzzy Time Series and SARFIMA for short-term load forecasting [19].

Artificial Neural Networks, Support Vector Machine and other intelligence algorithms dominate in the forecasting field for their powerful approximation between the dependent variable and independent variables [20]. It used wavelet analysis to decompose historical load data and then used support vector machine and neural network to select appropriate parameters [21,22]. The single branch predictions for each sequence are separately made and each branch prediction results are reconstructed to achieve ultimate load forecasting [23]. It proposed the goa-svm model, which predicts short-term load for local climate conditions. The results show that the prediction accuracy was better than that of the traditional model and other mixed models [24]. A deep belief network model was incorporated into a feed-forward neural network. And the model was applied to short-term electricity load forecasting [25]. An improved empirical mode decomposition (EMD) model combined with Elman neural network was proposed to predict the building electricity load. Effectiveness of the proposed model was carried out to real-world engineering test case in comparison with other prediction models [26]. Neural network was combined with optimization techniques for finding optimal network parameters to reduce the forecasting error. Further, the proposed algorithm was integrated with neural network for the proper tuning of network parameters to solve the real-world problem of short term load forecasting [27]. It proposed an improved grey model to enhance the disadvantage of the general GM (1,1) model when the load mutation was large. A practical application verifies that, compared with the existing grey forecasting models. The proposed model is a stable and feasible forecasting model with a higher forecasting accuracy [28].

However, these functions require massive training samples and the performances are sensitive to model parameters and input. Until now, more efforts have been put to tune the model parameters and to select proper input. Wavelet Decomposition [29–31], Empirical Mode Decomposition(EMD) [32,33], Complete Ensemble Empirical Mode Decompositions with adaptive noise(CEEMDAN) [34] broke down the original sequence into several more regular sequences for modeling. The effectiveness of such techniques has been validated.

Random Forest (RF) is a novel machine learning algorithm developed in recent years [35–38]. RF is robust to the input and number of samples. The great advantage of RF has been validated in many forecasting contests. Someone proposed a short-term load predictor, able to forecast the next 24 h of load using RF [39].

The above traditional methods consider less economic data but in actual life, economic factors have a great impact on the load. The reason for the small consideration is that there are fewer economic data samples, more variables. There is redundancy between variables and the correlation between variables and load is low. So, the traditional method cannot solve this problem and random forest can solve the problem. At the same time, the law of medium and long-term load fluctuation is complicated and there may be multiple regular superpositions using EEMD decomposition. This paper uses random forests to overcome these problems for accurate monthly load forecasting.

The other sections of this paper are organized as follows: the basic principles and modeling process of EEMD and RF algorithms were introduced in the second section, then an experimental study of monthly electricity consumption forecasting was carried to validate the proposed method and the discussion and conclusion were made at the end section.

2. Methods

In the field of signal analysis, EMD is widely used in various engineering fields. Because it has obvious advantages in dealing with non-stationary and nonlinear data compared with other algorithms. Meanwhile, it has a high signal-to-noise ratio to guarantee data availability. In contrast to EMD, EEMD incorporates normally distributed white noise to aid analysis, which makes the signal continuous at different scales, thereby reducing the degree of modal aliasing. The introduction of the noise in load forecasting is mainly to resist the damage of bad data on the accuracy of prediction results and improve the robustness of the model.

The subsequent RF algorithm is an algorithm based on a combined decision tree. Because of its insensitivity to default on problems and its high tolerance to noise or outliers, it is widely used on the field of classification and regression. This paper uses RF algorithm to make use of its many advantages in the good adaptability of multiple data sets, excellent fitting ability and insensitivity to irrelevant variables.

2.1. EEMD Fundamental Principle

In the signal-processing process of EMD, if there is an uneven distribution of signal extreme points, modal aliasing problems will occur. In response to this problem, Huang proposed adding uniformly distributed white noise to the decomposed signal. The noise with a mean value of zero will be canceled out as the result after several times of average elimination on signals of different time scales. Specific steps are as follows:

(1) Add a random uniform Gaussian white noise sequence $H(t)$ to the original sequence $Y(t)$ to get the new sequence $Y_0(t)$;

$$Y_0(t) = Y(t) + H(t) \tag{1}$$

(2) Decompose the noise-added sequence $Y_0(t)$ into $IMF_i(t)$ and a residual series $R_n(t)$ using EMD;

$$Y_0(t) = \sum_{i=1}^{n} IMF_i(t) + R_n(t),\ (i = 1, 2, \ldots, n) \tag{2}$$

(3) Repeat steps (1) and (2) until a smooth decomposition signal is obtained;

(4) Calculate the average value of each decomposed $IMF_i(t)$ component as the result. N is the number of Gaussian white noise added

$$IMF_i(t) = \frac{1}{N}\ IMF_{ij}(t) \tag{3}$$

$$Y(t) = \sum_{j=1}^{n} IMF_i(t) + R(t) \tag{4}$$

The result of EEMD is shown as Formula (4). After increasing the uniform distribution of white noise, the occurrence of modal aliasing can be well improved and the degree of coincidence of each Y_IMF component to the overall trend and the fluctuation trend can be improved.

2.2. RF Fundamental Principle

RF is a collection method that aggregates many decision tree predictions and there is no correlation between each decision tree. The representation of RF is mainly reflected in the random sampling of features when the specimen is put back into a random number of the samples (bootstraps) and a decision tree is constructed. The introduction of this randomness is very helpful to the performance improvement of RF. Because of it, RF is not easy to fall into over-fitting and has good noise immunity (e.g., Insensitive to default). The specific modeling steps are as follows:

(1) Assume that the number of original data samples is N and the number of decision trees in RF is k. k decision trees are extracted from the N by resampling and the number of training specimens in each decision tree is n.
(2) Assume that the feature dimension of the input variable is M and any feature set whose number is m ($m < M$ and m remains unchanged) in M. Through these m features, the optimal splitting node is determined.
(3) RF consists of the k decision trees that grow as much as possible and do not require pruning.
(4) In the regression algorithm, the result of each decision tree is weighted and averaged to obtain the result.

2.3. Diebold Mariano Test

Diebold and Marino proposed the DM test to determine whether a model's predictive power is significantly different from another model [40]. Specific assumptions are as follows:

$$H_0 : \mathrm{E}[\mathrm{F}(e_t^1)] = \mathrm{E}[\mathrm{F}(e_t^2)] \tag{5}$$

$$H_1 : \mathrm{E}[\mathrm{F}(e_t^1)] \neq \mathrm{E}[\mathrm{F}(e_t^2)] \tag{6}$$

Formulas (5) and (6) are the null hypothesis and alternative hypothesis of the DM test, respectively e_t^1 and e_t^2 are the prediction errors between actual values and forecasted values of the different models and the function F is the loss function of forecasting errors.

$$\overline{d} = \frac{1}{L}\sum_{t=1}^{L}[\mathrm{F}(e_t^1) - \mathrm{F}(e_t^2)] \tag{7}$$

In Formula (7) $\overline{d}$ is the sample mean loss differential difference and L is the length of forecasting values.

$$DM = \frac{\overline{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{L}}} \rightarrow N(0,1) \tag{8}$$

From Formula (8) we can see the DM value converges to the normal distribution. $\hat{f}_d(0)$ is the zero-spectral density and $2\pi\hat{f}_d(0)$ is a consistent estimate of the asymptotic variance of $\sqrt{\mathrm{T}}\overline{d}$. So, after calculating DM value $|DM|$, we draw a conclusion by comparing $|DM|$ with $|Z_{\alpha/2}|$ from the standard normal distribution table. If $|DM|$ is less than $|Z_{\alpha/2}|$, we can accept the null hypothesis and consider the difference between the predictive powers of the two models to be inconspicuous. For example, if $|DM| \leq 1.96$, we accept the null hypothesis. Otherwise, $|DM| > 1.96$, then the null hypothesis is rejected at the 5% level.

2.4. Modeling Process

The specific modeling process is shown in Figure 1. The process is divided into three parts. First, the primary, secondary, tertiary industry and residential electricity original sequences are respectively decomposed into six components of Y_IMF1~Y_IMF5 and Y_R by EEMD. Then combine them into three components of high, medium and low frequency separately excepting Y_IMF1. Because the fluctuation frequency of Y_IMF1 is too large to be suitable for modeling. Secondly, the combined sequences are used for correlation analysis with economic and weather variables. The factors with higher correlation are selected as the input of different frequency models. Thirdly, the models are established by using the selected input and relative target value. Afterwards, the predicted values of different frequency sequences of different industries can be obtained through the models. The monthly load of the industry can be obtained by adding different frequency sequences of the same industry.

These industrial loads add up to the total social load.

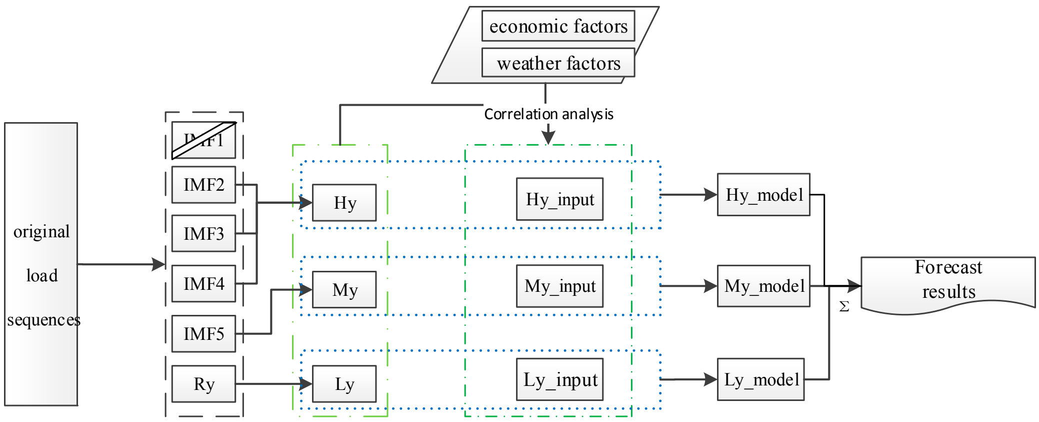


Figure 1. Monthly load forecasting flow chart based on EEMD-RF. (Notes: Hy: High frequency sequence; My: Medium frequency sequence; Ly: Low frequency sequence).

3. Empirical Research

3.1. Data Description and Data Processing

This article adopts the China's electricity consumption data from July 2009 to November 2017 from the National Bureau of Statistics of China and some power company. The electricity consumptions of primary, secondary, tertiary industries and resident are shown in Figure 2. Table A1 shows the input variables of economic and weather factors for modeling.

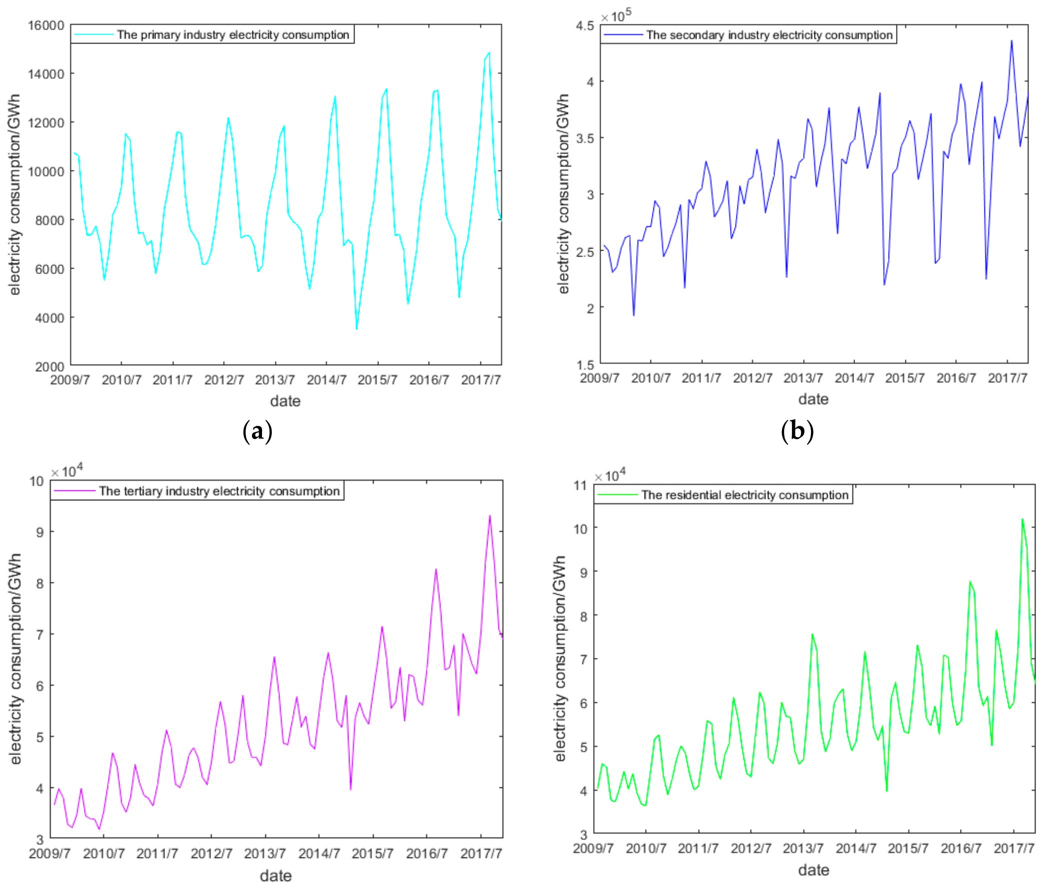


Figure 2. (**a**) the primary industry electricity consumption; (**b**) the secondary industry electricity consumption; (**c**) the tertiary industry electricity consumption; (**d**) the residential electricity consumption.

To avoid the influence of seasonal factors and other cyclical factors in the forecast results, the growth rate forecast method is adopted to handle four original power load sequences and the growth rate is to compare the data of the previous year.

In the prediction sequence, there is a lack of power consumption data for December 2009~2012. There are two main methods for missing data imputation. One is to use the 7~11 month-on-year growth average to reverse the missing data from 2013. The other is to use the average of the electricity consumption in December in the second half of the year to calculate the missing data. The specific method is selected based on the estimated errors in 2013~ 2017.

3.2. Data Set Division and Experimental Evaluation Index

Data sets are divided into training sets, validation sets and test sets according to different time spans. The goal of this article is to make accurate monthly load forecasts for the next six months, so the data from June to November of 2017 will be set as the final test set. The data of six months before November 2016 are randomly selected as the validation set for adjusting experimental parameters and verifying the effectiveness of the algorithm. The rests are training set for training models.

Based on the monthly national load demand forecast, this paper selects the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) as evaluation indicators. The expression is:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|T_i - P_i| \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - P_i)^2} \tag{10}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{T_i - P_i}{T_i}\right| \tag{11}$$

Among them, T_i is a real value. P_i is a prediction value and n is the number of selected prediction points. If the obtained MAPE is tinier, there is smaller difference between predicted value and actual load value. It shows that the prediction is more accurate.

3.3. Analysis of Specific Modeling Process

3.3.1. EEMD Factorization Variable

Use EEMD to decompose the primary, secondary, tertiary industrial electricity and residential electricity consumption sequences that need to be predicted. Since July 2009 to November 2017, there are 101 sets of data. In this paper, the electricity consumption is predicted two quarters ahead of time and the influential factors in the third quarter before the forecast periods are selected as the initial input variables. Because of the growth forecast, the data for the initial 12 months will be used as a basis. So, the N that needs to be decomposed is 80 ($101 - 6 - 3 - 12 = 80$). The number of components after EEMD can be obtained by the Formula (8), where the *fix* is rounded to 0. The number of solution scores is 5. The decomposition results are shown in Figure 3.

$$m = fix(\log2(N)) - 1 \tag{12}$$

In the process of EEMD decomposing the four original sequences into five components (Y_IMF1~Y_IMF5) and one residual component Y_R respectively, the standard deviation of added Gaussian white noise (Nstd) is 0.2 and the number of noise added is 100. From the decomposition of EEMD in Figure 3, it is unfavorable for the RF modeling prediction in the later period that the frequency of some component oscillations is very fast, so the high-frequency Y_IMF1 is discarded. For the latter low-frequency sequences, the components are superposed and combined in order to avoid that the single decomposition sequence has too great influence on the prediction accuracy. The combination method is that Y_IMF2, Y_IMF3 and Y_IMF4 make up high-frequency data. Y_IMF5 is regarded as a medium frequency sequence (My) and remainder Y_R is regarded as a low-frequency sequence (Ly).

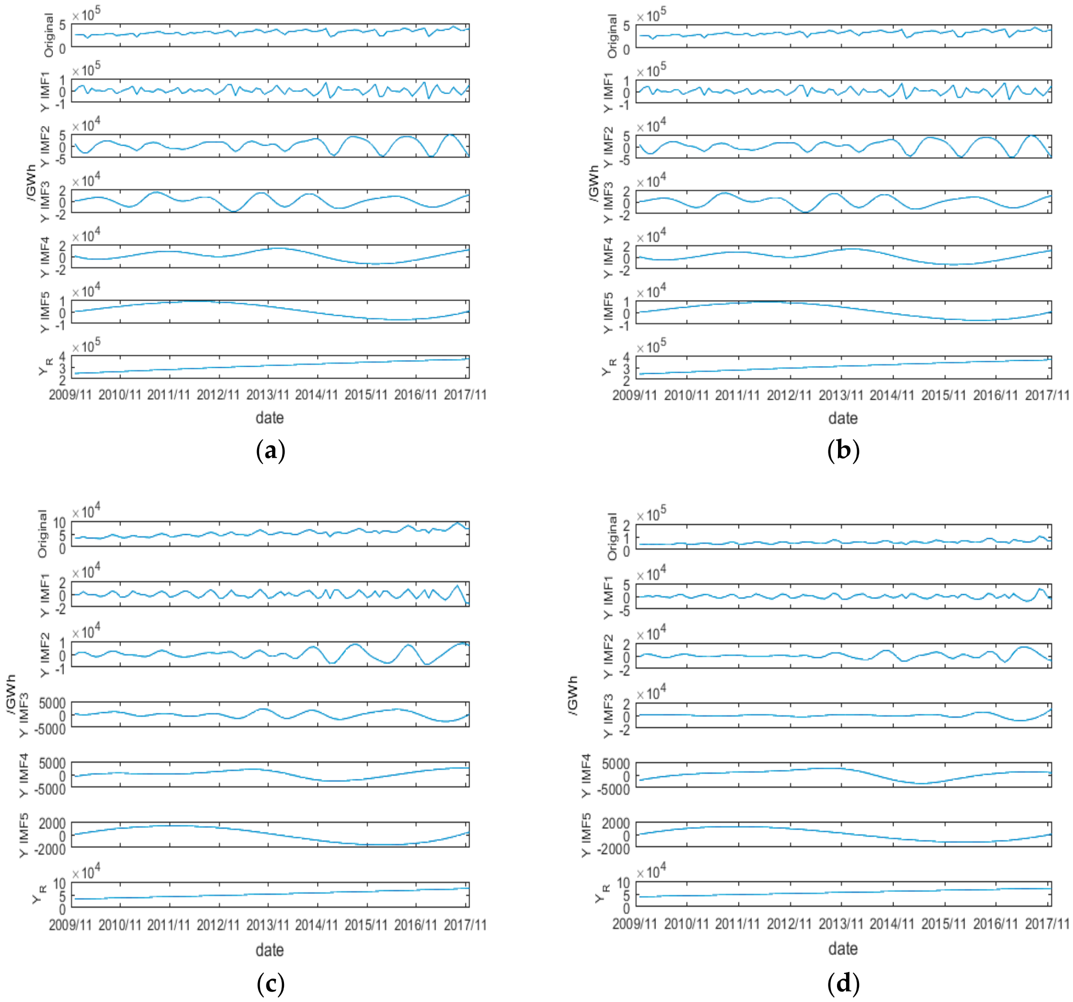


Figure 3. (**a**) EEMD decomposition of monthly the primary industrial electricity consumption; (**b**) EEMD decomposition of monthly the secondary industrial electricity consumption; (**c**) EEMD decomposition of monthly the tertiary industrial electricity consumption; (**d**) EEMD decomposition of monthly the residential electricity consumption.

3.3.2. Random Forest Modeling

Since the lead time of this paper is set at six months, the input of random forest is the external economic and weather index from seventh to the ninth before the predicted month. The total number of one month's relevant indices that can be found is 303. If you enter all the three-month indices into the model, it will undoubtedly bring infinite challenges to the complexity and accuracy of the model. To simplify the model and improve the accuracy of the model, this paper introduces the Kendall correlation coefficient to filter the input variables of the corresponding different frequency sequences of varied industry. By controlling the size of the correlation and the Kendall coefficient return value p, the final size of each model input variable is controlled to be between 15 and 40. Although random forests are highly inclusive for redundant data, proper screening of variables can also improve model prediction accuracy. Meanwhile, random forest is the tree regression model that does not require normalization of selected input variables. However, when the comparison models are established, the input variables must be normalized to remove the dimension of the variables.

In the RF modeling of high, medium and low frequency sequences, the number of random forests is the key to the effect on the model. Using MAPE as a criterion, RF modeling was performed on 50 to 1500 trees in the training set. In the case of different numbers of trees, the verification set MAPE behaves as shown in Figure 4.

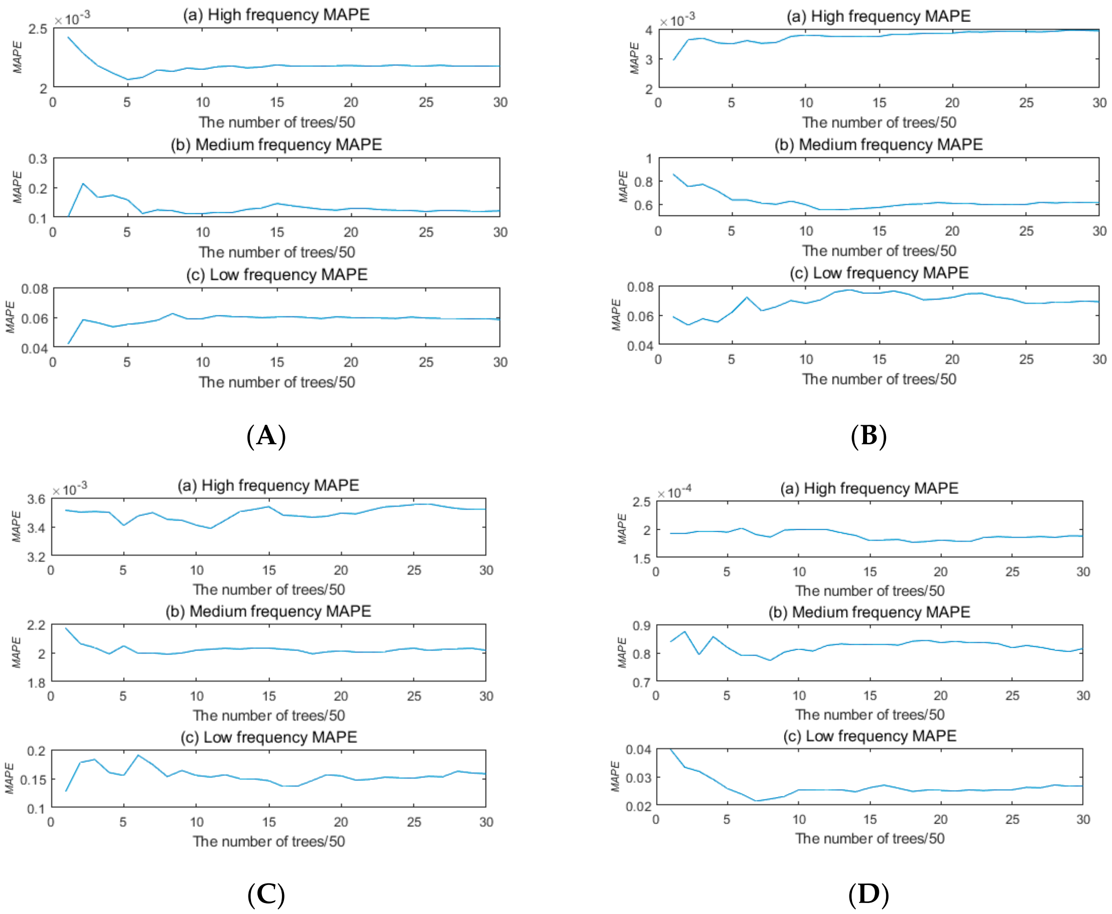


Figure 4. (**A**) Diverse serial verification set mean absolute percentage error (MAPE) for primary industries electricity for different number of trees; (**B**) Diverse serial verification set MAPE for secondary industries electricity for different number of trees; (**C**) Diverse serial verification set MAPE for tertiary industries electricity for different number of trees; (**D**) Diverse serial verification set MAPE for residential electricity for different number of trees.

From Figure 4, we can see that in the random forest modeling process of the first industry, the different frequency models achieve the optimal at 250 (5×50), 50 (1×50) and 50 (1×50) trees respectively. In the verification, the MAPE of the model is the smallest showing excellent adaptability. The test set modeling is then modeled using its optimal number. Similarly, it can be concluded that the best number of high, medium and low frequency data for the secondary and tertiary industries and residential electricity consumption are respectively 50 (1×50), 550 (11×50), 100 (2×50), 550 (11×50), 400 (8×50), 50 (1×50), 900 (18×50), 400 (8×50), 350 (7×50).

3.3.3. Cross Validation and Contrast Model Establishment

The models are tested multiple times with the set validation set before final testing. The validation set is randomly selected from data other than the test set. Table A2 shows six verification set errors.

This paper selects SVM and seasonal naïve method that has been approved by many experts and scholars in recent years for comparative analysis and compares the effect of adding EEMD on the accuracy of the model. Input variable selection methods of RF and SVM are the same as before.

Among them, the SVM needs to be normalized to the input before modeling. Seasonal naïve method only needs to be used for preliminary finishing of the original four power sequences.

4. Results Analysis

The model prediction results are divided into three parts. One is the forecast of electricity consumption by sub-industries. The second part is the forecast of the total social electricity consumption superimposed on the electricity consumption of sub-industries and the last part is the completion of the whole society electricity forecast for the simple use of combination forecasts. At the same time, because there is no essential difference between RMSE and MAE in a single month calculation, only MAE is marked in the table and RMSE is used as a reference when comparing results. The primary, secondary and tertiary industries and residential forecast results are shown in Table 1.

Table 1. The forecast error of the primary, secondary and tertiary industries and residential electricity.

	Date	RF		SVM		Seasonal Naïve		EEMD+RF	
		MAE/GWh	MAPE/%	MAE/GWh	MAPE/%	MAE/GWh	MAPE/%	MAE/GWh	MAPE/%
primary industry	June 2017	759.01	6.32	932.42	7.77	1219.64	10.16	178.52	1.49
	July 2017	885.42	6.09	839.29	5.77	1325.85	9.12	35.26	0.24
	August 2017	826.59	5.57	628.12	4.23	1562.18	10.53	360.82	2.43
	September 2017	336.60	3.11	230.92	2.14	317.48	2.94	560.39	5.19
	October 2017	229.35	2.73	39.85	0.47	298.55	3.55	348.28	4.14
	November 2017	17.89	0.23	36.37	0.46	241.46	3.06	310.50	3.93
	average	509.14	4.01	451.16	3.47	827.53	6.56	298.96	2.90
Secondary industry	June 2017	10,153.86	2.66	8146.92	2.13	19,551.72	5.11	3854.71	1.01
	July 2017	36,299.22	8.32	17,527.41	4.02	38,641.13	8.86	12,005.20	2.75
	August 2017	18,760.53	4.82	11,782.69	3.03	9453.57	2.43	6522.62	1.68
	September 2017	25,011.87	7.31	4318.14	1.26	16,010.54	4.68	6794.00	1.99
	October 2017	13,456.31	3.69	13,432.03	3.68	10,273.23	2.81	11,723.03	3.21
	November 2017	13,253.66	3.40	13,077.42	3.35	13,394.27	3.43	8633.36	2.21
	average	19,489.24	5.03	11,380.77	2.91	17,887.41	4.55	8255.49	2.14
Tertiary industry	June 2017	500.59	0.71	1745.41	2.49	6995.11	9.97	393.32	0.56
	July 2017	628.84	0.75	2678.48	3.19	9759.58	11.62	455.03	0.54
	August 2017	349.02	0.37	2213.77	2.38	10,524.40	11.30	919.70	0.99
	September 2017	99.37	0.12	1034.56	1.24	8814.73	10.56	281.07	0.34
	October 2017	445.60	0.63	1321.19	1.87	7861.93	11.11	1521.72	2.15
	November 2017	1619.15	2.36	2096.29	3.05	5426.42	7.90	1878.78	2.73
	average	607.10	0.82	1848.28	2.37	8230.36	10.41	908.27	1.22
Residential	June 2017	511.08	0.85	191.98	0.32	4150.09	6.92	136.92	0.23
	July 2017	1716.82	2.37	1808.31	2.50	5180.11	7.15	200.42	0.28
	August 2017	10,646.75	10.43	6006.67	5.88	14,459.13	14.16	7968.42	7.80
	September 2017	7485.38	7.85	4537.75	4.76	10,017.71	10.51	3856.98	4.05
	October 2017	1065.12	1.55	2274.33	3.30	5572.24	8.10	705.25	1.02
	November 2017	1161.40	1.81	823.43	1.28	4785.48	7.46	404.79	0.63
	average	3764.43	4.14	2607.08	3.01	7360.79	9.05	2212.13	2.33

The sub-industry fit and prediction curve is shown in Figure 5. The left side of the vertical line is the fitted curve and the right side is the predicted curve. It can be seen from the fitting curve that seasonal naïve method has a poor fitting effect, because of reflecting volatility earlier or later.

After comparing the four methods of MAE, MAPE and RMSE, it was found that the EEMD-RF model about primary industry had the highest degree of agreement with MAE of 298.96 GWh, MAPE of 2.90% and RMSE of 340.35 GWh. The SVM and RF that were not processed by EEMD were the next with MAE of 451.16 and 509.14 GWh, MAPE of 3.47% and 4.01% and RMSEs of 580.89 and 606.84 GWh. The poor performance of seasonal naïve method in the primary industry forecast is since the algorithm does not reflect the external changes in time. When the EEMD is not used for decomposition the RF cannot recognize the increase in the error caused by the external weather-related load.

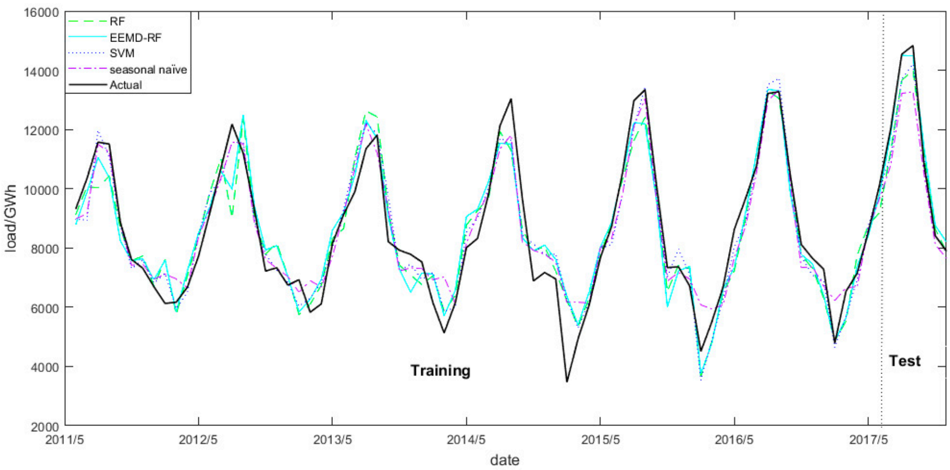
The secondary industry fit and prediction curve is shown in Figure 5b. After the three evaluation criteria, the same EEMD-RF model was found to have the highest degree of agreement with MAE of 8255.49 GWh, MAPE of 2.14% and RMSE of 8752.63 GWh. The performance of SVM and seasonal naïve method followed with MAE of 11,380.77 and 17,887.41 GWh, MAPE of 2.91% and 4.55% and RMSE of 12,127.78 and 20,437.14 GWh. The RF model has the same problems as the primary industry forecast. Under the premise of setting a long lead time, the useful information cannot be distinguished well and the accuracy of the model is reduced. In the secondary industry forecast, EEMD optimizes its input variables for RF where the impact of noise is less than the benefits of the EEMD decomposition variables, so the results increase slightly.

The tertiary industry fitting and prediction curve is shown in Figure 5c. After comparing, the RF model was found to be in leading state and the MAE was 607.10 GWh, the MAPE was 0.82% and the RMSE was 774.37 GWh. The RF treated with EEMD and SVM performed second with MAE of 908.27 and 1848.28 GWh, MAPE of 1.22% and 2.37% and RMSE of 1090.27 and 8405.35 GWh. The good fit into the RF model is related to the third industry load characteristics. The tertiary industry is mainly the service industry. The load of such industries is relatively stable and there is no obvious fluctuation in demand. In the parameter, selection is not taken into account but a large-scale input like other industries into the model. This makes the RF insensitivity to the variables fully utilized and achieves results higher than the EEMD decomposition model.

The residential electricity fitting and prediction curve is shown in Figure 5d. Residual electricity forecast results can be found from Table 1. The forecasting effect was consistent with that of the secondary industry. The EEMD-RF model had the highest degree of agreement with MAE of 2212.13 GWh, MAPE of 2.33% and RMSE of 3630.70 GWh. The SVM model and RF followed with MAE of 2607.08 and 3764.43 GWh, MAPE of 3.01% and 4.14% and RMSE of 3312.32 and 5401.80 GWh, respectively. The seasonal naïve method performed poorest.

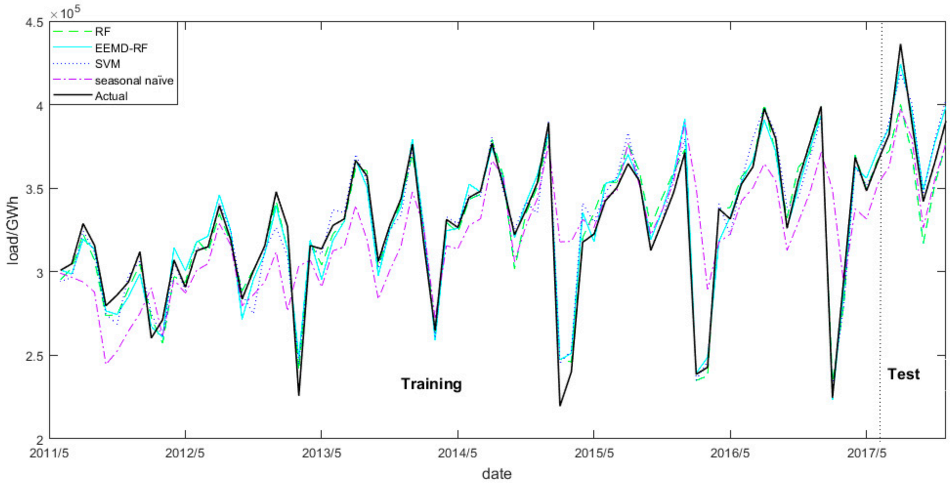
For each method, the six-months electricity consumption forecast of the whole society is shown in Table 2. We can see that the best method is the EEMD-RF method with MAPE of 1.34% and MAE of 7447 GWh. Followed by SVM and RF, EEMD-RF accuracy stands out. The seasonal naïve method provides a comparison index, which proves that other algorithms have certain feasibility.

The two methods EEMD-RF and SVM with the best average effect on the verification set are used to perform combined forecasting. The two methods are simply averaged to obtain the final forecast result, as shown in Table 3. From the combined forecasting results, we can see that the last forecasting accuracy is about 10% higher than that of the single model, with the MAE raised to 6828 GWh and the MAPE raised to 1.24%. However, this completely depends on the average fitness of the selected model. If there is a poor fit of a single model, it can easily affect the effect of its combined forecast. This is why we have to give up the direct modeling of SVM and RF.



(**a**)

Figure 5. *Cont.*



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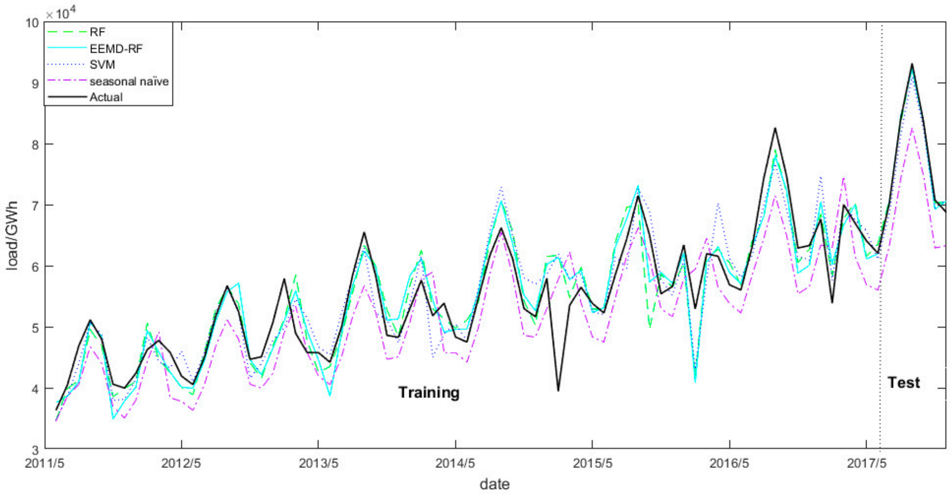
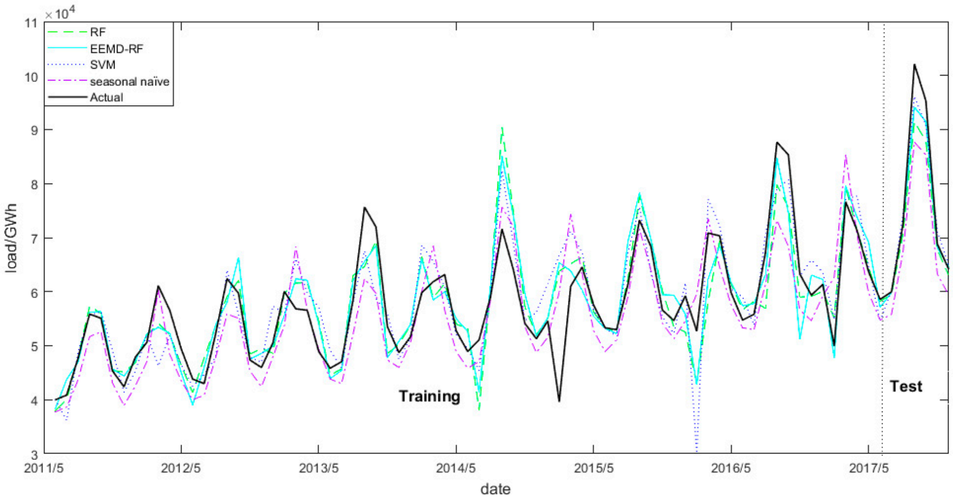


(**c**)



(**d**)

Figure 5. (**a**) Fitting situation of monthly the primary industrial electricity consumption; (**b**) Fitting situation of monthly the secondary industrial electricity consumption; (**c**) Fitting situation of monthly the tertiary industrial electricity consumption; (**d**) Fitting situation of monthly the residential electricity consumption.

Table 2. Six months' electricity forecast for each method/GWh.

Date	Orig	RF	MAE	MAPE/%	SVM	MAE	MAPE/%	Snaïve	MAE	MAPE/%	EEMD-RF	MAE	MAPE/%
June 2017	524,442	513,518	10,923	2.08	532,349	7907	1.51	492,525	31,917	6.09	526,236	1794	0.34
July 2017	607,242	567,712	39,530	6.51	590,055	17,187	2.83	552,336	54,907	9.04	592,323	14,919	2.46
August 2017	599,108	568,525	30,583	5.1	603,907	4799	0.8	563,109	35,999	6.01	595,088	4020	0.67
September 2017	531,682	499,621	32,061	6.03	531,793	111	0.02	496,522	35,160	6.61	534,145	2463	0.46
October 2017	512,995	498,258	14,738	2.87	528,296	15,301	2.98	488,989	24,006	4.68	523,040	10,045	1.96
November 2017	531,016	518,202	12,814	2.41	546,499	15,484	2.92	507,168	23,848	4.49	542,461	11,445	2.16

Table 3. Six months' electricity consumption combined forecasting for the whole society/GWh.

Date	Primary Industry	Secondary Industry	Tertiary Industry	Residential	Pred	Orig	MAE	MAPE/%
June 2017	11,587	387,474	69,039	59,778	527,878	524,442	3436	0.66
July 2017	14,210	425,028	81,535	72,450	593,224	607,242	14,018	2.31
August 2017	14,225	400,253	90,895	93,865	599,237	599,108	129	0.02
September 2017	11,206	348,348	82,307	90,031	531,892	531,682	209	0.04
October 2017	8652	377,706	69,236	68,610	524,204	512,995	11,208	2.18
November 2017	8128	400,536	69,901	64,418	542,984	531,016	11,968	2.25

5. Discussion

DM test is used to verify the validity of the model being developed. All other models were compared to the EEMD-RF model. According to the DM test principle proposed above, the null hypothesis is that the prediction abilities of the two models are similar and the other hypothesis is that there are significant differences in the prediction performance of the two models. Table 4 shows us the DM value about EEMD-RF and other models with MAE and MAPE.

Table 4. DM test of different models.

	DM-MAE				DM-MAPE			
	Primary	**Secondary**	**Tertiary**	**Residential**	**Primary**	**Secondary**	**Tertiary**	**Residential**
RF	1.968	2.149	2.155	1.700	1.987	2.408	2.054	1.856
SVM	1.977	2.687	2.284	1.653	2.015	2.741	2.368	1.743
snaïve	1.950	1.968	5.502	2.629	2.090	1.972	9.222	5.181

Except for residential electricity DM value less than 1.960, other values are more than 1.960. It indicates that the EEMD-RF model is different from the other models at a 5% significance level in sub-industry load forecasting. Thus, the null hypothesis could be rejected at a 5% significance level. The DM value of residential electricity is less than 1.960 and greater than 1.645, indicating EEMD-RF model is different from RF and SVM at a 10% significance level. Thereby, the null hypothesis could be rejected at a 10% significance level. Therefore, the proposed EEMD-RF model significantly outperforms the other models.

6. Conclusions

In this paper, the input of the model, the optimization of the model parameters and combinatorial prediction are used to forecast the electricity load of the whole population in China. On the model input, selecting the economic data from the National Bureau of Statistics of China as the model input increases the accuracy of the model by about 15% over the pure use of power data and other data. At the same time, EEMD is used to decompose the prediction sequence, analyze the original sequence fluctuation trend and improve the correlation between the predictor and the input variable. In the optimization of model parameters due to fewer random variables in the RF, similar enumeration method is used to complete model optimization in a certain range of values. The idea of aggregation is respectively embodied in the model after EEMD decomposition, the prediction results are added together and the accuracy of the model is improved through the combination of prediction methods.

By applying EEMD and RF to the national monthly electricity usage data, it was found that the improved model achieved better accuracy than the traditional SVM and the error was reduced by 10~25% compared to the single random forest. It reflects the dynamic characteristics of the original sequence and verifies the effectiveness of the method in monthly load forecasting. At the same time, the advantage of using RF for variable insensitivity is reduced and the prediction error caused by unstable noise to the model is reduced, the model generalization ability is improved and it can be applied to different prediction fields. Because there are steps in the EEMD of the later reconstruction pre-diction results when each component is modeled in a RF merely the effects of a unitary model is considered. The parameters that make the single model topgallant are sought and the global optimum results cannot be obtained, only getting the sub-optimal results. Therefore, we can continue to carry out the next stage research on how to achieve the optimal parameters of combined forecasting.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Number and meaning of input variables.

Number	Meaning	Number	Meaning
001	average temperature	153	Export value of metal products export growth (%)
002	Average maximum temperature	154	Export value of general equipment manufacturing industry increased by year (%)
003	Mean minimum temperature	155	Export value of special equipment manufacturing industry increased by year (%)
004	Absolute maximum temperature	156	Export value of electrical machinery and equipment manufacturing industry increased by year (%)
005	Absolute minimum temperature	157	Export delivery value of computers, telecommunications and other electronic equipment manufacturing industry increased by year (%)
006	Precipitation	158	Export value of instrument manufacturing industry increased by year (%)
007	The number of days of precipitation equal to or greater than 1 mm	159	Exports of other manufacturing exports increased year-on-year (%)
008	The number of days of precipitation equal to or greater than 0.1 mm	160	Export delivery value of waste comprehensive utilization industry increased by year (%)
009	The number of snow days	161	The delivery value of electricity, heat production and supply industry increased by year (%)
010	Storm days	162	The delivery value of gas production and supply industry increased by year (%)
011	Foggy days	163	The delivery value of water production and supply industry increased by year (%)
012	Frost days	164	The value of cargo throughput at the port scale above sea level (ten thousand tons)
013	Maximum temperature (reliability index)	165	The current value of the throughput of foreign trade goods (ten thousand tons)
014	Minimum temperature (reliability index)	166	Value of freight volume (ten thousand tons)
015	Precipitation (reliability index)	167	The current value of railway freight volume (ten thousand tons)
016	Industrial producer purchasing price index (same month last year = 100)	168	The current value of highway freight volume (ten thousand tons)
017	Fuel and power purchase price index (same month last year = 100)	169	Current value of water transport freight volume (ten thousand tons)
018	Black metal material purchase price index (same month last year = 100)	170	Current value of civil aviation freight volume (ten thousand tons)
019	Purchase price index of nonferrous metals and wires (same month last year = 100)	171	Turnover of goods turnover (100 million tons)
020	Purchase price index of chemical raw materials (same month last year = 100)	172	The current value of railway freight turnover (hundreds of millions of tons)
021	Wood and pulp purchase price index (same month last year = 100)	173	The current value of highway cargo turnover (100 million tons)
022	Purchase price index of building materials and nonmetallic minerals (same month last year = 100)	174	The current value of the turnover of waterborne goods (hundreds of millions of tons)
023	Purchase price index of other industrial raw materials and semi-finished products (same month last year = 100)	175	Civil aviation cargo turnover current value (100 million tons)
024	Purchase price index of agricultural and sideline products (same month last year = 100)	176	Value of passenger traffic volume (ten thousand people)
025	Purchase price index of textile raw materials (same month last year = 100)	177	The value of railway passenger traffic volume (ten thousand people)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
026	Producer price index for industrial producers (same month last year = 100)	178	Traffic volume of highway passenger volume (ten thousand people)
027	Producer price index of producer goods (same month last year = 100)	179	Water transport passenger traffic volume (10,000 people)
028	Producer price index of producer of living goods (same month last year = 100)	180	Passenger volume of civil aviation passenger volume (10,000 people)
029	Producer price index of producer goods (same month last year = 100)	181	Turnover of passenger turnover (100 million kilometers)
030	Producer price index of producer goods for mining industry (same month last year = 100)	182	Railway passenger turnover in the current period (100 million kilometers)
031	Producer price index of producer goods for raw material industry (same month last year = 100)	183	Highway passenger turnover in the current period (100 million kilometers)
032	Processing industry producer goods producer price index (same month last year = 100)	184	Water transport passenger turnover rate (100 million kilometers)
033	Producer price index of producer of living goods (same month last year = 100)	185	Civil aviation passenger turnover in the current period (100 million kilometers)
034	Producer price index for food industry producers (same month last year = 100)	186	Cumulative value of total retail sales of consumer goods ($100 million)
035	Clothing factory producer price index (same month last year = 100)	187	Retail value of clothing, shoes, hats, needles and textile commodities: cumulative value (100 million yuan)
036	Producer price index for general consumer goods manufacturers (same month last year = 100)	188	Cumulative value of retail sales of clothing commodities (100 million yuan)
037	Durable consumer goods producer price index (same month last year = 100)	189	Cumulative value of retail sales of cosmetics commodities (100 million yuan)
038	Producer price index for metallurgical industry (same month last year = 100)	190	Cumulative value of retail sales of household appliances and audio-visual equipment (100 million yuan)
039	Producer price index for power producers (same month last year = 100)	191	Cumulative value of retail sales of furniture commodities (100 million yuan)
040	Producer price index of coal and coking industry producers (same month last year = 100)	192	Cumulative value of retail sales of building and decoration materials (100 million yuan)
041	Producer price index for oil producers (same month last year = 100)	193	Value of gold, silver and jewelry retail sales value (100 million yuan)
042	Producer price index of chemical industry (same month last year = 100)	194	Cumulative value of retail sales of grain, oil, food, beverages, cigarettes and alcoholic drinks (100 million yuan)
043	Producer price index for machinery industry (same month last year = 100)	195	Cumulative value of grain, oil and food retail sales (100 million yuan)
044	Producer price index for producer of building materials industry (same month last year = 100)	196	Cumulative value of retail sales of beverage commodities ($100 million)
045	Producer price index of forest industry producer (same month last year = 100)	197	Cumulative value of retail value of tobacco and wine commodities (billion yuan)
046	Producer price index of food industry (same month last year = 100)	198	Cumulative value of retail sales of other commodities ($100 million)
047	Producer price index of textile industry (same month last year = 100)	199	Cumulative value of retail sales of automobile commodities (100 million yuan)
048	Producer price index for sewing industrial producers (same month last year = 100)	200	Cumulative value of retail value of daily use commodities (billion yuan)
049	Producer price index of leather industry producer (same month last year = 100)	201	Cumulative value of retail sales of petroleum and products (100 million yuan)
050	Producer price index for producer of paper industry (=100 of last year)	202	Cumulative value of retail sales of books, magazines and magazines (100 million yuan)
051	Producer price index of industrial and cultural arts and Crafts Industrial producer (same month last year = 100)	203	Cumulative value of retail sales of sports and entertainment commodities (100 million yuan)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
052	Producer price index for other industrial producers (same month last year = 100)	204	Cumulative value of retail sales of communications equipment (100 million yuan)
053	Producer price index for industrial producers (same month last year = 100)	205	Cultural and office goods retail value (100 million yuan)
054	Industrial producer price index for coal mining and washing industry (same month last year = 100)	206	Cumulative value of retail sales of Chinese and Western medicines (100 million yuan)
055	Producer price index for industrial producer of oil and natural gas (=100 of last year)	207	Cumulative value of real estate construction area (10,000 square meters)
056	Black metal ore mining industry producer price index (same month last year = 100)	208	Cumulative area of newly built real estate (10,000 square meters)
057	Producer price index of industrial producer of nonferrous metal mining industry (same month last year = 100)	209	Cumulative value of completed area of real estate (10,000 square meters)
058	Producer price index of industrial producer of non-metallic mineral industry (=100 of last year)	210	Accumulative value of construction area of office building (ten thousand square meters)
059	Ex-factory price index for mining and auxiliary activities (=100 of last year)	211	The total area of newly built office buildings is accumulated (10,000 square meters)
060	Producer price index of industrial producers in agricultural and sideline products processing industry (same month last year = 100)	212	Accumulated value of office building area (10,000 square meters)
061	Producer price index of industrial producers in food industry (=100 of last year)	213	Accumulative value of construction area of commodity residence (ten thousand square meters)
062	Ex-factory price index for industrial producers of wine, beverages and refined tea (same month last year = 100)	214	Cumulative area of newly built commercial housing area (ten thousand square meters)
063	Producer price index for industrial products in tobacco industry (same month last year = 100)	215	Accumulated value of the completed area of a commodity house (ten thousand square meters)
064	Producer price index of textile industrial producers (same month last year = 100)	216	Cumulative area of commercial business space (10,000 square meters)
065	Producer price index of industrial producer of textile, clothing and apparel industry (same month last year = 100)	217	The accumulative value of construction area for commercial business premises (10,000 square meters)
066	Ex-factory price index for leather, fur, feather and its products and footwear manufacturers (same month last year = 100)	218	Cumulative area of commercial business space (10,000 square meters)
067	Ex-factory price index for timber processing and industrial producer of wood, bamboo, rattan, brown and straw products (same month last year = 100)	219	Cumulative value of sales area of office buildings (10,000 square meters)
068	Furniture producer industrial producer price index (same month last year = 100)	220	The total sales area of office buildings (10,000 square meters)
069	Producer price index for industrial producers of paper and paper products (same month last year = 100)	221	The total sales area of office buildings will be accumulated (10,000 square meters)
070	Printing and recording media reproduction industry producer price index (same month last year = 100)	222	Cumulative value of commodity housing sales area (10,000 square meters)
071	Producer price index for industrial producers in culture, education, industry, sports and entertainment products (same month last year = 100)	223	The total sales area of commercial housing is accumulated (10,000 square meters)
072	Petroleum, coal and other fuel processing industry producer price index (same month last year = 100)	224	The total sales area of commercial housing will be accumulated (10,000 square meters)
073	Producer price index for industrial producers of chemical raw materials and chemical products (same month last year = 100)	225	Accumulative value of sale area of commodity house (ten thousand square meters)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
074	Factory producer price index for pharmaceutical manufacturers (same month last year = 100)	226	The total sales area of commercial housing is about 10,000 square meters
075	Producer price index for industrial producer of chemical fiber industry (same month last year = 100)	227	The total sales area of commercial housing will be accumulated (10,000 square meters)
076	Producer price index for industrial producer of rubber and plastic products (same month last year = 100)	228	The total sales area of commercial business space is accumulated (10,000 square meters)
077	Ex-factory price index for industrial producers of non-metallic mineral products (same month last year = 100)	229	The total sales area of commercial business premises is accumulated (10,000 square meters)
078	Producer price index of industrial producers in ferrous metal smelting and calendaring processing industry (same month last year = 100)	230	The total sales area of commercial business premises will be accumulated (10,000 square meters)
079	Producer price index of industrial producers in nonferrous metal smelting and calendaring processing industry (same month last year = 100)	231	Total value of office building sales ($100 million)
080	Ex-factory price index for industrial producers of metal products (same month last year = 100)	232	Total value of present house sales of office building (100 million yuan)
081	Producer price index for industrial producer of general equipment manufacturing (=100 of last year)	233	Total value of office building sales volume ($100 million)
082	Producer price index of industrial producer for special equipment manufacturing industry (same month last year = 100)	234	Cumulative value of commodity housing sales ($100 million)
083	Ex-factory price index for industrial vehicle manufacturers (same month last year = 100)	235	Accumulative value of present house sales of commodity housing (billion yuan)
084	Ex-factory price index for industrial producers in railways, ships, aerospace and other transport equipment manufacturing industries (same month last year = 100)	236	Cumulative value of commodity housing sales volume ($100 million)
085	Producer price index of industrial producer for electrical machinery and equipment manufacturing (=100 of last year)	237	Cumulative value of commodity house sales ($100 million)
086	Producer price index for industrial producer computers, telecommunications and other electronic equipment manufacturers (same month last year = 100)	238	Accumulative value of present housing sales of commodity house (billion yuan)
087	Industrial producer price index for instrument manufacturing industry (same month last year = 100)	239	Cumulative value of commodity house sales volume ($100 million)
088	Producer price index for other manufacturing industries (same month last year = 100)	240	Cumulative value of commercial business housing sales ($100 million)
089	Ex-factory price index of industrial producer of waste comprehensive utilization industry (=100 of last year)	241	The total value of existing commercial housing sales is 100 billion yuan
090	Metal producer, machinery and equipment repair industry producer price index (same month last year = 100)	242	Cumulative sales value of commercial business premises (100 million yuan)
091	Producer price index of industrial producers in electricity, heat production and supply industries (same month last year = 100)	243	Cumulative value of land acquisition area of real estate (10,000 square meters)
092	Producer price index of industrial producer for gas production and supply industry (same month last year = 100)	244	Accumulated value of land transaction price of real estate industry (billion yuan)
093	Producer price index of industrial producers in water production and supply industry (same month last year = 100)	245	Cumulative value of real estate investment ($100 million)
094	Cumulative value of export value of industrial exports (100 million yuan)	246	Cumulative value of real estate investment ($100 million)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
095	Cumulative value of export value of coal mining and washing industry (100 million yuan)	247	Cumulative value of housing investment of 90 square meters and below (100 million yuan)
096	Cumulative value of export value of oil and natural gas extraction industry (100 million yuan)	248	Cumulative value of housing investment over 144 square meters (billion yuan)
097	The cumulative value of export value of non-ferrous metal mining and export industry (100 million yuan)	249	Accumulative value of villa and high-grade apartment investment (billion yuan)
098	Cumulative value of export value of non-metallic ore mining and export industry (100 million yuan)	250	Total value of investment in real estate office building (100 million yuan)
099	Export value of agricultural and sideline products processing industry accumulated value (100 million yuan)	251	Cumulative value of investment in commercial real estate business (100 million yuan)
100	The cumulative value of the export delivery value of the food manufacturing industry (100 million yuan)	252	Cumulative value of other real estate investment ($100 million)
101	Export value of liquor, beverages and refined tea manufacturing industry value accumulated (100 million yuan)	253	Cumulative value of investment in real estate development and construction projects (100 million yuan)
102	The cumulative value of the export delivery value of the tobacco products industry (billion yuan)	254	Cumulative value of investment in real estate development and installation projects (100 million yuan)
103	The cumulative value of the export delivery value of the textile industry (100 million yuan)	255	Cumulative value of investment in real estate equipment and equipment purchase (100 million yuan)
104	Export value of textile, clothing and apparel industry accumulated value (100 million yuan)	256	Cumulative value of other investment in real estate investment ($100 million)
105	Export value of leather, fur, feathers and their products and footwear industry accumulated value (100 million yuan)	257	Real estate land purchase fee accumulative value (100 million yuan)
106	Export value of timber processing, timber, bamboo, rattan, brown and straw products accumulated value (100 million yuan)	258	Total investment of real estate development plan (100 million yuan)
107	Total value of export delivery value of furniture manufacturing industry (billion yuan)	259	Added value of fixed assets investment in real estate development (100 million yuan)
108	Export value of paper and paper products, accumulated value (100 million yuan)	260	Accumulative value of the source of investment funds of real estate (billion yuan)
109	Cumulative value of export delivery value of printing and recording media reproduction industry (100 million yuan)	261	Accumulated value of capital surplus in real estate investment last year (100 million yuan)
110	The total value of delivery value of exports of culture, education, industry, sports and entertainment products (100 million yuan)	262	Real estate investment this year, the total amount of funds is accumulated (100 million yuan)
111	Export value of oil, coal and other fuel processing industry accumulated value (100 million yuan)	263	Real estate investment domestic loan accumulative value (billion yuan)
112	Export value of chemical raw materials and chemical products manufacturing value accumulated value (100 million yuan)	264	Total value of investment and utilization of foreign investment in real estate investment (billion yuan)
113	The cumulative value of the export delivery value of the pharmaceutical manufacturing industry (100 million yuan)	265	Accumulative value of self-financing of real estate investment (billion yuan)
114	Cumulative value of export value of chemical fiber manufacturing industry (100 million yuan)	266	Cumulative value of other funds for real estate investment ($100 million)
115	Export value of non-metallic mineral products industry accumulated value (100 million yuan)	267	The total value of the real estate investment should be paid ($100 million)
116	Export value of ferrous metal smelting and calendaring processing industry value accumulated value (100 million yuan)	268	Cumulative value of real estate investment projects ($100 million)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
117	Export value of non-ferrous metal smelting and calendaring processing industry value accumulated value (100 million yuan)	269	Fixed long distance telephone call duration (IP) and current value (ten thousand minutes)
118	The cumulative value of the export delivery value of the metal products industry (100 million yuan)	270	The value of a long term (ten thousand minutes) for a mobile phone call
119	Export value of general equipment manufacturing industry accumulated value (100 million yuan)	271	End value of subscriber number (ten thousand households) at the end of a fixed phone
120	Export value of special equipment manufacturing industry: cumulative value (100 million yuan)	272	End of user number (10,000) at the end of city phone year
121	Export value of electrical machinery and equipment manufacturing industry accumulated value (100 million yuan)	273	End of user number (ten thousand households) at the end of rural telephone year
122	Export value of computers, telecommunications and other electronic equipment manufacturing industry accumulated value (100 million yuan)	274	Terminal value of mobile phone users (10,000 households)
123	Export value of instrument manufacturing industry: cumulative value (100 million yuan)	275	Mobile SMS business volume (100 million)
124	Cumulative value of export value of other manufacturing exports ($100 million)	276	Number of letters in the current period (100 million)
125	Cumulative value of export delivery value of waste resources comprehensive utilization industry (100 million yuan)	277	The value of the number of packages (10,000 pieces)
126	Cumulative value of delivery value of electricity, heat production and supply industry (100 million yuan)	278	The current value of the bill of exchange (ten thousand)
127	Cumulative value of delivery value of gas production and supply industry (100 million yuan)	279	Number of newspapers in the current period (ten thousand)
128	The cumulative value of delivery value of water production and supply industry (100 million yuan)	280	Number of magazines in the current period (ten thousand)
129	Year-on-year increase in export value of industrial exports (%)	281	Value of express volume (10,000 pieces)
130	Export value of coal mining and washing industry increased by year (%)	282	The current value of the total telecommunications business (100 million yuan)
131	Export value of oil and natural gas extraction industry grew by year on year (%)	283	The end value of the supply of money and quasi money (M2)
132	The delivery value of non-ferrous metal mining and export industry increased by year (%)	284	Monetary and quasi currency (M2) supply growth (%)
133	The delivery value of non-metallic ore mining and export industry increased by year (%)	285	Money (M1) supply terminal value (billion)
134	Export value of agricultural and sideline products processing industry increased by year (%)	286	Money (M1) supply growth (%)
135	Food manufacturing export delivery value increase (%)	287	Cash (M0) supply at the end of the period (billion yuan)
136	Export value of wine, beverages and refined tea manufacturing increased by year (%)	288	Cash (M0) supply in circulation increased year-on-year (%)
137	Export value of tobacco products export growth (%)	289	Consumer price index (=100 of the same month of the previous year)
138	Export delivery value of textile industry increase (%)	290	Consumer price index for food, tobacco and alcoholic drinks (same month last year = 100)
139	Export value of textile, clothing and apparel industry increased by year (%)	291	Clothing consumer price index (same month last year = 100)
140	Export value of leather, fur, feather and its products and footwear industry increased by year (%)	292	Consumer price index for residential residents (same month last year = 100)
141	Export value of timber processing and timber, bamboo, rattan, brown and straw products increased by year (%)	293	Consumer price index for consumer goods and services (same month last year = 100)

Table A1. *Cont.*

Number	Meaning	Number	Meaning
142	Export value of furniture manufacturing export increase (%)	294	Consumer price index for transport and communications (=100 of last year)
143	Export delivery value of paper and paper products increased year by year (%)	295	Education, culture and entertainment consumer price index (same month last year = 100)
144	Export delivery value of printing and recording media replication industry increased year by year (%)	296	Consumer price index for health care residents (same month last year = 100)
145	The delivery value of exports of culture, education, industry, sports and entertainment products increased by year (%)	297	Consumer price index for other supplies and services (=100 of last year)
146	Export value of oil, coal and other fuel processing industries increased by year (%)	298	Food consumer price index (same month last year = 100)
147	Export value of chemical raw materials and chemical products manufacturing increased by year (%)	299	Food consumer price index (same month last year = 100)
148	Increase in export delivery value of pharmaceutical manufacturing industry (%)	300	The consumer price index of egg residents (=100 of the same month of the same year)
149	Export value of chemical fiber manufacturing industry increased by year (%)	301	Consumer price index for aquatic products (same month last year = 100)
150	Export value of non-metallic mineral products industry increased by year (%)	302	Fresh vegetable consumer price index (same month last year = 100)
151	Export value of ferrous metal smelting and calendaring processing industry increased by (%)	303	Fresh fruit consumer price index (same month last year = 100)
152	Export value of non-ferrous metal smelting and calendaring processing industry increased by (%)		

Table A2. Verification set error.

		V1	V2	V3	V4	V5	V6
primary	MAE	0.034	0.017	0.075	0.061	0.068	0.050
	RMSE	0.040	0.022	0.088	0.065	0.091	0.052
	MAPE	0.035	0.016	0.082	0.064	0.063	0.050
secondary	MAE	0.037	0.046	0.043	0.035	0.013	0.028
	RMSE	0.064	0.058	0.061	0.045	0.015	0.031
	MAPE	0.038	0.048	0.045	0.033	0.012	0.027
tertiary	MAE	0.027	0.025	0.021	0.028	0.019	0.027
	RMSE	0.030	0.028	0.024	0.040	0.022	0.029
	MAPE	0.025	0.024	0.019	0.027	0.018	0.025
residential	MAE	0.046	0.026	0.044	0.034	0.045	0.036
	RMSE	0.052	0.029	0.053	0.036	0.058	0.047
	MAPE	0.043	0.025	0.041	0.032	0.046	0.034
all	MAE	0.100	0.068	0.079	0.092	0.036	0.049
	RMSE	0.110	0.103	0.099	0.112	0.045	0.076
	MAPE	0.024	0.017	0.020	0.023	0.009	0.012

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