Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 5017751, 6 pages
https://doi.org/10.1155/2022/5017751

Research Article

Evaluation and Analysis of Electric Power in China Based on the ARMA Model

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Received 1 August 2022; Revised 17 September 2022; Accepted 20 September 2022; Published 30 September 2022

Academic Editor: Zaoli Yang

With the rapid development of China's economy, power demand has been closely linked with economic development in order to analyze and predict the future power situation in China. Based on the historical data of China's electricity consumption, this paper analyzes the data characteristics of China's electricity consumption by using Eviews software. The long-term trend of power consumption sequence is eliminated by fitting the regression curve, and then the residual sequence is analyzed and identified according to the relevant theory of time series. Using the data of China's power demand from 2004 to 2019, the ARMA time series model is used to analyze China's future power situation finally according to the test statistics of the model. Finally, the exponential regression ARMA model is selected to predict China's electricity consumption. The index regression analysis method extracts the long-term characteristic information of the sequence, which is conducive to the stability processing and empirical analysis of long-term prediction. The result predicts China's power demand in 2020 more accurately, which can provide a reference for the future productivity layout of China's power.

1. Introduction

The growth rate of China's power consumption is faster than expected mainly due to the obvious acceleration of power consumption growth in nonhigh energy consuming industries such as equipment manufacturing. Electricity consumption in some high energy consuming industries such as ferrous metals increased rapidly. The tertiary industry, such as modern service industry, has seen rapid growth in electricity consumption, as well as rapid growth in electricity consumption of urban and rural residents, and the impact of temperature. In the medium and long term, as China's economy enters a high-quality development stage, changes in economic growth momentum have a new impact on power demand. At the same time, accelerating the fight to win the blue sky defense war and building ecological civilization have put forward new requirements for the development of energy and power. Under this background, this paper analyzes the main factors affecting China's medium and long-term power demand under the new situation and further carries out scenario analysis on China's medium and long-term power demand.

At present, China's power use is increasing with the economic growth. However, it takes a certain period from investment to production of electricity. Therefore, it is necessary to forecast the electricity demand in advance in order to prepare for production. Many scholars have also made forecasts for electricity demand. Many scholars have previously used different power analysis impact functions to predict the long-term system planning of the region [1]. France has approved a new power system. The system can monitor and record the power consumption level in each region of the country. Through different data analysis results, the interaction of each region is obtained [2]. Soummane and Ghersi used a prediction and analysis model for power average calculation. By analyzing the demand of different power parts, the model results of the whole region are obtained [3]. Hirose used a base-extended variable coefficient model to forecast short- and medium-term electricity demand problems [4]. Jo et al. adopted a population polynomial to consider the effect of population age distribution on the electricity consumption of Korean residents [5]. Meher used the ARDL model to estimate residential electricity demand in Odisha [6]. Ma et al. used the cointegration theory error correction model to analyze China's electricity demand [7]. Ye and Kim used the principle of BP neural network to predict China's electricity demand [8]. Zhao et al. proposed a combined power load [9]. DeletedFan and Hao used the E-G cointegration test to analyze the factors of trade surplus [10]. Fan used the cross-sectional data of China's regional electricity consumption in 2010 to conduct an empirical test [11]. Velasquez et al. also adopted new methods to avoid errors in electricity demand forecasting [12]. Woo et al. made a correlation analysis between climate and different changes in regional electricity [13]. Samuel et al. have studied the impact of emergencies, such as city lockdowns and the Covid-19 pandemic, on electricity demand [14]. Condori et al. have studied the impact of changes in electricity prices and electricity demand [15]. The above scholars have used different methods to forecast China's electricity demand, and the methods are worthy of reference. Based on the above methods, this paper uses the ARMA demand of China's electricity, hoping to provide suggestions [16].

China's power consumption has been on the rise, which is approximately a smooth exponential curve. It can be seen that the annual net growth of China's power consumption shows an upward trend on the whole [17]. However, the net growth of China's power consumption showed a downward trend, which was closely related to the macroeconomic form of our country at that time. Since 1991, China's economy has been in a typical overheating state [18]. The excessively high GDP growth rate has caused a series of problems, such as the general decline in the economic benefits of state-owned enterprises, the aggravation of financial difficulties, the sharp increase in the scale of bank credit, and so on [19]. For this abnormal development speed, the government resolutely took measures to rectify the financial order and control the scale of investment. As a result, many state-owned enterprises with low efficiency and high energy consumption have been reorganized or even closed down. It has reversed the declining trend of economic growth over the years and entered a period of rapid development [20].

2. Research Method

Different random sequences can be adjusted by autonomous mode. Different historical data are needed to compare in the analysis of general principles. Through the fixed-point model investigation of the main sequence, the correlation of different points is predicted. Therefore, the series values under the same index are not necessarily the same. It is necessary to compare the autonomous regression model of ARMA model. Through the analysis of system noise state with different values, the model dynamically simulates and memorizes the noise memory value of the past system time content. Then, through statistical characteristics, the distribution content obtained by autonomous correlation is described in detail.

In the actual environment, there are white noise, color noise, and sharp point noise in the observation system at the same time. Existing studies only consider white noise or color noise. In this paper, all noises that may appear in the actual system are included in the observation equation, and a unified observation equation with white noise is derived. Based on the ARMA identification of colored noise, the new observation equation can be directly used in the traditional Kalman filtering algorithm, avoiding the expansion of dimension filtering. Therefore, the robust estimation of state parameters is reduced to the identification of ARMA parameters. The relationship between free parameter selection and input noise is emphatically studied, and the optimization problem of robust support vector regression machine is transformed into a maximum a posteriori estimation problem, which provides a theoretical basis for the reasonable selection of free parameters. Simulation results verify the effectiveness of the new algorithm.

The AR(p) model, that is, the p-order autoregressive model, has the form as follows:

$$\begin{aligned} y_t &= \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \mu_t \\ \mu_t &\sim \left(0, \sigma^2\right). \end{aligned} \tag{1}$$

The MA(q) model, the q-order moving average model, has the form as follows:

$$\begin{aligned} y_t &= \mu_t + \beta_1 \mu_{t-1} + \beta_2 \mu_{t-2} + \ldots + \beta_p \mu_{t-p} \\ \mu_t &\sim \left(0, \sigma^2\right). \end{aligned} \tag{2}$$

There are three steps to build a time series forecasting model: first is model identification, and then second is to determine the type and order of the model; third, parameter estimation, and test the rationality of the model. Apply the established model for short- and medium-term forecasting.

3. Sample Data Processing and Model Identification

Power demand forecasting has been widely concerned by scholars. The commonly used prediction methods mainly include regression analysis method, power elasticity coefficient method, grey prediction method, time series method, and neural network method.

Based on the data of electricity consumption over the years, this paper fits a similar exponential regression curve through its trend graph. The long-term trend of the original sequence is eliminated, and then the residual sequence is assumed to be a stationary process. According to the autocorrelation and partial correlation functions of time series, the specific form of ARMA is finally determined, and finally an exponential regression ARMA prediction model suitable for the characteristics of China's electricity consumption data is obtained. An important premise of building an ARMA model is that the data used to build the model must be stable, so it is necessary to judge and process the original time series data to obtain a new time series that satisfies the conditions of stationarity.

3.1. Source of Sample Data. The selection of sample data is the basis for establishing a prediction model, and rich and accurate sample data is conducive to ensuring the model prediction. This paper selects demand from 2004 to 2020 as the empirical data, and the sample data come from the statistical yearbook and annual statistical data. Since the establishment of the forecast model requires the verification of examples and the judgment of the accuracy of the model through comparative analysis, this paper selects China's power demand from 2004 to 2019 as the sample data for model building and selects the real power demand in 2020 as the test model for predicting the effect. The test data are shown in Table 1.

Using Eviews software to draw the time series data map of China's electricity demand from 2004 to 2019, see Figure 1. As can be seen from the figure, from 21,971 billion kWh in 2004, China's electricity demand increased to 75,214 billion kWh in 2019, an increase of 3.32 times in 16 years, with an average annual growth of 21 percent. Since the series contains an intercept term, which increases linearly with time, the data of China's electricity demand conforms time series.

3.2. Data Stationarity Test. By analyzing and supplementing different array data, this paper uses unit roots at different positions for judgment and analysis. After time satisfaction comparative analysis, the stable correlation of the original data is confirmed. At this time, it can be confirmed that different correlations are used for simulation investigation. The research can be judged by different difference values such as first order. Different unit root values are used to analyze and elaborate, and the test data values are obtained. The specific stationary process results are described in Table 2. It can be seen from Table 2 that the original array value is inconsistent with the horizontal value. There are certain differences in test values. After detection, its sequence unit is nonstationary, so it needs to carry out a difference detection of different square roots. The confidence level is one of the important indicators to describe the positional uncertainty of midline elements and surface elements in GLS. The confidence level indicates the assurance degree of interval estimation, and the span of the confidence interval is a positive function of the confidence level. That is, the greater the degree of assurance required, a wider confidence interval must be obtained, which correspondingly reduces the accuracy of the estimation. Therefore, this paper needs to conduct absolute value hypothesis analysis. After the significant level detection of the difference model of different sequences, the sequence has strong stability. The ADF unit root test of China's power demand is shown in Table 2.

3.3. Model Identification. Because the current general form of model recognition is based on random data, different data sources have certain differences. This leads to the fact that the data sequence studied does not follow the same Ma process. This causes great confusion to the correlation analysis of natural functions during process identification. The software that has been practiced mainly includes Eviews software. In this paper, the difference model after the sequence value of the function is used to analyze the partial objective function value. After the analysis of autocorrelation and lag models, new data columns are generated, as shown in Figure 2. It can be seen from the figure that the peak value of the autocorrelation function quickly tends to 0 after a lag of two periods, and the peak value of the partial autocorrelation function quickly tends to 0 after a period of lag of one period. Therefore, the model order is determined as $p = 1$, $q = 1, 2$. According to the determined model order, AR(1), ARMA(1,1), ARMA(1,2), AR(1), MA(1), and MA(2) models should be established. Figure 2 shows the sequence autocorrelation and partial autocorrelation.

4. Model Forecast

The above identification needs to be based on the AR(1) model and the MA(1), M(2) model categories of the first-order difference sequence, and the residual sequence correlation test is performed on the parameters estimated by the model to determine and judge the pros and cons of the constructed model. The estimation accuracy of the model is tested with real electricity demand data from 2004 to 2019. The adjusted R2 of AR(1), ARMA(1,1), and ARMA(1,2) is negative, and the AIC value and SC value are larger than the AR(1), MA(1), M(2) models, and AR (1), MA(1), M(2). The adjusted R2 of the model is 0.616, so this paper chooses AR(1), MA(1), and M(2) for forecast. Table 3 shows the comparison results of statistical parameter values of four time series models.

It can be seen from Table 3 that the reciprocals of the characteristic roots of the AR(1), MA(1), and M(2) models are all greater than 1. In order to further determine whether the AR(1), MA(1), and M(2) models are suitable, the model can be used to predict; if not, the model needs to be improved, and the results are shown in Figure 3. It can be seen from the residual correlation diagram that there is no serial correlation, and the residual sequence is a white noise sequence. The AR(1), MA(1), and M(2) models are reasonable.

In Eviews, the first-order difference sequence is increased to 2020, and the AR(1), MA(1), and M(2) models are statically predicted, and the difference value in 2020 is 3425. After calculating China's electricity demand in 2020, the predicted value is 76,277 billion kWh, and the actual value of electricity demand in 2020 is 75,214 billion kWh, with an error rate of 1.4%, and the forecast is very accurate. Figure 3 shows the correlation of the residual sequence.

Based on the historical data of China's electricity consumption, this paper analyzes the data characteristics of China's electricity consumption by using Eviews software. The long-term trend of power consumption sequence is eliminated by fitting the regression curve, and then the residual sequence is analyzed and identified according to the relevant theory of time series. Finally, the comprehensive

Table 1: China's power demand from 2004 to 2020 (unit: billion kwh).

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
Power demand	21971	24940	28588	32712	34268	36430	41923	46928	49591
Year	2013	2014	2015	2016	2017	2018	2019	2020	
Power demand	53223	55233	55500	59747	63625	69404	72852	75214	

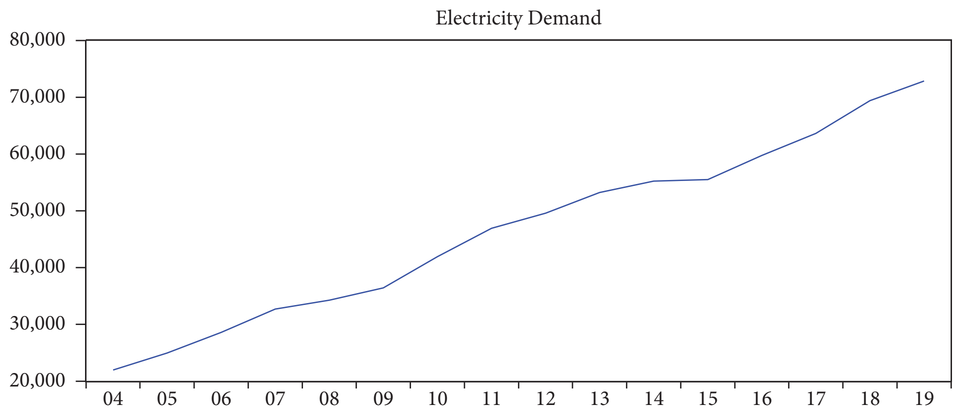


Figure 1: Growth trend of China's electricity demand from 2004 to 2019.

Table 2: ADF unit root test of China's power demand.

ADF inspection type	Lag order		
	0	First	Second
t-statistic	0.27754	−3.111634	−4.303663
Prob	0.9681	0.0489	0.0066
Stationary type	Instability	Stability	Stability

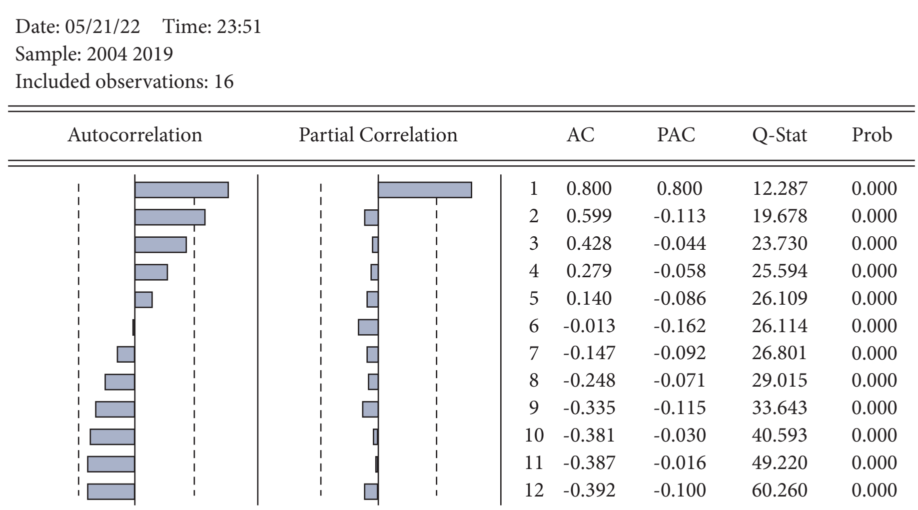


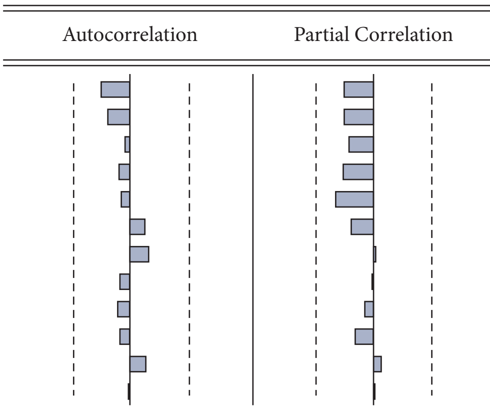
Figure 2: Sequence autocorrelation and partial autocorrelation.

analysis is carried out according to the test statistics of the model. The exponential regression analysis method extracts the long-term characteristic information of the series, which is conducive to long-term prediction, while the analysis and identification of the residual sequence is conducive to improving the short-term prediction effect. The ARMA model in this paper is simple, practical, and has high prediction accuracy. It is not only suitable for short-term prediction of

Table 3: Comparison of statistical parameter values of four time series models.

Model	Characteristic root	Adjust R^2	P	AIC	SC
AR (1)	0.862	−0.669	0.000	18.117	18.163
AR (1), MA (1)	1.010 1.000	−0.089	0.000 0.002	17.753	17.753
AR (1), MA (2)	0.950 0.900	−0.523	0.000 0.000	18.088	18.180
AR (1), MA (1), M (2)	0.98 0.945 —	0.616	0.000 0.035 0.046	16.765	16.902

Date: 05/22/22 Time: 12:32
Sample: 2004 2020
Included observations: 14



	AC	PAC	Q-Stat	Prob
1	-0.258	-0.258	1.1440	0.285
2	-0.192	-0.277	1.8338	0.400
3	-0.146	-0.210	1.8777	0.598
4	-0.089	-0.277	2.0570	0.725
5	-0.072	-0.348	2.1861	0.823
6	0.154	-0.193	2.8489	0.828
7	0.182	-0.028	3.9133	0.790
8	-0.087	-0.021	4.1934	0.839
9	-0.110	-0.081	4.7396	0.856
10	-0.082	-0.162	5.1189	0.883
11	0.140	-0.076	6.5730	0.833
12	-0.023	-0.021	6.6343	0.881

Figure 3: Correlation of residual sequence.

power consumption in China but also suitable for medium and long-term prediction.

5. Conclusions

This paper uses China's electricity demand and applies the ARMA time series model. After differential processing, on the basis of the first-order difference stationarity, and through the residual series correlation test of the parameters estimated by the model, it is concluded that p = 1, q = 1, 2, and there are four models. The regression results of the four models are compared, and it is found that the AR(1), MA(1), and M(2) models are reasonable. After forecasting, the predicted value of China's electricity demand in 2020 is 7,627.7 billion kWh, with an error of 1.4 percent from the actual value. The following conclusions and suggestions can be drawn: first, the prediction using the ARMA time series model is very accurate; second, it shows that China's future electricity demand will continue to increase significantly and; third, China's power sector should also invest heavily in power production in the future. Therefore, in the coming period of time, China's power production sector should carry out a reasonable layout of production capacity to increase power supply to meet social needs; at the same time, it is also necessary to ensure that the society can obtain sufficient and good power services at lower power costs. The research has certain limitations. ARMA requires that the time series data be stable, or stable after differential differentiation. Therefore, in essence, it can only capture linear relationships, and not nonlinear relationships. This provides a certain reference for the changing power application market, but it still needs further analysis.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by Humanities and Social Sciences Research Projects of Higher Education Institutions in Anhui Province of China: research on the effect of regional coordinated development based on the transfer of industrial clusters (No. SK2017A0481).

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