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The Prediction for the Consumer Price Index of Residents in Perspective of Time Series Method in Case of Chongqing

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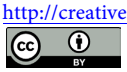

Abstract

The consumer price index (CPI) measures the relative number of changes in the price level of consumer goods and services over time, reflecting the trend and degree of changes in the price level of goods and services purchased by residents. This article uses the ARMA model to analyze the fluctuation trend of the CPI (taking Chongqing as an example) and make short-term predictions. To test the predictive performance of the model, the observation values from January to December 2023 were retained as the reference object for evaluating the predictive accuracy of the model. Finally, through trial predictions of the data from May to August 2023, it was found that the constructed model had good fitting performance.

Keywords

Consumer Price Index of Residents, Prediction, ARMA Model

1. Introduction

At present, both collectives and individuals in China generate massive consumption data every day on online e-commerce platforms, offline grocery stores, department stores, supermarkets, convenience stores, professional markets, specialty stores, shopping centers, farmers' markets, and other locations. The statistics of these data have important value for analyzing similar indicators such as consumption trends and purchasing power. The consumer price index of residents is a reference indicator used to describe such data [1] [2]. It specifically refers to the relative number of changes in the price level of consumer goods and services over time, reflecting the trend and degree of changes in the price level of goods and services purchased by residents. The annual rate of change is usually

used to reflect the degree of inflation or contraction. The CPI and its sub-indices are also important references for calculating the actual value of GDP, assets, liabilities, consumption, income, and other factors. At the same time, the CPI and its sub-indices affect the employment situation, determine how much consumers spend to purchase goods and services, affect the cost of business operations, and greatly affect the investment of individuals or enterprises and their quality of life.

According to the laws of economic activity, the benchmark value of CPI is generally set to 100, indicating that there is no significant change in prices compared to previous statistical data; if the consumer price index of residents is greater than 100, it indicates that the comprehensive price of the statistical period has increased compared to before. The higher the price index, the more prices have increased; the consumer price index of residents is less than 100, indicating a decrease in comprehensive prices compared to the previous period of the statistical cycle.

A time series is a random variable arranged in chronological order, which reflects the continuous trend of random variables over time. People have mastered a complete set of methods for studying and analyzing random variables through the study of a large amount of data sorted in chronological order, which provides a very good research strategy for predicting potential data that may occur after the same event. This article will use the autoregressive moving average model to analyze the CPI index of Chongqing in the past 31 months, and finally provide the predicted CPI values for the next 5 months.

The CPI data in this article are all sourced from https://data.stats.gov.cn/index.htm website.

2. Autoregressive Moving Average Model

The autoregressive moving average model is an important model proposed by American statisticians Jenkins and Box in the 1970s for time series analysis and processing. A model with the following structure is called an autoregressive moving average model, abbreviated as ARMA (p, q) [3] [4]:

$$\begin{cases} x_t = \phi_0 + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \\ \phi_p \neq 0, \theta_q \neq 0 \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t \varepsilon_s) = 0, s \neq t \\ E(x_s \varepsilon_t) = 0, \forall s < t \end{cases}$$

Especially, when $\phi_0 = 0$, it is called the centralized ARMA (p, q) model. By introducing a delay operator, the centralized ARMA (p, q) model can be abbreviated as:

$$\Phi(B) x_t = \Theta(B) \varepsilon_t$$

p-order autoregressive coefficient polynomial:

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$

q-order moving average coefficient polynomial:

$$\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

It is generally believed that the stationary conditions of the ARMA (p, q) model are:

The roots of the p-order autoregressive coefficient polynomial (B) = 0 are all outside the unit circle, indicating that the stationarity of the ARMA (p, q) model is entirely determined by the stationarity of its autoregressive part.

The ARMA model can be applied to various time series data, including financial data, economic data, meteorological data [5] [6] [7] [8] [9], etc. This is because the ARMA model can capture autocorrelation and lag errors in time series data. The parameters of the ARMA model (lag coefficient and lag error coefficient) have intuitive explanations. Due to its ability to capture autocorrelation and lag errors in time series data, the ARMA model can provide more accurate predictions. This is very important for situations that require long-term or short-term forecasting, as it can help us better understand future development trends and make wiser decisions.

Although the ARMA model has many advantages, there are also some potential drawbacks that need to be noted when using it. For example, for some non-stationary time series data, ARMA models may not be able to provide accurate predictions. In addition, the parameter selection of ARMA models also requires some experience and professional knowledge, otherwise it may lead to inaccurate results.

The limitations of the ARMA model:

1) Nonlinear problem: The ARMA model is constructed based on linear assumptions, which means it can only handle linear relationships. However, in practical applications, many time series data may have nonlinear relationships, and the ARMA model may not be able to provide accurate descriptions and predictions. To handle nonlinear problems, it may be necessary to introduce other models, such as ARIMA.

2) Non-stationarity issue: The ARMA model assumes that the data is stationary, meaning that the statistical characteristics of the data do not change over time. However, in practical situations, many time series data may have non-stationary characteristics, such as financial market data being affected by economic events, policy changes, and other factors, resulting in significant data volatility. For non-stationary data, ARMA models may not be able to provide accurate predictions and analysis.

Although the ARMA model has some limitations, it can still become a powerful tool for processing time series data through appropriate processing and improvement. When applying the ARMA model, full consideration should be given to the characteristics and requirements of the data to ensure the accuracy and effectiveness of the model.

3. Data Processing

According to the data provided by the statistics department's website, the con-

sumer price index of Chongqing residents has been updated for a total of 36 months since July 2020. The data is shown in Table 1.

The first 31 months of data were selected as training data and plotted as follows:

As shown in Figure 1, it appears that there is some significant fluctuation. When conducting a *kp* test with a p-value of 0.01, the null hypothesis cannot be rejected as there is a unit root in the data. In order to further study the data patterns, a differential operation was performed on the upper data once, and the p-value of the differential data was 0.0046. Therefore, the series of data can continue to be processed.

It can be seen, from Figure 2, that after the first differential operation, the data basically conforms to the variation pattern of stationary data, and can continue to operate according to the stationary random sequence data. In order to obtain the information contained in this data series, the autocorrelation function validation operation is first performed on the data to verify its stationarity. The results of the autocorrelation stationarity test are as follows:

The results of the partial autocorrelation stationarity test for the Consumer

Table 1. Chongqing consumer price index (2020.7-2023.6).

Data	Y/M	Data	Y/M	Data	Y/M	Data	Y/M	Data	Y/M	Data
102.8	2021/1	99	2021/7	100.3	2022/1	100.6	2022/7	102.7	2023/1	102.2
102.4	2021/2	98.2	2021/8	100.3	2022/2	101.2	2022/8	102.8	2023/2	100.5
101.6	2021/3	99.7	2021/9	99.8	2022/3	101.4	2022/9	103.5	2023/3	100.3
100.5	2021/4	100.9	2021/10	100.2	2022/4	101.7	2022/10	102.7	2023/4	100
99.4	2021/5	101.2	2021/11	101.6	2022/5	101.7	2022/11	102.5	2023/5	99.9
99.5	2021/6	100.9	2021/12	101	2022/6	102	2022/12	102.7	2023/6	99.8

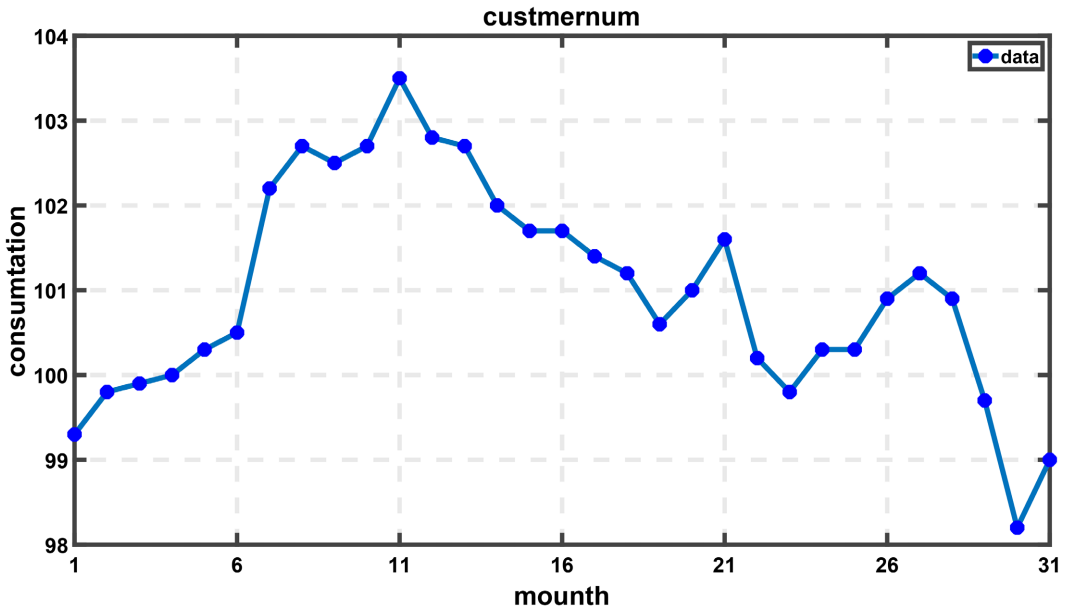

Figure 1. The first 31 months of the CPI data (2020.7-2023.1) were selected as training data.

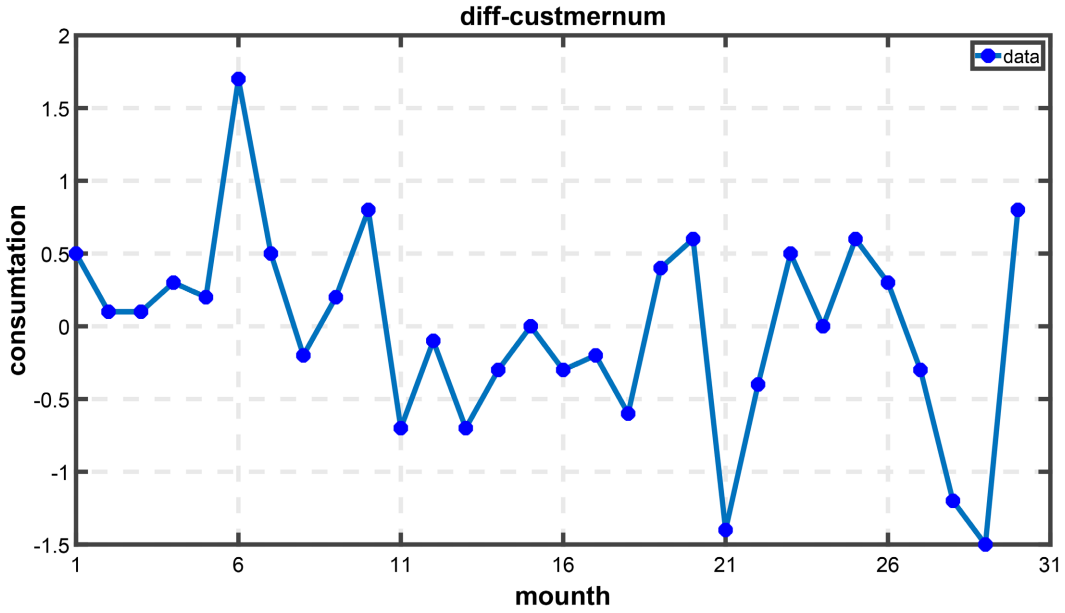

Figure 2. The first differential processing of the CPI data (2020.7-2023.1).

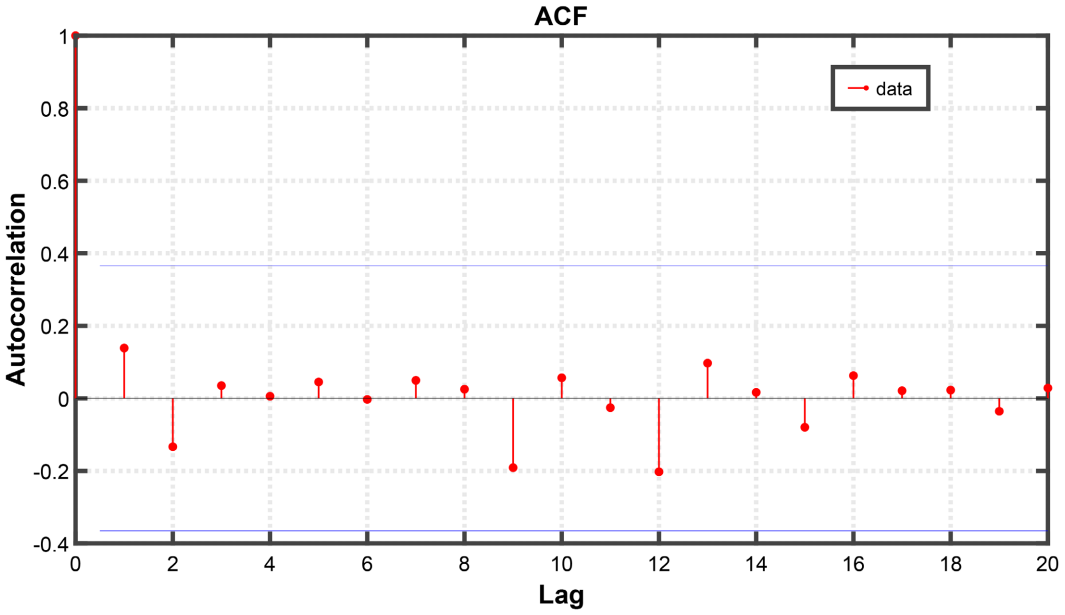

Figure 3. The ACF for the CPI data (2020.7-2023.1).

Price Index of Chongqing residents (July 2021-March 2023) are as follows:

From the specific distribution of autocorrelation (Figure 3) and partial autocorrelation (Figure 4), it can be seen that the data after one difference is basically stationary.

There are three main methods used to determine the order p and q of the ARMA model in the processing of time series data: analysis of autocorrelation and partial correlation function characteristics, FPE criterion method, AIC and BIC criterion [10] [11] [12]. Among them, the analysis of autocorrelation and partial correlation function characteristics and AIC and BIC criteria are the most

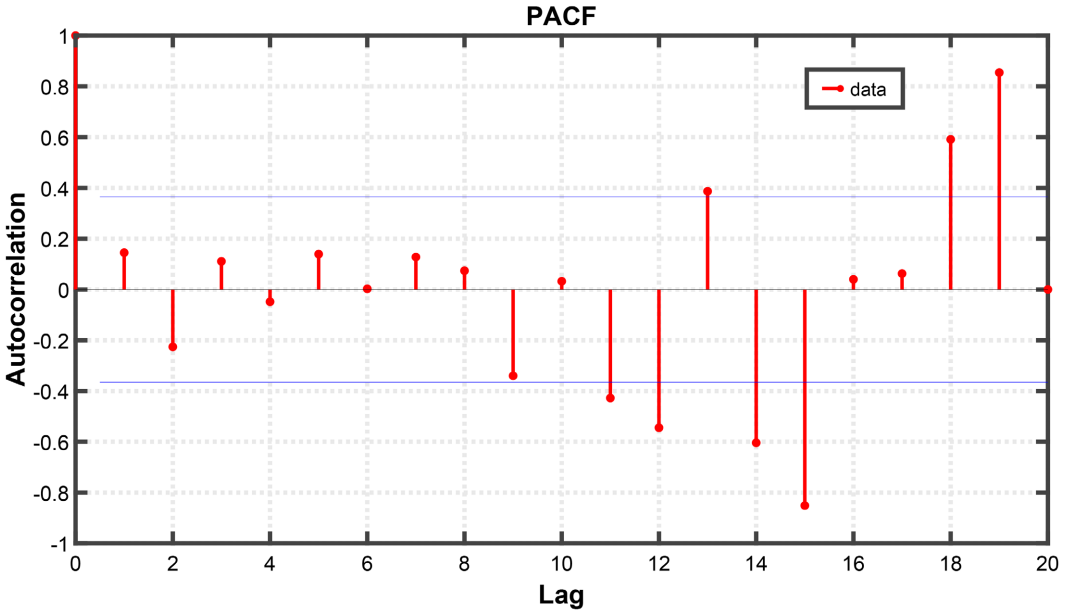

Figure 4. The PACF for the CPI data (2020.7-2023.1).

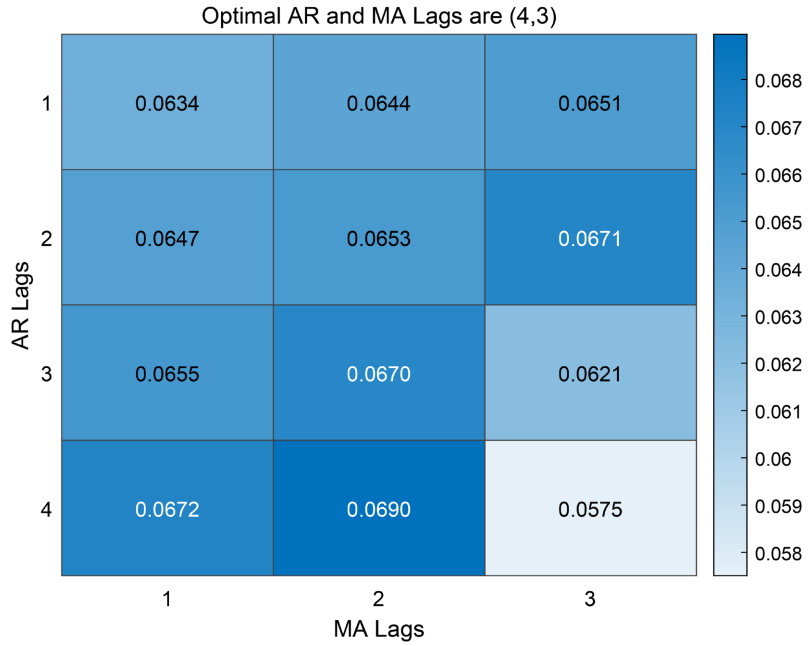

Figure 5. The optimal AR and MA Lags are (4, 3), the order (3, 2) for the ARMA model is given by the AIC and BIC criterion.

widely used.

The AIC and BIC criterion are defined as:

$$\mathrm{AIC}(n,m)=\ln\sigma_{\alpha}^{2}+2(n+m+1)/N$$

If AIC (p, q) = minAIC (n, m), then the order of the ARMA model is (p, q), the σ_{α}^{2} is the maximum likelihood estimate of the sequence being processed. The order (p, q) of the ARMA model given by the AIC and BIC criterion is shown in **Figure 5**. The order (3, 2) is given in **Figure 5**. The data are shown in

Table 2.

4. Prediction and Result Analysis

According to the AIC and BIC criteria, the order of data autoregression and moving average was determined (3, 2), and combined with a stationary data model, a 95% confidence interval prediction was performed to obtain the image shown in Figure 6. According to the prediction results, the model is suitable for CPI prediction, and the results provide certain guidance for residents to make reasonable consumption and consumer service trends.

In summary, this article attempted to process and study the consumer price index of Chongqing residents using the ARMA model. After stabilization processing, we trained and learned the data, extracted information, and obtained predicted data within a reasonable range, indicating that the prediction method and expansion order are in line with the current economic activity laws. This work informed

Table 2. ARIMA (3, 0, 2) model (Gaussian distribution).

	Value	Standard Error	t-statistic	p-value
Constant	−0.013543	0.012656	−1.0701	0.28457
AR {1}	1.6665	0.33923	4.9127	8.9848e−07
AR {2}	−0.96955	0.37197	−2.6065	0.0091471
AR {3}	0.24359	0.25324	0.96188	0.33611
MA {1}	−2	0.263	−7.6046	2.8578e−14
MA {2}	0.99999	0.38104	2.6244	0.0086805
Variance	0.26156	0.1157	2.2606	0.023784

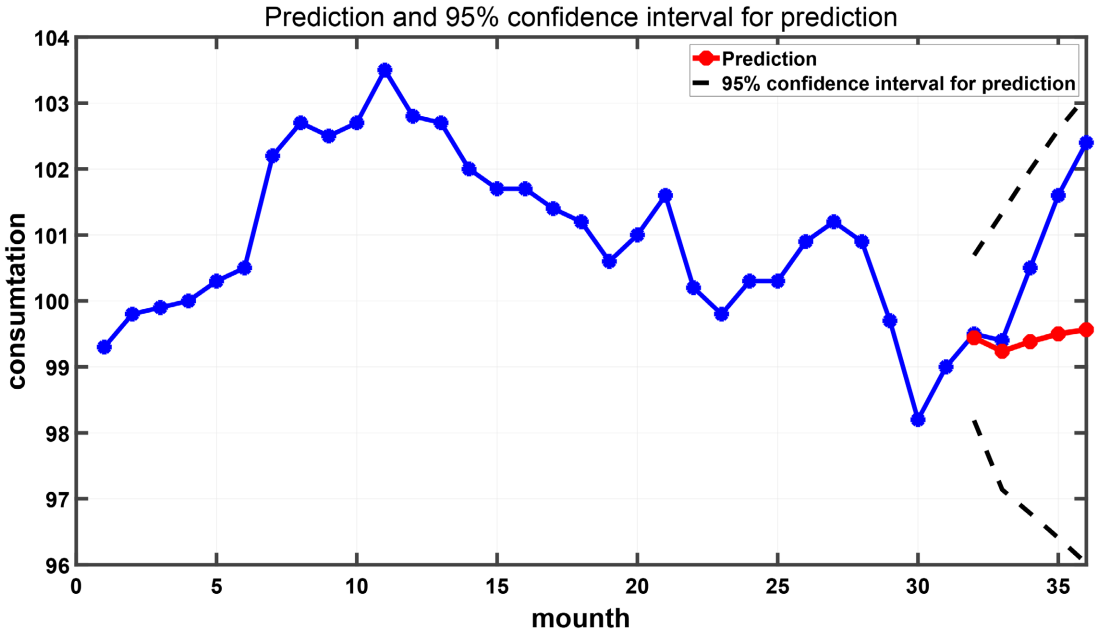

Figure 6. The CPI 95% confidence interval prediction chart.

that the ARMA model has unique advantages and characteristics in time series analysis, making it a very useful tool in economic activity. Compared with other models, the flexibility, intuitive interpretation, and prediction accuracy of the ARMA model are important advantages.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Fama, E.F. (1970) Efficient Capital Market: A Review of Hypothesis and Empirical Work. *Journal of Finance*, **25**, 383-417. https://doi.org/10.2307/2325486

[2] Judge, G. (1985) The Theory and Practice of Econometricst. John Wiley and Sons, New York.

[3] Hosking, J.R.M. (1984) Modeling Persistence in Hydrological Time Series Using Fractional Differencing. *Water Resources Research*, **20**, 1898-1908. https://doi.org/10.1029/WR020i012p01898

[4] Box, G., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M. (2015) Time Series Analysis: Forecasting and Control. John Wiley & Sons, Hoboken.

[5] Lv, Y. and Chen, B. (2017) Analysis and Prediction of Income Gap between Urban and Rural Residents Based on ARMA Model—Taking Gansu as an Example. *Business Economics Research*, **2**, 3.

[6] Chen, X. (2020) Analysis and Prediction of the Information Consumption Gap between Urban and Rural Residents in Hunan Province—Based on ARMA Model. *Fujian Quality Management*, **9**, 117.

[7] Lv, Y. and Zhao, Y. (2015) Analysis of the Information Consumption Gap between Urban and Rural Residents in Hebei Province Based on ARMA Model. *Journal of Baoding University*, **2**, 32-36.

[8] Lu, X. and He, G. (2012) Prediction of Income Trends of Rural Residents in Sichuan Province Based on ARMA Model. *Chinese Journal of Agronomy*, 110-114.

[9] Ren, Q. and Hou, D. (2011) Random Methods for Population Prediction: Based on Leslie Matrix and ARMA Model. *Population Research*, **35**, 28-42.

[10] Hu, Y., Wu, Z., Li, D. and Zhuo, M. (2006) Measuring Sustainable Development of Water Resources with Aquatic Ecological Footprint in Guangzhou Based on ARIMA Model. *Ecology and Environment*, **15**, 94-98.

[11] Akaike, H. (1974) A New Look at Statistical Model Identification. *IEEE Transaction on Automatics Control*, **19**, 716-723. https://doi.org/10.1109/TAC.1974.1100705

[12] Akaike, H. (1978) A Bayesian Analysis of the Minimum AIC Procedure. *Annals of the Institute of Statistical Mathematics*, **30**, 9-14. https://doi.org/10.1007/BF02480194