

Retraction

Retracted: Construction and Simulation of Economic Statistics Measurement Model Based on Time Series Analysis and Forecast

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Xu and W. Chen, "Construction and Simulation of Economic Statistics Measurement Model Based on Time Series Analysis and Forecast," *Complexity*, vol. 2021, Article ID 5963516, 9 pages, 2021.

Research Article

Construction and Simulation of Economic Statistics Measurement Model Based on Time Series Analysis and Forecast

Lu Xu ¹ and Weijie Chen ²

¹School of Economy, Fujian Normal University, Fuzhou 350117, China

²Ruijie Networks Co., Ltd., Fuzhou 350117, China

Correspondence should be addressed to Lu Xu; qbx20200005@yjs.fjnu.edu.cn

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Time series follow the basic principles of mathematical statistics and can provide a set of scientifically based dynamic data processing methods. Using this method, various types of data can be approximated by corresponding mathematical models, and then, the internal structure and complex characteristics of the data can be understood essentially, so as to achieve the purpose of predicting its development trend. This paper mainly studies the combined forecasting model based on the time series model and its application. First, the application prospects and research status of the combined forecasting model, the source of time series analysis, and the status of research development at home and abroad are given, and the purpose and significance of the research topic and the research content are summarized. Then, the paper gives the relevant theories about the ARIMA model and the basic principles of model recognition and explains the method of time series smoothing. Finally, the paper uses the ARIMA model to identify and fit the time series data and then the gray forecast model to fit and predict the time series data. Finally, by assigning reasonable weights and combining these methods, a combined forecasting model is proposed and carried out.

1. Introduction

Various things in the world are in motion, development, and change every day. In order to understand and grasp the laws of the operation and development of things or systems, people often make a series of observations in the order of time. Record the observed data according to the “time characteristics,” and one can get a variety of ordered data, called time series [1]. Time series analysis is establishing a dynamic model to find the regularity of development and changes by analyzing, researching, searching, and simulating the observed time series [2]. It also performs pattern recognition and parameter estimation and then uses these as the research object to scientifically predict and control the future development trend [3]. In ordinary industrial and agricultural production and social life, various types of time series are abundant, whether it is the sales volume of a certain product in a certain factory in the industrial field or a certain food in a certain area in the agricultural field. Output, or the number of tourists in a certain tourist area in the social field,

the number of patients in hospitals, and the flow of railway passenger traffic, etc., form a time series. With the in-depth research on the theory and application of time series [4], time series analysis has been compared with natural science fields such as computer networks, engineering technology, medical engineering, national economy, geophysics, signal processing, and mechanical vibration. Many aspects of the social sciences have a wide range of applications.

Time series analysis is a highly applicable branch of probability and statistics. It has a wide range of applications in many fields such as financial economy, meteorology and hydrology, signal processing, and mechanical vibration. It is an important method for dynamic data analysis and processing. It uses probability statistics as the theoretical basis to analyze random data sequences (or dynamic data sequences) and their laws, establish mathematical models for them, and further apply them to prediction and adaptive control. In many aspects, it is an applied research field with high practical value. As the time series analysis method matures, its application fields will become more and more extensive,

and more and more requirements will be put forward for the accuracy of the model. Time series refers to a series of numbers arranged by successive observations of the same phenomenon at different times. The basic idea of the time series forecasting method is when predicting the future changes of a phenomenon, use the past behavior of the phenomenon to predict the future. That is, through the historical data of the time series, the law of the phenomenon that changes with time is revealed, and this law is extended to the future, so as to predict the future of the phenomenon [5, 6]. The prediction results of these models may deviate from the actual economic development to a certain extent, and it does not necessarily indicate that the prediction has failed. For example, human intervention may cause a certain degree of deviation between the predicted results and the true value, which proves the ineffectiveness of economic forecasts. The changes in the time series in reality are affected by many factors, some of which play a long-term and decisive role, making the changes of the time series show a certain trend and a certain regularity, and some play a short-term, indecisive role, which makes the change of the time sequence present a certain irregularity.

The changes in the time series can be roughly divided into the following three types:

- (1) Trend change refers to a phenomenon that changes in a certain direction over time and presents a continuous and steadily rising, falling, or steady trend.
- (2) Periodic change (seasonal change) refers to the cyclical fluctuation change that the phenomenon is affected by seasonality and exhibits according to a fixed cycle.
- (3) Random variation refers to the irregular fluctuation time series of a phenomenon that is affected by accidental factors, which is generally a superposition or combination of the above several forms of variation. Time series forecasting methods are divided into two categories: one is the deterministic time series model method; the other is the random time series analysis method. The basic idea of the deterministic time series forecasting method is to use a definite time function to fit the time series [7, 8]. Different changes are described by different functional forms, and the superposition of different changes is described by different function superpositions. Specifically, it can be divided into trend forecasting method, smoothing forecasting method, decomposition analysis method, and so on. The basic idea of the random time series analysis method is to reveal the correlation structure of variables at different times by analyzing the correlation relationship between variables at different times and use this correlation structure to predict the time series. The time series forecasting method discussed in this article refers to the deterministic time series model method.

This paper mainly studies the combined forecasting model based on the time series model and its application.

The rest of the paper is organized as follows. Section 2 contains the literature review. Section 3 gives the application prospects and research status of the combined forecasting model, the source of time series analysis, and the status of research development at home and abroad, and the purpose and significance of the research topic and the research content are summarized. Section 4 gives the relevant theories about the ARIMA model and the basic principles of model recognition and explains the method of time series smoothing. Section 5 uses the ARIMA model to identify and fit the time series data and then the gray forecast model to fit and predict the time series data. Finally, by assigning reasonable weights and combining these methods, a combined forecasting model is proposed and carried out.

2. Related Work

The time series analysis method began in 1927 [9]. The autoregressive model was proposed by British statistician Yule. Later, the moving average model and autoregressive moving average model were adopted by the British mathematician and astronomer GT Walker. Ramos-Pérez et al. [10] used these theories when analyzing Indian atmospheric laws, and these theories laid the foundation for time series analysis methods. Jiang and Liu [11] jointly published the book "Time Series Analysis Forecasting and Control." Through a summary of previous studies, autoregressive integrated moving average (ARIMA) model order identification, parameter estimation, and significance test and the principles and methods of model prediction are systematically discussed [12]. Now these theories are called classic time series analysis methods. Moreover, the ARIMA model is mainly a linear model used for the same variance and univariate occasions.

With the further in-depth study of time series, people found that the ARIMA model theory has many limitations, so later, many statisticians began to analyze heteroscedasticity and multivariate [13], and the nonlinear time series analysis model has been studied, and many major breakthroughs have been made. For example, in 2003, the Nobel Prize in Economics was awarded to the American econometrician, statistician Engle and the British econometrician, statistician Granger to recognize their methods of analyzing economic time series [14]. Their contributions, especially the conditional autoregressive conditional heteroscedasticity (ARCH) model they proposed to study the British inflation rate modeling problem and the co-integration theory, have greatly promoted the multivariate time series analysis method development. At the same time, significant progress has also been made in nonlinear time series analysis, such as the classical model of nonlinear time series proposed by Professor Qian and Wang [15], a threshold autoregressive model. The progress in other aspects of time series includes nonstationary time series, nonlinear system models, spectral estimation, and space series.

At present, with the rapid development of computer technology and signal processing technology, the theory and methods of time series analysis are also being perfected, not

only in the method of model structure identification and parameter estimation, but even in the integration with intelligent computing. Both have achieved rich research results. Moreover, the application range of time series analysis is also widely used. For example, in the field of financial economy, the analysis of stock information can predict the future trend of stocks and make better decisions for decision-makers. Decisions provide scientific basis and avoid financial risks; in the field of computer technology, modeling and analysis of network traffic information can maximize the utilization of the network; in the field of database theory research, data mining. The use of time series methods to analyze data can be used to predict traffic flow and fuel and effectively improve corporate efficiency; in the field of electronic information, random signals can be more accurately modeled and analyzed using time series. Obtain the change trend of the signal; use the ARIMA model to predict the short-term traffic flow in the intelligent transportation system, which can provide real and reliable information for traffic management and control [16]. A time series is a sequence of numbers arranged by successive observations at different times. It uses the past behavior of the phenomenon to predict the future. The historical data of the time series reveals the law of the phenomenon that changes over time, extends this law to the future, and makes predictions about the future of the phenomenon. The changes in the time series in reality are affected by many factors, some of which play a long-term and decisive role, making the changes of the time series show a certain trend and a certain regularity, and some play a short-term, nondeterministic role, which makes the change of the time sequence present a certain irregularity.

3. Basic Theory of Economic Forecasting and Selection of Forecasting Schemes

3.1. Overview of Economic Forecasting Theory. Economic forecasting is the application of forecasting theory and forecasting methods to the economic system. The state of economic development generally has basic characteristics such as nonlinearity, dynamics, and uncertainty. The factors affecting economic development are numerous and complex, including resource structure, industrial development, transportation and logistics, capital introduction, talent introduction, and policy factors. The close relationship between them has resulted in the economic system becoming a complex giant system.

The major characteristics of economic forecasting can be summarized as follows:

The occurrence and development of economic phenomena have inherent regularity [17]. The economic system is a complex giant system, and its development process is affected by many parties. Although there are many influencing factors, most of these influences exist for a long time. This makes the development process of the economic system complex and changeable, but, at the same time, it also possesses certain regularity.

The accuracy of economic forecasting has limitations and relativity [18]. In addition to the factors that affect

economic development that mankind currently knows, there are many factors that are unknown to mankind. Due to the incomplete and inadequate collected data and a large amount of noise, the forecasting method used by the forecasting model cannot be absolutely accurate, which makes the economic forecasting results deviate from the real situation to a certain extent. But the contingent influence in economic development fluctuates randomly, and at the same time, it must follow the dynamic mechanism inside the system, which makes the direction of economic development inevitable.

The deviation of the economic forecast results from the actual economic development to a certain extent does not necessarily indicate the failure of the forecast [19]. Because the ultimate goal of economic forecasting is to formulate reasonable economic policies and local development plans. Therefore, if human intervention is effective and the prediction result deviates from the true value to a certain extent, it will prove the validity of the economic prediction.

3.2. Several Common Economic Forecasting Methods. In addition to the completeness of the data, the scientificity and rationality of the selected forecasting methods also greatly affect the forecasting results. Here are several typical quantitative analysis methods for economic forecasting.

3.2.1. Time Series Forecasting Method. Time series forecasting method is a very common economic forecasting method. The time series prediction method first arranges the collected historical data in the chronological order, then further finds out the long-term change trend and change law of the sequence, and then uses the law to predict the future development trend. The simple average method and moving average method are common analysis methods in time series forecasting.

3.2.2. Econometric Methods. The econometric method is based on the knowledge of economic theory and expresses the economic model in the mathematical form to show the relationship between economic variables. The research process of econometrics is shown in Figure 1:

Econometrics includes the following main steps:

- (1) Design a reasonable single-equation or multiple-equation measurement type according to economic theory and actual economic activities
- (2) According to the collected economic data, use appropriate parameter estimation methods to solve the unknown parameters in the equation
- (3) Through economic test, econometric test, statistical test, and other three aspects of tests, judge whether the model meets the standard
- (4) Practical application of the model

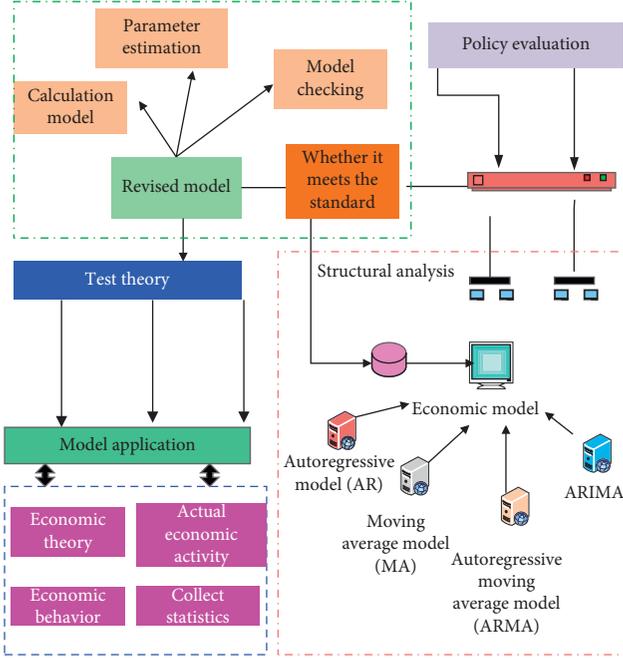


FIGURE 1: Schematic diagram of econometrics research steps.

4. ARIMA Model Principle and Simulation Experiment

The differential integrated moving average autoregressive model (ARIMA), also known as the moving average autoregressive model, is one of the commonly used analysis methods for time series forecasting. The ARIMA model is essentially an extension of the autoregressive moving average model (ARMA), which is a combination of the autoregressive model (AR) and the moving average model (MA), and is often used for the prediction of nonstationary time series [19].

4.1. Autoregressive Model (AR)

$$x_i = \mu + \sum_{i=1}^p \beta x_{i-1} + \varepsilon_i. \quad (1)$$

In the above equation, x_i represents the current value, μ is a constant term, ε_i is an error term, and $\sum_{i=1}^p \beta x_{i-1}$ represents that the current value is related to the previous p order. An autoregressive model is a model that uses its own data to make predictions. Its training dataset and test dataset are the same. This model is only suitable for predicting problems related to its own historical situation.

4.2. Moving Average Model (MA)

$$x_i = \mu + \sum_{i=1}^p \chi \varepsilon_{i-1} + \varepsilon_i. \quad (2)$$

In the above equation, x_i represents the current value, μ is a constant term, ε_i is an error term, and $\sum_{i=1}^p \chi \varepsilon_{i-1}$ means

accumulating the error term. The moving average method can effectively eliminate random fluctuations in the forecast.

4.3. *Autoregressive Moving Average Model (ARMA)*. The ARMA model is a combination of the AR model and the MA model:

$$x_i = \mu + \sum_{i=1}^p \beta x_{i-1} + \sum_{i=1}^p \chi \varepsilon_{i-1} + \varepsilon_i. \quad (3)$$

4.4. *Autoregressive Integrated Moving Average Model (ARIMA)*. AR (p), MA (q), and ARMA (p, q) are all stationary random processes. However, the time series in econometrics is generally nonstationary, so it cannot be directly simulated by a stationary random process. The principle of the ARIMA (p, d, q) model is as follows: after transforming a nonstationary time series into a stationary time series, the lag value of $\sum_{i=1}^p \beta x_{i-1}$, as well as the random error value, and the lag value of the random error value $\sum_{i=1}^p \chi \varepsilon_{i-1}$ are regressed to establish a model. Its expression can be written as

$$x_i = \mu + \sum_{i=1}^p \beta x_{i-1} + \sum_{i=1}^p \chi \varepsilon_{i-1} + \varepsilon_i. \quad (4)$$

The specific modeling process of the ARIMA model can be summarized as following Figure 2.

After passing the stationarity test, if the time series is nonstationary, it must be stabilized by the method of stationarity processing. The stationarity processing adopts the difference method, which is mainly realized by calling the adjust method in the balance class. The specific algorithm idea is to store the time series to be processed in an array a , and set a conditional judgment statement whether the array in a is stable; if it is stable, return the array a directly; if it is not stable, enter the difference processing program: create a new array b with the same length as a , keep the first item of a unchanged, and store it in the first item of b , and store the second item of a in the difference of the first item [20]. For the second item of b , store the difference between the third item of a and the second item in the third item of b and so on; one can get a new array b and then replace the data in a with the data in b . The new array a is obtained as a new time series to judge its stationarity again; if it is stable, it will be output directly; otherwise, it needs to be smoothed again.

5. Application Analysis of Economic Statistics Econometric Model

Definition 1. If the difference passes d times, the sequence is X . It can become stationary, but the $d-1$ sequence, that is, the difference sequence is not stationary, so the sequence X is usually considered to be a single integer sequence of order d , which is denoted as $X \sim I(d)$. In particular, if the sequence X does not need to be differentiated, that is, it is stationary in itself, it can be called a zero-order single integer, denoted as $X \sim I(0)$.

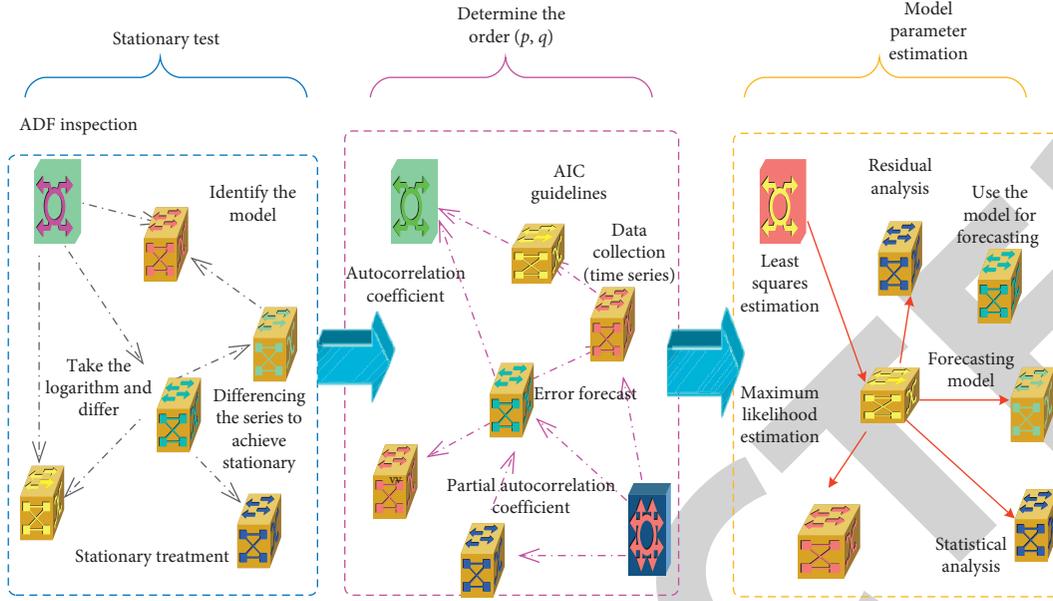


FIGURE 2: Schematic diagram of ARIMA model modeling steps.

Definition 2. Let x_i be a single integer sequence of order d , that is, $x_i \sim I(d)$, which is called $s_i = \partial^d x_i$, s_i is a stationary sequence, that is, $s_i \sim I(0)$. The establishment of the ARMA (p, q) model is as follows:

$$x_i = \mu + \beta_1 x_{i-1} + \dots + \beta_p x_{i-p} + \chi_1 \varepsilon_{i-1} + \dots + \chi_q \varepsilon_{i-1} + \varepsilon_i,$$

$$\begin{bmatrix} 1 & \beta_1 & \dots & \beta_{p-1} \\ \beta_1 & 1 & \dots & \beta_{p-2} \\ \dots & \dots & \dots & \dots \\ \beta_{p-1} & \beta_{p-2} & \dots & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_{p-1} \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_{p-1} \end{bmatrix},$$

$$\begin{bmatrix} 1 & \chi_1 & \dots & \chi_{q-1} \\ \chi_1 & 1 & \dots & \chi_{q-2} \\ \dots & \dots & \dots & \dots \\ \chi_{q-1} & \chi_{q-2} & \dots & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_{q-1} \end{bmatrix} = \begin{bmatrix} \chi_1 \\ \chi_2 \\ \dots \\ \chi_{q-1} \end{bmatrix}.$$

(5)

In the formula, $\beta_1 \dots \beta_p$ are the autoregressive coefficients, p is the specific order of autoregressive, $\chi_1 \dots \chi_q$ is the moving average coefficient of the sequence, q is the specific order of the moving average, and $\{\varepsilon_i\}$ is a standard white noise sequence.

Definition 3. The ARMA (p, q) model after d differential transformation is called the ARIMA (p, d, q) model.

5.1. Data Source and Description. The sample interval studied in this paper is set from 2000 to 2015, and the data comes from the statistical database of Economic Net. In order to better observe the data, this article draws the historical statistical data of GDP during the historical period, the first-order difference series, and the second-order

difference series. Figure 3 shows the historical data of the GDP, and then the data takes the natural logarithm.

Under normal circumstances, the order of the time series model will not exceed the fifth order. First, you can assume that the order is the first order, use the parameter estimation method to estimate the parameters of the first-order model, and establish the estimation function to obtain the first order. The estimated value of each item of the time series under the model can be used to obtain the residual variance of the first-order model. After that, assuming that the order of the model is second order, use the same method to find the residual variance of the second-order model and so on; one can obtain the residual variance of the first- to fifth-order models and then see which model has the smallest residual variance, as shown in Figure 4, and set the order of the model with the smallest residual variance as the final model order.

5.2. Determination of d in the ARIMA Model. There are three main models in the time series algorithm, namely, the autoregressive model AR, the moving average model MA, and the autoregressive moving average model ARMA. If the sequence is not stable, it needs to be differentiated first. Different estimation function equations can be established for different models. The number of terms in the known time series used in the equation is called the order of the equation. Two aspects need to be determined when establishing a specific estimation function: how many terms in the known time series are used to establish the equation, that is, the order of the equation needs to be determined, and the series of parameters in the equation are needed to be determined. Since it is impossible to determine in advance how many known time series items need to be used to establish the estimation function, it is necessary to determine the order of the model. After determining the order, it is necessary to estimate the parameters of the model to establish a complete estimation function equation [22–28].

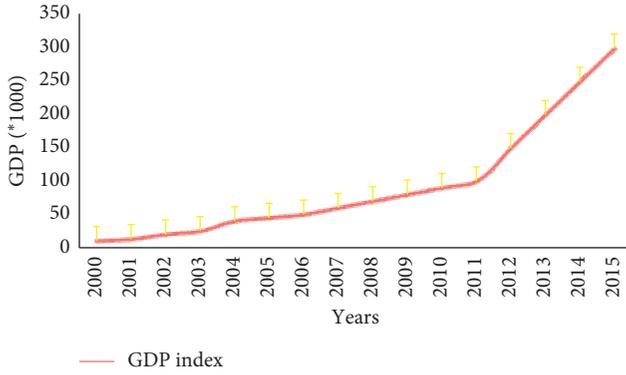


FIGURE 3: Economic statistics.

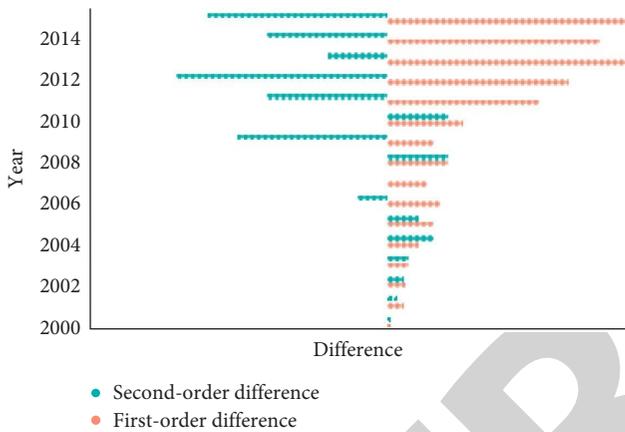


FIGURE 4: First-order and second-order difference sequence.

In the ARIMA model, d is the sequence X . After the difference transformation, it becomes the order of a stationary single integer sequence. Therefore, the unit root test method is used to test the stationarity of the sequence and obtain the d value. This paper uses the ADF (Augmented Dickey-Fuller) test. From the time series trend chart of GDP from 2000 to 2015, it is clearly observed that the rising trend of GDP is very obvious. Therefore, both the constant term and the time trend term should be taken into account in the unit root test, and the test results, as shown in Figure 5, show that the GDP series accepts the null hypothesis with a larger P value, that is, 100% probability, and accepts the conclusion that there is a unit root. Take the first-order difference of the GDP series, and then, perform the ADF test on GDP. At this time, the constant items and time trend items are selected. The test results show that the GDP series accepts the original with a larger P value, that is, with a probability of 98.14%. As shown in Figure 6, assume there is a conclusion of the unit root. Then, do the first-order difference of GDP, and do the ADF test of GDP. At this time, the choice does not contain the constant term and the time trend item. The test result shows that the second-order difference series $\partial^2 \text{GDP}$ rejects the null hypothesis at the 1% significance level and accepts the nonexistence. The conclusion of the unit root, therefore, can be determined that the GDP series is a 2-order single integer series, that is, the value of d is 2.

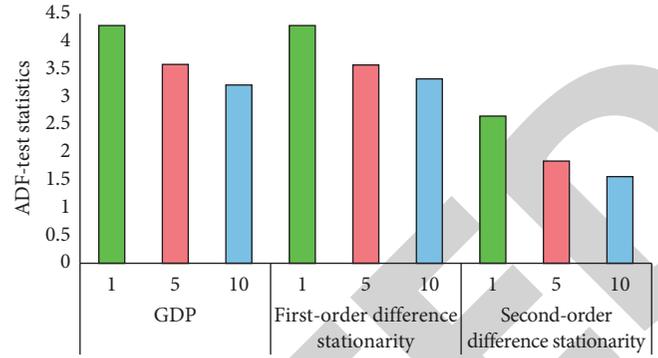


FIGURE 5: Stationarity of GDP series.

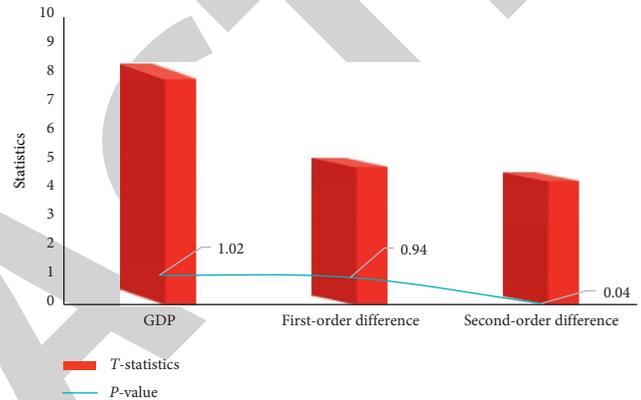


FIGURE 6: T-test of GDP series.

5.3. *Determination of p and q in the ARIMA Model.* Calculate and compare the autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) of the $\partial^2 \text{GDP}$ series, as shown in Figure 7. It can be seen that the autocorrelation coefficient AC of the $\partial^2 \text{GDP}$ series is truncated at the 4th order, and the partial autocorrelation coefficient (PAC) is truncated at the 4th order. Then, as shown in Figure 8, the order of the model is $p = 4$ and $q = 4$, and the ARIMA (4, 2, 4) model is established.

5.4. *Forecast of Economic Model.* Economic forecasting generally needs to follow the following: the larger the amount of data, the more accurate the result, and the shorter the time, the more accurate the possible errors must be estimated in advance, and the forecasting method must be tested before using. Based on these principles, the prediction experiment of this paper is designed.

5.4.1. *Determine the Forecast Target and Make a Plan.* The ultimate goal of economic forecasting is to meet the needs of decision-making and management. This article selects one representative economic indicator: gross domestic product (GDP) as the forecast target; focusing on the target factor, corresponding experimental programs have been formulated, including basic historical data and related data collection required for prediction and alternative program design.

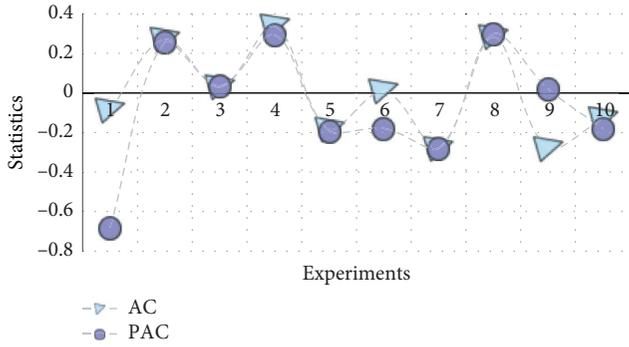


FIGURE 7: Autocorrelation coefficient and partial autocorrelation coefficient of GDP series.

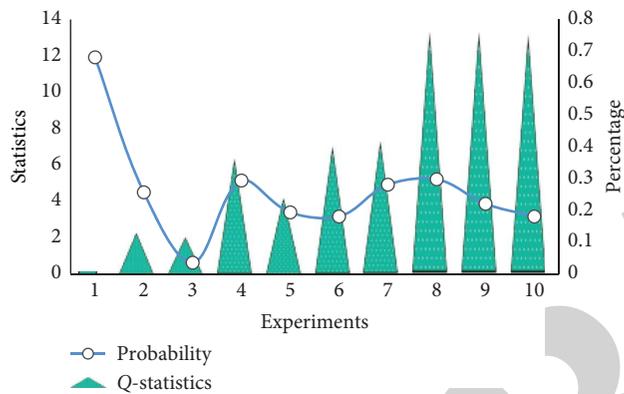


FIGURE 8: Q-test of GDP series.

5.4.2. Collection and Arrangement of Data. In order to ensure the accuracy and credibility of the prediction results, we must first ensure the accuracy, reliability, and timeliness of the data. The data is released for the country, and the data is true and reliable. Secondly, we need to unify data units, values, dimensions, etc., to ensure the consistency of the data and preprocess the collected data to ensure the smooth progress of subsequent experiments. In this experiment, the deviation standardization method is used to normalize the economic forecast data.

5.4.3. Determine the Appropriate Forecasting Method. After analyzing several typical and common economic forecasting methods, combined with the diversification and complexity of economic forecasting, the use of the neural network model for forecasting is an effective method. Throughout the literature research at home and abroad, many scholars have used neural networks in economic forecasting. Among them, the BP neural network is the most frequently used. However, the BP neural network does not take into account the temporal characteristics of economic data and has certain limitations. Therefore, this article will be based on the long short-term memory unit recurrent neural network model for economic forecasting. At the same time, considering the temporal characteristics of economic forecasting, this article introduces a gray

model suitable for small-sample forecasting and constructs combined models to achieve a more reasonable forecast of the future economy.

5.4.4. Evaluation of Prediction Results. Because of the dynamic nature of economic phenomena, its development is affected by many uncertain factors, so errors are inevitable. However, we can control the error within a reliable range by adjusting model parameters and other means to ensure the validity of the results. This article mainly uses mean square error (MSE) to evaluate the accuracy of the prediction results.

The statistical properties of the ARMA (p, q) model are combined by the statistical properties of the AR (p) model and the MA (q) model. Therefore, the recognition problem of the ARMA (p, q) model is similar to that of the AR (p) model and MA (q). The relevance of the model as well as the special features of the ARMA (p, q) model is discussed in three cases.

If the autocorrelation function of a stationary sequence $\{X\}$ shows censored, and the partial autocorrelation function shows tailing, the AR (p) model can be used to fit the sequence; if the autocorrelation function of a stationary sequence $\{X\}$ exhibits tailing and the partial autocorrelation function exhibits censored, the sequence can be fitted by the MA(q) model. In order to better predict the change trend of time series, it is necessary to find a suitable fitting model. In time series analysis, ARIMA is a model with better forecasting effect. The basic steps to establish an ARIMA (p, d, q) model are (1) obtain the sequence of observations to be analyzed from relevant data; (2) make the time series diagram, autocorrelation function diagram, and partial autocorrelation function diagram of the observation sequence, and judge whether the sequence is a stationary sequence; if it is a nonstationary sequence, the difference operation needs to be used to make the sequence stationary; (3) calculate the statistics of the sequence of observations and test the sequence for pure randomness; (4) determine the form of the ARIMA (p, d, q) model that fits the sequence according to the characteristics of the truncation and tailing properties of the autocorrelation function and partial autocorrelation function of the sequence, and the selected order should be appropriate, and we need to estimate the model parameters; (5) calculate the QLB statistics of the residual sequence. Only when the residual sequence is a white noise sequence, can the established fitting model be effective; (6) using the obtained fitting model to predict the sequence of changes, the predicted value can understand the future development trend of the observation sequence, so as to provide a scientific basis for our decision-making.

If the autocorrelation function and partial autocorrelation function of a stationary sequence $\{X\}$ both exhibit tailing, then the sequence is fitted by the ARMA (p, q) model. Use the ARIMA (4, 2, 4) model to perform intra-sample predictions on GDP data. The specific prediction results and relative errors are shown in Figure 9.

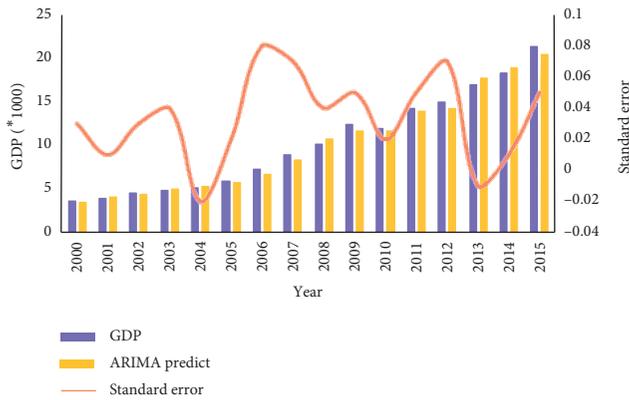


FIGURE 9: Comparison of model fitting results.

6. Conclusion

According to the forecast of the ARIMA model constructed in this article, firstly, the single-point accurate forecast of the first period of the sample period is carried out, and then, the sample period is expanded. Compared with the traditional trend model, the ARIMA time series model belongs to the extrapolation forecasting method and has its own unique advantages. Because traditional forecasting methods are basically only suitable for certain typical trend characteristic phenomena, in reality, the time series data shown by many economic phenomena does not have typical trend characteristics, and in most cases, it may be a kind of characteristic, completely random in nature, so that the traditional method modeling can not meet the requirements of random nature, which has a great impact on the prediction effect. First perform model identification based on a time series, then conduct continuous modeling experiments, add relevant diagnostic techniques, and then make necessary adjustments according to the situation. The identification, estimation, and diagnosis steps are repeated until the optimal model is found. Therefore, in terms of various time series, the ARIMA model is more suitable, and it is the most common model in time series forecasting so far. For nonstationary series, ARIMA can transform it into a stationary random series with zero mean by means of difference, natural logarithm, etc., for effective prediction and analysis. Through the addition of AR and MA terms, the residual error is entered into the model, which greatly improves the accuracy of the model. However, due to the assumed time series, whether it is the past model or the future development model, the ARIMA modeling method is regarded as consistent, so its forecasts are often only effective in the short term. This paper constructs an ARIMA model for the gross domestic product (GDP) from 2000 to 2015 through the process of stationary line test, order identification, parameter estimation, and model diagnosis. From the perspective of the fitting effect, of course, there is still room for further improvement. However, the precise predictions made in this article will undoubtedly provide a scientific basis for the work and planning of relevant departments.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Consent

Informed consent was obtained from all individual participants included in the study references.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

- [1] L.-Y. Wei, "A hybrid ANFIS model based on empirical mode decomposition for stock time series forecasting," *Applied Soft Computing*, vol. 42, no. 2, pp. 368–376, 2016.
- [2] P. Wang, H. Zhang, Z. Qin, and G. Zhang, "A novel hybrid-garch model based on ARIMA and SVM for PM_{2.5} concentrations forecasting," *Atmospheric Pollution Research*, vol. 8, no. 5, pp. 850–860, 2017.
- [3] Z. Deng, Y. Ke, H. Gong, X. Li, and Z. Li, "Land subsidence prediction in Beijing based on PS-InSAR technique and improved Grey-Markov model," *GIScience & Remote Sensing*, vol. 54, no. 6, pp. 797–818, 2017.
- [4] C. Zhou, K. Yin, Y. Cao, and B. Ahmed, "Application of time series analysis and PSO-SVM model in predicting the Bazimen landslide in the Three Gorges Reservoir, China," *Engineering Geology*, vol. 204, no. 4, pp. 108–120, 2016.
- [5] M. Ma, W. Cai, and W. Cai, "Carbon abatement in China's commercial building sector: a bottom-up measurement model based on Kaya-LMDI methods," *Energy*, vol. 165, no. 5, pp. 350–368, 2018.
- [6] Y.-S. Chen, C.-H. Cheng, C.-L. Chiu, and S.-T. Huang, "A study of ANFIS-based multi-factor time series models for forecasting stock index," *Applied Intelligence*, vol. 45, no. 2, pp. 277–292, 2016.
- [7] H. Lu, X. Ma, K. Huang, and M. Azimi, "Prediction of offshore wind farm power using a novel two-stage model combining kernel-based nonlinear extension of the Arps decline model with a multi-objective grey wolf optimizer," *Renewable and Sustainable Energy Reviews*, vol. 127, no. 7, p. 109856, 2020.
- [8] W. Zhang, Z. Qu, K. Zhang, W. Mao, Y. Ma, and X. Fan, "A combined model based on CEEMDAN and modified flower pollination algorithm for wind speed forecasting," *Energy Conversion and Management*, vol. 136, no. 6, pp. 439–451, 2017.
- [9] H.-J. Yang and X. Hu, "Wavelet neural network with improved genetic algorithm for traffic flow time series prediction," *Optik*, vol. 127, no. 19, pp. 8103–8110, 2016.
- [10] E. Ramos-Pérez, P. J. Alonso-González, and J. J. Núñez-Velázquez, "Forecasting volatility with a stacked model based on a hybridized artificial neural network," *Expert Systems with Applications*, vol. 129, no. 129, pp. 1–9, 2019.
- [11] P. Jiang and Z. Liu, "Variable weights combined model based on multi-objective optimization for short-term wind speed forecasting," *Applied Soft Computing*, vol. 82, no. 2, p. 105587, 2019.
- [12] Y. Hao and C. Tian, "A novel two-stage forecasting model based on error factor and ensemble method for multi-step wind power forecasting," *Applied Energy*, vol. 238, no. 8, pp. 368–383, 2019.

- [13] Z.-X. Wang, Q. Li, and L.-L. Pei, "A seasonal GM (1, 1) model for forecasting the electricity consumption of the primary economic sectors," *Energy*, vol. 154, no. 4, pp. 522–534, 2018.
- [14] E. Gidey, O. Dikinya, R. Sebego, E. Segosebe, and A. Zenebe, "Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia," *Modeling Earth Systems and Environment*, vol. 3, no. 4, pp. 1245–1262, 2017.
- [15] W. Qian and J. Wang, "An improved seasonal GM (1, 1) model based on the HP filter for forecasting wind power generation in China," *Energy*, vol. 209, no. 9, p. 118499, 2020.
- [16] M. Koopialipour, S. S. Nikouei, A. Marto, A. Fahimifar, D. Jahed Armaghani, and E. T. Mohamad, "Predicting tunnel boring machine performance through a new model based on the group method of data handling," *Bulletin of Engineering Geology and the Environment*, vol. 78, no. 5, pp. 3799–3813, 2019.
- [17] J. Wang, J. Heng, L. Xiao, and C. Wang, "Research and application of a combined model based on multi-objective optimization for multi-step ahead wind speed forecasting," *Energy*, vol. 125, no. 5, pp. 591–613, 2017.
- [18] J. Barunik, T. Krehlik, and L. Vacha, "Modeling and forecasting exchange rate volatility in time-frequency domain," *European Journal of Operational Research*, vol. 251, no. 1, pp. 329–340, 2016.
- [19] D. Wang, S. Wei, H. Luo, C. Yue, and O. Grunder, "A novel hybrid model for air quality index forecasting based on two-phase decomposition technique and modified extreme learning machine," *Science of the Total Environment*, vol. 580, no. 80, pp. 719–733, 2017.
- [20] C. Deb, F. Zhang, J. Yang, S. E. Lee, and K. W. Shah, "A review on time series forecasting techniques for building energy consumption," *Renewable and Sustainable Energy Reviews*, vol. 74, no. 4, pp. 902–924, 2017.
- [21] X. Zhang and Z. Wei, "A hybrid model based on principal component analysis, wavelet transform, and extreme learning machine optimized by Bat algorithm for daily solar radiation forecasting," *Sustainability*, vol. 11, no. 15, p. 4138, 2019.
- [22] T. A. Perkins, A. S. Siraj, C. W. Ruktanonchai, M. U. Kraemer, and A. J. Tatem, "Model-based projections of Zika virus infections in childbearing women in the Americas," *Nature Microbiology*, vol. 1, no. 9, p. 16126, 2016.
- [23] B. Wang, J. Cheng, and S. M. Zhong, "Bounded input bounded output stability for Lurie system with time-varying delay," *Advances in Difference Equations*, vol. 201813 pages, 2018.
- [24] K. Shi, Y. Tang, X. Liu, and S. Zhong, "Non-fragile sampled-data robust synchronization of uncertain delayed chaotic Lurie systems with randomly occurring controller gain fluctuation," *ISA Transactions*, vol. 66, pp. 185–199, 2017.
- [25] J. Yang, C. Ma, B. Jiang, G. Ding, G. Zheng, and H. Wang, "Joint optimization in cached-enabled heterogeneous network for efficient industrial IoT," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 5, pp. 831–844, 2020.
- [26] W. Wang, N. Kumar, J. Chen et al., "Realizing the potential of the internet of things for smart tourism with 5G and AI," *IEEE Network*, vol. 34, no. 6, pp. 295–301, 2020.
- [27] Y. Li and J. Yang, "Few-shot cotton pest recognition and terminal realization," *Computers and Electronics in Agriculture*, vol. 169, p. 105240, 2020.
- [28] R. Yu, J. Gao, M. Yu et al., "LSTM-EFG for wind power forecasting based on sequential correlation features," *Future Generation Computer Systems*, vol. 93, pp. 33–42, 2019.