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# Forecast of US GDP Growth Rate Based on the ARMA Model

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## Abstract

**Gross domestic product (GDP) can not only reflect the scale of a country's or region's economic development, judge the speed of its economic development and the overall strength of the economy, but also be an important basis for macroeconomic decision-making. The study was conducted on the real GDP growth rate of the United States from 1930 to 2022 (Source: Federal Reserve Economic Data). First, we use Rstudio to build a prediction model on the training set data. Secondly, according to the AIC and BIC criteria, the last four models with the highest amount of information were selected for prediction and analysis. Then, according to the prediction results of the four models, the optimal prediction model was selected by comparing the error results. Finally, the real GDP growth rate for the next year is predicted according to the optimal model.In addition, the time series data of 93 years compared with the time series data of 90 years can be approximated as the same, so we can directly use the time series data of 93 years to predict the real GDP growth rate of the next year using the best model.**

## Keywords

**Time series; ARMA model; GDP forecasts.**

## 1. Introduction

### 1.1. Background and significance

GDP is a fictitious entity. As an important indicator to measure the economic development status and development level of a country or region, GDP is not only the core indicator of national accounting, but also a means to measure and compare the quality of a country's operating conditions.

The United States is the world's largest economy, and its domestic economic situation has been the subject of much concern. However, in recent years, the U.S. economy has been plagued by the impact of the new crown epidemic, the escalation of the trade war, the intensification of financial market volatility, the increase in federal debt, and the high unemployment rate.

It is necessary to study the U.S. economy, discover the problems of the U.S. economy, and provide reference experience for the world's late-developing countries, especially for China's economic development, and develop an economy with Chinese characteristics that is in line with China's national conditions.

### 1.2. Research status

In 1927, the famous statistician Yule proposed an autoregressive model (abbreviated as the AR model). In 1931, Walker proposed the moving average model (abbreviated as the MA model). On this basis, Box and Jenkins created the autoregressive moving average model (abbreviated as the ARMA model), which we can also call the ARMA model the B-J methodIt is a short-term forecasting method that can be applied to time series with high accuracy[1]. Hu Yongqi (2021)[2] analyzed the GDP data of Shaanxi Province from 1986 to 2015, established the ARIMA (1,1,0)

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model, and predicted its future GDP development. Zhang Qiang (2019)[3] constructed a comprehensive GDP forecasting model based on the Cobb-Douglas production function and ARIMA model to calculate the total GDP and per capita GDP of each province in China from 2016 to 2050. Li Hui (2017)[4] based on the time series theory, based on the GDP of Yili Prefecture from 1978 to 2014, established the ARIMA model, and did not predict the GDP of the next three years, so as to provide scientific suggestions and empirical basis for the local authorities to formulate relevant development policies. Based on the GDP of Ji'an from 1978 to 2018, Zou (2020)[5] used the ARIMA(0,2,1) model to predict the GDP of Ji'an from 2019 to 2023. The forecast results can provide a scientific reference for Ji'an to set economic development goals. Zhou and Ou (2020)[6] based on the time series model, the GDP data of Fujian Province from 1978 to 2015 were fitted and analyzed, and ARIMA (4,2,2) and ARIMA (4.3.2) were establishedmodel. Then, the two models were used to test the GDP of Fujian Province from 2016 to 2018, and it was found that the ARIMA (4,3,2) model had a good prediction effect. Finally, the ARIMA (4,3,2) model is used to predict the GDP of Fujian Province from 2019 to 2023. Zhao(2021)[7], the main research is on the GDP development and forecast of the Inner Mongolia Autonomous Region from 1993 to 2020. The ARIMA model and time series forecasting were established to analyze the population development and the projected GDP index for the next five years. The results show that the GDP of the Inner Mongolia Autonomous Region will be further improved to a certain extent, and these data can be seen as a good assistant for the Inner Mongolia Autonomous Region government to plan the next stage of economic development. and guide the government in further planning and development. Yan Yanwen (2018)[8] analyzed the GDP of Shandong Province from 1975 to 2015 and established the ARIMA(1,1,1) model, and the test results showed that the ARIMA(1,1,1) model had excellent prediction effect.

### 1.3. The innovation point of this article

1.The data from 1930 to 2022 were selected to ensure that the data research was comprehensive and effective.

2.Comparing the prediction results of the four models and selecting the optimal model for the next step prediction, to a certain extent, it is more scientific and reasonable than the single model prediction.

## 2. Empirical analysis

### 2.1. Introduction to the ARMA model

The ARMA(p,q) model can be obtained by combining the AR(p) model and the MA(q) model. This model represents that the current value of some sequence x depends linearly on its previous value plus the combination of the current value of a white noise term and its previous value, in the form of:

$$\Phi(L)y_t = \Theta(L)\mu_t. \tag{1}$$

Thereinto:

$$\Phi(L) = 1 - \Phi_1 L - \Phi_2 L^2 - \dots - \Phi_p L^p. \tag{2}$$

$$\Theta(L) = 1 + \Theta_1 L + \Theta_2 L^2 + \dots + \Theta_q L^q. \tag{3}$$

And there are:

$$E(\mu_t) = 0;\ E(\mu_t^2) = \sigma^2;\ E(\mu_t\mu_s) = 0,\ t \neq s. \tag{4}$$

Obviously, when q=0, the ARMA(p,q) model degenerates into an AR(p) model; When p=0, the ARMA(p,q) model degenerates into the MA(q) model.

Therefore, the AR(p) model and the MA(q) model are actually special cases of the ARMA(p,q) model, which are collectively referred to as the ARMA(p,q) model. The statistical properties of

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the ARMA(p,q) model are also an organic combination of the statistical properties of the AR(p) model and the MA(q) model.

## 2.2. The model-building process

(1) Conduct a stationarity test. Firstly, a stationarity test was carried out on the obtained observation value series.

(2) Perform differential operations. If the observed sequence does not pass the stationarity test, it needs to be differentially operated until it passes the stationarity test, and then transferred to step (3);

(3) Conduct a white noise test. If the test is passed, proceed to step (4);

(4) Fitting the ARMA model. Model fitting of stationary non-white noise sequences;

(5) ARMA model test. If the model can pass the white noise test, the analysis is over;

(6) Forecasting.

## 2.3. Empirical analysis

### 2.3.1. Selection and source of data

The data used for the empirical analysis in this paper are derived from the Federal Reserve Economic Data, which selects a total of 93 data on the real GDP growth rate of the United States from 1930 to 2022.

A total of 90 samples from 1930 to 2019 in the United States were used as the training set, and a total of 3 samples from 2020 to 2022 were used as the test set, see Table 1.

Table 1 U.S. Real GDP Growth Rate from 1930 to 2022 (Unit: %)

| Date | Rate | Date | Rate | Date | Rate |
|---|---|---|---|---|---|
| 1930 | -8.5 | 1961 | 2.6 | 1992 | 3.5 |
| 1931 | -6.4 | 1962 | 6.1 | 1993 | 2.7 |
| 1932 | -12.9 | 1963 | 4.4 | 1994 | 4.0 |
| 1933 | -1.2 | 1964 | 5.8 | 1995 | 2.7 |
| 1934 | 10.8 | 1965 | 6.5 | 1996 | 3.8 |
| 1935 | 8.9 | 1966 | 6.6 | 1997 | 4.4 |
| 1936 | 12.9 | 1967 | 2.7 | 1998 | 4.5 |
| 1937 | 5.1 | 1968 | 4.9 | 1999 | 4.8 |
| 1938 | -3.3 | 1969 | 3.1 | 2000 | 4.1 |
| 1939 | 8.0 | 1970 | 0.2 | 2001 | 1.0 |
| 1940 | 8.8 | 1971 | 3.3 | 2002 | 1.7 |
| 1941 | 17.7 | 1972 | 5.3 | 2003 | 2.8 |
| 1942 | 18.9 | 1973 | 5.6 | 2004 | 3.8 |
| 1943 | 17.0 | 1974 | -0.5 | 2005 | 3.5 |
| 1944 | 7.9 | 1975 | -0.2 | 2006 | 2.8 |
| 1945 | -1.0 | 1976 | 5.4 | 2007 | 2.0 |
| 1946 | -11.6 | 1977 | 4.6 | 2008 | 0.1 |
| 1947 | -1.1 | 1978 | 5.5 | 2009 | -2.6 |
| 1948 | 4.1 | 1979 | 3.2 | 2010 | 2.7 |
| 1949 | -0.6 | 1980 | -0.3 | 2011 | 1.6 |
| 1950 | 8.7 | 1981 | 2.5 | 2012 | 2.3 |
| 1951 | 8.0 | 1982 | -1.8 | 2013 | 2.1 |
| 1952 | 4.1 | 1983 | 4.6 | 2014 | 2.5 |
| 1953 | 4.7 | 1984 | 7.2 | 2015 | 2.9 |
| 1954 | -0.6 | 1985 | 4.2 | 2016 | 1.8 |
| 1955 | 7.1 | 1986 | 3.5 | 2017 | 2.5 |
| 1956 | 2.1 | 1987 | 3.5 | 2018 | 3.0 |

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|---|---|---|---|---|---|
| 1957 | 2.1 | 1988 | 4.2 | 2019 | 2.5 |
| 1958 | -0.7 | 1989 | 3.7 | 2020 | -2.2 |
| 1959 | 6.9 | 1990 | 1.9 | 2021 | 5.8 |
| 1960 | 2.6 | 1991 | -0.1 | 2022 | 1.9 |

### 2.3.2. Test the stationarity of the data

1.Timing diagrams

Table 1 plots the time series plots of 90 data from 1930 to 2019 in the United States, see Fig. 1.

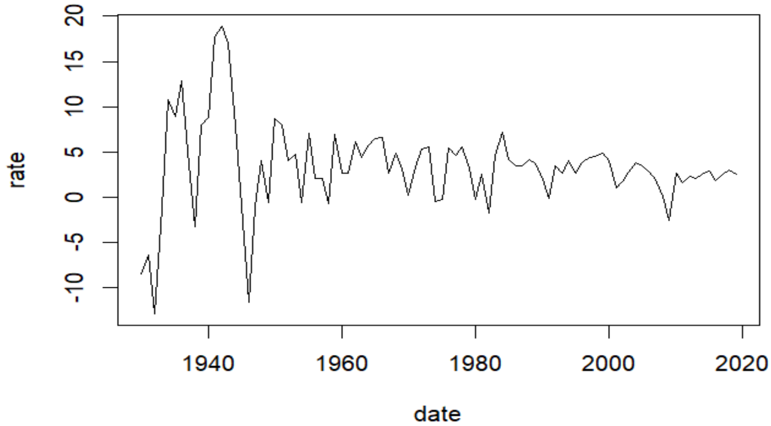


Fig. 1 Time series chart of US GDP growth rate from 1930 to 2019

Figure 1 shows that the GDP growth rate of the United States fluctuated greatly in the first 10 years of the series from 1930 to 2019, and the economic downturn from 1930 to 1932 may be due to the fact that the United States was in the Great Depression at that time. The economic recovery of 1934-1936 may have been due to Roosevelt's New Deal, when the United States emerged from the Great Depression; The economic boom in 1941-1943 may have been due to the fact that the outbreak of World War II did not affect the United States, and European capital fled to the United States; The reason for the economic downturn in the United States in 1945-1946 may be that the United States has not yet broken away from the wartime planned economy implemented in World War II. Looking at the growth rate time series diagram as a whole, we can see that the GDP growth rate of the United States fluctuates in a fixed range, so the GDP growth rate series is a stationary series.

2. ADF test (sequence stationarity test).

In order to further determine the stationarity of the series, we performed the ADF test for the time series, and the results of the ADF test are shown in Table 2.

Table 2 ADF test results

| Test Statistic | 1% Critical Value | 5% Critical Value | 10% Critical Value |
|---|---|---|---|
| -5.296 | -3.525 | -2.899 | -2.584 |

The ADF test results show that the value of the ADF test statistic for this sequence is less than the value at 5%, so we can confirm that the sequence is stationary. Now we should continue to test the sequence for pure randomness.

3.Pure randomness test (white noise test).

We perform a pure random test for stationary sequences, and the results are shown in Table 3.

Table 3 Box-Ljungtest

| Lag order | chi-square | P-value |
|---|---|---|
| 6 | 47.193 | 1.712e-08 |
| 12 | 72.418 | 1.127e-10 |

The white noise test results show that the P values of the LB statistic of the 6th and 12th order delays of the lag order are all less than 0.05, so we reject the null hypothesis, so the time series is not a purely random series. Therefore, we can assume that the sequence is not a white noise sequence, that is, the sequence is a stationary non-white noise sequence.

### 2.3.3. Fitting the ARMA model

If the ACF (or PACF) of the sample is significantly greater than the 2x standard deviation range at the initial r-order, and then almost 95% of the ACF (or PACF) falls within the 2x standard deviation range, decaying from a significant non-zero ACF (or PACF) to a small fluctuation, the process is very abrupt, and we usually consider the ACF (or PACF) to be truncated. where the truncated order is r.

If more than 5% of the ACF (or PACF) falls outside the 2x standard deviation range, or if the ACF (or PACF) decays from a significantly non-zero ACF (or PACF) to a small fluctuation, the process is discontinuous or slow, and we usually consider the ACF (or PACF) to be tailed.

Below, we examine the autocorrelation and partial autocorrelation plots of the US real GDP growth rate series from 1930 to 2019, as shown in Fig. 2.

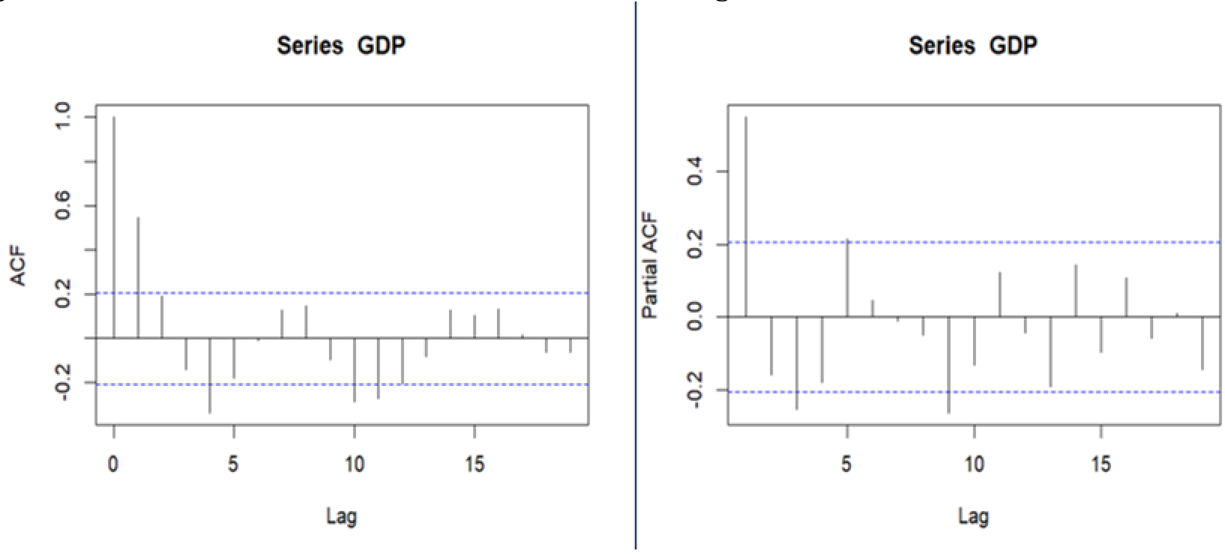


Fig. 2 Autocorrelation and partial autocorrelation

As we can see in Fig. 2, the process of decay from significant non-zero ACF and PACF to small fluctuations is discontinuous. At this point, we generally think of ACF and PACF as tailing. According to the basic principle of ARMA model grading, we consider fitting the ARMA(1,1) model to the US real GDP growth rate series from 1930 to 2019.

Although relying on the features of autocorrelation graphs and partial autocorrelation graphs can help us identify the order of the model, relying only on image recognition is very subjective. In order to reduce the influence of subjective judgment on fitting the ARMA model, we selected the relatively optimal ARMA model by referring to the AIC function value and BIC function value of each ARMA model based on the AIC criterion and BIC criterion.

The AIC function values for each ARMA model are shown in the table

Table 4 The AIC function values of each ARMA model

| ARMA model | AIC function value | ARMA model | AIC function value |
|---|---|---|---|
| ARMA(0,0) | --- | ARMA(2,0) | 509.5404 |
| ARMA(0,1) | 514.3551 | ARMA(2,1) | 506.8639 |
| ARMA(0,2) | 511.1871 | ARMA(2,2) | 498.4300 |
| ARMA(0,3) | 506.1998 | ARMA(2,3) | 499.8435 |
| ARMA(1,0) | 509.5963 | ARMA(3,0) | 506.7335 |
| ARMA(1,1) | 510.3464 | ARMA(3,1) | 507.0118 |

| | | | |
|---|---|---|---|
| ARMA(1,2) | 510.6918 | ARMA(3,2) | 499.9493 |
| ARMA(1,3) | 508.0510 | ARMA(3,3) | 500.4637 |

The BIC function values for each ARMA model are shown in the table

Table 5 The BIC function values of each ARMA model

| ARMA model | BIC function value | ARMA model | BIC function value |
|---|---|---|---|
| ARMA(0,0) | --- | ARMA(2,0) | 519.5396 |
| ARMA(0,1) | 521.8545 | ARMA(2,1) | 519.3630 |
| ARMA(0,2) | 521.1863 | ARMA(2,2) | 513.4288 |
| ARMA(0,3) | 518.6988 | ARMA(2,3) | 517.3422 |
| ARMA(1,0) | 517.0957 | ARMA(3,0) | 519.2325 |
| ARMA(1,1) | 520.3456 | ARMA(3,1) | 522.0107 |
| ARMA(1,2) | 523.1909 | ARMA(3,2) | 517.4479 |
| ARMA(1,3) | 523.0498 | ARMA(3,3) | 520.4261 |

As shown in Table 4 and Table 5, four of the bottom five of the AIC and BIC information are the same, namely ARMA (2,2), ARMA (2,3), and ARMA (3,2). )、ARMA(0,3)。 We choose these four models as fitted models for the real GDP growth rate in the United States.

### 2.3.4. ARMA model significance test

The validity of the model can be tested with the help of a significance test. If the information extracted by the model is sufficient, the fitting model is said to be significantly effective. A fitting model is better if it can extract information about most of the samples in the sequence. If there is no relevant information in the fitting residual term, then the residual sequence is a white noise sequence, and we call such a model a significant effective type.

Below we compare ARMA(2,2), ARMA(2,3), ARMA(3,2), and ARMA(0,3) model for significance testing. The results are:

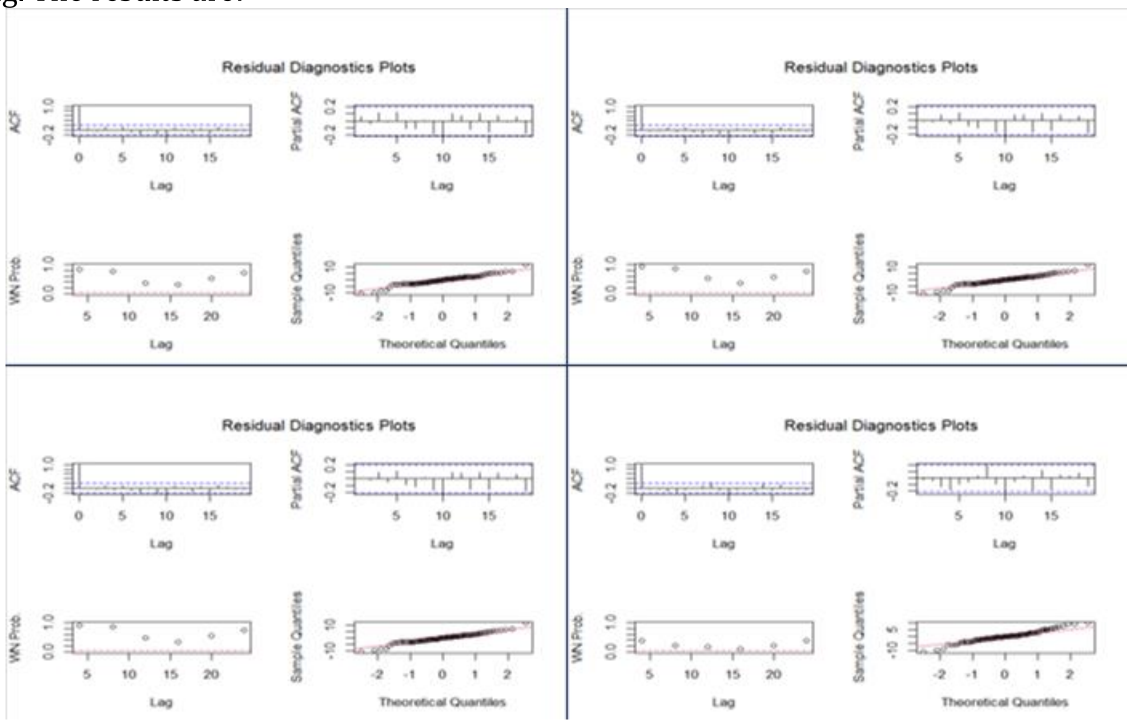


Fig. 3 Significance test of four models

We can judge whether the fitting model is significantly valid by using the white noise test plots of the residual sequence (3) in Fig. 3. The horizontal axis of Figure (3) represents the delay order, and the vertical axis of Figure (3) represents the P-value of the pure randomness test, also known as the value of the Q statistic, at this delay order. As shown in Fig. 3 above, the P values of all Q statistics are above the significance reference line of 0.05, then we can assume that the four models have passed the white noise test, that is, the four models are significantly true.

#### 2.3.5. Forecasting

We select the real GDP growth rate data of the United States from 1930 to 2019 as the training set, and use the ARMA model to predict the real GDP growth rate of the United States from 2020 to 2022 for a period of 3 years, and use the real data from 2020 to 2022 as the test set. After that, we compare the predicted value of the series with the true value of the series.

Based on the above four ARMA models, the forecast results of the real GDP growth rate of the United States from 2020 to 2022 are shown in Table 6.

Table 6 ARMA model prediction results

| year | True value | F-ARMA(2,2) | F-ARMA(2,3) | F-ARMA(3,2) | F-ARMA(0,3) |
|---|---|---|---|---|---|
| 2020 | -2.2 | 3.02 | 2.87 | 2.92 | 3.01 |
| 2021 | 5.8 | 3.11 | 2.91 | 2.94 | 3.07 |
| 2022 | 1.9 | 3.39 | 3.19 | 3.19 | 3.05 |

The difference between the forecasts of the above four models is not very large, and there is a big difference between them and the real values, which may be due to the decline in the real GDP data of the United States due to the epidemic, so that our forecast data is not very ideal.

## 3. Comprehensive analysis of prediction models

### 3.1. Model comprehensive analysis ideas

In the previous chapter, we chose four models as prediction models, because of the overall self-consistency of the stationary reversible ARMA model, that is, the AR model can be transformed into the MA model, and the MA model can also be transformed into the AR model, so there is no unique result for the end recognition of the ARMA model. Therefore, in this chapter, we compare the forecast errors of the four models and select the one with the smallest error to predict the real GDP growth rate in the next year.

In addition, in the previous chapter, we chose a time series of 90 years of data to model the real GDP growth rate for the last three years, and selected the one with the smallest forecast error from the four models to forecast the next year. Then, the time series of the 93 years of data can be approximated to consider the same as that of the 90 years of data, and we directly use the model with the smallest forecast error to predict the real GDP growth rate for the next year for the time series of all the 93 years of data.

### 3.2. Comprehensive analysis of forecast results

The following is a comparative analysis of the forecast and real values of the US GDP for 2020-2022. Wherein, absolute error = predicted value - true value; Mean absolute error = Σ|absolute error| / n。 The following Table 7 shows the analysis of the prediction results.

Table 7 Predicted results analysis

| year | F-ARMA(2,2) absolute error | F-ARMA(2,3) absolute error | F-ARMA(3,2) absolute error | F-ARMA(0,3) absolute error |
|---|---|---|---|---|
| 2020 | 5.22 | 5.07 | 5.12 | 5.21 |
| 2021 | -2.69 | -2.89 | -2.86 | -2.73 |
| 2022 | 1.49 | 1.29 | 1.29 | 1.15 |
| Mean absolute error | 3.13 | 3.08 | 3.09 | 3.03 |

As can be seen from Table 7, the average absolute error of the ARMA(0,3) model for the forecast of the US real GDP growth rate from 2020 to 2022 is 3.03%, which is the lowest among the four forecasting models, followed by the ARMA(2,3) model, and the largest error is ARMA(2,2).

model. However, the ARMA(2,2) model is the least informative model of AIC and BIC, which violates the information guidelines of AIC and BIC. The reason for this may be that the absolute error in the 2020 forecast is the largest, and we consider that the new crown pneumonia epidemic has caused a severe shock to the US economy, so that the US economy has not only not risen, but has declined relative to 2019, resulting in a negative growth rate.

### 3.3. Further Prediction Results

We use the ARMA(0,3) model of the US real GDP growth rate from 1930 to 2019 to forecast the next four years to obtain the US real GDP growth rate in 2023, as shown in Table 8.

Table 8 Four-year prediction results of the ARMA(0,3) model

| year | True value | Predicted value |
|---|---|---|
| 2020 | -2.2 | 3.01 |
| 2021 | 5.8 | 3.07 |
| 2022 | 1.9 | 3.05 |
| 2023 | --- | 3.23 |

Next, we directly use the 1930-2022 US real GDP growth rate time series to establish the ARMA(0,3) model to forecast the real GDP growth rate in 2023, and the results are shown in Table 9.

Table 9 The result of the ARMA(0,3) model prediction

| year | True value | Predicted value |
|---|---|---|
| 2023 | --- | 2.67 |

In the latest World Economic Outlook report released by the International Monetary Fund on October 10, the United States predicts that the GDP growth rate in the United States will be 2.1% in 2023; According to the World Bank's Global Economic Prospects 2023 report, the U.S. economy will grow by 1.1% in 2023. We find that the prediction results of the ARMA(0,3) model using the time series of data from 1930 to 2022 are more satisfactory and reasonable. Its forecasts are closer to those of the International Monetary Fund and very different from those of the World Bank. The reason for this may be that the large-scale interest rate hike policy in the United States over the past year and a half has continued to have an impact on the US economy, resulting in relatively limited growth.

## 4. Summary and outlook

### 4.1. Summary of the full text

In this paper, 93 years of data are prepared, and the first 90 years of data are used as the training set, and the last 3 years of data are the test set. First, the first 90 years of data were used for flat modeling. Then, according to the AIC and BIC information criteria, the last four ARMA models were selected to establish four models. Then, four models were used to predict the real GDP growth rate in the last three years. Finally, the ARMA model with the smallest error was selected to make a four-year forecast using the forecast data and the test data, and the GDP growth rate in 2023 was obtained.

Based on the above obtained model, we directly use the 93 year data to build the above model and forecast the growth rate in 2023.

After comparative analysis, it is found that the GDP growth rate predicted by using the 93 data is more in line with the forecast of the International Monetary Fund, and is also more in line with the current situation of the current economic decline caused by the continuous interest rate hikes and the rising unemployment rate in the United States. It also further verifies that there is no unique result for the order recognition of the ARMA model, and it is likely that the same sequence will appear, and a good fitting effect can be obtained by using different end recognition. Therefore, it is meaningful and valuable for us to further study the ARMA model

### 4.2. Deficiencies and outlook

First, we select a total of 93 data on the real GDP growth rate of the United States from 1930 to 2022 as the basis for the empirical analysis in this paper, which may have a certain impact on the accuracy of the forecast due to the relatively small number of data. In future studies, we can consider replacing annual data with quarterly data for more detailed research.

Second, we ignore the influence of some factors when fitting the model. In this paper, we use linear series as the basis for modeling, but in the study of practical problems, it is incomplete to use only GDP data for forecasting, without considering the impact of national policies, natural disasters, wars, or major infectious diseases. From the time series diagram, we can also see that there were several sharp fluctuations between 1930 and 1950, which were caused by factors such as economic crises, national policies, and wars. In addition, the pandemic had a drastic impact on GDP in 2020. In the future research, various factors can be added to the model to further improve the model.

Thirdly, the prediction result in this paper is that only one method model is used to make predictions, and the systematic error of the model cannot be removed by using only the same model. In the future research, it can be considered to use more methods to make predictions, and make combined predictions together to further improve the prediction accuracy of the model.

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