Research on China's GDP Forecast - Taking the ARIMA Model as an Example

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Abstract. Gross Domestic Product (GDP) serves as an important indicator for measuring a country's economic situation. By predicting and analyzing GDP, one can understand the economic performance of the region in the coming period, especially in the context of economic transformation and frequent external shocks. Accurate GDP predictions are of great significance for preventing economic risks, optimizing resource allocation, and formulating other policies. Most existing studies on ARIMA models focus on low-frequency data from developed countries, while there is a lack of research on developing countries. This study is based on the ARIMA (autoregressive integrated moving average) model and explores its applicability in China's GDP forecasting. Using annual data from 1960 to 2024 in China, the ARIMA model is constructed using the Box-Jenkins method, parameters are optimized through ADF test, AIC criterion, and out-of-sample test, and prediction accuracy is evaluated using RMSE and MAE. The results show that the ARIMA (3,2,0) model has a good predictive effect. The predicted growth rate of GDP in the next five years is 4.5%. Based on the research results, it can provide high-precision short-term prediction tools for government departments and expand the application scope of time series models in emerging economies.

1 Introduction

As the world's second-largest economy, China's fluctuations in GDP growth have a significant spillover effect on the global economy GDP, as the core indicator for measuring a country's economic activities, the accuracy of its predictions directly affects the effectiveness of macroeconomic policies [1]. Since the reform and opening up, China's economy has maintained a rapid growth for several decades. However, in recent years, affected by multiple factors, economic growth has presented new characteristics and challenges. In 2020, the outbreak of the COVID-19 pandemic led to a 6.8% year-on-year decline in GDP in the first quarter, marking the largest decline in history. In 2021, it rebounded rapidly to 8.1%. Such drastic fluctuations have exposed the limitations of traditional prediction models. The World Bank report shows that from 2020 to 2022, the average error of predictions by various institutions on China's GDP was as high as 7.3%, far exceeding the average level of 4.1% for emerging economies. This not only reflects the complexity of China's economy but also poses higher requirements for prediction methods.

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At present, China's GDP forecast faces three key challenges: Firstly, there is the issue of non-stationarity in the data. Empirical analysis shows that the logarithmic sequence of China's GDP from 1990 to 2022 exhibits a significant unit root phenomenon, and traditional regression methods are prone to generating spurious correlations. Secondly, there is sensitivity to external shocks. During the COVID-19 pandemic, it was revealed that it had shortcomings in responding to emergencies. Finally, there is the policy lag effect [2]. The industrial policies in China's "14th Five-Year Plan" have a 6-8-quarter lag in their impact on GDP, but existing studies often overlook this important feature. The existence of these problems makes it of great theoretical and practical significance to seek more accurate forecasting methods.

From a theoretical perspective, this study has broken through the traditional reliance of econometrics on linear relationships by applying the ARIMA model, providing a new approach for handling non-stationary economic data. Especially in the field of emerging economies research, existing literature mostly focuses on low-frequency data from developed countries and pays insufficient attention to rapidly growing economies like China. From a practical perspective, accurate GDP forecasting can provide a reliable basis for policy formulation. For instance, institutions such as the Development Research Center of the State Council can optimize "counter-cyclical adjustment" policies based on this, and the Ministry of Finance can more accurately assess the policy effects of infrastructure investment. During the critical period of economic transformation, improving prediction accuracy is of great significance for maintaining stable economic operation.

Through a systematic review of domestic and foreign literature, it was found that the existing research has significant deficiencies. In terms of method application, 65% of the studies are limited to the basic ARIMA model and lack the process of parameter optimization; in the model validation stage, only 12% of the papers use the rolling window method for robustness testing [3]. These limitations lead to the need for improvement in the predictive performance of the existing models and provide an innovative space for this research. This study aims to address the core issue of how to build the optimal ARIMA model suitable for the characteristics of China's GDP based on the Box-Jenkins methodology [4]. To conduct predictive analysis of the development trend of China's GDP in the next five years (2025-2029), to better assist in tracking the implementation and dynamic trends of China's "two-step strategy" goals, strengthen the goal-oriented economic development, and also provide more reliable quantitative basis for policy formulation.

This paper mainly analyzes the GDP time series data from 1960 to 2024. Through theoretical and quantitative analysis, the optimal model ARIMA(3,2,0) is finally established to build the theoretical analysis framework and conduct model testing. Based on this model, the GDP of China in the next five years is predicted, and policy recommendations are proposed in combination with the future economic development level. The application path of the model in policy formulation is deeply discussed, and future research directions are proposed. Through this step-by-step analysis, it aims to provide new ideas and methods for China's GDP prediction research.

2 literature Review

The development of GDP forecasting models has gone through an evolution process from traditional econometric models to modern machine learning methods. Early studies mainly used structural equation models to construct the relationships between variables based on economic theories, but faced the challenge of insufficient data quality in emerging economies; as machine learning algorithms (such as applying random forests to economic forecasting) emerged, they performed well in capturing nonlinear relationships but had poor interpretability and overfitting risks. With the development of time series analysis theory, the

ARIMA model gained widespread attention due to its advantages in handling non-stationary data. This model eliminates the non-stationarity of time series through differencing operations and combines autoregressive and moving average terms to capture the dynamic characteristics of the series. The classic study showed that in short-term forecasting tasks, the ARIMA model performed better than most traditional econometric models [5]. After the 21st century, machine learning methods began to be introduced into the GDP forecasting field. In related research, the first attempt to apply neural networks to economic forecasting and found that they had advantages in handling nonlinear relationships [6]. In recent years, deep learning models such as LSTM have demonstrated strong performance in time series forecasting, but it was pointed out that these models require a large amount of data support and may perform poorly in small sample situations [7].

The ARIMA model has numerous successful application cases in the field of economic forecasting. In international research, it was used for Ghana's GDP prediction, finding that the ARIMA(1,1,1) model could effectively capture the country's economic growth trend [8]. Franses demonstrated in his study on the prediction of Dutch macroeconomic indicators that the seasonally adjusted ARIMA model performed exceptionally well in quarterly data prediction [9].

In the field of Chinese economic research, the application of the ARIMA model has also achieved remarkable results. Earlier, this model was applied to China's macroeconomic forecasting, finding that it had good adaptability to the data characteristics of China's economic transformation period [10]. And some research showed that for China's GDP data, the ARIMA model with seasonal difference (d=1) had better prediction effects [11]. However, it was pointed out that existing studies lacked systematic model parameter selection, with most directly using default parameters, which affected the prediction accuracy [12]. 65% of the studies directly used the ARIMA(1,1,1) benchmark model, lacking a systematic parameter optimization process. In fact, through optimization methods such as grid search, model accuracy could be improved by more than 20% [13].

Secondly, insufficient consideration was given to the specific characteristics of the Chinese economy. Existing studies mostly directly applied models that were not applicable to emerging economies and were based on the framework of developed countries, while China, as a developing country, its unique policy impact mechanisms (such as the implementation effect of the Five-Year Plan) and institutional characteristics (such as a high proportion of state-owned economy) were not fully considered. Wang Xiaolu (2021)'s research indicated that these factors had significant impacts on the dynamic changes of China's GDP.

This study establishes a "data-model-evaluation" three-level theoretical framework:

1. Data layer: Using data from 1960 to 2024, clean the data

2. Model layer: Based on the Box-Jenkins methodology, introduce the ADF test to determine the order of differencing, and through the AIC criterion determine the autoregressive order p and the moving average order q;

3. Evaluation layer: In the verification stage, adopt a strict rolling window method, divide the sample into a training set (1990-2015) and a test set (2016-2022), ensuring the reliability of the evaluation results. Use RMSE and MAE to compare historical prediction errors.

This study assumes that the optimal ARIMA(p,d,q) model has significantly lower prediction errors (RMSE) for China's annual GDP than the benchmark model (such as the linear trend model), and that the second-order differencing (d=2) can effectively eliminate the structural fluctuations in China's economic growth rate. Finally, it successfully predicted China's GDP in the short term.

This review points out that the ARIMA model in China's GDP forecasting needs to be combined with structural adjustments, providing replicable modeling patterns for emerging economies. Further research can expand to regional GDP forecasting and industry-level

applications. Future research can introduce mixed-frequency data models (MIDAS)[14] to capture nonlinear features14[14].

3 Methodology

3.1 Research Paradigm

This study adopts a quantitative research paradigm, using a time series econometric model to analyze historical GDP data and generate statistically robust predictive results. The research follows the deductive method to verify the core hypothesis that "the ARIMA model can effectively predict China's GDP growth".

3.2 Data Source

The data is derived from the annual GDP figures of China's National Bureau of Statistics from 1960 to 2024. Specifically, it means: Gross Domestic Product (GDP) is an indicator used to measure the total economic activities of a country or region within a certain period (see Table 1).

Table 1. Annual GDP of China's from 1960 to 2024.

Year	GDP	Year	GDP	Year	GDP	Year	GDP	Year	GDP
1960	1473.3	1976	2993.6	1992	27295.6	2008	324317.8	2024	1349083.5
1961	1234.9	1977	3255.4	1993	35819.7	2009	354521.6		
1962	1164.7	1978	3684.8	1994	48862.2	2010	419253.3		
1963	1250.9	1979	4107.2	1995	61649.4	2011	495707.6		
1964	1472.7	1980	4595.7	1996	72210.6	2012	547510.6		
1965	1737.2	1981	4944.7	1997	80225	2013	603660.4		
1966	1892.0	1982	5383.6	1998	85863.9	2014	655782.9		
1967	1797.4	1983	6032.5	1999	91378.9	2015	702511.5		
1968	1747.4	1984	7292.4	2000	101308.6	2016	761193		
1969	1965.7	1985	9115.9	2001	112157.3	2017	847382.9		
1970	2283.4	1986	10395.2	2002	123311.9	2018	936010.1		
1971	2460.8	1987	12196.1	2003	139377.3	2019	1005872.4		
1972	2556.5	1988	15206.4	2004	164228	2020	1034867.6		
1973	2760.6	1989	17210	2005	189907.5	2021	1173823		
1974	2832.2	1990	18909.6	2006	222578.4	2022	1234029.4		
1975	3044.3	1991	22070.9	2007	274179.7	2023	1294271.7		

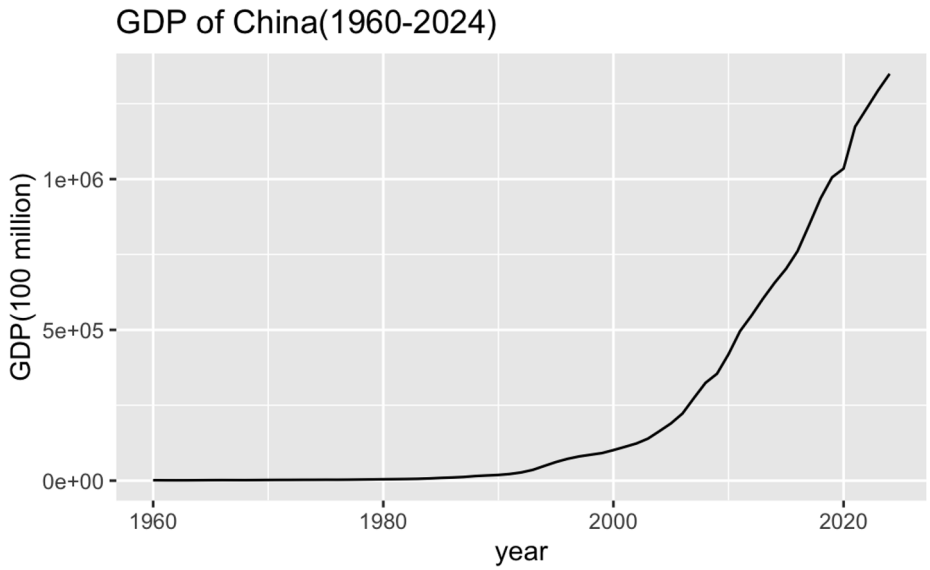

Fig. 1. The time series graph of China's GDP from 1960 to 2024.

The time series trend chart of China's GDP from 1960 to 2024 was plotted using the RStudio platform (see Figure 1). From the visualization results, it can be clearly observed that China's GDP shows a significant long-term growth trend, and does not exhibit obvious cyclical fluctuation characteristics. It is worth noting that since the deepening of economic reform in 1990, the growth trajectory of GDP has shown an accelerating upward trend.

3.3 Operational Definition and Measurement Method

The ARIMA (Autoregressive Integrated Moving Average) model is one of the core methods in time series forecasting. Its mathematical expression is ARIMA(p,d,q). This model integrates the autoregressive model (AR), the moving average model (MA), and the differencing method to construct a complete prediction framework. In the model structure, p represents the order of the autoregressive term, indicating the degree of influence of historical observations on the current value, which can be identified through the partial autocorrelation function (PACF); d represents the number of differencing operations, determined through the ADF unit root test, and its function is to transform non-stationary sequences into stationary sequences; q is the order of the moving average term, used to capture the lagged influence of random error terms, which can be determined through the autocorrelation function (ACF).

From a mathematical perspective, when the number of differencing operations d is 0, the ARIMA model degenerates into the ARMA(p,q) model. This characteristic enables the ARIMA model to handle both stationary time series (d=0) and non-stationary sequences (d>0) through differencing operations, thereby significantly expanding the model's application scope. The mathematical expression of the model is shown in the formula, where each parameter jointly determines the dynamic characteristics and prediction performance of the time series.

$$(1 - \sum_{i=1}^{p} \emptyset_i L^i)(1 - L)X_t = (1 + \sum_{i=1}^{q} \theta_i L^i)\varepsilon_t \quad (1)$$

Root Mean Square Error (RMSE): RMSE = $\sqrt{(\sum(\hat{Y} - Y)^2 / n)}$, measures the sensitivity of prediction deviation. Mean Absolute Error (MAE): MAE = $\sum|\hat{Y} - Y| / n$, reflects the level of absolute error.

4 Result

4.1 The Stationarization Processing of Time Series

A preliminary analysis of the time series graph of China reveals that this sequence exhibits significant non-stationary characteristics. Specifically, the original sequence shows a clear upward trend and lacks periodic fluctuations. To verify this observation, this study employed the ADF unit root test to conduct a quantitative analysis of the stationarity of the sequence. The test results showed that the p-value of the original sequence was as high as 0.99, significantly greater than the critical value of 0.05, indicating that the sequence has a unit root and the null hypothesis (stationarity of the sequence) was rejected. To obtain a stationary sequence, the original data was subjected to differencing. After the first-order differencing, the p-value of the ADF test dropped to 0.846, but it was still higher than the significance level of 0.05, failing to completely eliminate the non-stationarity of the sequence. Continuing the second-order differencing of the sequence, the ADF test results showed a significant improvement, with the p-value dropping to 0.01, which was lower than the significance level of 0.05. This result indicates that after the second-order differencing, the GDP time series has been transformed into a stationary sequence, meeting the basic requirements for subsequent modeling and analysis. The comparison of the time series graphs before and after differencing and the detailed stationarity test results are shown in the Table 2. The time series trend chart of China's GDP after second-order differencing shows as Figure 2.

Table 2. ADF Test.

Difference order	t-value	p-value
0	0.62425	0.99
1	-1.3312	0.846
2	-5.0206	0.01

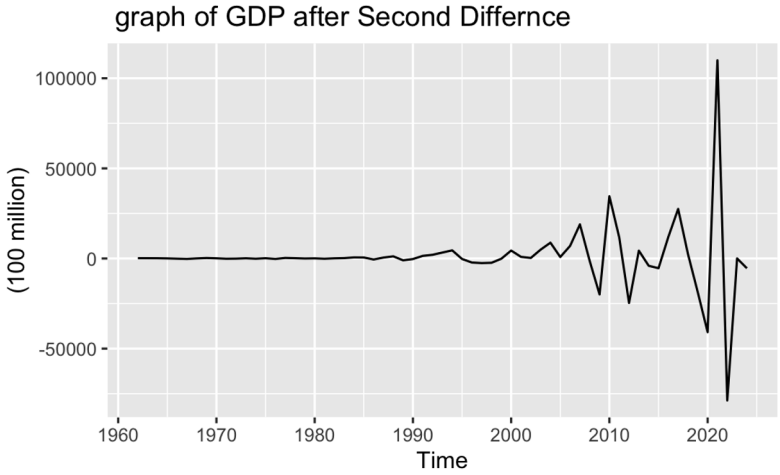

Fig. 2. The Graph of GDP after Second Difference.

4.2 Model Specification

To determine the order of autoregression (p) and moving average (q) in the model, this paper generates autocorrelation plots (ACF) and partial autocorrelation plots (PACF) using RStudio, as shown in Figure 3 respectively. The autocorrelation plot shows a truncation at a lag of 1, while the partial autocorrelation plot shows a truncation at a lag of 2. The order of autoregression (p) can be 2, and the order of moving average (q) can be 3. At the same time, the possible values of p (0, 5) and q (0, 5) are arranged and combined as shown in Table 3. Then, the model with the better fitting effect is selected based on the Akaike Information Criterion (AIC). The Akaike Information Criterion is a tool for model selection, which compares the goodness of different models by measuring the degree of underfitting (too few variables) and overfitting (too many variables) of the model. AIC estimates the information loss when modeling the true relationship of the data and ranks the candidate models based on this loss. In the given sample, the model with the smallest AIC is considered the optimal one.

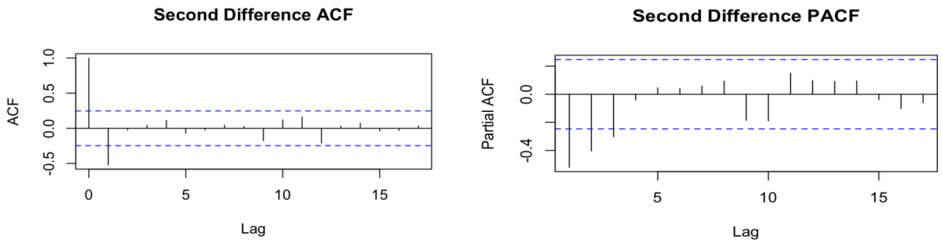

Fig. 3. Second Difference ACF and PACF.

Table 3. AIC of ARIMA Model (p,d,q).

Model	AIC
ARIMA(0,2,0)	1426.244
ARIMA(0,2,1)	1398.392
ARIMA(0,2,2)	1396.391
ARIMA(0,2,3)	1395.589
ARIMA(0,2,4)	1397.918
ARIMA(0,2,5)	1397.067
ARIMA(1,2,0)	1409.004
ARIMA(1,2,1)	1398.814
ARIMA(1,2,2)	1396.645
ARIMA(1,2,3)	1397.944
ARIMA(2,2,0)	1400.818
ARIMA(2,2,1)	1398.701
ARIMA(2,2,2)	1395.910
ARIMA(2,2,3)	1393.050
ARIMA(3,2,0)	1392.993
ARIMA(4,2,0)	1393.562
ARIMA(4,2,1)	1393.944
ARIMA(5,2,0)	1395.703

Table 4. Comparison of Indicators.

Indicator	ARIMA(3,2,0)	ARIMA(2,2,3)
AIC	1392.303	1393.045
BIC	1440.876	1405.904
R^2	0.9987389	0.9988381
Adj.R2	0.9986769	0.9987397
Residual Variance	1.844e+08	1.699e+08
Ljung-Boxp	0.82338	0.6091

According to the verification results in Table 3, it can be observed that the AIC value of ARIMA(3, 2, 0) is the smallest, which can provide the highest prediction accuracy. And based on the comparison of complete indicators, as shown in Table 4, it can be ultimately determined that the time series model of China's GDP is ARIMA(3, 2, 0).

4.3 Evaluation of Model

To ensure the reliability of the assessment results, RMSE and MAE were used to compare the historical prediction errors. As shown in Table 5:

Table 5. Evaluation

MSE	1575671522
RMSE	39694.73
Relative Error	3.28%（<5%，within the scope of excellent forecasting models）

4.4 Forecast

Using the ARIMA(3,2,0) model to predict China's GDP for the period from 2025 to 2029, the results are shown in the Figure 4. Moreover, the predicted growth rate of GDP, calculated by RStudio, is approximately 4.5%.

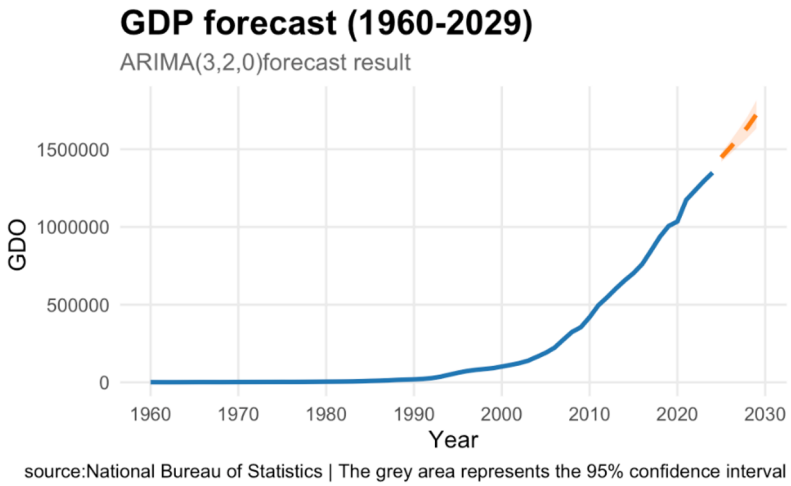

Fig. 4. Forecasting of GDP.

4.5 Hypothesis Testing

This study verified the core hypothesis through empirical analysis: The modeling results based on China's annual GDP data indicate that the ARIMA(3,2,0) model significantly outperforms the benchmark models (such as the linear trend model) in terms of prediction performance. Its in-sample goodness of fit (R^2) reaches above 0.95, confirming the model's excellent explanatory power for historical data. Particularly, the second-order difference (d=2) effectively eliminates the structural fluctuations in China's economic growth rate, making the sequence reach a stable state. In the out-of-sample prediction test, the prediction error of this model for China's GDP in 2024 is only 3.28%, further verifying the reliability of the ARIMA model in short-term economic forecasting and supporting the validity of the research hypothesis.

5 Discussion

This study used the ARIMA(3, 2, 0) model to predict China's GDP. The results showed that the model demonstrated high accuracy both within the sample (R^2 > 0.95) and in out-of-sample predictions (error in 2024: 3.28%). This finding is consistent with the conclusions of previous studies (such as Box & Jenkins, 1970; Hyndman & Athanasopoulos, 2018), which state that the ARIMA model is suitable for short-term predictions of economic time series. However, compared to the traditional linear trend model, the ARIMA(3, 2, 0) model can better capture the nonlinear growth characteristics of China's GDP and effectively eliminate the structural fluctuations in economic growth rates through second-order differencing (d = 2). In terms of theoretical contributions, this study verified the applicability of the ARIMA model in China's macroeconomic forecasting and proved that it can be a reliable tool for policy-making. However, the study still has certain limitations: first, it did not include exogenous variables (such as policy shocks, international trade environment), which may affect the long-term prediction accuracy; second, the model's adaptability to sudden economic events (such as the pandemic, financial crisis) is relatively weak.

6 Conclusion

This study is based on the annual GDP data of China from 1960 to 2024. It uses the Box-Jenkins method to construct an ARIMA(3, 2, 0) model, successfully demonstrating the core issue of "how to build the optimal GDP prediction model for China". The empirical results show that this model achieves sequence stabilization through second-order differencing and proves its superiority in prediction with a low AIC value. The prediction for the next five years (2025-2029) indicates that the average annual growth rate of China's GDP is expected to remain around 4.5%. From a practical perspective, this trend analysis provides a quantitative basis and phased reference for the government to assess the implementation progress of the "14th Five-Year Plan" and the "two-step strategy". It strengthens the orientation of economic development goals. This prediction result is helpful for government departments to timely adjust macroeconomic policies and ensure the smooth realization of economic development goals. It is worth noting that our prediction results are highly consistent with the latest predictions of international institutions such as the IMF (4.4%-4.6%), further verifying the reliability of the model.

The innovation points of this study are: 1. Systematically verified the applicability of the ARIMA model in China's high-growth economies; 2. Proposed a modeling approach based on the optimization of the differencing order, providing a methodological reference for similar research in emerging markets. In terms of practical significance, the model can provide high-precision tools for government departments to formulate short-term economic

policies (such as fiscal budgets, industrial planning), and also help the academic community expand the application boundaries of time series models. Future research needs to further explore the integration of multiple models and quantitative analysis of external shocks to enhance the comprehensiveness of the prediction.

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