Data Analysis and Prediction of Daily Closing Price of China Unicom based on ARIMA Model

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Abstract. This paper aims to analyze and forecast the daily closing price of China Unicom by using ARIMA (autoregressive integral moving average) model. With the increasingly complex and changeable financial market, the demand of investors for predicting stock price changes is increasing day by day. As one of the major telecom operators in China, the movement of China Unicom's stock price has important reference value for investors.

Keywords: time series; ARIMA model; Forecast; Stock price

1 INTRODUCTION

The stock market holds a pivotal position in the financial landscape, serving as a barometer that, to a certain extent, reflects the dynamic shifts in a nation's economic cycle through the fluctuations in stock prices. The stock price is very sensitive to the time factor, so the establishment of time series model can effectively analyze and forecast the stock price. As one of the three major telecom operators in China, the stock price fluctuation of China Unicom is not only concerned by the majority of investors, but also related to the development of the whole communication industry. However, in recent years, amidst the continuous expansion of China's communications market, the widespread adoption of novel technologies, particularly 5G, has emerged as a significant trend. The volatility of China Unicom's stock price (RMB) has presented complexity and uncertainty. As a classical method in time series analysis, the application of ARIMA model on the daily closing price (RMB) of China Unicom can not only verify the validity of the model, but also provide reference for actual investment decisions. This study mainly applies the time series analysis method of ARIMA model to conduct in-depth data analysis and forecast for the daily closing price (RMB) of China Unicom from 2022.9.1 to 2024.3.1, so as to understand the changing trend of China Unicom's stock price and provide a new perspective for the field of stock price prediction.

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2 LITERATURE REVIEW

Time series refers to a series of data points arranged in chronological order, which records the value of a certain phenomenon or variable at different points in time. In finance, time series data are widely used in market analysis, risk assessment and predictive decision-making. Through the mining and analysis of time series data, we can reveal the operation law of the financial market, predict the future market trend, and provide decision support for investors. Time series analysis involves many aspects, including data stationarity test, trend analysis, seasonal adjustment and so on. Through proper processing and analysis of time series data, we can better understand and grasp the dynamic changes of financial markets, and provide more accurate and reliable information for financial decisions. [1-4]Therefore, time series play an important role in finance and are an integral part of financial research and practice.

The modeling method used to study time series is usually autoregressive moving average model (ARMA), which contains more comprehensive information and explains more accurate information, but it is mostly used to deal with stationary time series. Since stock prices are usually non-stationary time series and need differential differentiation processing, differential autoregressive moving average model (ARIMA) is used to analyze stock price changes in practice. Therefore, using ARIMA model to analyze the time series of a specific stock price has important theoretical basis and practical significance.[1,3]

On the research of China Unicom stock price, scholars at home and abroad have achieved certain results. The early research mainly focused on qualitative analysis, such as the analysis of China Unicom's business development, financial status, market competition and other aspects. With the development of financial metrology, more and more scholars began to use quantitative analysis methods to study the stock price of China Unicom.

In terms of stock price volatility characteristics, some scholars have found that the stock price volatility of China Unicom has significant volatility aggregation and leverage effect by establishing GARCH model and EGARCH model. In addition, some scholars have found that the stock price fluctuation of China Unicom has significant seasonal characteristics and asymmetry.

In terms of influencing factors of stock price, scholars generally believe that policy adjustment, company performance, market environment and other factors will have a significant impact on China Unicom's stock price. Among them, policy adjustment, especially in the communications industry, has the most significant impact on China Unicom's stock price. In addition, the company's profitability, operating capacity and growth capacity and other financial indicators will also affect China Unicom's stock price.

In terms of stock price forecasting methods, the early research mainly uses linear regression model, exponential regression model and other traditional statistical models to forecast. With the continuous development of financial time series analysis, more and more scholars begin to use ARIMA model, VAR model, ECM model and other financial measurement models to forecast. The application of these models makes the accuracy and stability of stock price prediction significantly improved.

However, the existing research results still have some shortcomings. First of all, some studies fail to fully consider the nonlinear characteristics of China Unicom's stock price fluctuations, which leads to certain deviations in the forecast results. Secondly, the research on the factors affecting the stock price fluctuation of China Unicom is not deep enough, which makes it difficult for investors to fully grasp the risk of stock price fluctuation. Finally, few studies use ARIMA model to forecast China Unicom's stock price, which makes investors lack of effective forecasting tools. Therefore, this study aims to use ARIMA model to analyze and forecast the stock price of China Unicom more accurately.[2,5]

3 MODEL INTRODUCTION

3.1 ARIMA Model

The ARIMA (Autoregressive Integrated Moving Average) model, originally introduced by Box and Jenkins in the early 1970s, stands as a renowned approach for forecasting time series data. This model integrates the principles of autoregressive (AR) and moving average (MA) models, while incorporating the notion of differencing (I) to handle non-stationary time series. This integration allows the ARIMA model to effectively capture both trends and seasonal variations within the data.[8-10]

The basic idea behind the ARIMA model is to use historical data to predict future values. It assumes that the time series data is a linear function of its own past values and a linear function of the random error term. By fitting these data points, ARIMA models are capable of capturing the evolving patterns within time series data and providing insights into potential future trends.

An ARIMA model usually consists of three components: autoregressive term (AR), difference order (I), and moving average term (MA). The autoregressive term describes the relationship between the time series data and its own past values. The difference order is used to transform non-stationary time series into stationary series for subsequent analysis; Moving average takes into account the effect of random error term on time series.

When the ARIMA model is applied, the order of the model (p,d,q), that is, the order of the autoregressive term, the order of the difference term and the order of the moving average term, must be determined first. This is usually achieved by observing the characteristics of time series data, conducting correlation analysis and unit root test. Once the model order is determined, the parameters of the model can be estimated using least squares or other optimization algorithms.

(1) AR model. AR is a linear time series analysis model. The regression equation is established through the correlation (autocorrelation) between its current data and historical data. The formula is as follows:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \tag{1}$$

(2) MA model. This model is a weighted sum of the white noise series in a period of time series, and the moving average equation can be obtained, the formula is as follows:

$$Y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} \ldots + \theta_q \varepsilon_{t-q} \quad (2)$$

(3) ARMA model. The full name of this model is autoregressive moving average model, which consists of two parts: autoregressive and moving average model. The formula is as follows:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} - \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (3)$$

(4) ARIMA model. ARIMA(p,d,q) model is also known as differential autoregressive moving average model. The trend parameters are as follows:

p: trend autoregressive order; d: trend difference order; q: Trend moving average order.

3.2 ARIMA Model Modeling Steps [1-5]

Data Collection and Preprocessing. After collecting the original data, the data is preprocessed, and the stationarity test is carried out through the unit root (ADF) test. The difference operation is carried out on the sequences with large differences and periodic changes to complete the stationarity processing and make them tend to be stationarity to ensure that the data quality meets the requirements of ARIMA model.

Construction and Parameter Estimation of ARIMA Model. The ARIMA model is constructed according to the data after prestabilization. The model parameters p,d and q are determined according to the ACF diagram, and the appropriate ARIMA(p,d,q) model form is selected. Then, the parameters of the model are estimated by the least square method to determine the specific form of the model.

Model Diagnosis and Optimization. After the initial estimate of the ARIMA model is obtained, we need to diagnose the model to evaluate its fit and predictive power. This includes residual analysis, model stability test, etc., and white noise test is performed to determine whether the residual sequence is white noise.

Stock Price Prediction and Result Evaluation. Upon completion of the optimization process, we leverage the optimized ARIMA model to anticipate the future daily closing prices of China Unicom. Specifically, our predictions will span from March 4th, 2024, to March 8th, 2024. Subsequently, we intend to assess the model's forecasting efficacy by comparing the predicted values against the actual daily closing price data during this period.

4 EMPIRICAL ANALYSIS

4.1 Raw Data Processing

ARMA model is usually used to model data with stable changes, but many real time series (such as stock data) do not have constant and unchanged mean value, so ARIMA model is needed to model data with non-stationarity. Initially, a crucial step involves examining the stability of the original data, and then transform the unstable sequence into a stable sequence according to the difference method.

This paper selects the daily closing price data of China Unicom from September 1, 2022 to March 1, 2024 through Flush Finance, with a total of 361 samples.

First, this paper uses Eviews13 software to briefly analyze the original data of China Unicom's daily closing price and draw a time series diagram of the original sequence, as shown in Figure 1. As can be seen from Figure 1, the original daily closing price data of China Unicom did not show obvious rules within the sample time limit, and it can be seen that the short-term fluctuation is large. Therefore, according to the original time series line graph, we can roughly infer that the series does not meet the stationarity condition.

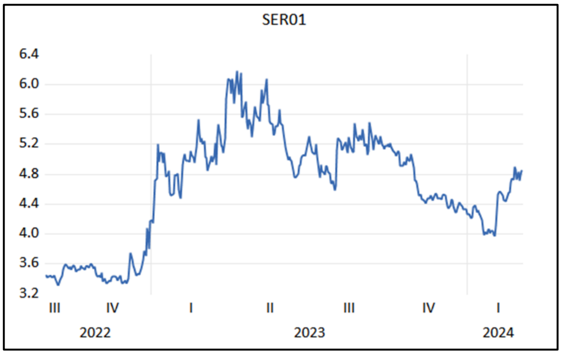


Fig. 1. Line chart of closing price time series of China Unicom stock trading day.

The next step is to perform differential processing on the raw data. Eviews13 software was used to draw the broken line trend diagram of the first-order difference sequence, as shown in Figure 2. It can be seen that the trend of the difference series is obviously more gentle and stable than that of the original data series, and there is a certain regularity in the fluctuation, so it can be inferred that the first-order difference series may belong to the stable time series. In order to further confirm its stationarity, ADF tests can be carried out on three cases: no intercept item without trend item, with intercept item without trend item, and with intercept item with trend item. The results are shown in Figure 3-5. It can be found that the P-values are all less than 0.05, and it can be concluded that the data after first-order difference processing is the required stationarity data.

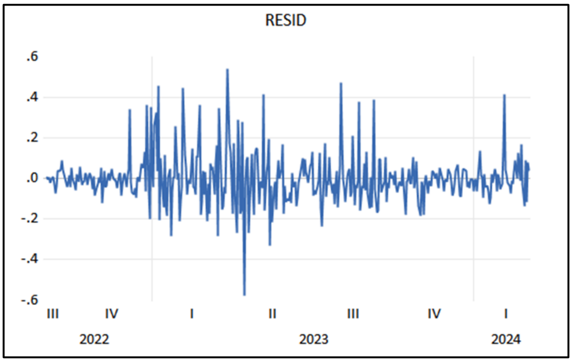


Fig. 2. Time series diagram of first-order difference series.

Null Hypothesis: DPRICE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.27208	0.0000
Test critical values:	1% level	-3.448363	
	5% level	-2.869374	
	10% level	-2.571011	

*MacKinnon (1996) one-sided p-values.

Fig. 3. There are intercept terms and no trend terms.

Null Hypothesis: DPRICE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.28206	0.0000
Test critical values:	1% level	-3.983828	
	5% level	-3.422391	
	10% level	-3.134057	

*MacKinnon (1996) one-sided p-values.

Fig. 4. There are intercept terms and there are trend terms.

Null Hypothesis: DPRICE has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.28254	0.0000
Test critical values:	1% level	-2.571419	
	5% level	-1.941709	
	10% level	-1.616108	

*MacKinnon (1996) one-sided p-values.

Fig. 5. There is no intercept term. There is no trend term.

4.2 Model building and Order Determination

According to the above processing results, the original time series achieves a state of stationarity after first-order difference. Next, select ARIMA (p,d,q) model to complete the modeling. Among them, since the stationary sequence is obtained by the first-order difference, the difference integration number d=1 can be obtained.

Firstly, the order of the model is determined. As shown in Figure 6, the autocorrelation graph (ACF) and partial autocorrelation graph (PACF) of the stationary sequence are both second-order truncated, but AIC information criteria, SC information criteria and t statistics should be used to make specific judgments if accurate values of the lag order p and q are to be obtained. And try to fit the model. According to previous empirical experience, most models of financial and economic variables meet the analysis model with p value and q value ≤2. The three models of ARIMA (2, 1, 0), ARIMA (2, 1, 2) and ARIMA (0, 1, 2) are analyzed and compared, as shown in Figure 7-9, so as to determine the optimal model order.

Date: 05/02/24 Time: 12:29
Sample (adjusted): 9/02/2022 3/01/2024
Included observations: 360 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.070	-0.070	1.7962	0.180
		2	-0.080	-0.086	4.1542	0.125
		3	0.043	0.031	4.8313	0.185
		4	-0.025	-0.026	5.0511	0.282
		5	-0.078	-0.076	7.2626	0.202
		6	0.097	0.081	10.696	0.098
		7	0.006	0.009	10.711	0.152
		8	-0.042	-0.023	11.356	0.182
		9	0.074	0.063	13.368	0.147
		10	-0.115	-0.116	18.321	0.050
		11	0.059	0.073	19.624	0.051
		12	-0.015	-0.039	19.710	0.073
		13	-0.073	-0.066	21.693	0.060
		14	0.083	0.084	24.268	0.043
		15	-0.008	-0.040	24.295	0.060
		16	-0.158	-0.124	33.746	0.006
		17	0.041	0.013	34.389	0.007
		18	0.004	-0.037	34.396	0.011
		19	-0.042	0.012	35.060	0.014
		20	-0.066	-0.120	36.718	0.013

Fig. 6. Sample autocorrelates and sample partial autocorrelates of first-order difference sequences.

Dependent Variable: DPRICE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/02/24 Time: 12:31
Sample: 9/02/2022 3/01/2024
Included observations: 360
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.075270	0.041033	-1.834396	0.0674
AR(2)	-0.084670	0.047777	-1.772191	0.0772
SIGMASQ	0.015895	0.000688	23.10122	0.0000

R-squared	0.011229	Mean dependent var	0.003611
Adjusted R-squared	0.005690	S.D. dependent var	0.126967
S.E. of regression	0.126605	Akaike info criterion	-1.287133
Sum squared resid	5.722319	Schwarz criterion	-1.254748
Log likelihood	234.6839	Hannan-Quinn criter.	-1.274256
Durbin-Watson stat	1.994677		

Inverted AR Roots	-.04-.29i	-.04+.29i

Fig. 7. ARIMA(2,1,0).

Dependent Variable: DPRICE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/02/24 Time: 12:33
Sample: 9/02/2022 3/01/2024
Included observations: 360
Convergence achieved after 55 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.059571	0.025756	-41.13943	0.0000
AR(2)	-0.978787	0.023700	-41.29907	0.0000
MA(1)	1.033944	0.039032	26.48932	0.0000
MA(2)	0.943543	0.036261	26.02105	0.0000
SIGMASQ	0.015520	0.000806	19.25361	0.0000

R-squared	0.034567	Mean dependent var	0.003611
Adjusted R-squared	0.023689	S.D. dependent var	0.126967
S.E. of regression	0.125454	Akaike info criterion	-1.298582
Sum squared resid	5.587256	Schwarz criterion	-1.244608
Log likelihood	238.7448	Hannan-Quinn criter.	-1.277121
Durbin-Watson stat	2.056499		

Inverted AR Roots	-.53-.84i	-.53+.84i
Inverted MA Roots	-.52+.82i	-.52-.82i

Fig. 8. ARIMA(2,1,2).

Dependent Variable: DPRICE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/02/24 Time: 12:33
Sample: 9/02/2022 3/01/2024
Included observations: 360
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.070614	0.042194	-1.673550	0.0951
MA(2)	-0.078687	0.046095	-1.707074	0.0887
SIGMASQ	0.015903	0.000687	23.15454	0.0000

R-squared	0.010782	Mean dependent var	0.003611
Adjusted R-squared	0.005240	S.D. dependent var	0.126967
S.E. of regression	0.126634	Akaike info criterion	-1.286683
Sum squared resid	5.724909	Schwarz criterion	-1.254299
Log likelihood	234.6029	Hannan-Quinn criter.	-1.273806
Durbin-Watson stat	2.005057		

Inverted MA Roots	.32	-.25

Fig. 9. ARIMA(0,1,2).

Considering the significance of AIC, SC and HQ information criteria and variables, AIC is the lowest at ARIMA(2,1,2), and AR(1), AR(2), MA(1) and MA(2) are all significant at 1% level. Based on this, the ARIMA(2,1,2) model is constructed in this study.

4.3 Model Diagnosis and Optimization

According to the above series of tests, the ARIMA (2,1,2) model is selected as the best prediction model, and various parameters of the model are estimated and calculated. As shown in Figure 10, the p values corresponding to all parameters of the model ARIMA (2,1,2) are 0, less than 0.01, indicating that the model parameters are significantly effective.

According to parameter estimation, the model can be written as follows:

$$\begin{cases} DPRICE_t = c + \emptyset_1 DPRICE_{t-1} + \emptyset_2 DPRICE_{t-2} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \epsilon_t \\ \emptyset_1 = -1.059571 \\ \emptyset_2 = -0.978787 \\ \theta_1 = 1.033944 \\ \theta_2 = 0.943543 \end{cases} \tag{4}$$

Dependent Variable: DPRICE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/02/24 Time: 12:33
Sample: 9/02/2022 3/01/2024
Included observations: 360
Convergence achieved after 55 iterations
Coefficient covariance computed using outer product of gradients

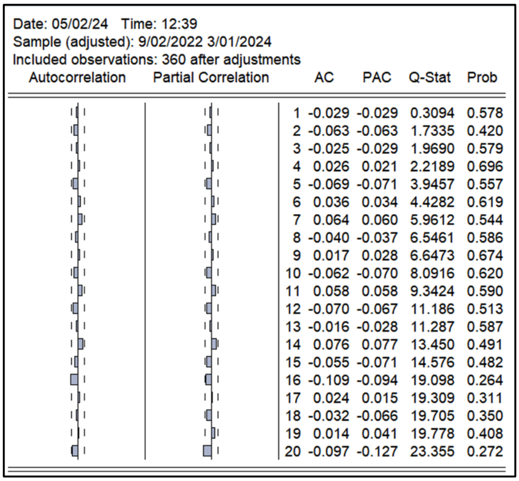
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.059571	0.025756	-41.13943	0.0000
AR(2)	-0.978787	0.023700	-41.29907	0.0000
MA(1)	1.033944	0.039032	26.48932	0.0000
MA(2)	0.943543	0.036261	26.02105	0.0000
SIGMASQ	0.015520	0.000806	19.25361	0.0000

R-squared	0.034567	Mean dependent var	0.003611
Adjusted R-squared	0.023689	S.D. dependent var	0.126967
S.E. of regression	0.125454	Akaike info criterion	-1.298582
Sum squared resid	5.587256	Schwarz criterion	-1.244608
Log likelihood	238.7448	Hannan-Quinn criter.	-1.277121
Durbin-Watson stat	2.056499		

Inverted AR Roots	-.53-.84i	-.53+.84i
Inverted MA Roots	-.52+.82i	-.52-.82i

Fig. 10. Model coefficient diagram.

After completing the above parameter estimation steps,the residual sequence of the fitting model should be tested to see whether it meets the definition condition of white noise. If the residual sequence exhibits characteristics of white noise, it signifies that the ARIMA model has effectively captured all relevant correlation information. As depicted in Figure 11, the white noise test results indicate that the P-values associated with the Q-test are all above 0.05, indicating the residual sequence satisfies the white noise criteria.Therefore, it can be inferred that the constructed ARIMA (2,1,2) model can extract all the correlation information of the time series data, and the time series fitting of the original data with it is optimal, and the model is effective.


Date: 05/02/24 Time: 12:39
Sample (adjusted): 9/02/2022 3/01/2024
Included observations: 360 after adjustments

	AC	PAC	Q-Stat	Prob
1	-0.029	-0.029	0.3094	0.578
2	-0.063	-0.063	1.7335	0.420
3	-0.025	-0.029	1.9690	0.579
4	0.026	0.021	2.2189	0.696
5	-0.069	-0.071	3.9457	0.557
6	0.036	0.034	4.4282	0.619
7	0.064	0.060	5.9612	0.544
8	-0.040	-0.037	6.5461	0.586
9	0.017	0.028	6.6473	0.674
10	-0.062	-0.070	8.0916	0.620
11	0.058	0.058	9.3424	0.590
12	-0.070	-0.067	11.186	0.513
13	-0.016	-0.028	11.287	0.587
14	0.076	0.077	13.450	0.491
15	-0.055	-0.071	14.576	0.482
16	-0.109	-0.094	19.098	0.264
17	0.024	0.015	19.309	0.311
18	-0.032	-0.066	19.705	0.350
19	0.014	0.041	19.778	0.408
20	-0.097	-0.127	23.355	0.272

Fig. 11. Autocorrelation and partial autocorrelation of residual sequence.

The model was used to fit the data of the daily closing price of 2022.9.1-2024.3.1. According to the model fitting effect diagram in Figure 12, the fitting value fits the data of the real value very well, and the simulation effect is good.

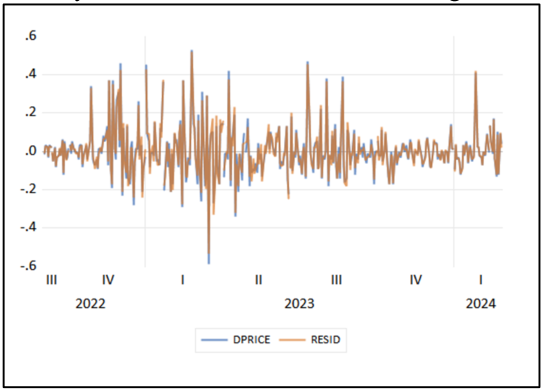


Fig. 12. Model fitting effect diagram.

5 STOCK PRICE FORECAST

Finally, the fitted ARIMA model was used to forecast the data of China Unicom for a total of five days from 2024.3.4 to 2024.3.8, and the results were compared with the actual data, as shown in Table 1. As shown in the figure, the predicted price based on the constructed ARIMA model is relatively close to the real daily closing price, and the error is small, indicating that the effect of using this ARIMA model to predict the daily closing price is relatively ideal. It further proves that the model constructed in this paper is correct and can accurately predict the opening price of stocks on the same day.

Table 1. Comparison with the predicted value and actual value.

date	Predicted value/RMB	Actual value/RMB	Error/RMB
2024.3.4	4.85	4.86	-0.011831
2024.3.5	4.84	4.84	-0.003383
2024.3.6	4.83	4.81	0.015165
2024.3.7	4.71	4.72	-0.012757
2024.3.8	4.83	4.83	-0.001326

6 CONCLUSION

This paper constructs ARIMA model through eviews13 software to smooth the data, construct the model and conduct empirical analysis on 361 sample data of China Unicom's daily closing price of 2022.9.1 to 2024.3.1. The ARIMA (2,1,2) models were obtained with good fitting results. The ARIMA model shows good adaptability in capturing and explaining the dynamic change of China Unicom stock price, which solves the problem of non-stationary time series.

In conclusion, this study systematically analyzes and forecasts the daily closing price of China Unicom by using ARIMA model, which provides a useful reference for investors. Nonetheless, it is crucial to recognize that forecasting stock prices is inherently intricate and demanding, and thus, no model can guarantee absolute precision in predicting future outcomes. Therefore, investors should consider a variety of factors when making investment decisions, including company fundamentals, industry trends, and market risks. Therefore, as an investor, it is necessary to choose investments carefully, fully realize the potential risks of the stock market, and make investment decisions after comprehensively mastering all kinds of information.[6-9]

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