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Forecasting Daily Ethereum Closing Price: An Autoregressive Integrated Moving Average (ARIMA) Approach

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ABSTRACT

Ethereum, a leading digital asset by market value, has gained increasing attention from investors and researchers because of its high price volatility and market unpredictability. This study forecasts Ethereum cryptocurrency daily closing prices using the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) methodology, drawing on data from January 1, 2019, to December 31, 2025. Stationarity analysis via the Augmented Dickey-Fuller ADF and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests confirmed that first differencing was required to render the series suitable for the modeling. Through systematic model identification, estimation, and comparison of ten candidate ARIMA specifications, the ARIMA(1,1,0) model emerged as the optimal fit, yielding the lowest information criterion values of Akaike information criterion, Bayesian information criterion (AIC = 24,943.883; AICc = 24,943.84; BIC = 24,955.12). Residual diagnostic tests, including the Ljung-Box test for serial correlation, the Autoregressive Conditional Heteroskedasticity (ARCH-LM) test for heteroscedasticity, and the Shapiro-Wilk test for normality, confirmed that the model residuals are free of serial dependence, although they exhibit time-varying volatility and non-normal distribution, features commonly associated with financial time series. The fitted model was subsequently applied to generate 30-day ahead forecasts with 95% confidence intervals, revealing relatively stable price expectations in the near term alongside progressively widening prediction bands that reflect growing uncertainty over longer horizons. These findings underscore the practical utility of the parsimonious ARIMA(1,1,0) model as a transparent and accessible tool for short-term Ethereum-price forecasting and investment risk assessment.

1. Introduction

The global financial crisis of 2008 significantly altered investor perceptions of traditional financial systems, contributing to a widespread loss of confidence in central bank-based, fiat currency-centered financial structures (Allen & Carletti, 2010; Carmassi et al., 2009). This crisis exposed fundamental weaknesses in the interconnected global financial system, leading investors to seek alternative decentralized assets that operate outside the control of monetary

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authorities (Bordo and Siklos, 2017; Cukierman, 2013). Consequently, cryptocurrencies have gained unprecedented prominence in financial discourse, with the market reaching over $2 trillion in market capitalization by 2022 (Kjaerland et al., 2018). Unlike traditional fiat currencies, cryptocurrencies operate on decentralized blockchain technology, offering fast, reliable, and low-cost exchange systems without central authority intervention (Barber et al., 2012; Hileman and Rauchs, 2017). Ethereum, proposed in 2013 by Vitalik Buterin and launched on July 30, 2015, has emerged as the second-largest cryptocurrency after Bitcoin, distinguished by its unique capability to deploy decentralized applications and smart contracts on its blockchain platform (Tapscott & Tapscott, 2016). Despite its rising popularity and growing market capitalization, Ethereum continues to face significant challenges, particularly concerning price volatility and market uncertainty, making accurate price prediction challenging for investors and traders (Bouri et al., 2019; Pinar et al., 2020).

Several studies have applied time-series models to forecast cryptocurrency prices. Jethin et al. (2018) used Twitter and Google Trends data to predict Bitcoin and Ethereum price changes, finding that tweet volume rather than sentiment was a predictor of price direction. Vasily et al. (2019) employed a Binary Autoregressive Tree (BART) model for short-term forecasting of Bitcoin, Ethereum, and Ripple, demonstrating that their approach was more accurate than ARIMA-ARFIMA models. Mahir et al. (2021) compared ARIMA, FBProphet, and XG Boosting for Bitcoin price forecasting and found ARIMA to be the best model with RMSE of 322.4. Caglar and Merih (2021) applied RNN-based models, including LSTM, GRU, and BiGRU, to forecast Ethereum closing prices, achieving the best performance with BiGRU (MAPE of 5.93). Monish et al. (2022) compared RNN, LSTM, and Bi-LSTM for Ethereum price prediction and concluded that bidirectional LSTM was the best model. Mohammad et al. (2022) compared ARIMA and LSTM variants for Ethereum forecasting, finding that LSTM surpassed ARIMA in long-term forecasting while ARIMA worked better for short-term prediction. Ziyang (2023) applied ARMA models to Bitcoin, Ethereum, and Ripple, concluding that ARMA performed better on cryptocurrencies with lower volatility. While existing studies have explored various machine and deep learning approaches, limited research has specifically focused on the application of the classical Box-Jenkins ARIMA methodology for Ethereum daily closing price forecasting over an extended period. Furthermore, most previous studies have employed complex models that may not be easily implemented by average investors, and few have provided rigorous model diagnostic checks and validation procedures specific to Ethereum. Therefore, this study aims to develop an ARIMA model for forecasting the daily closing prices of Ethereum using the Box-Jenkins methodology, based on data from January 2019 to December 2025. Specifically, this study seeks to explore the pattern of daily closing prices, identify the best-fitting ARIMA model through rigorous model identification, estimation, and diagnostic checking procedures, and forecast Ethereum daily closing prices for the next 30 days.

2. Methodology

2.1 Data Source

This study used daily closing prices of Ethereum (ETH) obtained from CoinMarketCap (www.coinmarketcap.com) covering the period from January 1, 2019 to December 31, 2025.

2.2 Test of Stationarity

The stationarity of the Ethereum daily closing price series was determined using the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Stationarity was achieved after first differencing.

2.3 ARIMA Model Methodology

The five principal steps required in ARIMA model building using Box-Jenkins methodology are: model identification, model estimation and selection, model diagnostic checking, model validation, and model use (Box & Jenkins, 1976). To identify the appropriate model, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the stationary data were plotted. The ARIMA(p,d,q) model is expressed as:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

where:

Y_t is value of the series at time t

c is a constant

ϕ_i are the parameters of the autoregressive (AR) terms, with order p

θ_j are the parameters of the moving average (MA) terms with order q

ε_t is the white noise or error term $N(0,\sigma^2)$ at time t

ε_{t-j} represent the error terms at the lagged time

In an ARIMA model, the data is differenced d times to achieve stationarity in R programming, ARIMA models are estimated using the auto.arima() functions available in the stats and forecast packages.

2.4 Model Identification

Model identification determined appropriate values of p, d, and q. Time series plots, autocorrelation function (ACF), and partial autocorrelation function (PACF) plots are generated in R using the ts(), acf(), and pacf() functions. The auto.arima() function was also employed to suggest candidate models based on information criteria.

2.5 Model Estimation and Selection

Model parameters were estimated using maximum likelihood estimation. Model selection is guided by the Akaike Information Criterion (AIC), corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC), defined as:

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{2}$$

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1} \tag{3}$$

$$\mathrm{BIC} = k\ln(n) - 2\ln(L) \tag{4}$$

where

k = number of estimated parameters in the model

n = number of observations

L = maximum value of the likelihood function

The ARIMA model with the lowest information criterion values was selected for forecasting.

2.6 Model Diagnostic Checking

Diagnostic check was conducted to ensure that the residuals of the fitted ARIMA model behave as white noise. The Ljung–Box Q-statistic was used to test for residual autocorrelation:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\widehat{\rho}_k^{\,2}}{n-k} \tag{5}$$

Residual normality is assessed using the Shapiro–Wilk test, while heteroscedasticity was examined using the ARCH–LM test implemented in R through the FinTS package:

$$\mathrm{ARCH–LM} = TR^2 \tag{6}$$

Where:

T is the sample size

R^2 is the coefficient of determination from the auxiliary regression

A model that satisfies all diagnostic tests is considered adequate for forecasting daily Ethereum closing prices.

3. Results and Discussion

3.1 Time Series Plot of Ethereum closing Price

Figure 1 below presents the daily closing prices of Ethereum over the observed period showing pronounced volatility, price clustering, and trending behavior which is characteristic of cryptocurrency price movements. The series displays both **short-term volatility** and **long-term trends,** suggesting the presence of **non-stationarity**. These features justify the application of differencing and ARIMA modeling to stabilize the mean and capture the underlying autoregressive and moving average patterns.

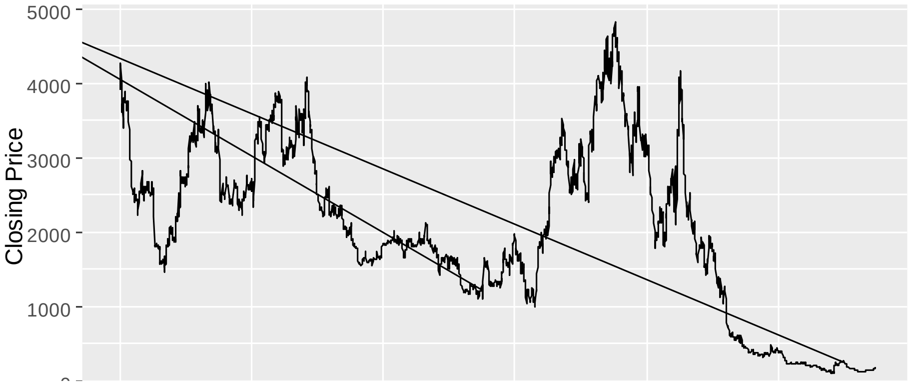

Figure 1: Time series plot of Daily Ethereum Closing Price

3.2 Descriptive Statistics of Ethereum Daily Closing Prices

The mean daily price of Ethereum is 2,009.80, while the median is 1,905.49, indicating near symmetry. The large standard deviation (1,144.08) confirms high volatility. The skewness is nearly zero (−0.0027), suggesting the distribution is approximately symmetric, while the kurtosis (2.1973) is close to the normal value of 3, indicating slight platykurtic behavior.

Table 1: Descriptive Statistics of Ethereum data

Statistic	Value
Mean	2009.8
Median	1905.49
Standard Deviation	1144.08
Minimum	110.61
Maximum	4812.09
Skewness	0.0027
Kurtosis	2.1973

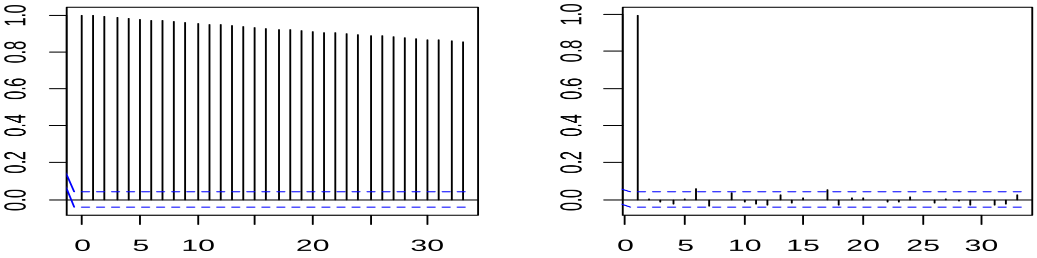

Figure 2: ACF and PACF plot of Ethereum Daily Closing Price from 2019 to 2025

3.3 Model Identification

The model identification process is a crucial stage in fitting an appropriate ARIMA model to Ethereum's daily closing prices, with stationarity being a fundamental prerequisite. To assess this, the ACF and PACF plots were examined, as presented in Figure 2. A stationary series is expected to have ACF values that decay rapidly toward zero, whereas a non-stationary series exhibits slowly decaying ACF spikes alongside a few significant PACF lags. As observed in Figure 2, the Ethereum closing price series displays slowly declining ACF values and a few significant PACF spikes, confirming that the series is non-stationary in its raw form and therefore requires differencing before a suitable ARIMA model can be identified and estimated.

3.4 Unit Root Test For Ethereum Daily Closing Prices

Stationarity was examined using the Augmented Dickey–Fuller (ADF) test for the presence of a unit root (non-stationarity) and KPSS tests test for level or trend stationarity directly

ADF:

H_0: The series has a unit root (i.e The series is non-stationary)
H_1: The series is stationary

KPSS:

H_0: The series is stationary
H_1: The series is non-stationary

Tables 2 and 3 present the results of the ADF and KPSS stationarity tests applied to the Ethereum daily closing price series respectively. The ADF test reported in Table 2 yields a t-value of −2.2726 with a p-value of 0.4629, which is well above the conventional significance level of 0.05, leading to a failure to reject the null hypothesis of a unit root and confirming that the series is non-stationary. This finding by the KPSS test in Table 3, which produces a t-value of 8.175 with a p-value of 0.01, resulting in a rejection of the null hypothesis of stationarity. The conclusions drawn from both tests are consistent and mutually reinforcing the Ethereum daily closing price series is non-stationary in its raw form, necessitating differencing to achieve stationarity before ARIMA model identification and estimation can proceed.

Table 2: ADF test for Ethereum Closing Price

Data	**(ADF) test**		**Remark**
	t-value	P-value	
Ethereum Daily Closing Price	-2.2726	0.4629	Non- stationary

Table 3: KPSS test for Ethereum Closing Price

Data	**KPSS**		**Remark**
	t-value	P-value	
Ethereum Daily Closing Price	8.175	0.01	Non- stationary

3.5 Differenced Closing Price

The plot of the first-differenced Ethereum daily closing prices exhibits fluctuations that oscillate around a constant mean close to zero, indicating that the differencing process has successfully removed the underlying trend present in the original series before differencing. The differenced data series shows no persistent upward or downward movement, suggesting that stationarity in the mean has been achieved. The series displays periods of heightened volatility, characterized by clusters of large positive and negative spikes, followed by intervals of relatively lower variability. This volatility clustering reflects the inherent instability and sensitivity of cryptocurrency markets to market news, speculative activity, and external shocks. Despite these fluctuations, the absence of long-term drift and the rapid reversion of values toward the zero mean indicate that shocks to the differenced series are temporary rather than permanent. Hence, the differenced series supports its suitability for ARIMA modeling, as it satisfies the key assumption of stationarity required for reliable estimation and forecasting of Ethereum price dynamics.

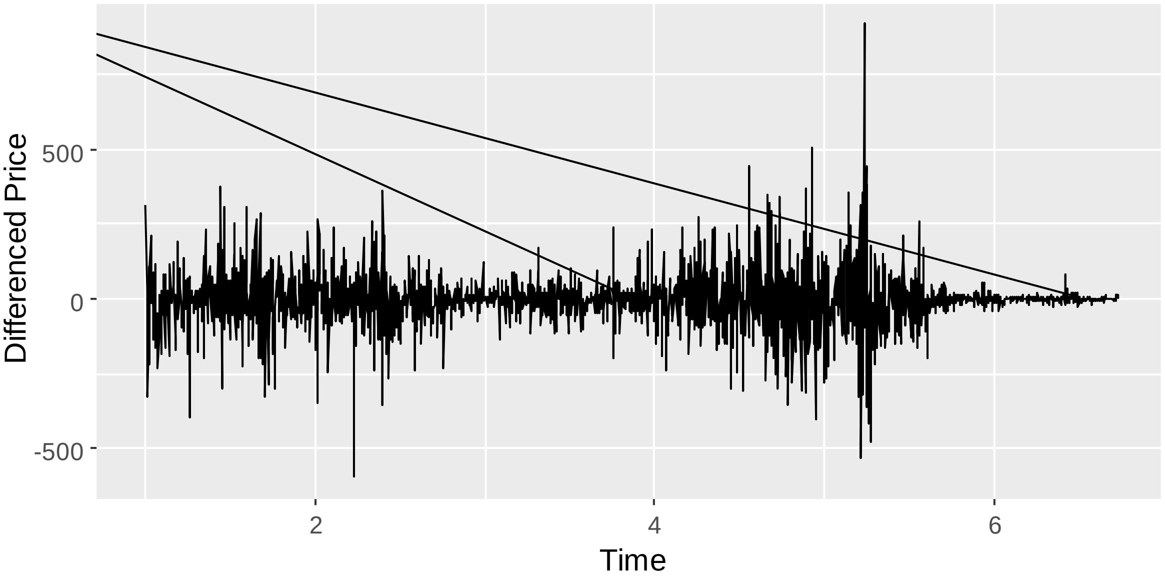

Figure 3: First-order Differenced Ethereum Closing Price Plot

The autocorrelation function (ACF) of the first-differenced Ethereum daily closing prices in figure 4 shows that most autocorrelation spikes lie within the 95 percent confidence bounds, indicating that serial dependence has been substantially reduced after differencing. The absence of a slow decay pattern in the ACF confirms that the differenced series is stationary and no longer exhibits long-term persistence. Similarly, the partial autocorrelation function (PACF) displays relatively small and irregular spikes across lags, with only a few marginally significant values that do not follow a clear cutoff pattern. This behavior suggests that no strong autoregressive structure remains in the differenced series and that any remaining dependence is weak and short-lived. The lack of pronounced spikes in both the ACF and PACF implies that the differencing process has effectively captured and has expressed series stationarity.

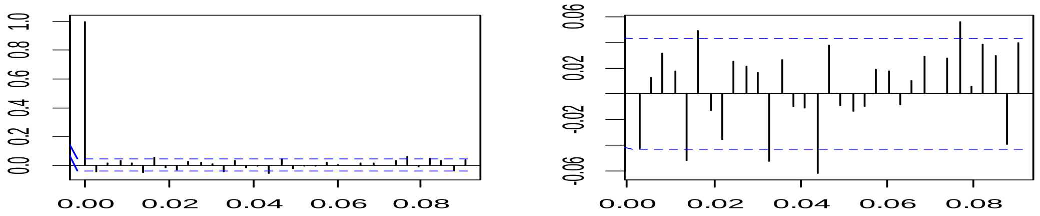

Figure 4: ACF and PACF of First-order Differenced Ethereum Closing Price

Tables 4 and 5 present the ADF and KPSS test results applied to the first-differenced Ethereum closing price series. As reported in Table 4, the ADF test yields a t-value of −12.424 with a p-value of 0.01, leading to a rejection of the null hypothesis of a unit root and confirming that the differenced series is stationary. This is further supported by the KPSS test in Table 5, which produces a t-value of 0.058412 with a p-value of 0.10, resulting in a failure to reject the null hypothesis of stationarity. The results from both tests are consistent and complementary, collectively confirming that one round of differencing is sufficient to induce stationarity in the Ethereum closing price series. This establishes the order of integration as d=1, providing a basis for proceeding with ARIMA model identification and estimation.

Table 4: ADF test for differenced series

Data	ADF test		Remark
	t-value	P-value	
Etherem Daily Closing Price	-12.424	0.01	Stationary

Table 5: KPSS test for differenced series

Data	KPSS		Remark
	t-value	P-value	
Etherem Daily Closing Price	0.058412	0.1	Stationary

3.6 Estimation of Model Parameter

Table 6 presents a comparison of ten tentative ARIMA(p,1,q) models evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Across all candidate models, the ARIMA(1,1,0) model records the lowest AIC and BIC values of 24943.83 and 24955.12 respectively, making it the best-fitting and most parsimonious model among those considered. The second-ranked ARIMA(0,1,1) model produces marginally higher AIC and BIC values of 24943.95 and 24955.24, while all remaining models record progressively higher information criterion values, indicating comparatively poorer fit. Since both the AIC and BIC consistently select the ARIMA(1,1,0) model as optimal, and given that the BIC imposes a stricter penalty for model complexity, the convergence of both criteria on the same model provides strong and reliable evidence in favour of ARIMA(1,1,0) as the preferred specification for forecasting Ethereum daily closing prices.

Table 6: Comparison of tentative ARIMA (p,1,q) models

Rank	Model	AIC	BIC
1	**ARIMA(1,1,0)****	**24943.83**	**24955.12**
2	ARIMA(0,1,1)	24943.95	24955.24
3	ARIMA(0,1,3)	24945.16	24967.75
4	ARIMA(0,1,2)	24945.29	24962.23
5	ARIMA(3,1,0)	24945.32	24967.9
6	ARIMA(2,1,0)	24945.46	24962.4
7	ARIMA(1,1,1)	24945.69	24962.63
8	ARIMA(1,1,2)	24946.23	24968.82
9	ARIMA(2,1,1)	24946.47	24969.06
10	ARIMA(2,1,2)	24947.15	24975.39

'**' represents the best fitted model based on the selection criteria (AIC and BIC).

Table 7: Parameter for ARIMA (1,1,0)

Model Fit Statistics				
AIC = 24,943.83		AICc = 24,943.84		BIC = 24,955.12
Coefficient	Estimator	Std. Error	t-value	p-value
AR(1)	-0.0431	0.0219	-1.9812	0.01

Table 7 presents the parameter estimates for the selected ARIMA(1,1,0) model. The model records AIC, AICc, and BIC values of 24,943.83, 24,943.84, and 24,955.12 respectively, confirming a well-fitting and parsimonious specification. The autoregressive coefficient AR(1) is estimated at −0.0431 with a standard error of 0.0219, yielding a t-value of −1.9812 and a p-value of 0.01, which is statistically significant at the 5% significance level. The negative sign of the AR(1) coefficient suggests a mild mean-reverting tendency in the first-differenced Ethereum price series, implying that a price movement in one direction is slightly followed by a correction in the opposite direction in the subsequent period. Overall, the results in Table 7 confirm that the ARIMA(1,1,0) model is statistically adequate and suitable for forecasting Ethereum daily closing prices.

$$y_t = -0.0431 y_t + \varepsilon_t$$

3.7 Diagnostic Check for Fitted Model

The residual diagnostics for the ARIMA(1,1,0) model indicate that the model provides an adequate representation of the Ethereum daily closing price series. The residual time plot in figure 5 shows random fluctuations around zero with no visible trend, confirming that the model errors are mean-stationary. Although periods of increased volatility are observed, particularly during episodes of heightened market activity, these variations do not exhibit systematic patterns.

The residual autocorrelation function (ACF) reveals that nearly all autocorrelation spikes fall within the 95 percent confidence bounds, suggesting the absence of significant serial correlation and indicating that the residuals behave like white noise. The histogram of residuals is approximately symmetric around zero, with a moderate concentration of observations near the center, implying that the normality assumption is reasonably satisfied. Overall, the diagnostic plots support the adequacy of the ARIMA(1,1,0) model for inference and forecasting**.**

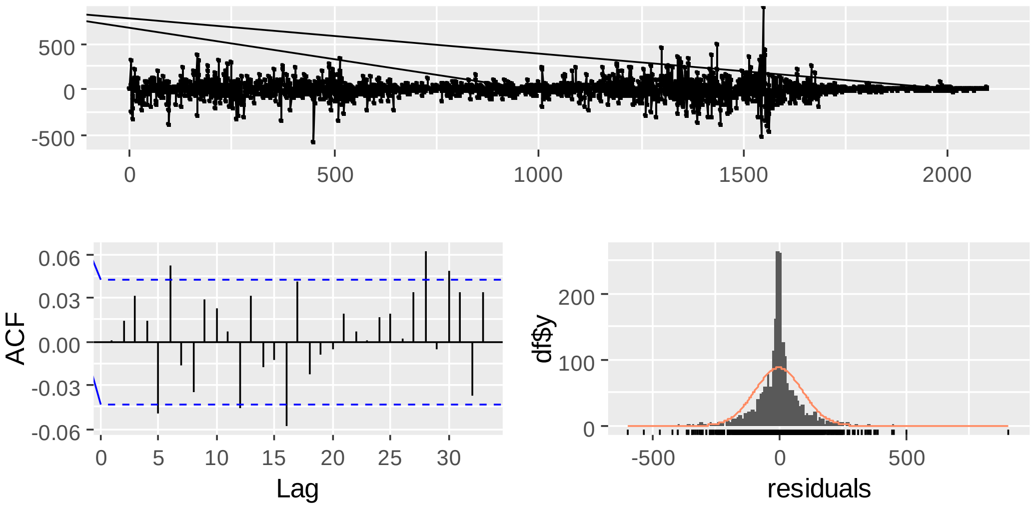

Figure 5: Residual Plot from ARIMA (1,1,0)

Tables 8 and 9 present the residual diagnostic test results for the fitted ARIMA(1,1,0) model. The Ljung-Box test reported in Table 8 yields a chi-squared statistic of 19.955 with 9 degrees of freedom and a p-value of 0.005469, leading to a rejection of the null hypothesis of no autocorrelation in the residuals. This suggests that some degree of serial correlation remains in the residuals, indicating that the model does not fully capture all the linear dependence structure in the series. The ARCH-LM test further produces a chi-squared statistic of 360.55 with 12 degrees of freedom and a p-value of less than 0.0001, strongly rejecting the null hypothesis of no conditional heteroscedasticity. This confirms the presence of significant volatility clustering in the residuals, implying that the variance of the series is not constant over time which is a characteristic commonly observed in cryptocurrency price data.

As reported in Table 9, the Shapiro–Wilk test statistic of 0.88417 with a p-value less than 0.0001 strongly rejects the null hypothesis of normality of the residuals. This indicates that the residuals of the ARIMA(1,1,0) model are not normally distributed. Consequently, although the model may adequately capture the short-run price dynamics of Ethereum, the residuals still exhibit departures from normality, suggesting the possible presence of skewness, heavy tails, or outliers not fully accounted for by the model.

Table 8: ARIMA (1,1,0) model residual diagnostic test

	Box-Ljung and ARCH-LM test statistics		
Test type	Chi-squared	Df	p-value
Ljung	19.955	9	0.005469
ARCH-LM	360.55	12	< 0.0001

Table 9: ARIMA (1,1,0) model residual diagnostic test

	Shapiro-Wilk test statistics	
Test type	Test statistics	p-value
Shapiro-Wilk	0.88417	< 0.0001

3.8 Forecast

The 30-day forecast from the ARIMA(1,1,0) model indicates that Ethereum prices are expected to hover around their most recent level, with no clear short-term upward or downward trend. While the point forecasts remain fairly stable, the prediction bands widen steadily from the first few days to the end of the forecast horizon, eventually covering several hundred price units on either side of the forecast, which reflects growing uncertainty over time. This pattern highlights the usefulness of the model for short-term price expectation and risk assessment, while underscoring the increasing caution required when interpreting longer-horizon forecasts in a highly volatile cryptocurrency market

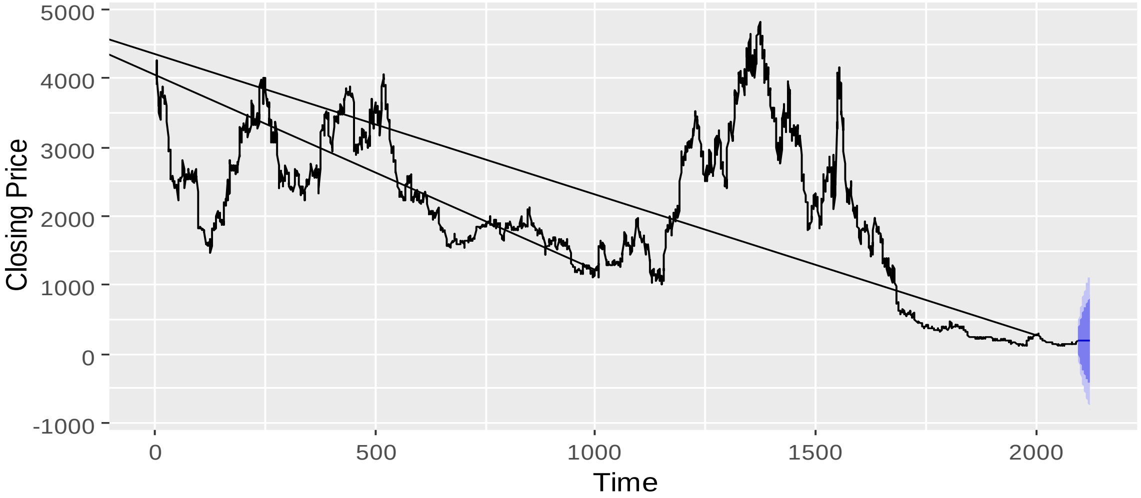

Figure 6: 30-day forecast plot for Ethereum price

4. Conclusion

This study applied the Box-Jenkins ARIMA methodology to forecast Ethereum's daily closing prices using data from January 2019 to December 2025. The series was found to be non-stationary in its raw form, with stationarity achieved after first differencing. Among ten candidate models evaluated, the ARIMA(1,1,0) model was selected as the optimal specification based on the lowest AIC and BIC values. Although residual diagnostics revealed the presence of volatility clustering and non-normality characteristics typical of cryptocurrency data, the model adequately captured the short-run price dynamics of Ethereum. The 30-day ahead forecasts indicated relatively stable near-term price expectations with widening prediction intervals over longer horizons, reflecting growing uncertainty. Future studies are encouraged to explore hybrid ARIMA-GARCH or machine learning frameworks and incorporate exogenous variables such as trading volume and market sentiment to improve forecasting performance.

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