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Forecast of Stock Prices with Arima, Rolling Forecast, and Garch: A Dynamic Approach in the Fluctuating Market

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Abstract. *This study proposes a hybrid approach by combining ARIMA, Rolling Forecast, and GARCH models to enhance the accuracy of stock price forecasting for Amazon, Apple, Google, and Vinamilk. ARIMA is employed to identify the autoregressive and moving average structures of the data, effectively capturing trends and seasonal patterns in stock prices. Rolling Forecast plays a pivotal role in improving adaptability by continuously updating predictions with new data, ensuring real-time responsiveness to market fluctuations, and minimizing the influence of outdated information. This dynamic updating mechanism helps maintain high forecasting accuracy, even in highly volatile conditions. Furthermore, GARCH is integrated to model and predict stock price volatility, refining risk assessment and enhancing overall predictive performance. By incorporating GARCH, the model becomes more adept at capturing sudden market shifts, making it a valuable tool for financial analysis. The proposed hybrid model is validated using real stock price data from Amazon, Apple, Google, and Vinamilk, allowing for a comprehensive evaluation of its forecasting capability compared to traditional methods. Experimental results demonstrate that the combination of ARIMA, Rolling Forecast, and GARCH not only improves prediction accuracy but also provides a more robust representation of market dynamics. This integrated approach offers a flexible and adaptive framework for investment analysis and risk management, underscoring the importance of combining statistical and econometric models to enhance financial decision-making.*

Keywords: ARIMA; SATIMA; GARCH; Rolling Forecast; Stock

1. **Introduction.** In recent years, forecasting securities prices has become an important research field in finance and data science. With the strong development of statistical and machine learning methods, many models have been applied to forecast stock price fluctuations to assist investors in making more accurate decisions. Among them, traditional models such as ARIMA, SARIMA, SARIMAX, and GARCH still play an important role thanks to the ability to analyze and forecast the time series effectively.

The ARIMA model (Autoregressive Integrated Moving Average) is one of the most common methods in the time series analysis. This model combines three main components: self-regression (AR), wrong fertilizer (I), and moving average (MA) to model the time series of time series. ARIMA is highly appreciated for their ability to handle data well and the short-term cycle. However, the ARIMA model has some limitations. Firstly, it assumes that the time series is linear, while the stock market often has non-linear and fluctuating elements. Secondly, ARIMA is ineffective when encountering data with seasonal factors, which makes the model unable to reflect cyclical oscillation models accurately.

To overcome the disadvantages of ARIMA, the SARIMA model (Seasonal ARIMA) is developed by adding seasonal components. SARIMA is especially effective in forecasting data with clear cycles such as monthly sales or seasonal stock prices. Although SARIMA significantly improves the forecast of data with seasonal factors, it still faces similar limitations to ARIMA when it is necessary to handle non-linear fluctuations and sudden impacts from external factors. In addition, the selection of parameters for the SARIMA model often requires many tests, increasing the complexity when deployed.

The SARIMAX model (Seasonal ARIMA with Exogenous Regressors) is an extension of SARIMA, incorporating external explanatory variables (exogenous variables) to enhance forecasting accuracy. By integrating factors such as economic indices, financial news, or market sentiment, this model becomes more flexible than ARIMA and SARIMA. However, the effectiveness of SARIMAX heavily depends on the appropriate selection of exogenous variables. If these variables are not chosen correctly, the model may become redundant or ineffective in practice.

The GARCH model (Generalized Autoregressive Conditional Heteroskedasticity) is used to model the changes in conditional variance over time. This model plays a crucial role in forecasting financial market fluctuations. The main advantage of GARCH is the ability to handle the unstable fluctuations of the stock market, which the ARIMA or SARIMA models cannot do. However, the disadvantage of GARCH is to assume that the data follows the standard distribution, while the stock market is often distributed with thicker tails. This can lead to deviations in the forecast.

To improve the accuracy of securities forecasting, this research has proposed a combination of ARIMA, Rolling Forecast, and GARCH to improve one of the above disadvantages. ARIMA helps forecast trends and model time without stopping. Rolling Forecast allows continuous updates to the model using sliding windows on past data, helping the model adapt to changes in the market. Finally, the GARCH is integrated to grasp the change in fluctuations, which ARIMA cannot do well.

The reason for using this combination model is that the financial market is unstable and fluctuates over time. ARIMA helps to determine the long-term trend, while the Rolling Forecast ensures the model is updated continuously with the latest data, and GARCH helps manage fluctuations. This combination significantly improves the ability to predict securities compared to using a single model. The expectation not only improves the forecast accuracy but also provides a comprehensive approach to stock price analysis, opening a potential direction in finance and risk management.

2. **Related Works.** Stock price prediction plays an important role in the field of finance and economy, helping investors make accurate transaction decisions to maximize profits and minimize risks. For example, in the 2008 financial crisis, inefficient forecasting models were not recognized as a risk of recession, leading to wrong investment decisions that caused great losses. In contrast, financial institutions apply accurate forecasts that can optimize the portfolio and limit risks to market fluctuations.

In the management of the portfolio, accurately forecasting the stock price fluctuations helps optimize the strategy of allocating assets, selecting potential stocks, and developing an effective hedging strategy. Financial institutions such as banking, securities companies, and investment funds use stock price predictions to set up trading strategies, manage portfolios, and determine the time of issuance or acquisition of stocks. In addition, the stock price forecast also plays an important contribution to quantitative economic research, especially quantitative finance and risk management. For example, the use of the ARIMA model to analyze stock price fluctuations can help researchers assess the risk level of a portfolio, thereby proposing the optimal loss strategy.

In recent years, many studies have applied models of ARIMA, SARIMA, and GARCH to forecast stock prices. Research [1] used ARIMA, neural network (NN), and LSTM network to forecast the price of Bursa Malaysia shares. The analysis based on RMSE and MAPE shows that the LSTM model reaches over 90% accuracy, especially effective during strong fluctuations due to the pandemic. With the article [2], the authors analyzed the fluctuations of the BSE-Sensex index of the Indian stock market with symmetrical and asymmetrical GARCH models. The results show that the asymmetric GARCH models are superior in modeling and forecasting conditional variance, confirming the leverage effect in the stock market.

Research [3] compared the effectiveness of the ARIMA and GARCH models in the Malaysian real estate market forecast. The results show that the ARIMA model works better in modeling and market asset forecasting compared to the GARCH. Also, with the GARCH model, the authors [4] proposed the method of combining GARCH with the LSTM network to forecast conditional variance. Experimental results on the Wig 20, S&P 500, and FTSE 100 index confirm the effectiveness of the model, opening up a new development direction in financial risk forecasting. By a hybrid model, research [5] applies the ARIMA model to forecast the Apple stock price. The results show that this hybrid model can model the cluster effect of fluctuations and accurately forecast the stock price than the single models. Similarly, Jialu Luo [6] combined ARIMA-SARIMA to improve the accuracy of stock price forecasts.

The results show that this combination model is superior to ARIMA or SARIMA alone, thanks to the integration of seasonal and non-linear factors. By the GARCH-MIDAS-TDW model [7], the study proposes a model to improve the volatile forecast by using the time weight. Experimental results in the Chinese stock market and S&P 500 show that this model is superior to the traditional GARCH-MIDAS. Using the LSTM deep learning model, [8] combines ARIMA, LSTM, and news analysis to forecast stock prices. Research results emphasize the role of market emotions in improving forecast accuracy. To update real-time data, Manish Adhikari [9] applied ARIMA with a rolling data window to forecast the Nepse index closing point. The results showed that this model achieved high accuracy, with a correlation of 0.995.

Instead of using sliding windows, the article [10] used LSTM, comparing the forecast efficiency between ARIMA and LSTM. The results showed that ARIMA had high accuracy in static forecasts, while LSTM was more effective in dynamic forecasts. Jilin Zhang and colleagues employed the GARCH(1,1), EGARCH, and GJR models to analyze and forecast stock return volatility in China's SSE and SZSE markets during both the developing and developed phases. Additionally, the VAR model was used to examine the dynamic correlation between the two markets through impulse response and variance decomposition analyses [11].

In Vietnam, over the past few years, numerous studies have employed a learning model combined with traditional quantitative methods to forecast the stock market, yielding quite positive results. The authors [12] evaluated the effectiveness of machine models, especially BC and LSTM, in the VN-Index forecast. The results show that LSTM has higher accuracy than traditional models. The research group [13] has forecasted long-term and short-term Vietnam stock indexes using a machine learning model that compared the performance of ARIMA, SVR, ARIMA-SVR, and LSTM in short-term and long-term forecasts. The results show that ARIMA is suitable for short-term forecasts, while LSTM is more effective for long-term forecasts.

3. Methods.

3.1. ARIMA [14].

The ARIMA model (Autoregressive Integrated Moving Average) is a common statistical method in the analysis and forecasting of time series, especially useful in areas such as finance and economics. ARIMA combines three main components:

- Autoregressive (AR): Using the relationship between the current value and previous values in the time series.
- Integrated (I): Converts the time series into a stationary series by differencing to eliminate the trend.
- Moving Average (MA): Modeling the relationship between the current value and noise (errors) of previous observations.

The process of building an ARIMA model includes the following steps:

1. **Identifying and Testing the Stationarity of the Time Series:** Use methods such as the Augmented Dickey-Fuller (ADF) test to determine whether the series is stationary. If the series is non-stationary, differencing should be applied to achieve stationarity.
2. **Determining the Model Parameters (p, d, q):** Use the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to estimate the orders of the AR (p), I (d), and MA (q) components.
3. **Estimating Model Parameters:** Apply methods such as least squares or maximum likelihood estimation to determine the coefficients of the model.
4. **Model Diagnostic Checking:** Assess the adequacy of the model by examining the residuals to ensure they follow a random distribution and exhibit no autocorrelation.
5. **Forecasting:** Use the constructed model to predict future values of the time series.

Following this procedure ensures that the ARIMA model is accurately built and effectively applied for time series forecasting.

3.2. GARCH [15].

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) algorithm is a widely used statistical method for analyzing and forecasting volatility in financial time series, particularly in estimating stock price and interest rate fluctuations. The GARCH model extends the ARCH model to overcome its limitation of requiring a high-order specification to accurately capture volatility dynamics.

The process of building a GARCH model includes the following main steps:

1. **Building an average model:** First, identify and estimate the average model suitable for time series, such as the ARIMA model, to eliminate the trend and determine the residual part.
2. **Check the ARCH effect:** Use statistical tests, such as ARCH-LM testing, to determine whether the residual part from the average model has a variance phenomenon that changes over time. If so, this shows the presence of the ARCH effect.

3. **Estimating the GARCH model:** After confirming the ARCH effect, proceed to estimate the parameters of the GARCH model by the Maximum Likelihood Estimation (MLE). The GARCH(p, q) model is generally performed as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

   where σ_t^2 is the conditional variance at time t, ϵ_{t-i}^2 is the squared residual at the previous time, and $\omega, \alpha_i, \beta_j$ are the parameters to be estimated.
4. **Model Validation:** Assess the adequacy of the model by examining the standardized residuals and conditional variance to ensure that they exhibit no autocorrelation and follow a normal distribution.
5. **Forecasting:** The GARCH model, once identified and validated, is used for forecasting the future fluctuations of the time series, supporting risk management and investment decisions.

The application of the GARCH model in financial analysis helps investors and managers better understand the fluctuations of the market, thereby providing more effective investment and risk management strategies.

3.3. **Rolling Forecast** [16]**.** Rolling forecast is a continuously updated financial and business forecast method, allowing businesses to adjust forecasts based on actual data and market fluctuations. Instead of making fixed forecasts for a certain period, the forecast is continuously updated when the old periods end, creating a more flexible and accurate vision of the future performance of the business.

Characteristics of Rolling Forecast:

- **Flexibility:** Always update and adjust according to the latest actual data.
- **Long-term vision:** Forecasting continuous cycles (e.g., always forecasting the next 12 months).
- **Suitable for fluctuating environment:** Helping businesses respond promptly to changes in market and business conditions.

Operation process of Rolling Forecast:

1. Determine the scope and forecast cycle: Determine the forecast period (usually 12 or 18 months). Make regular updates (monthly or quarterly).
2. Collect data and analyze: Collect the latest historical data and actual data from financial and business departments. Analyze trends and influence factors to update the forecast model.
3. Build forecasting models: Using statistical models such as ARIMA, SARIMA, or machine learning techniques. Combine factors such as crops, and market trends, to improve accuracy.
4. Update and adjust: Periodically update forecasts by adding the latest data and eliminating old data. Adjust the forecast model if major deviation is detected between forecasts and reality.
5. Analyze deviation and adjust: Compare actual results with forecasts to determine deviations. Analyze the causes of the misleading and adjust the forecast model.

Advantages of Rolling Forecast:

- Increase flexibility: Helps businesses quickly adjust forecasts according to market volatility.
- Improve accuracy: Regular updates help minimize forecast errors.
- Support strategic decision-making: Provides continuous forecast vision, risk management support, and long-term planning.

Limitations of Rolling Forecast:

- Complicated in deployment, requiring regular data collection and processing.
- Time and resources: Require continuous participation of financial and business departments.
- Depending on data quality, the accuracy of the forecast depends heavily on the input data.

Rolling Forecast is currently being widely used in businesses and financial institutions to improve financial management efficiency and support strategic decisions flexibly and timely.

3.4. **Proposed Model.** In this study, we proposed the combination of ARIMA, Rolling Forecast, and GARCH. The operation process is shown in Figure 1.

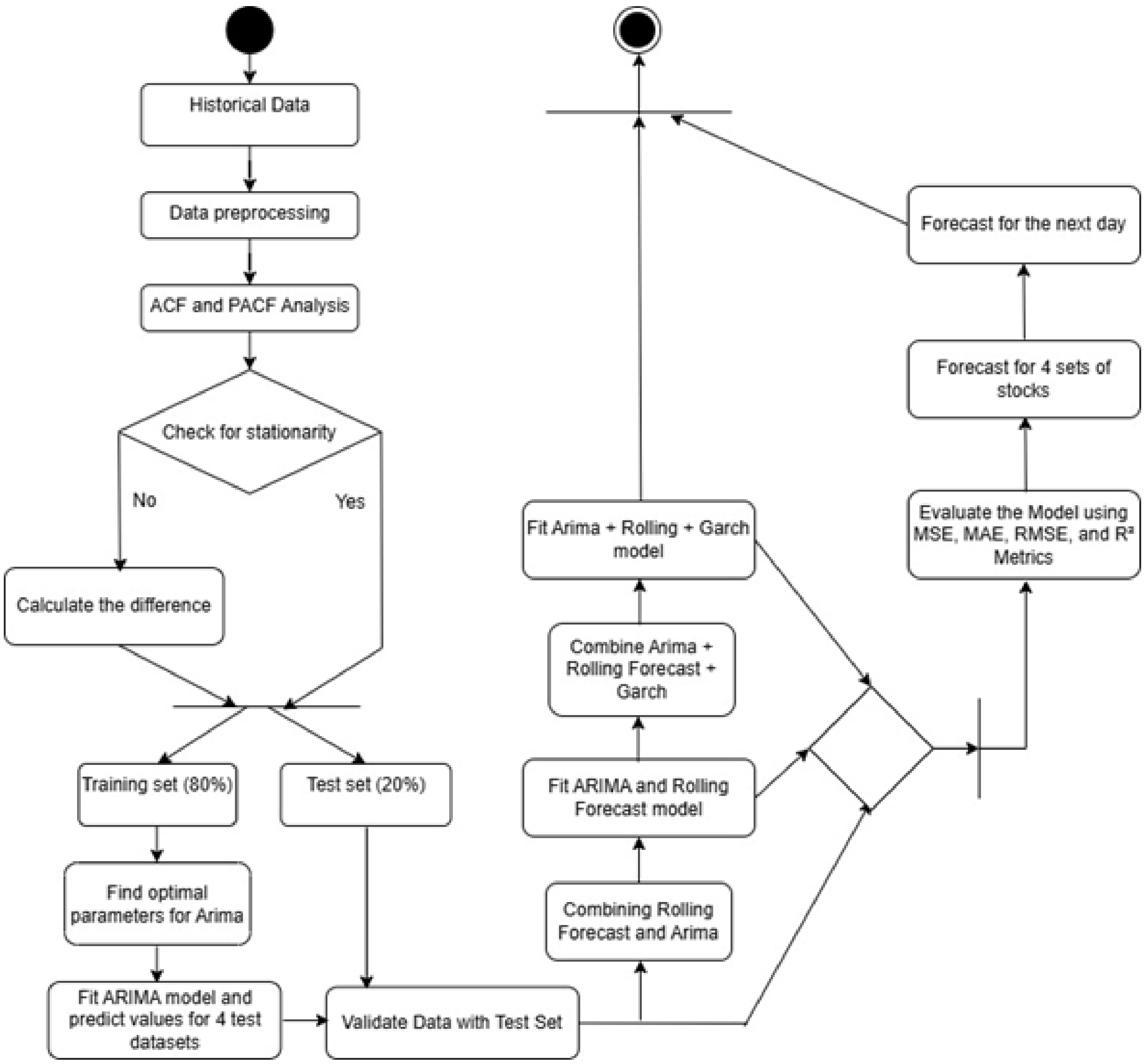

FIGURE 1. Proposed model

The diagram illustrates the operational workflow of a hybrid forecasting model combining ARIMA, Rolling Forecast, and GARCH to predict stock prices. The process is divided into four key phases, each contributing to enhancing prediction accuracy and model adaptability:

Phase 1: Data Preprocessing

1. Historical Data Collection: Historical daily stock prices are gathered for Apple, Google, Amazon, and Vinamilk.
2. Data Preprocessing: This phase involves cleaning the data, interpolating missing values, and normalizing where appropriate to ensure consistency across datasets.
3. ACF and PACF Analysis: The autocorrelation function (ACF) and partial autocorrelation function (PACF) are applied to the "Close" price series to estimate suitable lag orders for the ARIMA model.
4. Check for Stationarity: Stationarity is a fundamental requirement for ARIMA. A unit root test is used:
   - If the series is non-stationary, differencing is applied.
   - If the series is already stationary, the process moves to model training.

Phase 2: ARIMA Modeling and Validation

5. Train-Test Split: The dataset is split into:
   - Training set (80%) for fitting the ARIMA model.
   - Test set (20%) for evaluating predictive accuracy.
6. Parameter Optimization: The best parameters (p, d, q) for each dataset are selected by minimizing AIC/BIC and verifying ACF/PACF lags.
7. Model Fitting: The ARIMA model is trained and used to generate forecasts on the test data for all four datasets.
8. Model Validation: Forecasts are compared against actual values using standard error metrics to assess baseline performance.

Phase 3: Enhancing Short-Term Forecasts with Rolling Forecast

9. ARIMA with Rolling Forecast: The model is retrained iteratively at each new time step, simulating a real-time forecasting environment. This rolling window strategy allows the model to continuously adapt to recent changes in the data.
10. Combination Strategy: ARIMA is combined with the Rolling Forecast mechanism to produce dynamic and up-to-date predictions.
11. Prediction: The updated model is applied to predict next-day stock prices across all four companies.
12. Evaluation: Model performance is evaluated using a suite of error metrics: MSE, MAE, RMSE, MAPE, and R^2.

Phase 4: Integrating GARCH for Volatility Modeling

13. GARCH Integration: GARCH (Generalized Autoregressive Conditional Heteroskedasticity) is applied to model time-varying volatility of residuals from the ARIMA model. This step enhances the model's ability to capture market volatility and sudden shifts.
14. Model Combination: The ARIMA + Rolling Forecast structure is integrated with the GARCH component, forming a robust hybrid capable of modeling both trend and conditional variance.
15. Final Forecasting: The complete model forecasts next-day stock prices and volatility levels for Apple, Amazon, Google, and Vinamilk.
16. Final Evaluation: The model's effectiveness is assessed again using the same evaluation metrics. A significant performance boost is expected compared to standalone ARIMA.

The hybrid model combines ARIMA for capturing trends and autocorrelations, Rolling Forecast for real-time adaptability, and GARCH for modeling volatility dynamics. This integration not only enhances forecasting accuracy but also makes the model more responsive to sudden market fluctuations, which is essential in real-world financial forecasting tasks.

4. **Experiment Results.** This study utilizes historical stock price data for four companies: Apple, Amazon, Google, and Vinamilk. Each dataset contains daily trading records over a multi-year period, with key financial indicators used to support time series forecasting. For Apple, Amazon, and Google, the datasets include the following columns: Date (the date of the transaction), Open (the stock's opening price for the day), High (the highest price reached during the day), Low (the lowest price during the day), Close (the unadjusted closing price), Adj Close (the adjusted closing price, reflecting splits and dividends), and Volume (total number of shares traded). For Vinamilk (VNM), the dataset includes: Date, Open, High, Low, Close, Adj Close, Volume, and Change (the daily percentage change compared to the previous session).

Although the column structures vary slightly between data sources, the Adj Close column is consistently selected for all four datasets as the main variable for modeling. This column provides a more accurate reflection of the stock's true market value by adjusting for corporate actions such as dividends and stock splits. Ensuring this consistency helps improve the quality and comparability of the forecasting models across different stocks.

First, we collect historical stock price data for Amazon [17], Apple [18], and Google [19], covering the period from July 10, 2013, to January 16, 2025. The dataset for Vinamilk [20] includes transaction records from July 10, 2013, to November 15, 2024. To ensure consistency across datasets, we extract the "Adj Close" column as the primary variable representing the stock's end-of-day price. Missing values in this column are handled appropriately to maintain a continuous time series. This preprocessing step is crucial for accurate analysis using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The insights from ACF and PACF help determine the appropriate lag values for the Auto-Regressive (AR) and Moving Average (MA) components when building the ARIMA model. This step forms the foundation for developing effective time series forecasting models for stock prices. Next, the model conducts a stopping test; otherwise, the differencing is calculated. The results are displayed in Table 1.

Table 1. Results of the stationarity test for 4 datasets

	Apple	Amazon	Google	Vinamilk
DF Statistic	0.7034, p=0.9899	1.2000, p=0.9960	0.1670, p=0.9703	-1.4052, p=0.5798
ADF Statistic	-16.7502, p=0.0000	-11.6588, p=0.0000	-11.0888, p=0.0000	-28.5167, p=0.0000
Results	The series has become stationary after differencing			

The model continues to split the dataset into a training set (train) and a testing set (test) for the stocks, with a ratio of 80% train and 20% test. The optimal parameters for the ARIMA model for Apple, Google, Amazon, and Vinamilk are determined using the `pmdarima` library in Python. The results are shown in Table 2.

Table 2. Optimal Parameters for the ARIMA Model

	Apple	Amazon	Google	Vinamilk
Model	ARIMA(0,0,1)(0,0,0)[0]	ARIMA(2,0,2)(0,0,0)[0]	ARIMA(1,0,3)(0,0,0)[0]	ARIMA(0,0,0)(0,0,0)[0]
Total fit time (s)	6.100	22.428	31.006	0.567
Best parameters (p,d,q)	(0,0,1)	(2,0,2)	(1,0,3)	(0,0,0)

Note: ARIMA(0,0,1)(0,0,0)[0] is an ARIMA model with the following specific parameters: (0,0,1) indicates 0 autoregressive (AR) component, 0 differencing, and 1 moving average (MA) component; (0,0,0)[0] indicates no seasonal ARIMA component, with a seasonal period of 0 (i.e., no seasonality).

After training and forecasting using the ARIMA model, the results are presented in Table 3.

TABLE 3. Measurement metrics of 4 stock datasets with the ARIMA model

	Apple	Amazon	Google	Vinamilk
MSE	7.21	8.49	6.74	768728.10
RMSE	2.69	2.91	2.60	876.77
MAE	1.98	2.16	1.87	637.98
MAPE	8.63e13%	1.04e14%	100.75%	4.21e17%
Actual value (15/01/2025 or 15/11/2024)	4.58	5.59	5.93	-1290.90
Next day predicted value	0.06	0.11	0.01	-125.52

Below are the graphs illustrating the forecasting results.

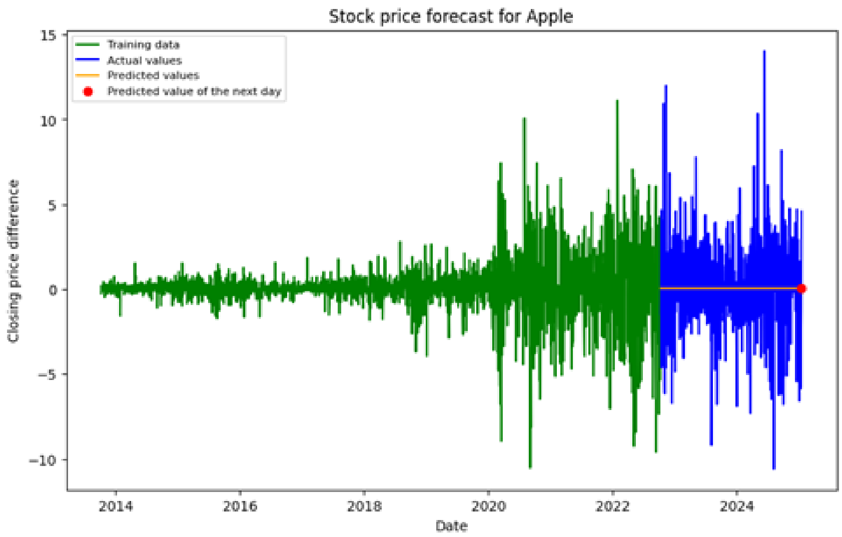

FIGURE 2. Stock price forecast for Apple by ARIMA model

Based on the four stock price forecast images for Apple, Google, Amazon, and Vinamilk using the ARIMA model, the following observations can be made: The ARIMA model is capable of capturing the overall trend of historical data. However, in the forecasted section (red), the model appears to produce predictions that are nearly an average value or show very little fluctuation compared to actual price movements. This suggests that ARIMA struggles to handle highly volatile data, such as stock prices.
Apple, Google, Amazon: The ARIMA forecast is relatively flat compared to actual values (blue). The model may be experiencing underfitting, failing to capture strong market fluctuations.
Vinamilk: The data exhibits high volatility with some extreme outliers. Since ARIMA assumes stationarity, it may not perform well in this scenario.

Continue to forecast stock prices for 4 episodes by combining ARIMA + Rolling Forecast, the recorded results are shown in Table 4.

When comparing the pure ARIMA model with the combined ARIMA and Rolling Forecast model, it can be seen that the addition of the Rolling Forecast significantly improved the forecast accuracy. The MAPE index in the pure ARIMA model has very

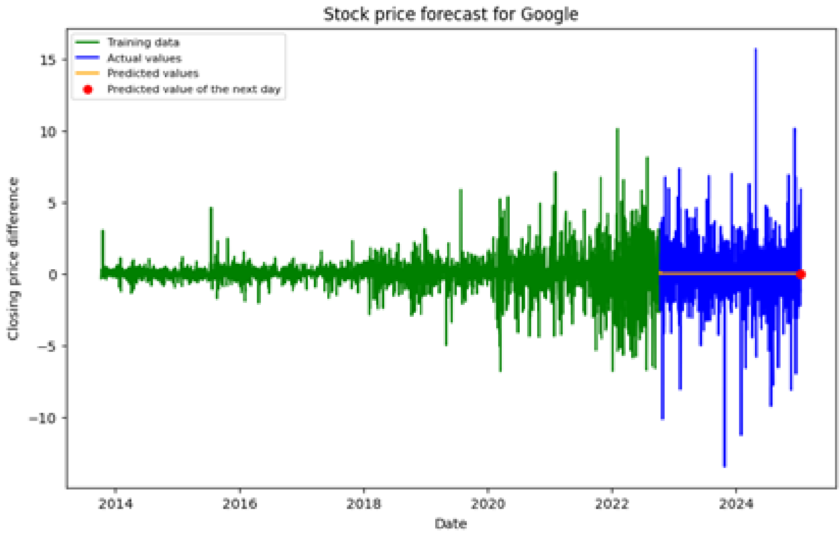

FIGURE 3. Stock price forecast for Google by ARIMA model

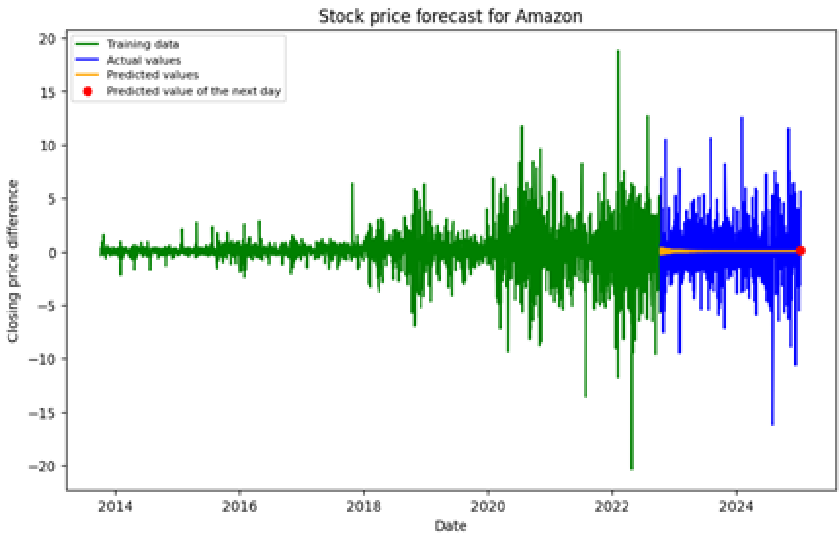

FIGURE 4. Stock price forecast for Amazon by ARIMA model

TABLE 4. Measurement metrics of 4 stock datasets with the ARIMA model combined with Rolling Forecast

	Apple	Amazon	Google	Vinamilk
MSE	7.24	8.50	6.74	767331.48
RMSE	2.69	2.92	2.60	875.97
MAE	1.99	2.16	1.88	636.57
MAPE	1.11%	1.52%	1.41%	0.94%
R^2	0.99	0.99	0.99	0.95
Actual value	237.61	223.35	196.98	63205.40
Next day predicted value	234.17	218.50	192.30	64495.30

high values, especially for Apple and Amazon, with values of $8.63 \times 10^{13}\%$ and $1.04 \times 10^{14}\%$, respectively. After combining with Rolling Forecast, the MAPE dropped sharply to 1.11%

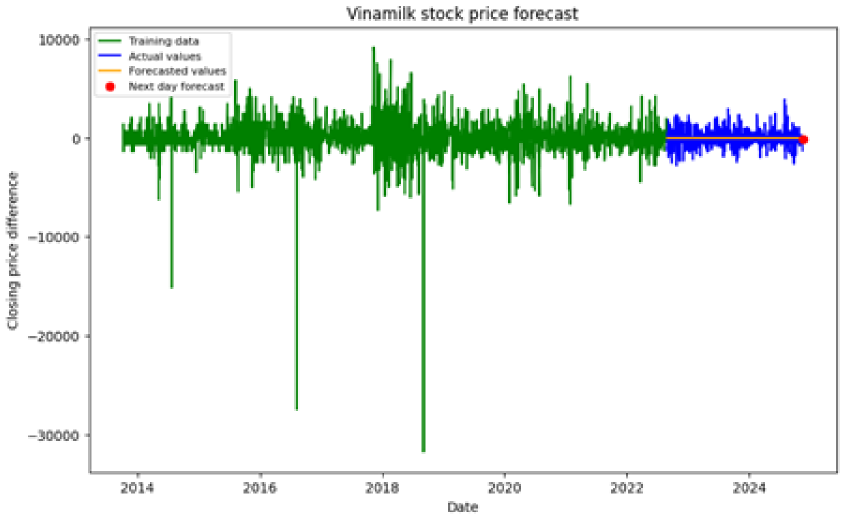

FIGURE 5. Stock price forecast for Vinamilk by ARIMA model

(Apple), 1.52% (Amazon), 1.41% (Google), and 0.94% (Vinamilk). This proves that Rolling Forecast significantly improves forecast accuracy.

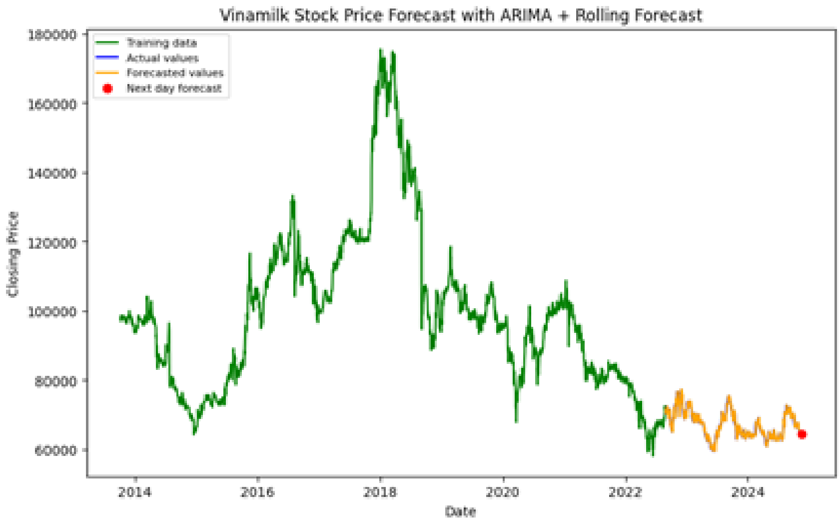

FIGURE 6. The stock price forecast for Vinamilk with the ARIMA model combined with the Rolling Forecast

Vinamilk's stock price exhibited significant fluctuations during the 2017–2019 period before gradually declining. The model's forecast (orange) appears to closely follow the actual trend but may struggle to capture strong volatility. The next-day forecast point (red dot) indicates that the model's prediction remains fairly accurate compared to the most recent trend.

All three stocks—Google, Amazon, and Apple—have shown strong growth trends over time. ARIMA appears to perform well in tracking long-term trends but may struggle with short-term fluctuations. The next-day forecast point (red dot) is positioned right on the forecasted line, indicating that the model is still functioning reasonably well. However, if a sudden reversal occurs, the model may not respond quickly enough. Combining the ARIMA model with the Rolling Forecast significantly improved the forecast accuracy

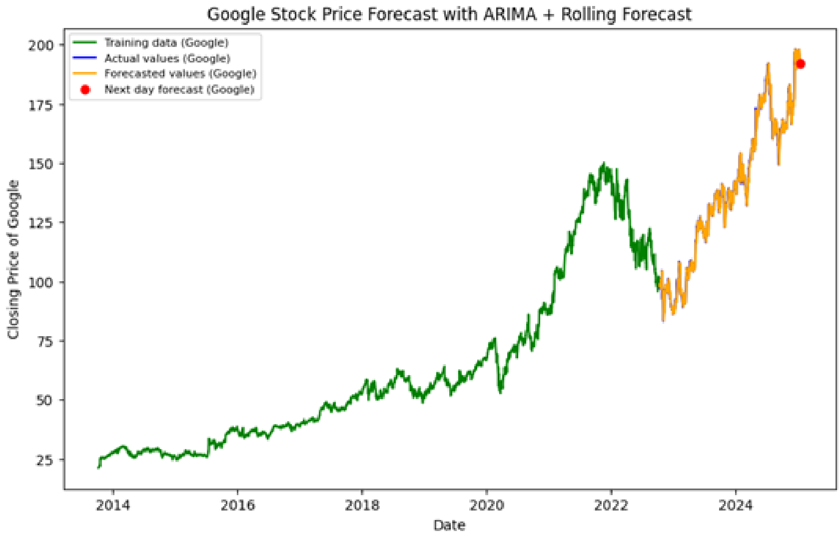

FIGURE 7. The stock price forecast for Google with the ARIMA model combined with the Rolling Forecast

FIGURE 8. The stock price forecast for Amazon with the ARIMA model combined with the Rolling Forecast

compared to the ARIMA model alone. MAPE dropped sharply to a low level (below 2%), while R^2 reached a high value (nearly 0.99).

Finally, incorporating GARCH into the above-trained ARIMA + Rolling model, the results are shown in Table 5.

When continuing to combine GARCH into the ARIMA + Rolling Forecast model, the model quality assessment indicators did not change significantly. MAPE remained the same, R^2 remained at a high level, but MSE and RMSE tended to increase slightly. This shows that adding GARCH did not significantly improve the forecast accuracy in this case. In fact, for some stocks such as Google and Vinamilk, the model's forecasts were somewhat less accurate.

5. **Conclusion.** This study presents a hybrid forecasting model that combines ARIMA, Rolling Forecast, and GARCH to enhance stock price prediction. The integration of

FIGURE 9. The stock price forecast for Apple with the ARIMA model combined with the Rolling Forecast

TABLE 5. Evaluation metrics for the ARIMA + Rolling Forecast and GARCH model on four stock datasets

	Apple	Amazon	Google	Vinamilk
MSE	7.27	8.54	6.79	768946.82
RMSE	2.70	2.92	2.61	876.90
MAE	2.00	2.16	1.88	637.75
MAPE	1.11%	1.52%	1.41%	0.94%
R^2	0.99	0.99	0.99	0.95
Actual value	237.61	223.35	196.98	63205.40
Next day predicted value	233.03	217.81	191.06	64495.30

these three components enables the model to capture both linear trends and volatility dynamics in financial time series. Specifically, ARIMA is effective in modeling trend and autocorrelation in stationary data, while GARCH handles conditional variance and volatility clustering. The Rolling Forecast mechanism further improves adaptability by continuously updating the model with new data, making it more responsive to short-term market changes.

Experimental results show that the hybrid model achieves high forecasting accuracy across multiple datasets, demonstrating superiority over standalone ARIMA or GARCH models. The model's ability to adapt to non-stationary data and irregular market fluctuations enhances both the precision of mean value forecasts and the reliability of volatility estimates. Furthermore, the model supports improved confidence interval calculation and risk assessment in financial decision-making.

Despite its advantages, the model has certain limitations. The combination of ARIMA, Rolling Forecast, and GARCH increases computational complexity, especially when processing large datasets that require frequent retraining. Rolling Forecast introduces additional overhead due to step-by-step rolling predictions. The model is also sensitive to parameter selection and may be prone to overfitting if not carefully tuned. Moreover, ARIMA assumes linearity and stationarity, while GARCH assumes conditional normality—assumptions that may not hold under extreme market volatility.

To address these limitations and further improve performance, future research should explore the integration of deep learning architectures, such as LSTM and Transformer, to better capture nonlinear relationships and long-term dependencies. Reinforcement Learning could be incorporated to optimize trading strategies in real time based on model predictions. In addition, the inclusion of exogenous variables—such as macroeconomic indicators, market sentiment from social media, and financial news—can enhance predictive accuracy.

Further advancements should also focus on automated parameter optimization using techniques like Bayesian Optimization or Genetic Algorithms, and employ parallel computing or GPU acceleration to improve processing speed, particularly in rolling forecasts. Finally, implementing Time Series Cross-Validation will help improve model stability, while ensemble learning methods (e.g., XGBoost, Random Forest) may boost the model's generalization ability across diverse market conditions.

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