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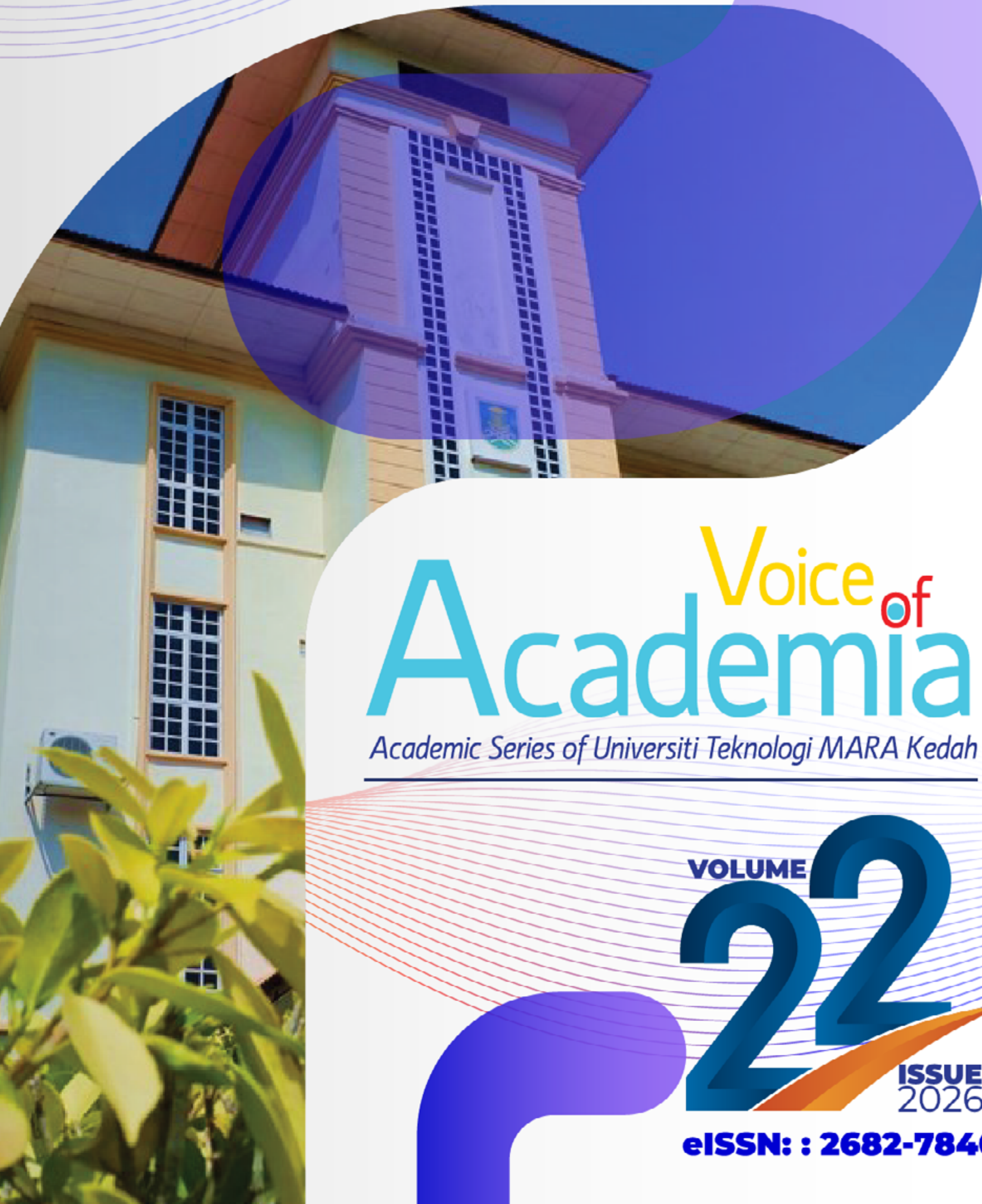

Voice of Academia

Academic Series of Universiti Teknologi MARA Kedah

VOLUME 22

ISSUE 1 2026

eISSN: : 2682-7840

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e-ISSN:2682-7840

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Academic Series of Universiti Teknologi MARA Kedah

Voice of Academia Vol.22 Issue (1) 2026

Voice of Academia

e-ISSN: 2682-7840

FORECASTING THE MALAYSIAN RINGGIT (MYR) EXCHANGE RATE: ARIMA VS GARCH

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ARTICLE INFO

Article history:

Received Aug 2025
Accepted Oct 2025
Published Jan 2026

Keywords:

Exchange rate forecasting, Malaysian Ringgit (MYR), ARIMA model, GARCH model & Time series analysis

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ABSTRACT

The purpose of this study was to forecast the Malaysian Ringgit (MYR) exchange rate against the US Dollar (USD) and identify the optimal model for short-term forecasting purposes. Daily exchange rate data from December 1, 2003, to December 31, 2024, were analysed through the time series modeling technique known as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The modelling process involved testing for stationarity, fitting the corresponding ARIMA and GARCH specifications, and evaluating model performance using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). Models were fitted with ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (1,1,2), ARIMA (2,1,2), and GARCH (1,1). ARIMA (2,1,2) had the lowest error values and was accepted on MLR residual diagnostics. Using ARIMA (2,1,2), a five-day forecast and 95% confidence intervals were calculated, which included both point estimates and upper and lower bounds of future exchange rate values. The analysis reveals that the ARIMA (2,1,2) model outperformed the GARCH (1,1) model in short-term predictions of the MYR/USD exchange rate. This highlights the model's effectiveness for predicting future short-term currency movements. This study also emphasises the importance of appropriate data processing, thorough model testing, and careful model selection to forecast exchange rates. Future research could incorporate external economic data and explore more advanced or hybrid modelling methods to improve forecasting accuracy.

1. Introduction

Foreign exchange rates play a crucial role in shaping trade relations, investment flows, and economic stability among nations. Defined as the number of units of a nation's currency exchangeable for one unit of a foreign currency, exchange rates directly impact imports, exports, foreign investment, and broader macroeconomic performance. Consequently, accurate analysis and forecasting of exchange rate fluctuations are essential for policymakers, businesses, and investors.

The Malaysian Ringgit (MYR) has experienced periods of both stability and significant volatility, particularly in response to major global events such as the Asian Financial Crisis (1997–1998), the Global Financial Crisis (2008), and the COVID-19 pandemic (2020). Notably, its performance against the US Dollar (USD) remains a central point due to the USD's dominance in global trade and finance. Variations in the MYR/USD rate have had considerable implications for Malaysia's trade competitiveness, investment flows, and monetary policy decisions. For example, the unpegging of the MYR from the USD in 2005 and subsequent economic events have caused marked swings in the exchange rate, including lows of more than RM4.70 per USD in recent years.

Given the MYR's sensitivity to global and domestic economic changes, short-term exchange rate forecasting is crucial for mitigating currency risk. Time series models such as the Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) provide analytical frameworks for understanding and predicting currency behavior. ARIMA is commonly applied for modelling and forecasting based on past trends and error terms, whereas GARCH is particularly suitable for modeling volatility patterns common in financial time series.

Despite numerous studies on MYR exchange rate forecasting, there remains limited comparative research evaluating the short-term predictive performance of ARIMA and GARCH models using consistent datasets and accuracy metrics. Addressing this gap, the present study uses daily MYR/USD exchange rate data from 1 December 2003 to 31 December 2024 to model, compare, and forecast short-term exchange rate movements. By assessing model accuracy through Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), this research aims to identify the most effective short-term forecasting approach, providing valuable insights for traders, investors, policymakers, and businesses seeking to manage currency exposure and enhance economic resilience.

2. Literature Review

Previous studies have examined various modelling approaches for exchange rate forecasting, offering insights relevant to the MYR/USD context. Wang et al. (2005) applied an ARMA–GARCH model to seasonal foreign exchange data, demonstrating the hybrid model's ability to improve volatility handling, thus suggesting the potential benefit of combined ARIMA–GARCH analysis. Lien and Yang (2009) compared ARIMA and GARCH in high-volatility markets, finding that GARCH yielded a lower Mean Squared Error (MSE), supporting its inclusion in MYR/USD performance evaluations. Onasanya and Adeniji (2013) used ARIMA via the Box–Jenkins method on Nigeria/USD data, identifying ARIMA (1,2,1) as the best fit for short-term forecasting, which reinforces ARIMA's applicability to MYR/USD modelling. Gharleghi et al. (2014) highlighted the weakness of ARIMA in handling volatility by showing that a hybrid SETAR–EGARCH approach outperformed ARIMA in financial series, further justifying the inclusion of GARCH in volatile markets. Babu and Reddy (2015) demonstrated ARIMA's superiority over other models for INR, USD, GBP, EUR, and JPY, underscoring its short-term predictive performance.

Palavani and Roshan (2015) confirmed that hybrid ARIMA–GARCH–EGARCH models improved forecast accuracy, aligning with arguments for combined approaches. Gupta and Kashyap (2016) found that GARCH is effective in capturing volatility and enhancing accuracy for exchange rates, supporting its role in forecasting MYR/USD. Kamal (2019) found that ARIMA (3,1,3) provided the best fit for TRY/USD, demonstrating ARIMA's adaptability to multiple currencies. Liu et al. (2020) reported that GARCH better captured dynamic interactions between MYR/USD and oil prices than ARIMA, validating GARCH's value in volatile markets. Escudero et al. (2021) compared ARIMA, RNN, and LSTM for the EUR/USD exchange rate, finding LSTM to be superior overall and noting ARIMA's limitations, which encouraged consideration of advanced or hybrid models. Finally, Kongwiriyapisal (2023) examined nine ASEAN currencies, including MYR, and confirmed that GARCH and its variants (TGARCH, PGARCH) are well-suited for modelling volatility and leverage effects, reinforcing the importance of volatility modelling in MYR/USD research.

3. Methodology

This study uses secondary data obtained from the official website of the Department of Statistics Malaysia (DOSM), with the source being Jabatan Digital Negara. The dataset contains daily records of MYR exchange rates against USD from 1st December 2003 to 31st December 2024.

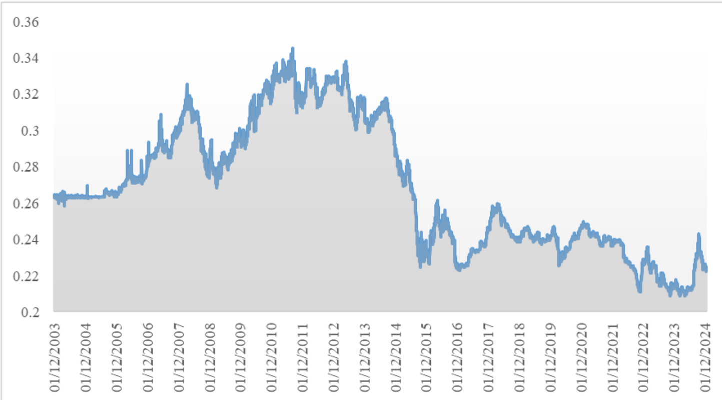

Figure 1 Daily Malaysian Ringgit Exchange Rates against US Dollar from 1st December 2003 to 31st December 2024

Figure 1 shows the historical trend of the MYR exchange rates against the USD for the period December 2003 to December 2024. The exchange rates fluctuate approximately between 0.2 and 0.3 MYR per USD. There is a distinct peak around 2010-2011, which indicates a strong MYR (higher exchange rate against the USD). Following 2010-2011, a noticeable downward trend is observed (around 2014-2015), and the rates appear to settle at their lowest point before beginning to rise, as seen between 2023-2034. The graph depicts minimum and maximum random movements and is very volatile and somewhat deterministic; therefore, using ARIMA and GARCH models for analysis and predictions was appropriate.

The Box-Jenkins methodology is a systematic approach for identifying, estimating, fitting, and validating models for time series data, specifically ARIMA models. Developed by George Box and Gwilym Jenkins in the 1970s, this methodology provides a structured process for analyzing and forecasting time series data. Figure 1 shows the stages involved in fitting an ARIMA model, starting from model identification to applying the model for forecasting.

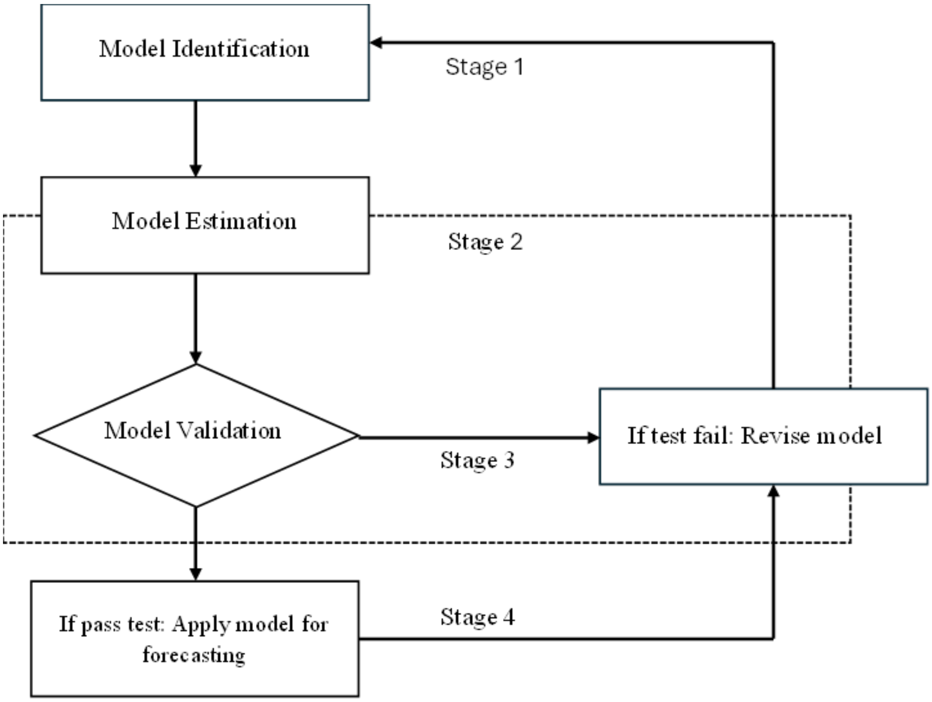

Figure 2 Box-Jenkins Methodology

To build a Box-Jenkins model, it is necessary to first establish whether a time series is stationary. According to Lazim (2013), stationarity is an important concept in time series analysis for understanding the behaviour of stochastic processes. It is possible to determine an initial overall model of ARIMA using a time series plot. If the data series appears to fluctuate randomly around a constant value, it indicates that the data series is stationary and is likely an ARMA (p,q) model. However, if the data consists of a trend, a first-order differencing is needed, and an ARIMA (p, d, q) model can then be applied.

Non-stationary series can be identified by:

1) Time series plot
If a time series plot exhibits fluctuations around a constant mean, without any pattern, it indicates a stationary time series. However, if the plot shows a clear trend and systematic behavior over time, it implies that the series is non-stationary.

2) Statistical test: Augmented Dickey-Fuller (ADF) Test
The Dickey-Fuller Test is a statistical procedure used to determine the presence of a unit root in a time series, as the existence of a unit root signifies that the series is non-stationary. The test evaluates the following hypothesis:

$H_0: \delta = 0$,there is exists a unit root in the time series (non-stationary)
$H_1: \delta < 0$,there is no unit root in the time series (stationary)

The coefficient δ is tested using the student-t ratio denoted as $\hat{\tau}$ where $\hat{\tau} = \frac{\hat{\delta}}{SE_{\hat{\delta}}}$. If the $\hat{\tau}$ is less than the Dickey-Fuller critical value or if the p-value is greater than 0.05, the null hypothesis is not rejected. This indicates that the series is non-stationary. When more lagged variables are included to account for higher-order autocorrelation, the Augmented Dickey-Fuller (ADF) test is employed alternatively.

1) Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

The order of the ARIMA model can be determined using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF is an essential tool in time series analysis that measures the correlation between observations of a time series and its lagged values over various time lags. The autocorrelation at lag k is defined as follows:

$$r_k = \frac{\mathrm{cov}(y_t, y_{t+k})}{\sqrt{\mathrm{var}(y_t)\mathrm{var}(y_{t+k})}}$$

where

- $cov(y_t, y_{t+k})$ is the covariance between y_t and y_{t+k}
- $var(y_t)$ is the variance of the time series

Hence, the first-order autocorrelation can be defined as:

$$r_k = \frac{\mathrm{cov}(y_t, y_{t+1})}{\sqrt{\mathrm{var}(y_t)\mathrm{var}(y_{t+1})}}$$

Model validation is the third step in the Box-Jenkins methodology, following model identification and estimation. This step involves evaluating the model's residuals and overall performance to ensure that the residuals meet key assumptions: they are normally, independently and randomly distributed with mean zero and constant variance. The residuals must satisfy the white noise specification, which indicates that the ARIMA model is suitable for forecasting. The standard statistical measures used to validate the ARIMA models are:

1) Ljung-Box statistics

The Ljung-Box statistic was employed to check whether the residuals of a time series model are significantly autocorrelated. It is approximately distributed as a chi-square distribution, $\chi^2_{1-\alpha,h}$ where h represents the degrees of freedom and is calculated as $h = m - p - q$.The equation for the Ljung-Box test is:

$$Q = T(T+2)\sum_{k=1}^{m}\frac{r_k^2}{T-k}$$

where

- r is the estimated total number of parameters
- r_k^2 is the k^{th} sample of autocorrelation of residual terms

- T is the number of observations in time series
- k is the time lag
- m is the maximum lags being tested
- p is the number of AR terms
- q is the number of MA terms

H_0: The residuals are white noise

H_1: The residuals are not white noise

If the p-value from the Ljung-Box statistic is less than the 5% level of significance, reject H_0, indicating that the residuals are not white noise. Conversely, if the residuals resemble white noise, the model is considered well specified and may be a candidate for the best-fitting model.

2) Akaike's Information Criterion (AIC)

A common indicator of an ARIMA model's goodness-of-fit is the Akaike Information Criterion (AIC). The AIC is intended to estimate the relative quality of statistical models for a given dataset. Its purpose is to select the model that provides the best balance between goodness-of-fit and complexity, where a smaller AIC value indicates a superior model among competing alternatives. The AIC can be expressed as:

$$AIC = -2\,log(L) + 2(p + q + k + 1)$$

where L is the likelihood of the data. $k = 1$ if $\phi_0 \neq 0$ and $k = 0$ if $\phi_0 \neq 0$. For ARIMA models, the corrected AIC was defined as follows:

$$AIC_c = AIC + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}$$

3) Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC), like AIC was applied for model selection but has a stronger penalty for model complexity and is penalized more than AIC since it includes a term that grows with the sample size. Similar to AIC, lower BIC values indicate a better-fitting model. The BIC is calculated using the following formula:

$$BIC = AIC + [log(T) - 2](p + q + k + 1)$$

The process for developing GARCH models is illustrated in Figure 2 (Salem et al., 2021). Before applying a GARCH model, it is essential to first identify the best-fitting ARIMA model and test for ARCH effects in the residuals. The presence of significant ARCH effects indicates time-varying volatility, justifying the use of a GARCH model for more accurate modelling and forecasting.

Figure 3 Steps in developing GARCH

The Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced by Robert F. Engle in 1982 (Bollerslev Tim et al., 1992). ARCH effects indicate that the variance in a time series is not constant over time but depends on past residuals or squared values of prior observations (Chand et al., 2012). In this study, an ARIMA model is first fitted to the data, as the ARCH model is used to represent the conditional variance of the residuals after a suitable mean equation has been established (Kumar, 2020).

The Lagrange Multiplier (LM) Test, as well as other methods including AIC, BIC, maximum likelihood estimation (MLE), and assessment of model adequacy, can all be used to determine the presence of an ARCH effect. The LM test, also referred to as an ARCH-LM test, is one of the most popular methods for identifying conditional heteroskedasticity.

Destiarni et al. (2021) describe that the LM test utilizes the squared values of residuals from a time series model to detect the presence of autoregressive conditional heteroskedasticity. If the squared variable is autocorrelated, it indicates the presence of heteroskedasticity. The LM test is one of the most frequently used specification tests in univariate time series analysis, and it tests the null hypothesis of no conditional heteroskedasticity against the alternative hypothesis of the presence of an ARCH effect (Catani & Ahlgren, 2017). The test statistic is computed with

When ARCH effects are present in the residual of the best-fitting ARIMA model, it may indicate a problem with the model's ability to capture volatility. This issue can be addressed by applying a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, specifically the best-fitting GARCH(p,q) model.

In summary, this chapter outlines the procedures applicable to model evaluations were

$$H_0 = \alpha_1 = \alpha_2 = \dots = \alpha_q = 0 \text{ ,there are no ARCH effects}$$
$$H_1 \text{ at least one } \alpha_i \neq 0 \text{ ,presence of ARCH effects}$$

reduced again for clarity in the case of the ARIMA and GARCH models. The first step was to test for stationarity using the Augmented Dickey Fuller (ADF) test and apply differencing where necessary. Second, model identification was conducted, starting with values on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to find appropriate p, d, q parameters for the ARIMA model.

In the case of GARCH, the net residuals were backtracked to determine if they exhibited ARCH effects to validate the lag length applied. The third step was to estimate parameters using maximum likelihood estimation (MLE) and compare the competing ARIMA and GARCH models using Akaike information criterion (AIC), Bayesian information criterion (BIC), mean absolute percentage error (MAPE), and mean square error (MSE) model fit criteria to select the best-performing model. Fourth, a series of residual diagnostic tests, including the Ljung–Box Q test and ACF/PACF plot analysis, were conducted to verify that the residuals behaved as white Gaussian noise. Finally, in the case of GARCH, additional checks were performed to confirm that an adequate level of volatility clustering had been modelled. The final step was to generate forecast outputs for the test dataset using the models selected in step four for both ARIMA and GARCH, and compare the predictive performances concluded for the short-term forecast periods of the MYR/USD exchange rate over the test dataset period.

4. Results

As a first step in the modeling process, the raw daily MYR/USD exchange rate data from December 2003 to December 2024 were investigated for stationarity. The Augmented Dickey-Fuller (ADF) test accepted the null hypothesis of non-stationarity and determined the need for a first-order difference to achieve stationarity. Once transformed by differencing, the ADF test, as well as visual inspections of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, confirmed that the data met the stationarity requirement for ARIMA modeling.

Table 1 presents the result of the ADF test conducted after first-order differencing of the MYR/USD exchange rate series. The p-value obtained is 0.01, which is significantly less than 0.05, leading to the rejection of the null hypothesis that the series is non-stationary. Hence, it can be concluded that the exchange rate series becomes stationary after differencing once.

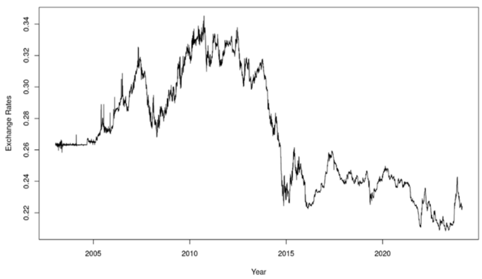

Figure 4: Before Differencing

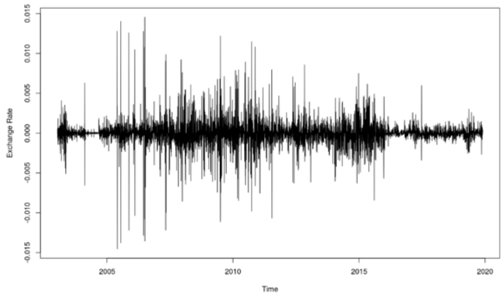

Figure 5: After Differencing

Table 1
Augmented Dickey Test after First-Order Differencing

Hypothesis	ADF test statistic	p-value	Conclusion
H_0: The exchange rate of MYR/USD is not stationary H_1: The exchange rate of MYR/USD is stationary	-18.698	0.01	Reject H_0. Hence, the exchange rate of MYR/USD is stationary

The first modeling approach involved creating and assessing several ARIMA models. All models were evaluated using residual diagnostics and forecasting accuracy measures. The Ljung-Box test was applied to the model residuals as a method to check for white noise behavior. Table 2 shows that only the ARIMA (2,1,2) model yields a p-value of 0.7282, leading to the failure to reject the null hypothesis and indicating that the residuals from the ARIMA (2,1,2) model are white noise. While all other models have extremely small p-values, resulting in rejection of the null hypothesis.

Hence, ARIMA (2,1,2) is the most appropriate for modeling the MYR/USD exchange rate because it produces residuals statistically indistinguishable from white noise. This indicates that the model has effectively captured the structure in the data without leaving significant autocorrelation in the errors.

Table 2
Summary of Portmanteau Test

	ARIMA (1,1,1)	ARIMA (2,1,1)	ARIMA (1,1,2)	ARIMA (2,1,2)	ARIMA (0,1,1)
p-value	0.000	0.0344	0.0016	0.7282	0.000
Decision	Reject H_0	Reject H_0	Reject H_0	Failed to reject H_0	Reject H_0

Conclusion	The residuals are not white noise	The residuals are not white noise	The residuals are not white noise	The residuals are white noise	The residuals are not white noise

To determine the presence of conditional heteroscedasticity in the residuals of the ARIMA (2,1,2), the ARCH Lagrange Multiplier (LM) test was conducted. The result from Table 3 indicates a highly significant test statistic with a p-value less than 0.05. Given that the null hypothesis of no ARCH effects is rejected, this confirms that the residuals exhibit time-varying volatility (ARCH effects), which violates the constant variance assumption of the ARIMA model. Therefore, it is appropriate to extend the model by fitting a simple GARCH and ARMA-GARCH model, as these models account for volatility and provide more reliable forecasts by capturing the dynamic behavior of the conditional variance.

Table 3
ARCH LM Test

Test	Null Hypothesis	Chi-Squared	Degree of freedom	p-value	Conclusion
ARCH LM Test	No ARCH effects in residuals	753.87	5	0.000	Reject null hypothesis, ARCH effects are present. Then proceed with GARCH modeling.

The adequacy of the model can also be determined by the normal quantile plot. The errors are assumed to be normally distributed and uncorrelated. In addition to that, the error terms should have zero mean and constant variance. The normal quantile plot is for the purpose of checking whether the error terms are normally distributed or not.

Figure 6 assesses the normality of the standardized residuals from the GARCH (1,1) model. Ideally, if the residuals are normally distributed, the points should closely follow the 45-degree reference line. However, in this plot, there are noticeable deviations in the tails, particularly at both the lower and upper ends. These deviations indicate fat tails, suggesting that the residuals have more extreme values than would be expected under a normal distribution. This implies that the GARCH (1,1) model residuals do not follow a normal distribution completely, but rather a distribution with heavier tails.

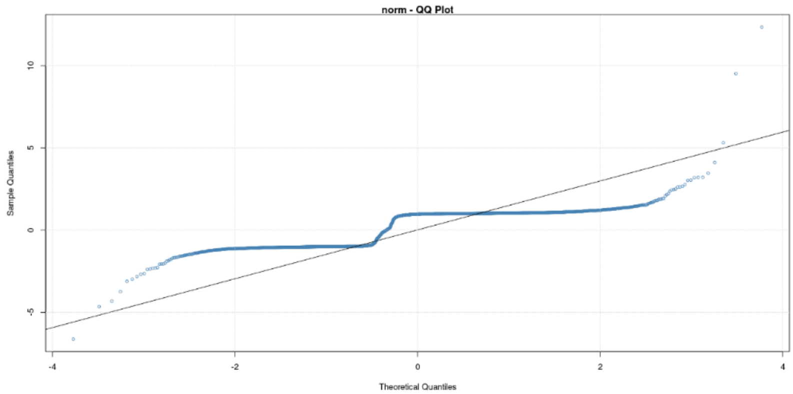

Figure 6 Standardized Residuals of GARCH (1,1)

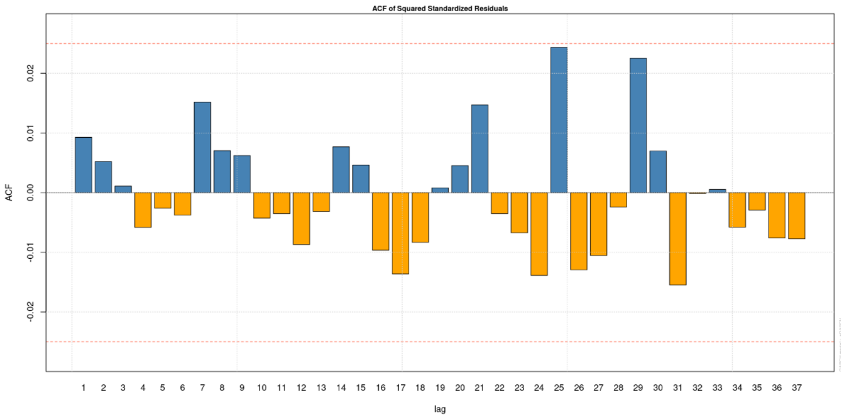

Figure 7 Squared Standardized Residuals of GARCH (1,1)

The complete autocorrelation function graph is used to determine whether there is a problem of autocorrelation in the error terms. If the autocorrelation value is more than the dotted line, it indicates that the correlation value is statistically significant.

The ACF (Autocorrelation Function) plot of the squared standardized residuals helps assess whether there is remaining autocorrelation in the variance after fitting the GARCH (1,1) model. Figure 6 shows that most of the lags fall within the confidence interval, but a few spikes slightly exceed the boundaries. This suggests that while the GARCH (1,1) model has captured much of the conditional heteroskedasticity in the series, some minor autocorrelation may remain in the squared residuals.

Overall, the model performs reasonably well. However, the presence of a few significant lags may suggest that a more complex GARCH specification could further enhance the fit.

In Table 4, the forecasting accuracy of both ARIMA(2,1,2) and GARCH(1,1) models using MSE and MAPE was evaluated. ARIMA(2,1,2) produced the lowest MSE and MAPE, which indicates the best forecasting performance, whereas GARCH(1,1) yielded higher error values. Overall, these results demonstrate that ARIMA(2,1,2) is the most accurate and reliable for short-term MYR/USD exchange rate forecasting.

Table 4
Model Comparison

	ARIMA (2,1,2)	GARCH (1,1)
MSE	0.0003	0.0014
MAPE	6.5734	15.8496

After assessing model performance, the ARIMA(2,1,2) model was identified as the most suitable for short-term forecasting, as it had an MSE and MAPE lower than those of the other models. A 5-day forecast was produced, with point estimates predicting exchange rate values between 0.2191 and 0.2225, and the 95% confidence intervals indicating a narrow range. This suggests some degree of precision in the provided forecast. The forecast indicates that the MYR/USD exchange rate is expected to remain stable, with a slight decline. The relative stability of the forecast supports the MYR's usefulness for short-term financial planning as it will enable businesses and policy-makers time to anticipate currency movements with greater certainty.

Table 5
Forecast Values for 5 days

Point forecast	Lower 95% CI	Upper 95% CI
2024.1315	0.2225	0.2257
2024.1342	0.2218	0.2262
2024.1370	0.2210	0.2264
2024.1397	0.2201	0.2267
2024.1425	0.2191	0.2270

Figure 8 depicts the forecast of the Malaysian Ringgit (MYR) to US Dollar (USD) exchange rate computed with an ARIMA model, where the black line represents the past values and the blue shaded area indicates the range of forecasted values with the confidence intervals. We observe in the forecast that the exchange rate has generally exhibited a downward trend from late 2023 to 2024 with some fluctuations, but the forecasted values show relative stability with a slight downward trend, suggesting the exchange rate is expected to remain low.

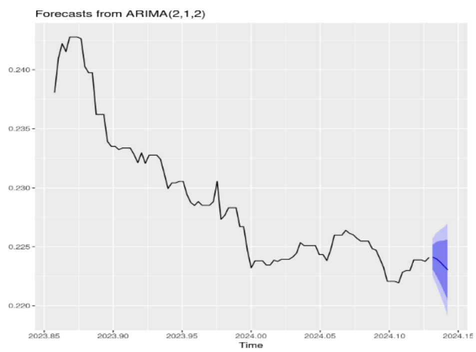

Figure 8: Forecast the next 5 periods ahead using ARIMA (2,1,2)

5. Discussion

The results of this study demonstrate that time series modeling is an effective method for forecasting the Malaysian Ringgit (MYR) exchange rate, consistent with findings in prior research. The study by Mustafa et al. (2017a) illustrates how ARIMA can accurately model and forecast the USD/MYR exchange rate, whereas the GARCH model captures the time-varying volatility. Kargar (2021) and Clerk and Savl'ev (2022) highlighted the GARCH model's performance in modeling various financial instruments, including foreign exchange rates.

Several ARIMA models, including ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (1,1,2), ARIMA (0,1,1), and ARIMA (2,1,2), along with a GARCH (1,1) model, are developed and evaluated using historical daily exchange rate data. Among these, the ARIMA (2,1,2) model is identified as the best-fitting model as it produced the lowest MSE and MAPE values. This finding aligns with studies by Rubi et al. (2022), which demonstrated that ARIMA (2,1,2) was effective in forecasting the movement of market capitalization at the Dhaka Stock Exchange, illustrating its application in stock price prediction. Conversely, while GARCH (1,1) models are important for modeling volatility, they generally yield less precise outcomes for direct forecasting applications, when the primary goal is to generate forecasts. For example, Mustapa and Ismail (2019) found that although the integration of GARCH in a hybrid model enhanced volatility predictions for the S&P 500 index, it did not exceed the predictive abilities of the ARIMA component of the model. Moreover, GARCH models emphasize capturing the conditional heteroskedasticity of returns, making them useful for risk assessment. Studies indicate that while ARIMA can provide consistent forecasts in stable conditions, GARCH remains essential for understanding the risk and variability of returns over time (Lama et al., 2015).

In conclusion, for many forecasting applications observed in financial contexts, the ARIMA (2,1,2) model often emerges as a preferable choice for time series prediction compared to GARCH (1,1), especially when the focus is on achieving high accuracy in forecasting.

6. Conclusion

This research is conducted with the aim of modelling, evaluating, and forecasting the Malaysian Ringgit (MYR) exchange rate using time series analysis. The study focuses on three principal objectives. Through a structured methodology involving data preparation, model selection, and forecast evaluation, all research goals are successfully achieved. For the first objective, the Malaysian Ringgit exchange rate is modelled, applying two common time series models. Historical daily exchange rate data were analyzed and pre-processed for stationarity to allow for the fitting of the time series data. Subsequently, several ARIMA models (i.e., ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (1,1,2), ARIMA (2,1,2), and ARIMA (0,1,1)) and a GARCH (1,1) model were fitted to represent the exchange rate series.

In meeting the second objective of the current study, the results of diagnostic checking on the residuals for all ARIMA models indicated that the residuals for ARIMA (2,1,2) behaved like white noise, suggesting that the residuals were random, uncorrelated, and approximately normally distributed. These findings indicate that the model effectively captures the characteristics of the exchange rate series and that there are no significant autocorrelations in the errors. The performance of the ARIMA and GARCH models is then assessed using two standard error measures: Mean Squared Error (MSE) and the Mean Absolute Percentage Error (MAPE). The ARIMA (2,1,2) model had lower values for both MSE and MAPE, indicating it was more consistent in producing accurate predictions than the GARCH (1,1) model. Accordingly, the ARIMA (2,1,2) model was selected as the best fit and, therefore, the preferred model for this study.
To complete the third goal, the ARIMA (2,1,2) model is employed to create short-term forecasts for

the next five days, including both point forecasts and confidence intervals to determine estimates of future values of Exchange Rates, as well as uncertainty surrounding them. The successful generation of accurate short-term forecasts further demonstrates the applicability of the ARIMA model for working with this type of financial time series data.

Future research should investigate advanced and hybrid forecasting models to improve accuracy and adaptability. While this study focused on traditional ARIMA and GARCH approaches, combining them with machine learning techniques has shown notable gains in financial time series forecasting (Najamuddin & Fatima, 2022). Hybrid ARIMA–GARCH frameworks, as demonstrated by Mustafa et al. (2017b), can enhance performance in high-volatility environments, particularly for USD/MYR. Additionally, incorporating macroeconomic and other exogenous variables may enhance predictive power. Zhu (2023) found that univariate ARIMA models underperform compared to multivariate regression models with ARIMA errors when forecasting exchange rates such as USD/EUR. To enhance explanatory power, future research could employ Vector Autoregression (VAR) and Vector Error Correction Models (VECM) that integrate macroeconomic covariates, including variables such as oil prices, interest rate differentials, and global risk sentiment indicators (DeğiRmen et al., 2023).

With the sensitivity of exchange rates to external shocks and policy changes, future studies should also consider structural breaks and regime shifts. Zumaquero and Rivero (2014) showed that structural breaks related to exchange rate regimes and financial crises significantly affect real exchange rate volatility, highlighting their importance in reliable modelling. Future studies should apply models such as Markov-Switching ARIMA/GARCH or Bai-Perron structural break tests, which enable researchers to capture distinct volatility regimes (Aloui et al., 2015).

Acknowledgement

I would like to express my sincere gratitude to Universiti Teknologi MARA (UiTM) Seremban, Faculty of Computer and Mathematical Sciences, for providing the facilities and resources necessary to carry out this research. I am deeply thankful to Dr. Nurul Nisa' for her invaluable guidance, constructive feedback, and continuous encouragement throughout the study. I also acknowledge the use of publicly available exchange rate data sources, which played a crucial role in enabling the completion of this work.

Funding Details
This study received no specific grant from any funding agency.

Authors Contributions
All authors have significantly contributed to the content.

Conflict of Interest
There are no conflicts of interest.

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eISSN: : 2682-7840