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Application of Box-Jenkins Models for Forecasting Global Rubber Market Trends

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Abstract

Global rubber prices are subject to fluctuations influenced by market demand, supply dynamics, and economic factors, making accurate forecasting essential for producers, traders, and policymakers. This study aims to apply the Box–Jenkins ARIMA model to forecast monthly global rubber prices from October 2021 to April 2025 and evaluate the forecasting performance. Monthly rubber price data from the Federal Reserve Economic Data (FRED) database, covering the period from January 1990 to April 2025, were analysed, with the dataset split into 90% for training and 10% for testing. Two models, ARIMA(0,1,1) and ARIMA(1,1,0), were developed and compared based on forecasting accuracy using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Results indicate that ARIMA(0,1,1) provided slightly better accuracy (MAE = 15.82, RMSE = 18.70, MAPE = 16.83%) than ARIMA(1,1,0), suggesting that ARIMA(0,1,1) produces good predictions for short-term projections of global rubber prices. These projected results may offer useful insights for Malaysia, as one of the world's leading natural rubber exporters, in guiding trade planning, supporting risk management, and informing future strategies. Future research could integrate volatility models, exogenous economic variables, or hybrid approaches to strengthen predictive performance and enhance the practical relevance of modelling outcomes.

Keywords **:** *Arima Model; Box-Jenkins; Global Rubber Price; Time Series Analysis*

I. INTRODUCTION

Natural rubber is vital for industries such as automotive tyres, industrial goods, and medical equipment, making price volatility a critical concern for producers, manufacturers, and policymakers. Since 2020, commodity markets have faced sharp fluctuations, with the World Bank reporting both short-term shocks and persistent drivers of volatility [1]. Accurately forecasting these fluctuations remains a challenge, particularly for natural rubber prices, which require precise model specification and transparent communication of uncertainties [2], [3], [4], [5].

The Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) framework provides a structured and interpretable approach for univariate forecasting, consisting of four stages: model identification, parameter estimation, diagnostic checking, and forecasting [6], [7], [8]. While contemporary reviews increasingly compare ARIMA with machine learning and hybrid methods, ARIMA remains a robust and interpretable benchmark for practical applications [9]. Recent studies conducted after 2020 on rubber and other commodities have highlighted the applicability of ARIMA, while also underscoring its limitations when exposed to market shocks and variance shifts.[10].

This study employs the Global Price of Rubber (PRUBBUSDM) monthly series from the Federal Reserve Bank of St. Louis (FRED), a publicly available dataset with well-documented sources [11], [12], [13]. Forecasting guidelines recommend reporting prediction intervals alongside point forecasts to capture uncertainty, while recent applications of deep learning highlight potential gains depending on data and horizon [14]. Within this broader modelling landscape, ARIMA continues to serve as a standard reference [15], [16]. The objective of this study is to apply the Box–Jenkins ARIMA approach to forecast monthly global rubber prices from October 2021 to April 2025 and to assess the forecasting accuracy of the model.

II. LITERATURE REVIEW

Forecasting commodity prices has been studied using a wide range of methods. The Box-Jenkins ARIMA framework remains one of the most widely applied and interpretable approaches, while alternatives such as state-space models, hybrid statistical-machine learning methods, and deep learning models have been introduced to address

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nonlinearity, structural breaks, and volatility. Comparative studies show that no single method consistently outperforms others, with accuracy often depending on the forecasting horizon and dataset characteristics. In agriculture and food markets, frequent shocks and regime changes complicate forecasting, making transparency, out-of-sample testing, and uncertainty communication essential.

In the context of rubber and other agri-commodities, ARIMA often serves as the benchmark for univariate forecasting. In India, the Box-Jenkins methodology was applied to weekly RSS-1 prices, selecting ARIMA(1,1,4) as the optimal specification [10]. Research in Malaysia using monthly SMR 20 data reported ARIMA(1,1,0) as the best-fitting model [17]. Further analysis of Indian rubber series, including RSS 4, Latex 60% DRC, and ISNR 20, found ARIMA(3,1,2) and ARIMA(4,1,3) to be suitable, depending on the series [18]. A study conducted in Thailand compared ARIMA and ARIMAX models and found that ARIMAX(0,1,1), which included external variables, achieved higher accuracy with a MAPE of 1.11% [19]. At the international level, the application of the SARIMA model to TOCO's RSS 3 series successfully captured both trend and seasonality in global rubber prices [20].

While ARIMA models have been widely applied in rubber price forecasting, most prior studies have focused on shorter data spans or national markets [21]. By contrast, relatively few studies have systematically applied the Box–Jenkins ARIMA methodology to long-run monthly global rubber price data, which motivates the present study.

III. DATA AND METHODOLOGY

A. Data Description

This study utilises the monthly Global Price of Rubber time series from Federal Reserve Economic Data (FRED), series code PRUBBUSDM, Global Price of Rubber, expressed in U.S. dollars per metric ton (US$/MT). The dataset covers the period from January 1990 to April 2025, consisting of 424 monthly observations. Exploratory data analysis (EDA) was first conducted to identify potential anomalies and understand the overall trend and seasonality. The dataset was divided into a 90% training set (January 1990 to September 2021) for model development and a 10% testing set (October 2021 to April 2025) for model validation.

B. ARIMA Model Development

The modelling follows the Box–Jenkins methodology, which has four stages: model identification, parameter estimation, diagnostic checking, and forecasting. The general framework is illustrated in Figure 1.

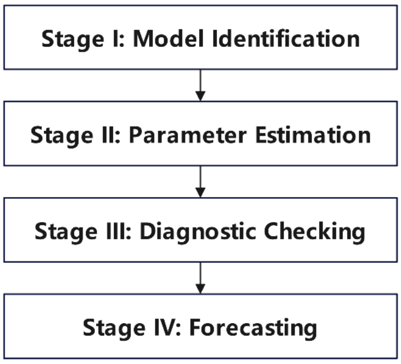

Figure 1: General framework of Box-Jenkins modelling [22]

In the first stage, the series is examined for stationarity in variance and mean. A Box-Cox transformation was applied to stabilise the variance [23]. The formula of the Box-Cox transformation for positive series, $y_t > 0$ is given in Equation 1.

$$y_t^* = \begin{cases} \dfrac{y_t^\lambda - 1}{\lambda}, \lambda \neq 0 \\ \log_e\left(y_t\right), \lambda = 0 \end{cases}$$ **Equation 1**

Mean stationarity is assessed using time plots, the sample autocorrelation function (ACF), the partial autocorrelation function (PACF), and the Augmented Dickey–Fuller (ADF) unit-root test [24]. If nonstationarity is detected, nonseasonal differencing is applied until stationarity is achieved. Once the appropriate differencing order d is determined, the general ARIMA(*p,d,q*) model can be expressed as Equation 2.

$$\phi\left(B\right)\left(1-B\right)^d y_t = \theta\left(B\right)\varepsilon_t$$ **Equation 2**

where $\phi\left(B\right) = 1 - \phi_1 B - \ldots - \phi_p B^p$ is the autoregressive operator, $\left(1-B\right)^d$ represents differencing of order d, $\theta\left(B\right) = 1 + \theta_1 B + \ldots + \theta_q B^q$ is the moving average operator, and ε_t is the white noise term.

Stage II of the Box–Jenkins method estimates the autoregressive (AR) and moving average (MA) parameters of the ARIMA model. Parameters are obtained using least squares or maximum likelihood estimation (MLE). Model fit is

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then evaluated with the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), where lower values indicate a better-fitting model [25], [26].

Stage III of the Box–Jenkins method involves diagnostic checking to verify model adequacy. Residuals are examined using the ACF and the Ljung–Box Q test to ensure that no significant autocorrelation remains [27]. A model is considered adequate when residuals resemble white noise, indicating that the systematic structure of the series has been captured. If the diagnostics suggest inadequacy, alternative model specifications are considered.

Stage IV is forecasting, where the validated model is used to generate future values of the series. Forecast performance is assessed by comparing predicted values against the testing dataset using accuracy measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) as in Equations 3,4, and 5. The interpretation of MAPE follows Lewis [28], as shown in Table 1.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \qquad \textbf{Equation 3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2} \qquad \textbf{Equation 4}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100 \qquad \textbf{Equation 5}$$

Table 1: Interpretation of typical MAPE [28]

MAPE(%)	**Evaluation**
<10%	High accuracy prediction
10%-20%	Good prediction
20%-50%	Reasonable prediction
>50%	Inaccurate prediction

IV. RESULTS AND DISCUSSION

The monthly global rubber price from January 1990 to April 2025 exhibited significant fluctuations, with values ranging from about 25 US$/MT in the early 2000s to a peak exceeding 260 US$/MT in 2011, as shown in Figure 2. A gradual increase in prices is visible during the mid-1990s, followed by cycles of rises and declines throughout the 2000s. The most significant increase was observed between 2009 and 2011, likely associated with the global economic recovery after the financial crisis, followed by a marked decline from 2012 onwards. More recently, the series displays recurring volatility with moderate rebounds, which is consistent with the broader volatility observed in commodity markets.

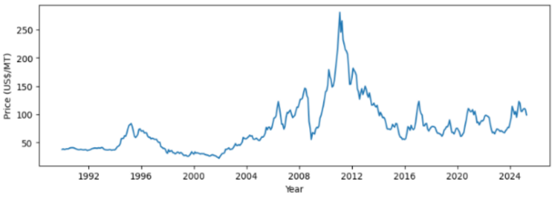

Figure 2: Time series plot of global rubber price

The series was split 90:10, with the training dataset covering January 1990 to September 2021 and the testing dataset covering October 2021 to April 2025. Variance stationarity on the training dataset was checked, yielding $\lambda = -0.2018$ Accordingly, Box-Cox was applied to stabilise the variance. Mean stationarity was then assessed using an ACF and PACF plot, and the ADF test was used to check stationarity. Figure 3 displays the ACF and PACF plots for the Box-Cox transformed training series. The ACF decays slowly, while the PACF shows a single dominant spike at lag 1 shows the series is not stationary in mean. The ADF test confirms with an ADF statistic was -1.784 with $p = 0.388\,(> 0.05)$, indicating the series is not stationary in mean, hence first differencing is needed, $d = 1$. The ADF test on the first-differenced Box–Cox series (ADF = –15.00, $p < 0.01$) rejects the null of a unit root, confirming stationarity with values fluctuating around zero as shown in Figure 4.

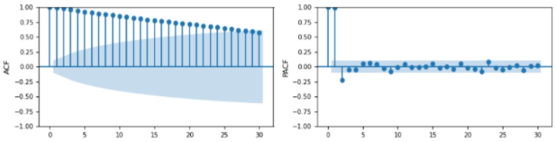

Figure 3: ACF and PACF plot for transformed series

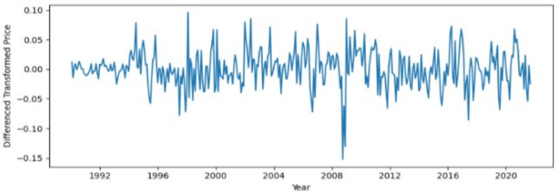

Figure 4: Time series plot after transformation and first differencing

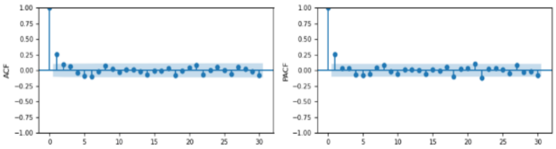

Figure 5: ACF and PACF plots after transformation and first differencing

The ACF and PACF of the transformed and differenced series are shown in Figure 5. The ACF shows a sharp drop after lag one, while the PACF

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has a significant spike at lag one and then decays. These features suggest that low-order terms with $p = 1$ and $q = 1$ may be appropriate for the ARIMA model. Therefore, tentative models such as ARIMA(1,1,0) and ARIMA(0,1,1) will be evaluated further to identify the optimal order. Table 2 presents the results of ARIMA(1,1,0) and ARIMA(0,1,1) model analysis for forecasting the global rubber price.

Table 2: Tentative models of ARIMA

ARIMA Model	Parameter Estimation	AIC	BIC
(0,1,1)	$\phi = 0.2319(0.000)$	-1574	-1566
(1,1,0)	$\phi = 0.2521(0.000)$	-1577	-1569

Based on Table 2, ARIMA(1,1,0) recorded the lowest AIC and BIC values; however, the difference compared to ARIMA(0,1,1) was not statistically significant. Both models were therefore considered for further evaluation, and the Ljung-Box test results $(p > 0.05)$ indicated no significant autocorrelation in the residuals. The model performance was then assessed using MAE, RMSE, and MAPE on the testing dataset. As shown in Table 3, both models produced comparable results with ARIMA(0,1,1) demonstrating slightly better performance. Therefore, ARIMA(0,1,1) was selected as the final model to forecast monthly global rubber prices, and the forecasting performance from October 2021 to April 2025 is illustrated in Figure 6.

Table 3: Model performance comparison

Model	MAE	RMSE	MAPE
ARIMA(0,1,1)	15.82	18.70	16.83%
ARIMA(1,1,0)	15.88	18.85	16.83%

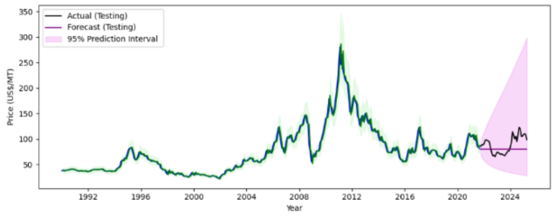

Figure 6: Forecast of global rubber prices in US dollars per metric ton using the ARIMA(0,1,1)

The forecasts are stable around 100 US dollars per metric ton, although the prediction intervals widen towards the end of the horizon. This widening reflects growing uncertainty in long-term forecasts, which is common in volatile commodity markets, and it underlines the need for careful planning to manage potential risks in trade and pricing strategies. The stable outlook suggests no major short-term disruptions in supply and demand, but the broader range indicates vulnerability to shocks such as oil price fluctuations, global demand shifts, or trade policy changes. For Malaysia, as a key rubber exporter, these forecasts provide valuable input for trade negotiations, export planning, and risk management.

V. CONCLUSION

This study applied the Box–Jenkins ARIMA methodology to forecast monthly global rubber prices from October 2021 to April 2025, and the findings show that ARIMA(0,1,1) achieved slightly better predictive accuracy than ARIMA(1,1,0), producing reliable short-term forecasts. The widening prediction intervals towards the end of the horizon highlight the uncertainty of long-term projections, which is common in volatile commodity markets. A limitation of this study is that it uses a univariate model, which does not account for external factors such as crude oil prices, exchange rates, and global demand changes. From a business and policy perspective, these forecasts can serve as a useful reference for Malaysia as one of the world’s leading natural rubber exporters. Policymakers may take these projected results into account when designing trade policies, preparing for potential market risks, and supporting evidence-based planning. Industry stakeholders, including producers and traders, may also rely on the modelling outcomes to guide production planning, inventory management, and risk assessment. Future research may address current limitations by incorporating external variables and applying volatility models, or hybrid approaches, which could improve predictive accuracy and make rubber price forecasting more relevant for policy and decision-making.

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