ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY
e-ISSN: 2773-6385

EKST

Vol. 5 No. 2 (2025) 452-461
https://publisher.uthm.edu.my/periodicals/index.php/ekst

Forecasting Natural Rubber Price in Malaysia using ARIMA and Long Short-Term Memory

Eng Chun Kit[1], Kamil Khalid[1]*

[1] *Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600 Pagoh, Muar, Johor, MALAYSIA.*

*Corresponding Author: kamil@uthm.edu.my
DOI: https://doi.org/10.30880/ekst.2025.05.02.053

Article Info

Received: 30 December 2024
Accepted: 18 January 2025
Available online: 19 December 2025

Keywords

Natural Rubber, SMR20, Time Series Forecasting, ARIMA, LSTM, Performance Metrics

Abstract

Natural rubber is a critical agricultural commodity in Malaysia, contributing significantly to the national economy and the global rubber market. However, the pricing of Standard Malaysia Rubber 20 (SMR20) is highly volatile, influenced by diverse economic and environmental factors, posing challenges for stakeholders. The objectives of this study are to apply reliable forecasting models for SMR20 prices in Malaysia, assess their accuracy using performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), and identify the best model that provides the most accurate predictions for decision-making and market stability. The study finds that the Long Short-Term Memory (LSTM) model outperforms the ARIMA model in forecasting SMR20 prices, demonstrated by its superior accuracy and lower error metrics: MAE of 791.706, RMSE of 88.383, and MAPE of 9.398%. While ARIMA, based on the Box-Jenkins methodology, provides a reasonable fit for traditional time series data, it struggles to capture nonlinear dependencies in price patterns, whereas LSTM excels at modelling complex, non-linear relationships and long-term trends. These findings highlight the potential of advanced machine learning techniques like LSTM in agricultural commodity forecasting. The study emphasizes the significance of machine learning models in forecasting systems to enhance decision-making, risk management, and market stability in Malaysia's rubber industry. Future research should explore incorporating external variables, such as climate dynamics and global economic factors, to further improve forecasting accuracy and expand model applicability.

1. Introduction

Natural rubber, primarily derived from Hevea brasiliensis, is a key agricultural commodity in Malaysia, underpinning both the national economy and global markets. As one of the world's leading producers, Malaysia generates approximately 996,000 metric tons of natural rubber annually. Among its products, Standard Malaysia Rubber 20 (SMR20) stands out as the most utilized grade due to its affordability and versatility in various industrial applications [1]. However, the industry is frequently challenged by significant price volatility, which creates uncertainties for stakeholders and complicates market stability.

The fluctuating prices of SMR20 are driven by diverse economic and environmental factors, including global demand, crude oil price trends, and climate variability [2]. These variations disproportionately affect smallholders reliant on predictable incomes and policymakers striving to ensure market balance. Accurate forecasting of SMR20 prices is therefore critical to enabling stakeholders to mitigate risks and make informed decisions.

Traditionally, time-series forecasting methods such as the Autoregressive Integrated Moving Average (ARIMA) model have been used to predict prices of agricultural commodities, including natural rubber [3]. ARIMA models leverage past observations and error terms to predict future values, making them effective for capturing linear relationships and short-term dependencies. Despite their utility, ARIMA models face inherent limitations when applied to data with non-linear patterns or long-term dependencies, as is often the case with volatile commodities like natural rubber.

Advancements in machine learning have introduced method such as Long Short-Term Memory (LSTM) networks, which are well-suited for modelling non-linear relationships and identifying complex, long-term patterns in data. LSTM, a specialized Recurrent Neural Network, is equipped with memory cells and gates that allow it to retain and utilize information over extended periods, indicating a useful tool for analysing dynamic time-series data [4]. This has positioned LSTM as a promising alternative to traditional statistical methods for commodity price forecasting [5].

LSTM's potential has been demonstrated in a range of fields, from finance to energy, and particularly in forecasting time-series data. In the agricultural sector, LSTM networks have been successfully applied for price prediction in commodities such as coffee, maize, and cotton. Compared to ARIMA, LSTM can better capture intricate patterns, making it an emerging alternative for agricultural price forecasting.

In summary, this research aims to apply forecasting models for natural rubber price SMR20 prediction using ARIMA and LSTM methods. The study will evaluate and compare the accuracy of these models using performance metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). By identifying the most accurate and reliable forecasting model, the research will then utilize the best-performing model to predict the future price of natural rubber SMR20.

2. Research Methodology

2.1 Data Description

The dataset employed in this research consists of monthly price data for natural rubber SMR20, sourced from the official website of the Malaysia Rubber Board (MRB) [6] via http://www3.lgm.gov.my/mre/MonthlyPrices.aspx. The data spans from January 2014 to December 2024, encompassing a total of 132 observations. For the purpose of model training and evaluation, the dataset is partitioned into two distinct subsets: the training dataset, which comprises 120 observations from January 2014 to December 2023, and the testing dataset, consisting of 12 observations from January 2024 to December 2024. Statistical software, including MINITAB and Python, will be utilized for data analysis and the development of the forecasting models.

2.2 ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model is one statistical approach designed for time series prediction, particularly effective in capturing linear trends. The ARIMA model incorporates three components: autoregression (AR) moving averages (MA), and differencing (I), which work together to model and forecast stationary data.

Box-Jenkins approach is also known as the ARIMA method. Generally, The Box-Jenkins methodology consists of three steps which include model identification, parameter estimation, and diagnostic checking as shown in Fig. 1. Box-Cox transformation was applied to stabilize variance in the dataset.

First, model identification is the crucial step of the ARIMA Box-Jenkins methodology. The goal is to select an appropriate model structure for the time series data. This involves ensuring that the data is stationary, which may require differencing to stabilize the mean and variance [7]. Autocorrelation analysis is then conducted using ACF and PACF plots to understand the relationships within the data, guiding the selection of model parameters [8]. The ACF helps identify the moving average (MA) component, while the PACF indicates the autoregressive (AR) component. Through these steps, the optimal values for the AR, differencing, and MA parameters are determined, leading to the selection of an initial ARIMA(p,d,q) model structure.

Once a model is identified, the next step is parameter estimation. In this step, the focus is on identifying the optimal ARIMA model by estimating its parameters and evaluating the model's performance. Parameters with p-values less than the significance level of 0.05 are considered statistically significant and vice-versa. Model fit is then assessed by comparing the Mean Squared Error (MSE), where model with the lowest MSE represents best fit in terms of prediction accuracy. To further validate the model, the Ljung-Box test is performed to check for autocorrelation in the residual [9]. A non-significant p-value from the Ljung-Box test suggests that the residuals exhibit no autocorrelation, implying that the method has adequately identified the core patterns within the time series data. Lastly, the Akaike Information Criterion (AIC) is used to evaluate the trade-off between model fit and complexity; a lower AIC indicates a more efficient model.

Lastly, diagnosis checking is conducted after identifying the optimal ARIMA model. This process involves validating the model's residuals to ensure that the fitted model is appropriate. The residuals should resemble white noise, meaning they have no discernible patterns and exhibit characteristics of randomness, such as having a mean of zero and no autocorrelation. If the residuals exhibit significant autocorrelation or other patterns, it may be necessary to refine the model by adjusting the parameters. Diagnosis checking helps to confirm that the model adequately captures the underlying time series process and is capable of generating reliable forecasts.

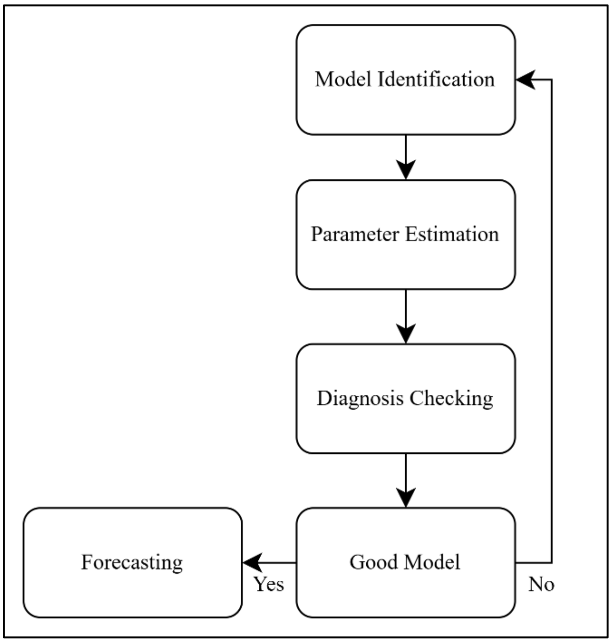

Fig. 1 Flow Chart of ARIMA method

The general equations of ARIMA or Box-Jenkins method is shown as below;

$$\emptyset_p(\beta)\nabla^d y_t = \theta_q(\beta)e_t \tag{1}$$

where

$$\nabla^d = (1-\beta)^d \tag{2}$$

$$\emptyset_p(\beta) = 1 - \emptyset_1\beta - \emptyset_2\beta^2 - \cdots - \emptyset_p\beta^p \tag{3}$$

$$\theta_q(\beta) = 1 - \theta_1\beta - \theta_2\beta^2 - \cdots - \theta_q\beta^q \tag{4}$$

After substitution (2), (3), and (4) into Eq. (1), equation of ARIMA model is shown in Eq. (5):

$$\left(1 - \emptyset_1\beta - \cdots - \emptyset_p\beta^p\right)(1-\beta)^d y_t = \left(1 - \theta_1\beta - \cdots - \theta_q\beta^q\right)e_t \tag{5}$$

where

y_t = the ith observation in time series data,
β = backward shift operator, $(\beta^j y_t = y_{t-J})$
$\emptyset$'s = non-seasonal autoregressive parameters,
θ's = non-seasonal moving-average parameters,
p = order of autoregressive part,
d = degree of first differencing involved,
q = order of the moving average part,
e_t = white noise

2.3 LSTM

The LSTM model, a specialized variant of Recurrent Neural Networks (RNNs), is designed to encounter the limitations of traditional methods by modelling non-linear patterns and capturing long-term dependencies in sequential data. Its architecture includes memory cells, input gates, forget gates, and output gates, which work together to retain or discard information across time [10]. This capability makes LSTM particularly suitable for volatile and dynamic time-series datasets like SMR20 prices. The LSTM model is trained using backpropagation through time, and hyperparameters such as learning rate, number of hidden layers, and epochs are optimized to enhance predictive accuracy.

In forget gate, a sigmoid function is applied to determine which information should be removed from the LSTM memory [11]. In second gate, input gate determines what new information should be stored in the cell which includes the sigmoid layer and tanh layer [12]. The sigmoid layer identifies which values to update while the tanh layer generates a vector of the new candidate values to be added to the memory cell. The last gate is the output gate. This gate manages the information extracted from the cell state and decides how much of the current cell state should be transferred to the following concealed state [13]. The architecture of LSTM is shown in Fig. 2.

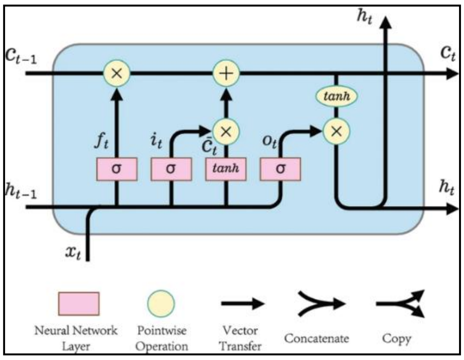

Fig. 2 Architecture of LSTM [6]

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{6}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{7}$$

$$\widetilde{C_t} = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{8}$$

$$C_t = f_t * c_{t-1} + I_t * \widetilde{C_t} \tag{9}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t * tanh(C_t) \tag{11}$$

where

f_t	=	forget gate,
i_t	=	input gate,
o_t	=	output gate,
$\widetilde{C_t}$	=	cell state at timestamp, *t*,
C_t	=	candidate cell state at timestamp, *t*,
σ	=	sigmoid activation function,
W_x	=	weight for the associated gate (x) neurons
h_{t-1}	=	output of the previous LSTM block at preceding time step,
x_t	=	input at the current time step,
b_f	=	biases applied to the respective gates (x),
h_t	=	final output,
$tanh$	=	*tanh* function ().

2.4 Performance Metrics

To assess the forecasting accuracy of the ARIMA and LSTM models, this research utilizes three performance metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMS). These performance metrics offer valuable insights into the model's predictive capabilities and are selected to ensure a comprehensive evaluation. The model exhibiting the lowest values for MAE, RMSE, and MAPE will be deemed the most suitable for forecasting [14]. The Mean Absolute Error (MAE) represents the absolute value of forecast error which is the difference between actual and anticipated value as in Eq. (12).

$$MAE = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n} \tag{12}$$

Meanwhile, the Root Mean Square Error (RMSE) in Eq. (13) is used to calculate the standard deviation of error. It is also known as a scale-dependent error so it cannot be used for comparison with the other series.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{13}$$

Finally, the Mean Absolute Percentage Error (MAPE) in Eq. (14) is used to determine the average of absolute percentage differences between the actual values and prediction values.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|}{n} \times 100 \tag{14}$$

where:

y_t = actual price at period t,
$\hat{y}_t$ = forecast price at period t,
n = number of observations.

3. Result and Discussion

This part presents the forecasting analysis of Standard Malaysia Rubber 20 (SMR20) monthly prices using two established methodologies: Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks. These models were selected based on their proven capabilities in time series forecasting, offering complementary strengths in modelling linear trends and capturing complex, non-linear patterns.

The analysis utilized a dataset of 126 monthly observations spanning January 2014 to December 2024, representing a decade of SMR20 price trends. Preprocessing steps ensured data consistency and quality, facilitating accurate model training and evaluation. ARIMA was calibrated for optimal lag orders, differencing, and moving average components, while LSTM leveraged its recurrent architecture to learn intricate temporal dependencies from the data. Model accuracy was rigorously evaluated using standard forecasting accuracy metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The comparative results demonstrated that LSTM outperformed ARIMA in handling the highly volatile and non-linear nature of SMR20 prices, while ARIMA proved effective in capturing straightforward linear patterns.

3.1 Time Series Plot

The time series plot in Fig. 3 shows there are no obvious trends and seasonality present in the data. The SMR20 monthly price data from 2014 to 2023 is used as the training set to build the model while the remaining data in 2024 is used as a testing set to evaluate the forecasting model accuracy.

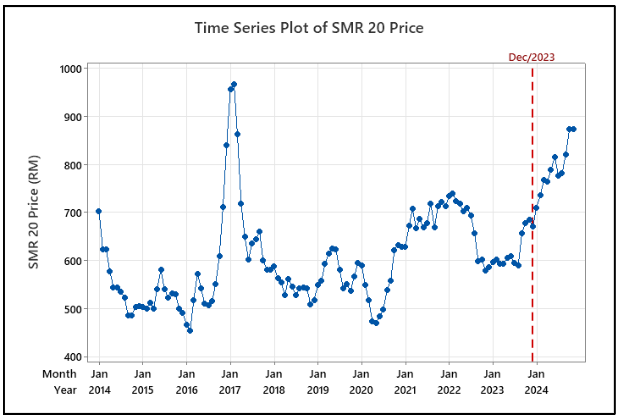

Fig. 3 Time Series Plot of Natural Rubber SMR 20 Price (RM) in Malaysia from 2014 to 2024

3.2 ARIMA Results

Before applying the ARIMA method, a Box-Cox plot is utilized to check the stability of variance. The analysis revealed that the variance is not constant as the interval did not include a value of 1. Consequently, Box-Cox transformation is performed to stabilize the variance and ensure the suitability of the data for ARIMA modelling.

The rounded result of -1.00 indicated applying a power transformation of -1, which is equivalent to the inverse of the SMR20 price. Fig. 4 shows the time series plot of the SMR20 price after transformation. Since the points are not scattered around zero, thus the data may not be stationary. Besides, the ACF plot indicates the ACF dies down slowly. Thus, this shows that the time series is not stationary.

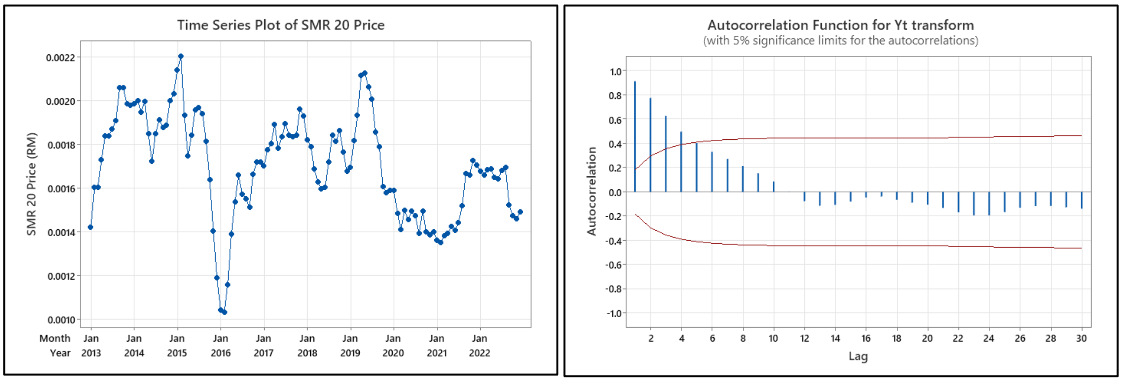

Fig. 4 Time Series and ACF plot of Natural Rubber SMR 20 Price (RM) after transformation

After the first differencing process, the time series in Fig. 5 fluctuates around zero indicating the data is stationary. In addition, the ADF test of first differences data reveals the *p*-value equal to 0.018, which is smaller than 5% significant level. Thus, the data is stationary after the first differencing.

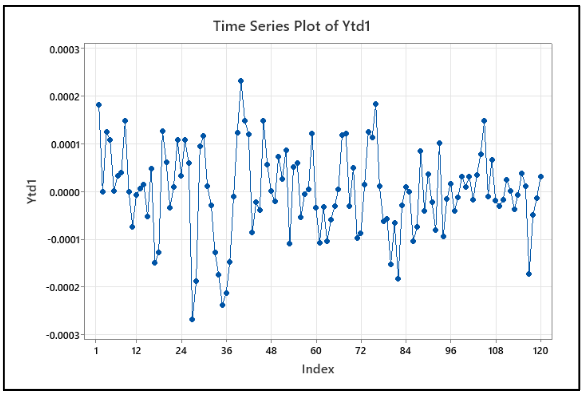

Figure 5 Time Series plot for first differencing data

Based on Fig. 6, the ACF and PACF display notable peaks at lag one. Thus, it suggests that AR component of order 1 or MA component of order 1 may be appropriate for model identification.

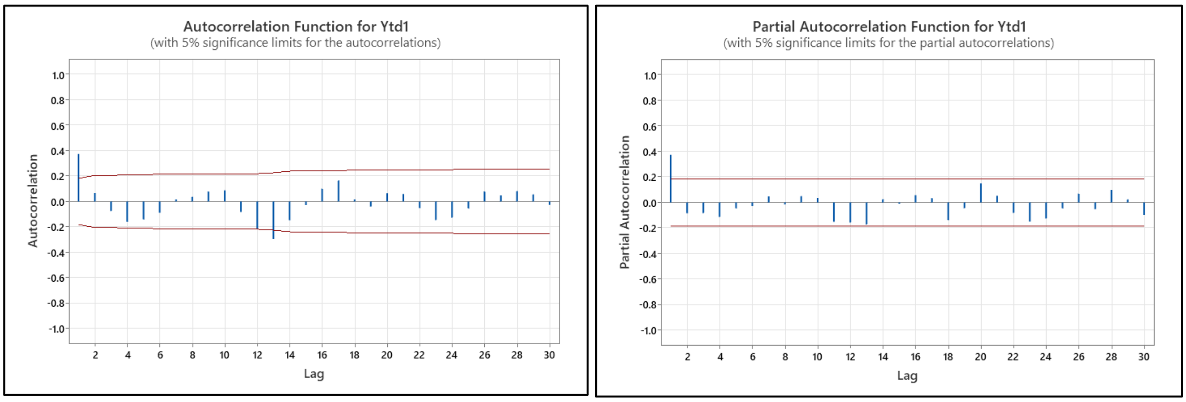

Fig. 6 ACF and PACF for first differencing data

The possible ARIMA models are ARIMA (0,1,1), ARIMA (1,1,1), and ARIMA (1,1,0). The result of parameter estimation is shown in Table 1. For ARIMA (1,1,1), the parameters are not statistically significant as the *p*-values of AR (1) and MA (1) are larger than 0.05. Thus, ARIMA (1,1,1) is not considered. Lastly, ARIMA (1,1,0) is chosen as the best model due to the significant parameter, no significant autocorrelation in residuals, small MSE, and the lowest AIC as compared to ARIMA (0,1,1)

Table 1 Possible Models of ARIMA

Possible Model	Parameter p-value	Ljung-Box Test p-value	MSE	AIC
ARIMA (1,1,1)	AR (1): 0.335 MA (1): 0.393	Lag 12: 0.671 Lag 24: 0.335 Lag 36: 0.441 Lag 48: 0.269	$7.322e^{-9}$	-1886.50
ARIMA (1,1,0)	AR (1): 0.000	Lag 12: 0.639 Lag 24: 0.239 Lag 36: 0.347 Lag 48: 0.178	$7.320e^{-9}$	-1887.75
ARIMA (0,1,1)	MA (1): 0.000	Lag 12: 0.611 Lag 24: 0.305 Lag 36: 0.368 Lag 48: 0.164	$7.318e^{-9}$	-1887.58

Eq. (16) presents the ARIMA (1,1,0) model.

$$\begin{gathered}\emptyset_1(\beta)\nabla^1 y_t = \theta_0(\beta)e_t \\ (1-\emptyset_1\beta^1)(1-\beta)^1 y_t = e_t \\ y_t = (1+\emptyset_1)y_{t-1} - \emptyset_1 y_{t-2} + e_t\end{gathered} \tag{15}$$

Based on Fig. 7, the ACF plot of residuals shows that most autocorrelation values fall within the 95% confidence limit. Therefore, the residuals of the ARIMA (1,1,0) model are independent and show no significant autocorrelation. Besides, the residual plot of ARIMA (1,1,0) indicates that residuals are randomly scattered around zero with consistent variance. Thus, this concludes that ARIMA (1,1,0) is a good fit model to forecast.

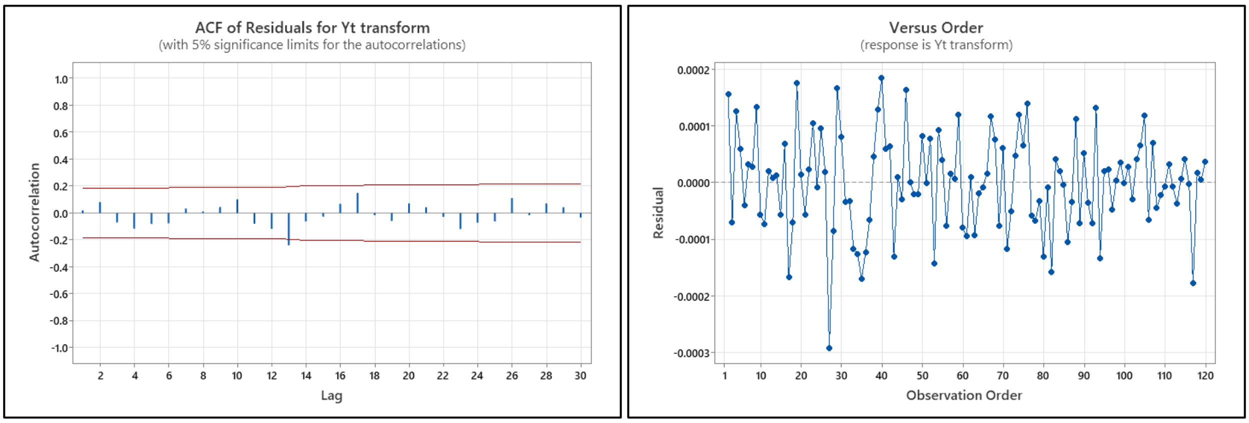

Fig. 7 Diagnostic Checking on ARIMA (1,1,0)

Fig. 8 shows the forecast SMR20 price using ARIMA (1,1,0). The forecast value indicates a steady future trend while the testing value is consistently increasing upward in 2024. This highlights that ARIMA model increases uncertainty in long-term forecasting.

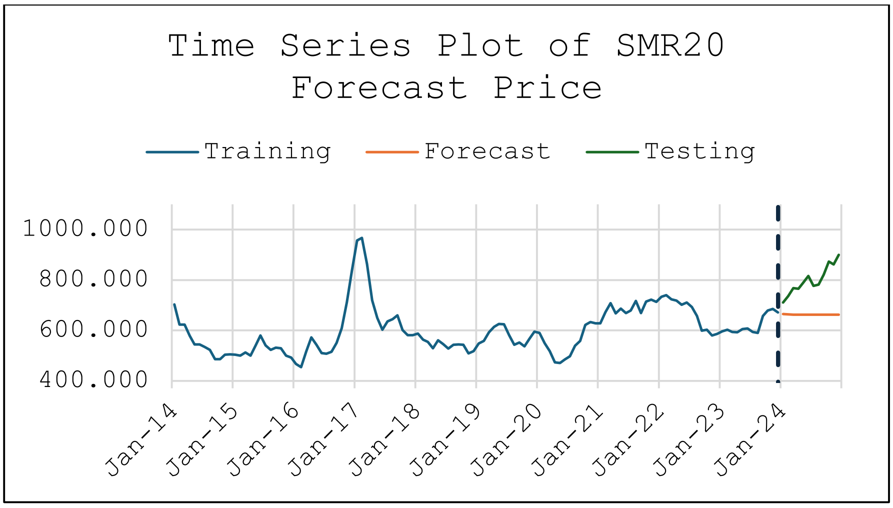

Fig. 8 Forecast SMR20 Price using ARIMA (1,1,0)

3.3 LSTM Model and Forecasting SMR20 Price in 2024

The LSTM model was employed to forecast the price of SMR20 natural rubber as illustrated in Fig. 9. The forecasted prices for the year 2024 demonstrate the capability of the LSTM model to capture complex temporal dependencies and trends inherent in the natural rubber price data.

The forecasted prices for 2024 (orange line) show a declining trend, suggesting that the SMR20 natural rubber prices are expected to decrease gradually over the year. This downward movement may reflect patterns captured by the model, such as anticipated reductions in demand, improved supply chain conditions, or market corrections following previous fluctuations.

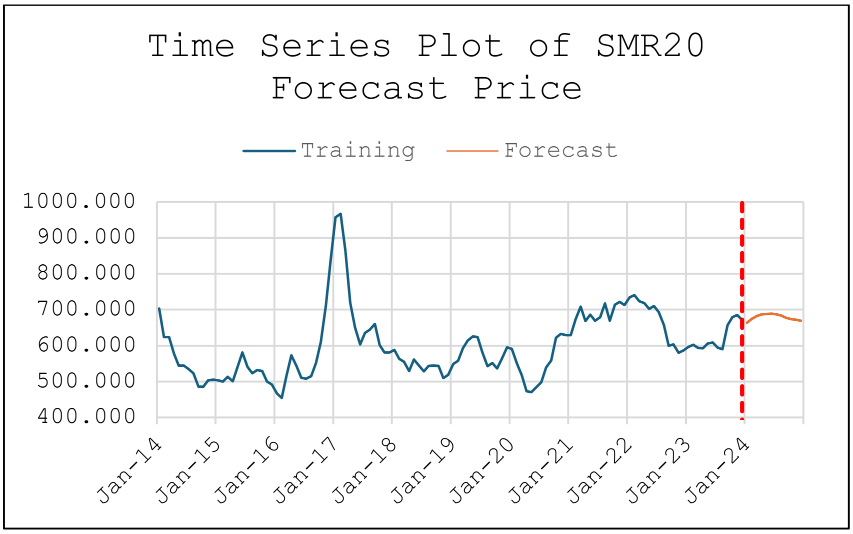

Fig. 9 Forecast SMR20 Price using LSTM

Lastly, LSTM was applied to predict the natural rubber SMR20 price in Malaysia for 2024. Fig. 10 indicates a downward trend in forecast SMR20 prices starting from March 2024. In contrast, the actual SMR20 price exhibits a consistent upward trend throughout the year. The downward trend highlighted by the forecast underscores the LSTM model's ability to capture complex temporal dependencies. However, it may lack the granularity to account for external shocks or irregular market behaviours. These forecasts are valuable for stakeholders seeking to anticipate longer-term market dynamics and strategize accordingly.

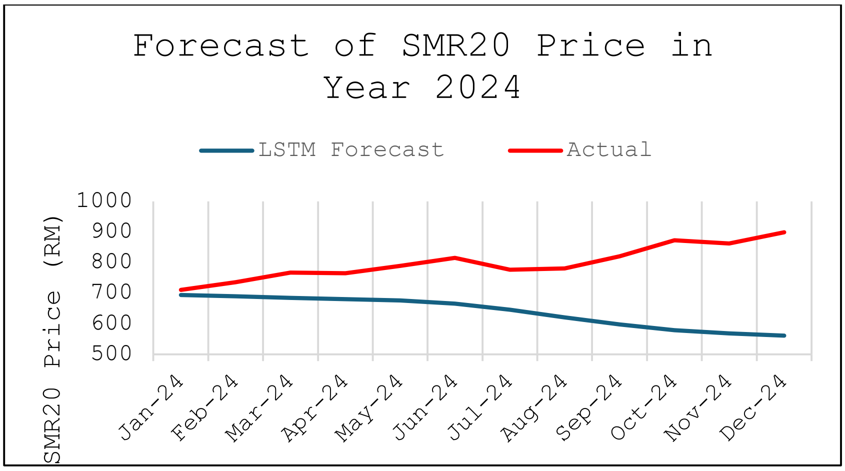

Fig. 10 Actual and Forecast of SMR20 Price in 2024

3.4 Forecasting Performance Evaluation

The accuracy of forecasting models is evaluated using MAE, RMSE, and MAPE as shown in Table 2. Based on the findings, the best forecasting model is LSTM because it has the least MAE (71.706), RMSE (88.383), and MAPE (9.398%) in performance evaluation. Besides, LSTM is considered a highly accurate forecasting model as the MAPE is lower than 10%. Thus, LSTM is the best model for SMR20 price forecasting in Malaysia.

Table 2 Forecasting Performance Evaluation

Model	Training			Testing		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
ARIMA (1,1,0)	24.391	32.732	3.984	129.126	138.225	15.988%
LSTM	44.537	64.921	7.195	71.706	88.383	9.398%

4. Conclusion

In conclusion, this study successfully achieved its objectives. Box-Jenkins methodology was applied statistical techniques to address non-stationarity in the data. In contrast, the LSTM model employed advanced deep learning architectures to capture nonlinear dependencies and dynamic patterns. Based on the performance evaluation, the LSTM model significantly outperformed ARIMA in predicting accuracy, achieving lower error metrics, including MAE of 791.706, RMSE of 88.383, and MAPE of 9.398%. These results demonstrate the LSTM model’s robustness in handling complex time series data, making it a more reliable option for navigating the inherent volatility of the natural rubber market.

The study shows that LSTM model predicts a downward trend in SMR20 prices for 2024, potentially indicating market adjustments or changes in supply and demand dynamics. This underscores LSTM’s ability to capture long-term dependencies while offering practical insights into future market behaviour. This study recommends that stakeholders in Malaysia's natural rubber industry, including policymakers and the Malaysian Rubber Board, adopt advanced forecasting models like LSTM to improve decision-making, enhance risk management, and support strategic planning for smallholders and investors. Integrating external factors such as climate change, global economic trends, and crude oil prices into forecasting systems could make predictions more comprehensive, while expanding the dataset to include daily or seasonal data may offer deeper insights into short-term price fluctuations and trends.

However, the study's focus on SMR20 prices in Malaysia, excluding other rubber grades or international markets, limits the generalizability of the findings. Additionally, reliance on historical monthly data may overlook short-term market shocks, and the computational demands of the LSTM model could pose challenges for organizations with limited resources. Addressing these limitations in upcoming study would improve the broader applicability of forecasting models for the natural rubber industry.

Acknowledgement

The authors would like to thank the Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia, for its support.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Eng Chun Kit, Kamil Khalid;* ***data collection:*** *Eng Chun Kit;* ***analysis and interpretation of results:*** *Eng Chun Kit, Kamil Khalid;* ***draft manuscript preparation:*** *Eng Chun Kit, Kamil Khalid. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Malaysian Rubber Board. (2023). Annual Rubber Digest. www.lgm.gov.my
[2] Pareed, S., & Kumaran, P. (2017). Volatility of natural rubber markets: An overview. Journal of Economics, 12(5), 18–24.
[3] Zhou, T. et al. (2022). Forecasting commodity prices using ARIMA models. Economics Letters, 209, 110017.
[4] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.
[5] Ali, M. F., Akber, M. A., Smith, C., & Aziz, A. A. (2021). The dynamics of rubber production in Malaysia: Potential impacts, challenges and proposed interventions. Forest Policy and Economics, 127, 102449.
[6] Malaysian Rubber Board. (2024). Reference Prices For Physical Rubber (Free On Board). http://www3.lgm.gov.my/mre/MonthlyPrices.aspx
[7] Kabbilawsh, P., Kumar, D. S., & Chithra, N. R. (2022). Forecasting long-term monthly precipitation using SARIMA models. Journal of Earth System Science, 131(3), 1–20.
[8] Setyowibowo, S., As'ad, M., Sujito, S., & Farida, E. (2022). Forecasting of Daily Gold Price using ARIMA-GARCH Hybrid Model. Jurnal Ekonomi Pembangunan, 19(2), 257–270.
[9] Shad, M., Sharma, Y. D., & Singh, A. (2022). Forecasting of monthly relative humidity in Delhi, India, using SARIMA and ANN models. Modeling Earth Systems and Environment, 8(4), 4843.
[10] Guan, Y. J. (2022). Financial time series forecasting model based on CEEMDAN-LSTM. CTISC 2022 - 2022 4th International Conference on Advances in Computer Technology, Information Science and Communications.
[11] Abdelsalam, A. A., Hassanin, A. M., & Hasanien, H. M. (2021). Categorisation of power quality problems using long short-term memory networks. IET Generation, Transmission and Distribution, 15(10), 1626–1639.
[12] Ning, Y., Kazemi, H., & Tahmasebi, P. (2022). A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet. Computers & Geosciences, 164, 105126.
[13] Casado-Vara, R., del Rey, A. M., Pérez-Palau, D., De-La-fuente-valentín, L., & Corchado, J. M. (2021). Article web traffic time series forecasting using LSTM neural networks with distributed asynchronous training. Mathematics, 9(4), 1–22.
[14] Saif, S., Das, P., & Biswas, S. (2021). A Hybrid Model based on mBA-ANFIS for COVID-19 Confirmed Cases Prediction and Forecast. Journal of The Institution of Engineers (India): Series B, 102(6), 1123–1136.