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Modelling Malaysia Production of Logs using Box-Jenkins Model

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Abstract: Comprehending Malaysia's logs production not only explaining the trend of the Malaysia's GDP. It is also essential for the country as it influences revenue and shapes policies regarding forest resources. Studying the time series of Malaysia logs production is very important for providing comprehensive understanding in making decisions regarding economic development, resource management, and environmental sustainability. Thus, this study aims in determining the best time series model for forecasting the Malaysia logs production by applying the Box-Jenkins model. Based on historical yearly data of Malaysia's logs production from year 1947 to 2021, in overall, the data series exhibit increasing trend and cyclical patterns. ARIMA(0,2,1) is found to be the best model for forecasting the Malaysia's logs production where it forecasts values are having decreasing trend.

Keywords: Box-Jenkins, Forecasting, Forestry, Logs production, Time series

1 Introduction

Timber is processed wood that is used for construction, furniture, and various other applications. It comes from the cutting, processing, and shaping of logs obtained from trees. Therefore, the timber industry is directly dependent on the production of logs. Malaysian Timber Industry Board (MTIB) is responsible for controlling and monitoring timber export and import, timber in transit and the local timber market. It is reported that RM22.744 billion of the country's total GDP in year 2021, are contributed by the exports of timber [1]. Since both exports of logs and timber are highly depending on the logs production, forestry and logging industry are significantly contributes to GDP and socio-economic of Malaysia. However, the rate of deforestation has declined in recent decades [2]. Thus, the decreasing trend of the contribution of forestry and logging industry towards Malaysia's GDP can be explained by the production of logs.

Other than explaining the trend of the Malaysia's GDP, comprehending the trend of logs production is essential for Malaysia as it influences revenue and shapes policies regarding forest resources [3]. Illegal logging is shown to harm forests, causes revenue losses, and negatively impact the economy overall. When there is a high demand for logs, individuals might resort to illegal logging activities to meet this demand and earn profits. Furthermore, rapid economic growth often leads to an increase in domestic demand for timber products, which in turn can fuel illegal logging operations aimed at meeting the heightened demand for logs [4].

Forestry industry gives significant contribution towards Malaysia GDP where logs production is the third highest resources for the industry [5]. However, since 1970's, it was reported that the forestry and logging industry are having decreasing trend in their contribution towards Malaysia GDP. According to Wahob et al. (2018) from 1980 to 2015 there is a 24% reduction in harvested area which explains why there is a decrease in production because of the concerning reduction rate [6]. For the forest sector, timber depletion rate continues to fall over the years but at a lower rate from 1997-2008 [7]. Other than that, sustainable forestry will be challenging due to illegal logging activity. The decreasing of the contribution of forestry towards Malaysia GDP increase the demand of forestry products including timber and logs. This will lead to an increase in illegal logging activities and negatively impact the economy. Studying the time series of Malaysia logs production is very important for providing comprehensive understanding in making decisions regarding economic development, resource management, and environmental sustainability.

The overall annual time series data of United States logs production from 1997 to 2019 do not shows any significant trend [8]. However, the productions were drop sharply in 2008 and 2009 but began to rebound in 2010. Since 2008 to 2009 was the economic downturn in United States, this situation indicates that logs production is seriously affected to the economic recession. Meanwhile, Britwum Acquah et al. (2014) reported that the monthly data of wood products in Ghana from year 1997 to 2013 shows decreasing trend [9]. Other than that, the monthly data also shows the existence of seasonal components on the series. The application of time series analysis of logs and wood products has been conducted on several countries including Siberia, China, Ghana, and neighbouring country, Indonesia [9-12]. In Ghana, since the monthly data series of the exports of wood was found to have decreasing trend component and seasonal effect, seasonal ARIMA model was applied [9]. SARIMA(3,1,0)(0,1,9) was found to be best model for the dataset which demonstrating the flexibility of ARIMA model for forestry-related time series data. For yearly production of one type of log species which called as larch in Korea, ARIMA(5,1,1) was found to be the suitable model for the data series [13]. The findings shows that the log supply which may have long-term trends or cyclical changes are amenable to ARIMA modelling. Two studies were found to successfully fit ARIMA model on log productions in the country. Huda et. al. (2023) concluded that ARIMA(0,2,1) was the best Box-Jenkins model for the yearly log productions, while Rizqi et.al. (2022) found ARIMA(3,1,1) as the best model for quarter series [12,14].

In Malaysia, a study on the trend of logs production and export was conducted in Sarawak using 10 years of annual data from 1997 to 2006 [3]. The result shows that the volume of logs production and export in Sarawak was having decreasing trend. Bintulu division was found to be the major producer of logs from the hill forest while Miri division is the major producer of logs of the peat swamp forest. Semilan et al. (2022) reported that the logs production on Sarawak was peak in 1990 with 20 million cubic meters [15]. However, the trend has gradually declined to 2.3 million cubic meters in 2021. Nevertheless, the logs production from planted forest in Sarawak has shown an improvement from the year 2011 to 2021.

Despite the importance of logs production, there are very limited study have been done on this area. Furthermore, no study has been conducted in modelling the time series data of Malaysia logs production. Although there are only few works has been done regarding logs production, more studies must be conducted since logs production gives important roles in contributing to Malaysia's GDP. Understanding time series of logs production is crucial for evaluating the environmental impact of logging activities, tracking changes in global demand, and compliance to sustainable forestry. Thus, determining the best Box-Jenkins model for forecasting the Malaysia logs production is the aim of this study.

2 METHODOLOGY

This time series study involved secondary data obtained from The Department of Statistics Malaysia (DOSM) which provides 75 yearly historical information on log production of in Malaysia from 1947 to 2021. For time series modelling, the data was divided into two parts which are modelling part and evaluation part. The modelling part was used for the estimation of the model whereas the evaluation part is used to evaluate the model. This study applies the common opinion of 25% of the data series as the evaluation part as suggested by Mohd Alias (2011) [16]. Thus, out of 75 years of the available data, the first 56 years, which from the year 1947 to 2002, are allocated for the modelling part. Meanwhile, the other 19 years (2003 – 2021) will be used for evaluation purposes.

A Initial Data Investigation

The initial data investigation conducted by examining the whole Malaysia logs production data. The existence of four time series components which are trend, seasonal, cyclical, and irregularity were observed by constructing the time plot, Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF). The trend is the long-term direction in the data and can be examined by the overall upward or downward movement from the time plot and observing the lag in the ACF and PACF plot. Thus, the trend components can be either decreasing or increasing trend or can be no trend at all [16]. The seasonal patterns are recurring trends that happen at fixed intervals, detected by the repeated fluctuations of the time plot and the existence of wave like movement in the ACF plot.

Meanwhile, the cyclical patterns which refer to rise and falls of the series over unspecified period while irregularities referring to the existing of peculiarities in the time series [16]. Both cyclical and irregular components can be observed in the time plot. However, the occurrence of cyclical and irregular components could not be predicted. Thus, the identification of both components is just for descriptive purposes. Other than that, the existence of trend and seasonal components are very important in Box-Jenkins methodology as it determined the stationarity of the data and helps in model identification.

B Model Selection and Model Fit

To ensure accurate time series forecasting, it is crucial to first check for stationarity, a key assumption of the Box-Jenkins methodology. Stationarity implies that the statistical properties of the series, such as mean and variance, remain constant over time. To test for stationarity, the ADF test is used. The ADF test evaluates the null hypothesis that a unit root is present in the time series, indicating non-stationarity. If the p-value from the ADF test is higher than a chosen significance level (commonly 0.05), therefore fail to reject the null hypothesis, suggesting the series is non-stationary. In such cases, apply differencing to the data, which involves subtracting the previous observation from the current observation, to achieve stationarity. Differencing can be performed iteratively until the series becomes stationary, which allowed to proceed with the Box-Jenkins approach for model identification and estimation.

Box-Jenkins ARIMA model has been used widely in many areas of Time Series analysis [17]. Being one of the earliest models, ARIMA's performance is constantly being evaluated and is frequently used as a standard against other time series models. The autoregressive (AR) and moving average (MA) models are combined to form the Box-Jenkins model. Time series data that are assumed to be stationary are typically modelled using a Mixed Autoregressive Moving Average (ARMA) model with parameters (p, q). The parameter p is the order of AR while the parameter q is the estimated order of MA model. However, the non-stationary data needs to go through the trend differencing to make it stationary. Thus, Mixed Autoregressive Integrated Moving Average (ARIMA) is be used for non-stationary data. The parameter for this model are *(p, d, q)* where the d refers to Integrated (I) number which shows how much difference must be made on the time series data for it to become stationary.

The basic model of AR(p) model is generally expressed as:

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \tag{1}$$

where:

μ and $\emptyset_j$ (j=1, 2,...p) are constant term or parameter to be estimated
y_t is the dependent or current value.
y_{t-p} the pth order of lagged dependent or the current value.
ε_t is the error term, which is assumed iid with zero mean and variance, σ_{t2}.

Meanwhile, the basic model of MA model can be expressed as:

$$y_t = \mu - \theta_1 \varepsilon_t - 1 + \varepsilon_t \tag{2}$$

Thus, the mixed of AR(p) and MA(q) model for ARMA(p,q) will give following equation:

$$(1 - \emptyset_1 B - \emptyset_2 B^2 + \cdots + \emptyset_p B^p) yt = \mu + (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^z) \varepsilon_t \tag{3}$$

Meanwhile, the equation of ARIMA (p, d, q), the y_t is substituted with the differenced data w_t as follows:

$$w_t = y_t - y_t - 1 \tag{4}$$

The order identification of Box-Jenkins model p, d, and q are selected based on the significant spikes observed in ACF and PACF plots of the whole data. The possible combination orders of the model were then will be fitted to the modelling part.

C Model Validation and Diagnostic Checking

The key objective of diagnostics checking in Box-Jenkins model are to ensure the stationarity of the residuals, e_t where they are assumed normally, randomly, and independently distributed with mean zero, and variance, σ_ε^2. The values of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were calculated and compared for the fitness of the model. Among the competing models, models with better fit have been chosen based on the smallest AIC and BIC value. A well fitted Box-Jenkins model should have residuals that fulfill the property of white noise. This indicates that there are no autocorrelations of residuals, or the residuals are stationary [16]. The resemblance of white noise characteristics can be observed in ACF and PACF plot. The residuals can be concluded as white noise when there are no significant autocorrelations coefficients, and no significant partial autocorrelations coefficients exist in the plots. Other than that, the Ljung-Box Q statistic can also be used for testing the white noise of residuals. This statistic holds the alternative hypothesis that errors are non-random (not white noise).

D Model Evaluation

The models that have been fit to the estimation part were forecasted throughout the evaluation years. From the forecast performance obtained, the residuals of the evaluation parts will be obtained for each model. Next, the error measures calculated and compared for measuring the model's performance. Three types of error measures that were used in this study are Mean Absolute Error (MAE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE).

MAE calculates the average absolute differences between the predicted and observed values. The formula for MAE is given by:

$$\text{MAE} = \frac{1}{n}\Sigma|\ y_t - \hat{y}_t| \tag{5}$$

Where n is the size of the test set and $\hat{y}_t$ is the predicted value of y_t.

RMSE measures the average of the squared differences between predicted and observed values. RMSE is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\Sigma(\text{yt} - \hat{\text{y}}\text{t})^2} \tag{6}$$

MAPE is defined as absolute percentage error which calculated on the fitted values for a particular forecasting method. It can be measured by using following formula:

$$\text{MAPE} = \frac{\left|\Sigma\left({}^{e_t}/_{y_t}\right)\times 100\right|}{n} \tag{7}$$

Where n is the size of the test set, and $\hat{y}_t$ is the estimated value of y_t.

The best Box-Jenkins model was decided based on the smallest error measures obtained.

3 Results

The analysis of the logs production data revealed several distinct patterns and components. Initially, a clear trend component was observed, indicating a general increase or decrease in production over time. Based on the data provided by Department of Statistics Malaysia (DOSM), the time series of Malaysia logs production exhibits a cyclical pattern. Figure 1 shows that logs production is having an increasing trend from 1940s up to 1992 and started to move downward until 2021. According to the study on log production in Sarawak, Malaysia, the decline is primarily due to the financial crisis of 1997-1998, which slowed logging activities, and the implementation of sustainable forest management practices by the Sarawak government [3]. These factors led to a consistent reduction in log production from both hill and peat swamp forests between 1997 and 2006. Major log-producing regions like Sibu, Bintulu, Miri, and Kuching all experienced decreased outputs, particularly in species such as Meranti [3].

In particular, the time plot of the logs production data in Figure 1 showed a rising trend over the years, reflecting an overall increase in production. The presence of cyclical patterns suggested that economic cycles might impact the production levels.

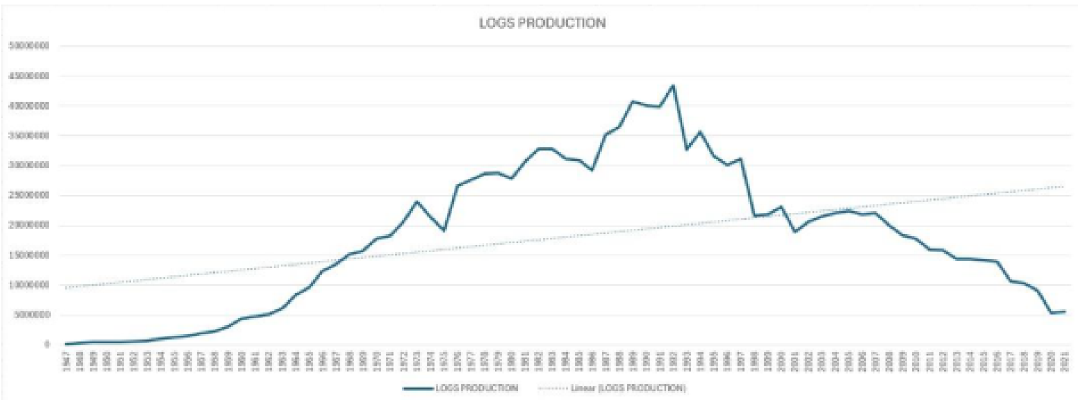

Figure 1: Time plot of Malaysia's Log Production from 1940 to 2021

The ACF plot of the time series exhibits significant positive autocorrelations that decay gradually over time, indicating the presence of a trend and suggesting that the series is non-stationary. In contrast, the

PACF plot shows a sharp cutoff at lag 1, which is characteristic of an AR (1) process, implying that the time series has significant autoregressive behaviour at lag 1 but not beyond. The combination of these patterns suggests that the data series needs differencing to achieve stationarity, as the slow decay in the ACF plot confirms the non-stationarity, while the PACF plot provides insight into the autoregressive nature of the series.

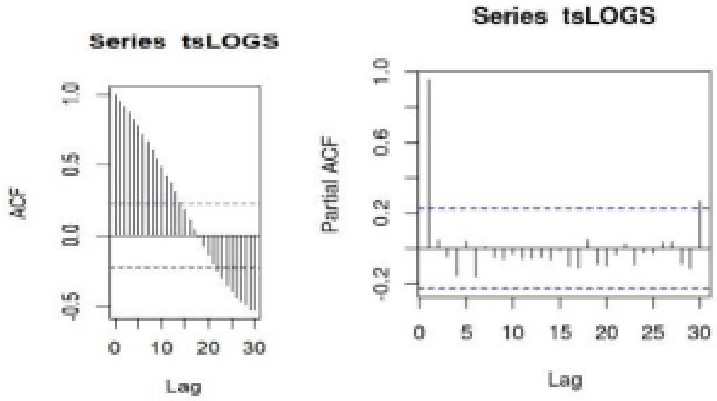

Figure 2: ACF and PACF plots for production of logs in Malaysia

The ACF and PACF plots after performing the first difference are shown in Figure 3. The ACF Plot shows that the data has become stationary after the 1st differencing of actual data. The PACF also improves with several significant spikes that can be observed in the plot. However, referring to Table 1, the ADF test indicates non-stationarity since the *P*-value obtained is 0.0571 which higher than the significance value, 0.05. This indicates that we fail to reject the null hypothesis of a unit root, implying that the series remains non-stationary even after first differencing. This possibly due to complex underlying structures or residual trends not fully addressed by first differencing. Thus, the second differencing need to be performed.

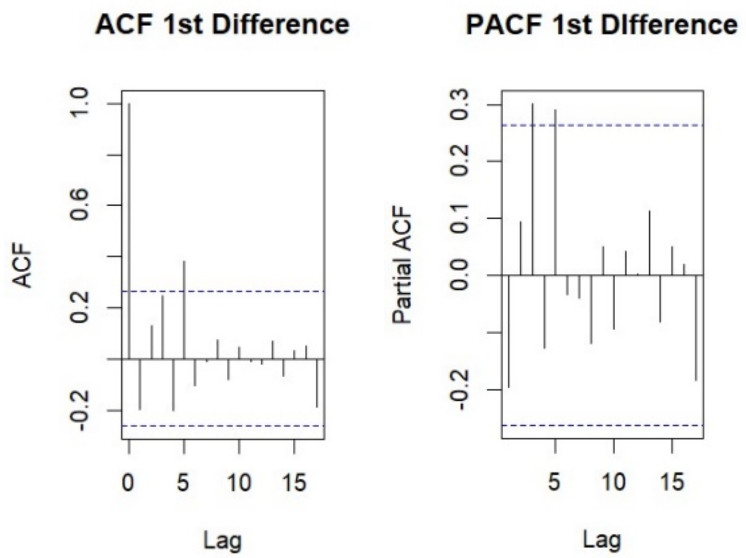

Figure 3: ACF and PACF plots for production of logs in Malaysia after first differencing

Figure 4 shows that the ACF and PACF plots of the second differenced data. Both plots suggest that the series has achieved stationarity. The lack of significant spikes in both plots after the second differencing indicates that this transformation successfully addressed any remaining trends or patterns, making the series stationary.

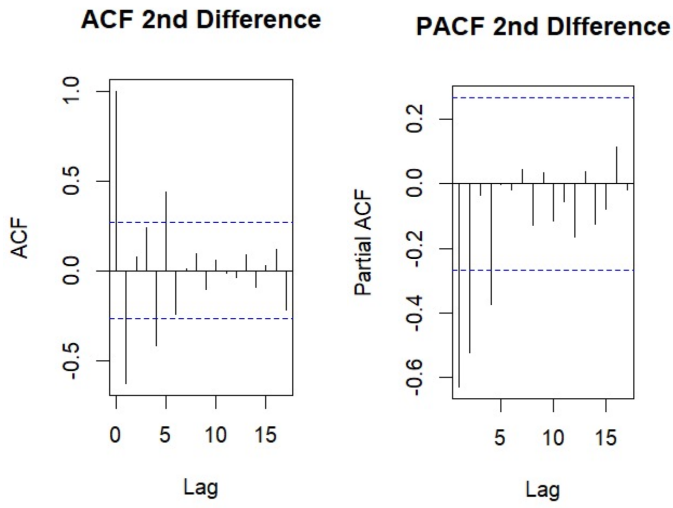

Figure 3: ACF and PACF plots for production of logs in Malaysia after second differencing

Furthermore, the ADF test results for the second differenced data as in Table 1 show a Dickey-Fuller statistic of -7.4625 and a *P*-value 0.01 indicating that null hypothesis of non-stationarity can be rejected. Therefore, the data now can be concluded as stationary and the possible ARIMA order can be identified with d=2. The ACF plot shows significant spikes at lag 1 and a few smaller ones, indicating the presence of a Moving Average (MA) component. This helps determine the value of (q). Similarly, the PACF plot has a significant spike at lag 1 and some smaller spikes, suggesting an Auto-Regressive (AR) component, which helps determine the value of (p).

Table 1: Augmented Dickey-Fuller Test of production of logs

Order of Differencing	Dickey-Fuller Statistics	Lag Order	*P*-value
1st	-3.4508	3	0.0571
2nd	-7.4625	3	0.01

Model validation and diagnostic checking began by ensuring the logs production data was stationary through second differencing, an essential step for accurate ARIMA modelling. The Ljung-Box test was then applied to check for autocorrelation in the residuals, helping to identify any remaining patterns the model might have missed. Several ARIMA models were considered, including ARIMA(2,2,1), ARIMA(1,2,1), ARIMA(0,2,2), ARIMA(0,2,1), ARIMA(1,2,0), and ARIMA(2,2,0), to find the best fit. The residuals of each model were analysed using ACF and PACF plots, along with the Ljung-Box test, to ensure they approximated white noise, indicating the models effectively captured all underlying patterns. Table 2 summarised the model validation and the diagnostic checking for the ARIMA models. All ARIMA models that have been estimated to the data series show that the L-Jung Box test is not significant. This indicates that all the ARIMA models are white noise and fit the model. Other than that, in comparing the information criterion, ARIMA (2,2,2) has the smallest AIC value while ARIMA (0,2,2) has the smallest BIC value. However, the values are not hugely different compared to other models.

Among the ARIMA models evaluated for forecasting Malaysia's log production, the ARIMA (0,2,1) model stands out as the best performer based on key error metrics. This model has the lowest MAE of 2,146,219.11, meaning its predictions are closest to the actual values on average compared to other model. It also boasts the lowest MAPE at 16.57%, indicating it has the smallest average percentage error and thus provides relatively accurate forecasts. Additionally, the ARIMA (0,2,1) model also has the lowest RMSE of 2,479,976.49, which indicates the smallest average squared error and effectively captures the variance in the data.

Table 2: Comparison of Box-Jenkins Model on Malaysia's log production

	ARIMA (2,2,2)	**ARIMA (2,2,1)**	**ARIMA (2,2,1)**	**ARIMA (1,2,1)**	**ARIMA (0,2,2)**	**ARIMA (0,2,1)**	**ARIMA (1,2,0)**	**ARIMA (2,2,0)**
Q Calculated (p-value)	16.915 (0.9736)	22.607 (0.831)	22.607 (0.831)	24.8 (0.7347)	24.738 (0.7377)	38.501 (0.1373)	50.379 (0.01132)	30.109 (0.4601)
Decision	Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0	Reject H_0	Accept H_0
AIC	1760.59	1764.92	1764.92	1763.57	1763.54	1767.02	1783.14	1767.54
BIC	1770.538	1772.872	1772.872	1769.541	1769.506	1770.998	1787.123	1773.507
RMSE estimation	2548262	2714973	2714973	2731547	2731134	2871880	3373964	2849445
MAE estimation	1683187	1750623	1750623	1777430	1734131	1759390	2107082	1873941
MAPE estimation	10.63	11.06	11.06	11.08	10.96	10.51	11.82	10.93
RMSE evaluation	9260943.11	9830336.41	9830336.41	8675013.84	10511800.6	2479976.49	2870900.32	3076462.08
MAE evaluation	8941282.48	9485237.01	9485237.01	8412103.06	10117772.1	2146219.11	2510802	2790404.68
MAPE evaluation	73.48	78.38	78.38	68.32	84.23	16.57	19.19	18.68

These metrics collectively indicate that the ARIMA (0,2,1) model delivers the most reliable and accurate predictions for log production, making it the preferred choice for forecasting. Finally, the ARIMA (0,2,1) model closely follows the actual data, particularly during stable periods, but lags slightly during abrupt changes. Overall, the ARIMA (0,2,1) model strikes the best balance, effectively capturing the overall trend and providing a good fit despite some lag during rapid changes. The graphical representation of the forecasted values using the ARIMA (0,2,1) model is shown in Figure 4.

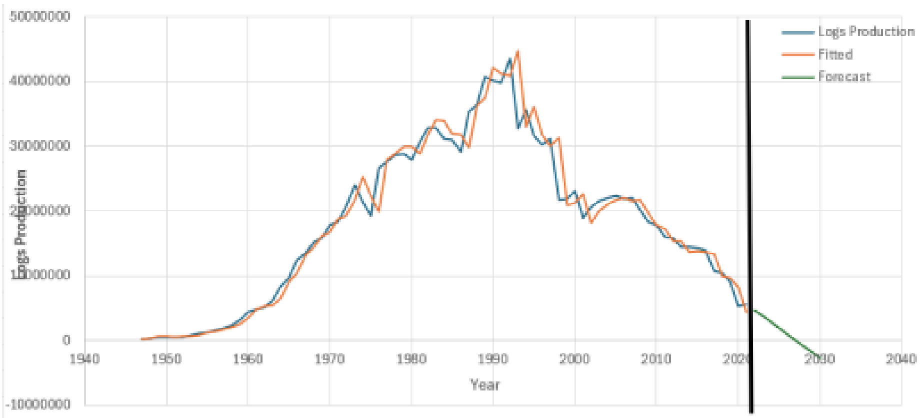

Figure 4: Time plot of hostorical and forecast period using ARIMA(0,2,1)

The plot shows that the forecasted values are having downward movement. Although the overall trend of the historical data is increasing, the cyclical effect where the trend started to decrease during 1990s lead to decreasing trend of the forecast values. However, starting from year 2028, the forecasted values started to become negative values. This also resulted from the behaviour of the data series where starting on 1990s, the trend is steeply downward.

4 Conclusion and Discussion

Time series data of Malaysia logs production exhibit increasing trend and cyclical components. However, the trend increased up to the year 1990 and started to decrease steeply due to cyclical effects.

This condition occurred due to the implementation of sustainable forest management practices during the 1990s. Thus, cyclical behaviour that exists in the data series depicting the effectiveness of the practices. Malaysia logs production data series need to be transformed to second order differencing to achieve stationary. Thus, ARIMA model has been applied to the Malaysia logs production data series. By comparing the RMSE, MAE, and MAPE, ARIMA (0,2,1) was found to be the best ARIMA model for forecasting the data series. Intersetingly, study conducted in Indonesia on Indonesia's yearly logs production also found that ARIMA (0,2,1) is the best ARIMA model that fit the logs production of that country [12].

The forecasting shows that Malaysia logs production is predicted to decrease over the nine years of forecasting period. This occurrence is due to the decreasing trend of the historical data since year 1990s. However, the forecasted values on Indonesia logs production using ARIMA(0,2,1) shows an upward movement since the historical data series of the country are having increasing trend. Other than that, since the historical trend is decreasing sharply, the forecasted values of Malaysia logs production started to be negative values in 2028. This condition is also due to the cyclical nature of the data as the finding obtained in a time series study conducted on Croation industrial production [18]. Based on the study, the negative forecasted values obtained were due to high volatility and the cyclical nature of the data.

In conclusion, Malaysia logs production is predicted to decreasing over next nine years from the historical data. However, since the data series are volatile and cyclical in nature, the prediction of the forecasted values in 2028 onwards are having negative values which could not representing the logs production for those years. ARIMA models are suitable for handling data series that exhibit trend and cyclical components [13]. However, since the data are steeply downward since the year 1990 onwards, the forecasted values started to be negative after eight step-ahead of forecasting. This indicate that the forecast values only plausible for the first eight-step-ahead. Thus, it is recommended for future study to consider on this issue either by using transformation or other techniques to ensure the forecasts values remain non-negative and more accurately reflect the real-world constraints of the data. Regularly evaluating and validating the models against actual data is also crucial to maintain their accuracy and reliability. This continuous reassessment can help adapt to any structural changes in the data. Furthermore, conducting a thorough analysis of the time series components, such as trends, seasonality, and cyclical patterns, will enhance our understanding and improve forecasting accuracy.

The downward forecasted values of Malaysia logs production indicate that the production of logs in Malaysia is predicted to decrease. Since Malaysia GDP are also depending on the logs production, more alternatives should be considered for ensuring better economy. Although forestry and logging industry seem to be important contributors to Malaysia economy, it should be balanced with the sustainable forestry. Furthermore, the decrease of logs production will lead to higher demand of timber and wood products. This condition will lead to an increasing problem of illegal logging which will be the main contribution to the failure of sustainable forestry.

Conflict of Interest Statement

The authors agree that there are no potential conflicts of interest that may influence the research, authorship, or publication of this manuscript.

Author Contributions

Tengku Mardhiah Tengku Jalal and Norshaieda Abdullah performing the review and editing while Muhammad Wabeel Luqman Shahrimal and Muhammad Irfan Haqiem Hairan conducted the analysis and writing.

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