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A comparative study of ARDL model, ARIMA model: Forecast of the imports in Malaysia.

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Abstract: *For more than a century, forecasting models have been crucial in a variety of fields. Models can offer the most accurate forecasting outcomes if error terms are normally distributed. Finding out a good statistical model for time series predicting imports in Malaysia is the main target of this study. The decision made during this study mostly addresses Autoregressive Distributed Lag (ARDL)' bound test model, and ARIMA model. The imports of Malaysia from the first quarter of 1991 to the first quarter of 2023 are employed in this study's quarterly time series data. The forecasting outcomes of the current study demonstrated that the ARIMA (1,1,1) model offered more probabilistic data, which improved forecasting the volume of Malaysia's imports. The (ARIMA) model and ARDL model in this study are linear models based on responses to Malaysia's imports. Future studies might compare the performance of nonlinear and linear models in forecasting.*
Keywords: *ARDL Model, ARIMA Model, Forecasting.*

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I. INTRODUCTION

Prediction is a difficult art, especially when the future is involved. Forecasting is a process of making statements on events in which their actual outcomes (typically) have not occurred. The art of forecasting the future is a vital and important exercise to determine the economic performance of countries. Malaysian economists would like to determine the future imports to formulate their policy properly, and Malaysian analysts would like to determine the future performance of imports to guide their influencing factors.

Many investigations have been made to determine how Malaysian imports behave. Including [1], [2], and [3]. These estimated a traditional (classical) import demand function was computed using them, where the level of real income and relative prices serve as the explanatory variables, and the response variable is the number of imports. These analyses' fundamental presumption is that the data are stationary. The studies mentioned above were done prior to 'co-integration analyses' and 'error correction models' (ECM) were standard practice in time series analysis. To estimate the import demand function, they employed conventional (OLS) ordinary least squared regression models or partial adjustment techniques. These researches presume that the model's explanatory variables and import volume have an underlying equilibrium connection. [4] if the stationary assumption is violated, this could result in spurious regression, therefore beware. As a result, the OLS method's standard statistical inference would be uncertain. In a late study,[5] used the [6] multivariate co-integration method to determine the long-run elasticities of import demand. They revealed how present income and relative pricing have an impact on import growth in the near run Employing the error correction model (ECM).The assumed ECM's error correction term, however, was not relevant at the 10% level, demonstrating the absence of a long-term connection. [7] reveal that for statistics with little test measure, no co-integration connection can be made among factors that are coordinated of order one, I (1). [8] states that the ECM, [6] and [9] methods are not reliable for studies that have small sample size, such as the study in [5]. [10] reinvestigated the Malaysia import demand function over the sample period from 1970 to 1998 using other estimation method known as the Unrestricted Error Correction Model – Bounds Test Analysis. [11] has chosen the dynamic Vector Error Correction Model to estimate the long run behaviour of Malaysia imports over the sample period from 1980-2010 to overcome the limited number of observations. [12] Examined the long-run relationship of import demand of Malaysia using time series analysis techniques that address the problem of non-stationary.[13] identified the integration vectors based on the maximal eigenvalue and the Trace tests. The results imply that the relationship between G.D.P, export, import and exchange rate are not spurious. [14] used Johansen's co-integration analysis to study a long-run relationship (co-integration) between Malaysian imports and exports for the annual period 1959 to 2000. [15] applied two tests for co-integration namely, Engle-Granger and Johansen tests, and the stability tests also found Malaysian economy such as, Augmented Dickey-Fuller (ADF). [16] The Dickey and Fuller (1979) and Phillips and Perron (1988) unit root test statistics show that all variables are integrated of the same order. The results of the Johansen (1988) co-integration method show that there is long-run relationship between trade balance and commodity terms of trade, but no long-run relationship between trade balance and income terms of trade in Malaysia. [17, 18] Examined the composite model provides better forecasts than the regression equation or time series model alone. [19]Developed basic artificial neural network (ANN) models in forecasting the in-sample gross domestic product (GDP) of Malaysia. [20] Developed Autoregressive Integrated Moving Average (ARIMA) model and Artificial Neural Network (ANN). After comparing the forecasting method using ANN and ARIMA (1, 1, 1) time series, they find that feed forward neural network exhibits a smaller (MSE) and (RMSE) as compared to ARIMA (1, 1, 1). [21] applied two tests for Malaysia's imports namely, ARIMA model and (ANN) models. The result showed that the Artificial Neural Network (ANN) models is more accurate than ARIMA models. [22] They also developed a time series ARIMA model by referring to the Box-Jenkins method. The forecasting results for imports showed that the ARIMA (2,1,2) model had the best fit. the ARIMA models, ARFIMA models and autoregressive (ARAR) algorithm were used for in order to forecast Malaysia imports [23].[24] analysed the imports of Malaysia for goods and used multiple regression model, Input-output model, composite model and ARIMA model. The ARIMA model was eventually identified as the best- fitting model. [25] Applied Autoregressive Integrated Moving Average (ARIMA) model. As a result, the ARIMA (0,1,1) model was identified as the best forecasting model. [24] They developed ARIMA model by the Box-Jenkins method. The forecasting results for imports showed that the ARIMA (1,1,1) model had the best fit. [26]used multiple linear regression to study the important of macroeconomic variables that affecting the total volumes of Malaysia's imports and exports. [27] Concluded that the artificial neural network is the most successful model for forecasting imports and exports.

Although the ARDL model and ARIMA were used to predict future Malaysian imports, most researchers believe that the ARDL model gives better results than using such as, OLS method, the Johansen method, and contributes to solving problem spurious regression. However, the accuracy of ARDL model, and ARIMA model should be investigated further. Almost ARIMA model, and ARDL model predictions use accuracy measures for selecting a best-fit model, however, the forecast values will not necessarily equal the actual values observed for the same time period. This can be due to several factors such as the various restrictions imposed by the Malaysian authorities to limit imports and the degree to which suppliers comply with these restrictions. Therefore, this study's primary goal is to forecast Malaysian imports in order to make future plans. Applying proper statistical criteria to select the optimal prediction model after testing contrasting the proposed approaches. As far as we are aware, no researches using the same statistical techniques have been conducted that addressed the same methods.

II. MATERAL AND METHODS

1.1 Material.

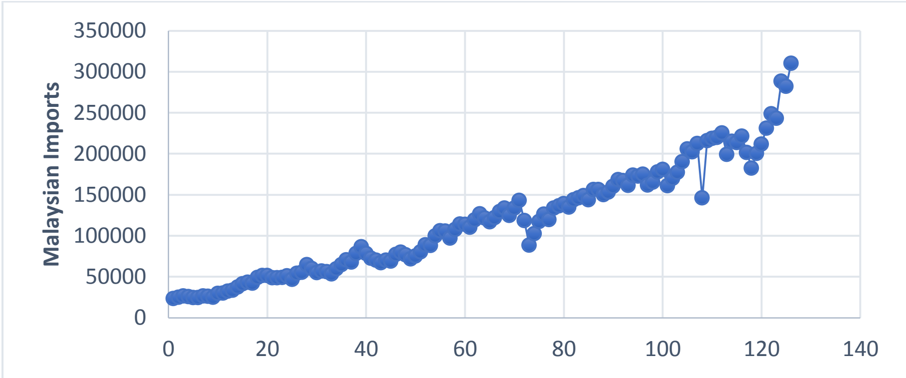
This part explains the case study, which is thought to be a successful research strategy for examining and contrasting the suggested models. In accordance with the procedures below, this case research was selected.

1.2 Data Collection

This study is steered using data on Malaysia imports. The achieved data covers 129 observations, starting from the first quarter of 1991 to the first quarter of 2023. The data source is the Department of Malaysia statistics based on Malaysian Ringgit (RM). The figure below shows the time series.

These data were collected from the official data portal of the Department of Statistics of Malaysia. The data for total imports, exports, and GDP rates are all expressed in Malaysian ringgit. Figure (1) graphically illustrates the raw data of these variables.

Figure (1): Time Series of Malaysian Imports



1.3 **Evaluation of the forecasting performance indices**

A very common accuracy measurement functions are used to assess the performance of each model described below, these performance functions are:

- Akaike's Information Criterion (AIC)[28]

$$AIC(k) = n \ln \sigma^2 + 2k \quad (1)$$

where σ^2 is the variance of error, k is the number of parameters, and n is the number of observations.

- mean absolute percentage error (MAPE)[29]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|e_t|}{y_t} \quad (2)$$

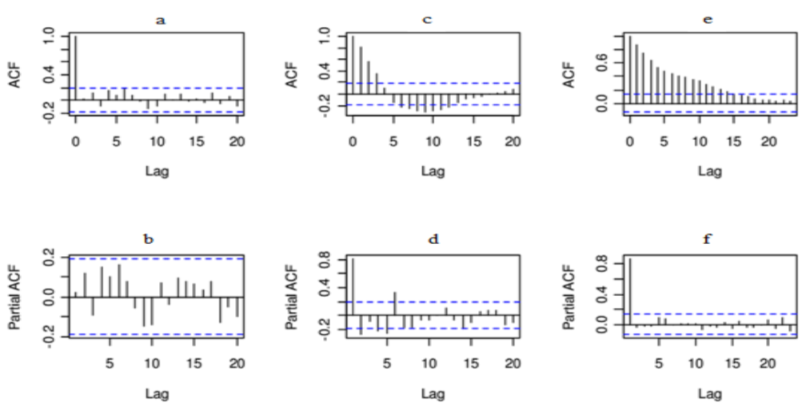
- Coefficient of determination (R^2)[30]

$$R^2 = 1 - \frac{\sum e_i^2}{\sum (y_i - \bar{y})^2} \quad (3)$$

1.4 **stationarity tests**

A time series is a collection of observations on a variable that are regularly taken across time at predefined intervals. If a time series' mean and variance are constant and its covariance totally depend on the interval or lag between two periods rather than the actual time the covariance is calculated, the time series is said to be covariance stationary (weakly or simply stationary) [31-33]. To model a time series with ARIMA and exponential smoothing methods, the time series must be stationary. It is common practice to estimate the model coefficients using OLS regression. The stochastic process must be stationary in order for OLS to be effective. The use of OLS can result in inaccurate estimations when the stochastic process is nonstationary. Such estimates are what Granger [34]] referred to as "spurious regression" results since they have high R2 values and t-ratios but no discernible economic significance. The ADF and PP unit root tests of stationarity are run in this study to exclude structural effects (autocorrelation) in the time series. Additionally, this study utilizes the autocorrelation function (ACF) and partial autocorrelation function (PACF) to assess the data's stationarity. A nonstationary series' autocorrelation function (ACF) also displays a pattern with a gradual decline in autocorrelation size. In Figure 2, six instances of such series are shown.

Figure (2): The PACF and ACF[35]



2.5 The ARIMA method

Ten different temporary ARIMA models were covenanted to the data. These ARIMA models are ARIMA (1,1,0), ARIMA (1,1,1), ARIMA (0,1,1), ARIMA (0,1,0), ARIMA (1,1,2), ARIMA (2,1,2), ARIMA (3,1,1), ARIMA (1,1,3). For non-seasonal series, [36, 37] formulated an ARIMA (P,D,Q) process as

$$\emptyset(\beta)(1-\beta^{d})y_t = c + \theta(\beta) + e_t, \quad (4)$$

where y_t is the time series, e_t is a white noise process with 0 mean and σ^2 variance, β is the backshift operator, d is difference parameter and $\emptyset(z)$ and $\theta(z)$ are the polynomials of orders p and a, respectively.

2.6 **ARDL model**

According to [38], the ARDL modelling approach is particularly useful when the variables are integrated in different orders. This particularisation is the most important feature of the ARDL technique, and it is its distinguishing characteristic from the Johansen method. The ARDL approach can be applied to $I(1)$ and/or $I(0)$ regressors. This approach means that ARDL can avoid the pretesting problems associated with the standard co-integration that requires the variables to be pre-classified into $I(1)$ or $I(0)$.

The ARDL model used in this study may be expressed as

$$y_t = f(x_{1t}, x_{2t}, x_{3t}, e_t). \quad (5)$$

The error correction version of the ARDL framework, as shown in Equation (3.84), can be rewritten as

$$\begin{aligned}\ln(y)_t = \beta_0 + \sum_{i=1}^{n}\beta_1\ln(y)_{t-1} + \sum_{i=1}^{n}\beta_2\ln(x_1)_{t-1} \\ + \sum_{i=1}^{n}\beta_3\ln(x_2)_{t-1} + \sum_{i=1}^{n}\beta_4\ln(x_3)_{t-1} + \varphi_1\ln(y)_{t-1} \\ + \varphi_2\ln(x_1)_{t-1} + \varphi_3\ln(x_2)_{t-1} + \varphi_4\ln(x_3)_{t-1} + e_t.\end{aligned} \quad (6)$$

For parameter $\varphi_i, i = 1,2,3,4$ denotes the corresponding long-run multipliers whilst for $\beta_i, i = 1,2,3,4$ denotes the short-run dynamic coefficients of our ARDL model. e_t denotes a serially uncorrelated disturbance with a zero mean and constant variance whilst Δ denotes the first difference operator.

After confirming a long-run relationship amongst the variables, the following long-run model for imports can be estimated:

$$\ln(y)_t = \beta_0 + \varphi_1\ln(y)_{t-1} + \varphi_2\ln(x_1)_{t-1} + \varphi_3\ln(x_2)_{t-1} + \varphi_4\ln(x_3)_{t-1} + e_t. \quad (7)$$

To determine the appropriate lag length of the ARDL model, one usually depends on the literature and conventions to determine how many lags must be used. Several selection criteria, such as final prediction error (FPE), SC, HQ and AIC, are mainly used to determine the order of the ARDL model.

To estimate the short-run dynamics, the following error correction model is formulated:

$$y)_t = \beta_0 + \sum_{i=1}^{n}\beta_1 ln(y)_{t-1} + \sum_{i=1}^{n}\beta_2 ln(x_1)_{t-1} + \sum_{i=1}^{n}\beta_3 ln(x_2)_{t-1} + \sum_{i=1}^{n}\beta_4 ln(x_3)_{t-1}ECT + e_t, \quad (8)$$

where $i = 1,2,3,4$ are the short-run parameters for β_i and ECT is the lagged error correction term obtained from the long-run equilibrium relationship that represents the adjustment coefficient. This variable must be negative, less than one and statistically significant in order to confirm a co-integration relationship.

III. RESULTS AND DISCUSSIONS

3.1. Stationarity Tests

The following unit root tests were used: the ADF and PP tests (for which the null hypothesis are nonstationary).

Table (1): Results of the ADF test for the linear variables.

		Level	First Difference
		Constant and Trend	**Constant and Trend**
$(\boldsymbol{lny_t})$	*	-3.428	-14.941
	**	-3.446	-3.446
	***	0.052	0.000
$(\boldsymbol{lnx_{1t}})$	*	-3.156	-9.521
	**	-3.446	-3.447
	***	0.098	0.000
$(\boldsymbol{lnx_{2t}})$	*	-2.131	12.865
	**	--3.446	-3.446
	***	0.523	0.000

* ADF statistic value, ** Critical value (5%), *** Prob

Table (2): Results of the PP test for the linear variables.

		Level	First Difference
		Constant and Trend	Constant and Trend
$(\boldsymbol{lny_t})$	*	-3.151	-16.397
	**	-3.446	-3.446
	***	0.099	0.000
$(\boldsymbol{lnx_{1t}})$	*	-6.377	-88.375
	**	-3.446	-3.446
	***	0.000	0.000
$(\boldsymbol{lnx_{2t}})$	*	-2.021	-13.173
	**	-3.446	-3.446
	***	0.584	0.000

* PP statistic value, ** Critical value (5%), *** Prob

Tables 1 to 2 show that the null hypothesis of (y_t, x_{1t}, x_{2t}) has a unit root and cannot be rejected at the 5% level of significance in both the ADF and PP tests. Therefore, all variables are non-stationary in their level form and both the mean and variance are not constant. However, all variables are stabilised at the first level.

3.2 Lag Order Selection

Selecting the number of the lags is crucial in the conception of a VAR model. Lag length is often selected by using a fixed statistical criterion, such as LR, FPE, AIC, SC and HQ.

Table (3): Lag order selection

VAR Lag Order Selection Criteria						
Lag	Log L	LR	FPE	AIC	SC	HQ
0	-4369.787	NA	1.62e+26	71.70143	71.79337	71.73877
1	-3928.296	846.7950	1.51e+23	64.72616	65.18584	64.91287
2	-3882.073	85.62666	9.24e+22	64.23070	65.05812*	64.56677
3	-3864.806	30.85275	9.07e+22	64.20994	65.40510	64.69538
4	-3824.018	70.20939*	6.06e+22*	63.80358*	65.36647	64.43838*

The results of LR, FPE, AIC, and HQ as shown in the above table clearly indicate that the number of optimal delays in our model is equal to 4. Meanwhile, the results of SC indicate that the number of optimal delays is equal to 2. After comparing these delays based on the accuracy of the model results, we find that the number of optimal delays in our model is equal to 4.

3.3 (ARDL) Bound Testing Approach

Table 3 reports the calculated F-statistics when imports (y_t) is considered a dependent variable in the ARDL–OLS regressions.

Table (4): Co-integration test results.

Level of Significance	Critical Values		F-Value
	$I(0)$	$I(1)$	
1%	4.13	5	22.54
2.5%	3.55	4.38	
5%	3.1	3.87	
10%	2.63	3.35	

The F-test results and the critical values from [39] are reported in Table 3. The F-statistic is 6.909 at lag 4 and is higher than the upper bound critical values at the 1%, 2.5%, 5% and 10% significance levels. Therefore, our variables are co-integrated. This result is in line with the findings of [10] in Malaysia, who found that import value and its determinants (i.e. GDP and relative prices) are co-integrated despite their small sample size (28 observations). Another study in Malaysia conducted by [40] revealed a long-run equilibrium relationship between imports and its determinants.

3.3.1 Short-run Estimates in the ARDL Model

We construct an ECM to identify the short-run relationships and check the stability of the long-run parameters. The results are reported in Table 5.

Table (5): ARDL model results in the short run

		Panel (A)		
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**Prob**
C	1380.59	1546.16	0.892915	0.3738
$D(lnx_1)$	0.318800	0.038797	8.217101	0.0000
$D(lnx_1(-1))$	0.172293	0.043278	3.981128	0.0001
$D(lnx_1(-2))$	0.089559	0.042981	2.083665	0.0394
$D(lnx_1(-3))$	0.332373	0.039125	8.495103	0.0000
$D(lnx_2)$	0.328854	0.052381	6.278175	0.0000
ECM (-1)	-0.640439	0.066567	-9.620979	0.0000
		Panel (B)		
R^2	0.67%	Adjusted-R^2	0.66%	
D.W	1.67			

$$D(y_t) = 1380.59 + 0.319D(x_{1t}) + 0.172D\big(x_{1t}(-1)\big) + 0.090D\big(x_{1t}(-2)\big) + 0.332D\big(x_{1t}(-3)\big) + 0.329(x_{2t}) + e_t, \quad (9)$$

Panel A of Table 5 shows that the error correction term is statistically significant at the 1% level and bears a negative coefficient, which is desirable. Therefore, the model is reliable. Meanwhile, the value of -0.64 suggests that the long-run equilibrium relationship eventually returns to the steady state when the system faces some shocks. However, the coefficient has a moderate value, which indicates that restoring such relationship to its steady state will not take long when the system faces some disturbance. This finding is consistent with those of [40], who considered the same restrictions for Malaysia's imports in his work. [41] used ARDL to check the relationship between imports and their determinants and found that exchange rates do not have a significance influence on Turkey's imports in the short run. These findings are consistent with the theoretical and empirical predictions.

3.3.2 Diagnostic Tests

The significance of the variables are evaluated whilst the serial correlation, normality, heteroscedasticity and structural stability of the model are assessed by performing diagnostic tests. Table 6 presents the results of these tests.

Table (6): Diagnostic test results.

	Test	**P-Value**
Serial Correlation	LM test	0.070
Heteroscedasticity	ARCH	0.648
Normality	Jarque–Bera	0.807

The LM test of 6 can be used to detect the autocorrelation problem, which conclude that no serial correlation exists. The results of the Jarque-Berra (JB) test in Table 6 confirm that the residual is normally distributed. Nevertheless, I confirm that heteroscedasticity no existing in our model because the results of ARCH test confirm that the series is not suffers from the effect of heteroscedasticity on error variances.

3.4 Box-Jenkins Approach for Univariate Models (ARIMA)

The ARIMA model is typically applied to time series analysis, forecasting and control. The Box-Jenkins (ARIMA) modelling approach has three major stages: model identification, model estimation and validation and model application.

3.4.1 Model Identification

Firstly, a series of stationary conditions should be imported. To achieve this, the stationarity of the import series is analysed via ADF and PP tests. The results are presented in Table 1 and Table 2. The series is stationary in the first level.

3.4.2 Model Estimation and Validation

This step is initiated by estimating the 8 specifications of ARIMA models as shown in Table 7. Then, the optimal model amongst the studied models can be selected in accordance with the specifications. The initial estimates are presented in Table 7.

Table (7): Initial estimates of the parameters of different ARIMA models.

Model	**Parameters**	**Estimate**	**St. Error**	**t-value**	**P-value**
(1,1,1)	AR (1)	0.621	0.088	7.082	0.000*
	MA (1)	0.998	0.403	2.480	0.015*
(1,1,0)	AR (1)	-0.249	0.088	-2.829	0.005*
(0,1,1)	MA (1)	0.352	0.086	4.094	0.000*

(1,1,2)	AR (1)	0.724	0.139	5.210	0.000*
	MA (1)	1.157	7.826	0.148	0.883
	MA (2)	-0.157	1.270	-0.124	0.902
(2,1,1)	AR (1)	0.586	0.099	5.944	0.000*
	AR (2)	0.068	0.099	0.684	0.495
	MA (1)	1.000	1.844	0.542	0.589
(2,1,2)	AR (1)	-0.323	1.600	-0.202	0.841
	AR (2)	0.590	0.975	0.605	0.546
	MA (1)	0.056	3.663	0.015	0.988
	MA (2)	0.944	3.288	0.287	0.775

Note: * and ** indicate statistical significance at the 1% and 5% levels, respectively.

As indicated in Table 7, all the parameters in the first, second and third models are significant, whereas the rest of the other models are insignificant. The (1,1,1) model, the (1,1,0) model and the (0,1,1) model random walk model are optimal and appropriate to help achieve a part of the first objective of the present study, i.e., to forecast Malaysia's imports. The selected model also approximately fulfils the basic criteria for model selection with minimum values of Bayesian information criterion (BIC), root-mean-square error (RMSE) and mean absolute error (MAE) with a high correlation of coefficients and an insignificant Ljung-Box value.

Table (8): Comparative results from various ARIMA models for Malaysia's imports.

Model	**RMSE**	**MAE**	**BIC**
(1,1,1)	11942.317	6702.567	18.892
(1,1,0)	12406.732	7442.073	18.929
(0,1,1)	12284.933	7326.373	18.910

Amongst the models assessed in the present study, the identified optimal model is the (1,1,1) model, where of RMSE, MAE, and BIC are slightly smaller than those of the other models. Thereafter, the mean and the variance of the series become stationary. This condition should be present in the appropriate model, i.e., the (1,1,1) model. Table 9 presents the p-values for the Ljung-Box test. A good forecasting model should have residuals that are simply white noise after fitting the model; furthermore, insignificant values are expected when evaluating the residuals.

Table (9): Ljung-Box test for the residuals of the fitted (1,1,1) model.

Ljung-Box	D.F	P-value
22	16	0.06

Table 9 shows that the Ljung-Box test provides an insignificant p-value, thereby indicating that the residuals appear to be uncorrelated and the model is suitable for prediction.

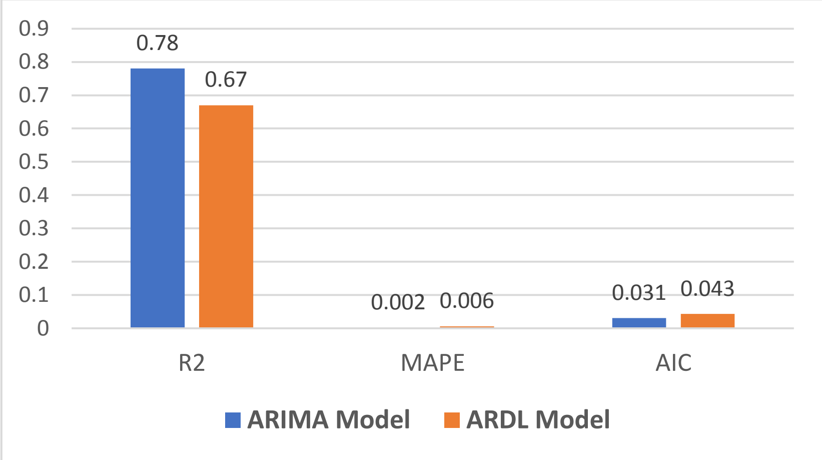
3.5 Analysis of the forecasting abilities of various models

The two models, the ARDL model and the ARIMA model, are contrasted as seen in Table 10. These models were compared based on a range of error metrics. Table 10 and Figure 3 below provide summaries of the outcomes of the forecasting performance of these two models.

Table (10): Statistical measures of forecast error for Malaysia's imports.

Models	**ARIMA Model**	**ARDL Model**
R^2	0.78	0.67
MAPE	0.002	0.006
AIC	0.031	0.043

Figure (3): The outcomes of comparing the forecasting abilities of the various models.



The results shown in Table 10 and Figure 3 were evaluated and analysed by the author in light of the pertinent problems. The selected model demonstrates excellent performance as reflected in its explained variability and predictive power.

2.6 Discussion

The results presented in Table 10 revealed that the MAPE and AIC of ARIMA model are 0.002, and 0.031, respectively, for the time series of the Malaysia's imports. Such results clearly indicate that all results are lower than those of the other method and R^2 in the model is higher than that in the other model. Based on that, Since the ARIMA model had the best match out of all the models, it performed the best. Figure 4 displays the ACF and PACF of the residuals. To create a satisfactory forecasting model, the residuals should only contain white noise after the model has been fitted. Insignificant values are anticipated for these statistics when looking at the residuals.

Figure (4): PACF and ACF of the residuals of Malaysia's imports from the composite model

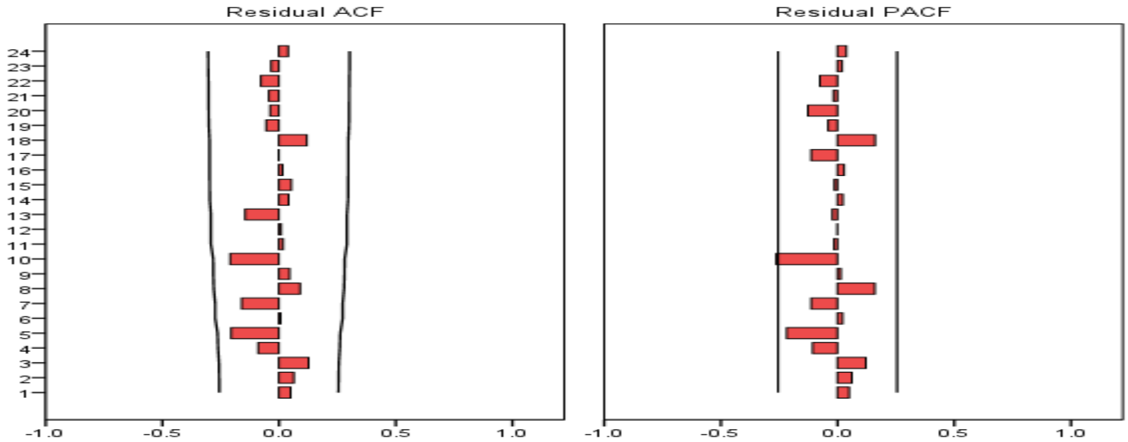
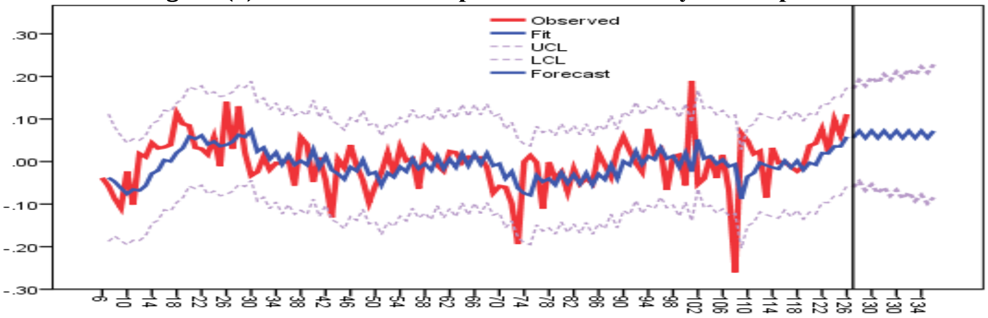


Figure 4 illustrates that the residual errors' ACF and PACF are insignificant, proving that the composite model is the best choice for projecting Malaysia's imports.

3.7 Forecasting Malaysia's imports using the ARIMA: The forecasts for upcoming values of the time series can be predicted using this model. Figure 5 shows the actual values for the period starting with the first quarter of 1991 to the first quarter of 2023 as well as the values that our ARIMA (1,1,1) model expected.

Figure (5): Forecast for the production of Malaysia's imports



The chosen model performs exceptionally well, as evidenced by its explained variability and predictive capacity. The forecasted import values for two quarter of 2023 to the two quarter of 2024 are close to the actual values. These results support the argument of [22], [23], [24], and [25] that Box-Jenkins techniques are useful in modelling time series. The results are also consistent with those of previous studies that elected ARIMA models as the most appropriate model. For example, [20] adopted the ARIMA (1,1,1) model to forecast the imports of Malaysia. [24] proposed the use of the ARIMA model (1,1,1) model to model and forecast Malaysia's imports. On the other hand, we found that there were previous studies such as [20] and [21], that did not agree with the result of this study, and the reason is that the ARIMA models are linear models, meaning that if the time Serie contain non-linear patterns, the ARIMA models will be weak in forming a model suitable for prediction.

IV. CONCLUSION

The methods for predicting imports in Malaysia were suggested and assessed in this study. The proposed models, that are, the ARDL model and ARIMA model were assessed by comparing them with one another using Malaysia's import time series. This study has made a valuable contribution to the literature as it was the first empirical study in this field to compare ARDL model and ARIMA model. The achieved findings have proven the significance and worth of such ARIMA model as a potent forecasting technique that improves the precision of import value prediction and strengthens forecasting techniques in the Malaysian context. As observed from the results that the ARIMA model is suitable for use it in forecasting Malaysian imports, the author recommends the proposed ARIMA models and ARDL model are a linear model that relies on the reactions to Malaysia's imports. However, future research should better describe the use of non-linear models, such as neural network models. The same procedures described in this study can be also applied to these models. Afterwards, the forecasting performance of non-linear and linear models may be compared.

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