International Journal of Economics and Financial Research
ISSN(e): 2411-9407, ISSN(p): 2413-8533
Vol. 10, Issue. 1, pp: 1-11, 2024
URL: https://arpgweb.com/journal/journal/5
DOI: https://doi.org/10.32861/ijefr.101.1.11

Academic Research Publishing Group

Original Research **Open Access**

Composite Model Analysis in Forecasting the Malaysian Imports

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Article History
Received: 21 December, 2023
Revised: 13 February, 2021
Accepted: 15 March, 2024
Published: 21 March, 2024

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 Vector Error Correction Method (VECM), composite model (Combined regression-ARIMA), 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 composite model offered more probabilistic data, which improved forecasting the volume of Malaysia's imports. The (ARIMA) mode, composite model, and VECM 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: Composite model; VECM model; ARIMA model; Malaysia imports.

1. 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.

Forecasting is beneficial as it provides useful data to various stakeholders and thus aiding in future decision makings. Forecasting for short periods predicts estimates in a distant future. The future cannot be forecasted accurately because forecasting coms with a margin of error. The margin of error increases, particularly when forecasting deep into the future that is, predicting the future. Variables and their expected influence may change (with social, economic and political changes) and other new variables may emerge. These errors arise because of the level of inaccuracy of the base information, the method used to forecast the future and the selection of an inappropriate methodological framework for time series data analysis, thereby providing biased an unreliable estimate. Given this condition, the selection of a forecasting method is pivotal in predicting the future.

2. Literature Review

Many investigations have been made to determine how Malaysian imports behave. Including Alias (1978), Semudram (1982), and (Awang, 1988). 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. Granger and Newbold (1974), 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, Tang and Alias (2000) used the Johansen (1988) 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. Kremers *et al.* (1992), 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). (Mah,

2000) states that the ECM, Johansen (1988) and Johansen and Juselius (1990) methods are not reliable for studies that have small sample size, such as the study in Tang and Nair (2002).

Tang and Nair (2002), 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.Mohamad (2012), 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. Bakar (2000) Examined the long-run relationship of import demand of Malaysia using time series analysis techniques that address the problem of non-stationary. Hashim and Masih (2014), 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. Tang (2005), 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. Rahman (2011), 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). (Rahman, 2011; Tsen, 2006) Applied 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.

Milad M. *et al.* (2017), Milad M. and Ross (2016) Examined the composite model provides better forecasts than the regression equation or time series model alone. Sanusi *et al.* (2020), developed basic artificial neural network (ANN) models in forecasting the in-sample gross domestic product (GDP) of Malaysia. Yee and Samsudin (2021), 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). (Urrutia *et al.*, 2019) 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. Ramlan (2021) 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 (Wee Mah and Nanyan, 2020).

Merous and Asfaria (2017), 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. Fauzi and Bakar , Applied Autoregressive Integrated Moving Average (ARIMA) model. As a result, the ARIMA (0,1,1) model was identified as the best forecasting model. Merous and Asfaria (2017) 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. Beh and Yong , used multiple linear regression to study the important of macroeconomic variables that affecting the total volumes of Malaysia's imports and exports. Luchko *et al.* Concluded that the artificial neural network is the most successful model for forecasting imports and exports.

Although the composite model (which combining regression and ARIMA) was used to predict for Malaysia imports future, most researchers believe that the composite model gives better results than using the two methods separately, and contributes to solving regression problems such as, autocorrelation and heterogeneity in variance. However, the accuracy of vector error correction (VECM) model, composite model, and ARIMA -based prediction should be investigated further. Almost composite model, VECM model and ARIMA-based 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.

3. Material and Method

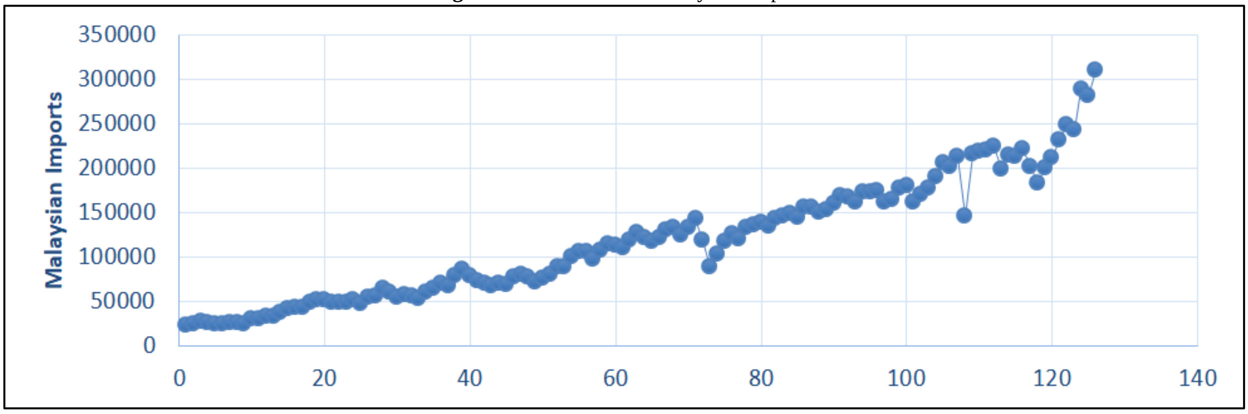
3.1. Material

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.

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 are all expressed in Malaysian ringgit. Figure 1 graphically illustrates the raw data of these variables.

Figure-1. Time Series of Malaysian Imports



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), mean absolute percentage error (MAPE), coefficient of determination (R^2) and Ljung-Box test (Q^*) (Alzahrani *et al.*, 2020; Campolieti and Ramos, 2022; Fisher, 2011; Milad M. A. H., 2020).

$$AIC(k) = n \ln \sigma^2 + 2k \tag{1}$$

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2} \tag{3}$$

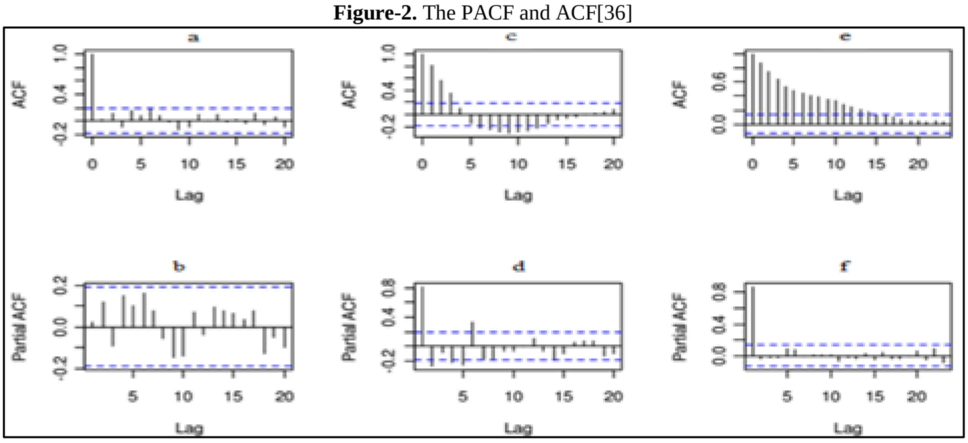
$$Q^* = n(n+2)\sum_{i=1}^{m} r_i^2/n - i \tag{4}$$

3.2. Methods

3.2.1. Stationarity Test

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) (Brockwell and Davis, 2013; Chatfield, 2000; Enders, 2008). 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 (1981) 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[36]



3.2.2. 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, (Hyndman and Khandakar, 2007; Salman and Kanigoro, 2021) formulated an ARIMA (P,D,Q) process as.

$$\emptyset(\beta)(1-\beta^d)y_t = c + \theta(\beta) + e_t, \quad (5)$$

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.

3.2.3. Composite Model

The composite (combined regression–ARIMA) model has been proven useful in many areas, such as in economic business forecasting. This method is based on excellent documentation (Co and Boosarawongse, 2007) and has been proven to be computationally efficient. This model is expressed as

$$Y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_p x_p + \emptyset^{-1}(B)\theta(B)\eta_t, \quad (6)$$

where y_t is the dependent variable, $x_1, x_2, x_3, \ldots\ldots, x_p$ are the independent variables, $\beta_0, \beta_1, \beta_2, \beta_3, \ldots\ldots, \beta_p$ are the regression parameters, $\emptyset$ and θ are the AR and MA parameters, respectively, and η_t is the error random variable.

This composite model can be used to process a high degree of autocorrelation in residuals. Therefore, this study integrates CO-VECM into this model to improve its performance.

3.2.4. Vector Error Correction Method (VECM):

A Vector Error Correction method (VECM model) is a restricted Vector Autoregression (VAR) designed for use with non-stationary series that are known to be cointegrated and is known as the error correction method (ECM MODEL) since the deviation from long-term equilibrium is corrected gradually through a series of partial short-term adjustments. In this study, the VECM equation econometric model for Malaysia's imports can be specified as follows.

4. Results

4.1. 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
(lny_t)	*	-4.654	-15.763
	**	-2.768	-4.786
	***	0.062	0.000
(lnx_{1t})	*	-4.243	-8.765
	**	-4.896	-3.564
	***	0.093	0.000
(lnx_{2t})	*	-2.456	11.874
	**	-4.546	-4.466
	***	0.673	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
(lny_t)	*	-4.342	-15.453
	**	-3.654	-3.764
	***	0.089	0.000
(lnx_{1t})	*	-2.377	-9.385
	**	-3.646	-4.646
	***	0.086	0.000
(lnx_{2t})	*	-2.054	-12.166
	**	-3.784	-3.875
	***	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.

4.2. 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.

4.3. (VECM) Vector Error Correction Approach

Table-4. VECM model results in the short run

Panel (A)					
Variable	Coefficient	t-statistic			Prob
C	2.435	0.887			0.002
$D(lnx_1)$	0.318800	8.217101			0.0000
$D(lnx_1(-1))$	0.172293	3.981128			0.0001
$D(lnx_2(-1))$	0.089559	2.083665			0.0394
ECM (-1)	-0.640453	-9.62564			0.0000
Panel (B)					
Tests	Normality test (Jarque-Bera)	Serial Correlation LM test			White test for Heteroscedasticity
	1.675	1.564	4.678	3.435	$\chi^2 = 44.242$
	(0.534)	(0.785)	(0.563)	(0.765)	(0.431)
	$R^2 = 0.87$	Adjusted-R^2 0.86	D.W 2.03	F-Stat 9.65	

$$D(y_t) = 2.435 + 0.172D\big(x_{1t}(-1)\big) + 0.090D\big(x_{2t}(-1)\big) + e_t,$$

Panel A of Table 4 shows that the (VECM) model 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 Pindyck and Rubinfeld (1998), who considered the same restrictions for Malaysia's imports in his work.

4.3.1. Diagnostic Tests

Panel B of Table 4 shows that The LM test can be used to detect the autocorrelation problem, which conclude that no serial correlation exists. The results of the Jarque-Berra (JB) test confirm that the residual is normally distributed. Nevertheless, we confirm that heteroscedasticity no existing in our model because the results of white test confirm that the series is not suffers from the effect of heteroscedasticity on error variances.

4.4. 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.

4.4.1. 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.

4.4.2. Model Estimation and Validation

This step is initiated by estimating the 8 specifications of ARIMA models as shown in Table 5. Then, the optimal model amongst the studied models can be selected in accordance with the specifications. The initial estimates are presented in Table 5.

Table-5. 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 5, 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-6. 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 7 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-7. Ljung-Box test for the residuals of the fitted (1,1,1) model

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

Table 7 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.

4.5. Composite Model

We develop composite model that use VECM to obtain short-term forecasts.

$$\mathrm{D}(y_t) = 2.435 + 0.172\mathrm{D}\big(x_{1t}(-1)\big) + 0.090\mathrm{D}\big(x_{2t}(-1)\big) + e_t, \quad \textbf{(5)}$$

We construct an ARIMA model for the random error variable in VECM by performing a time series analysis. The residuals in this model, such as e_t, are analysed as follows by using the ARIMA model.

The ARIMA (1,1,2) model of the residual series is combined with VECM to develop the MARMA composite model for forecasting Malaysia's imports. The results are presented in Table 8.

Table-8. Results of the MARMA composite model

	Panel (A)			
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**Prob**
C	2.435	0.887	0.002	C
$D(lnx_1(-1))$	0.172293	3.981128	0.0001	0.172293
$D(lnx_2(-1))$	0.089559	2.083665	0.0394	0.089559
AR (1)	-0.889	0.008	-112.564	0.000
MA (1)	-0.435	0.087	-3.404	0.001
	Panel (B)			
R^2		0.879		
Adjusted-R^2		0.868		
Predicted-R^2		0.877		
Std. error of regression		0.0012		
F-statistic Critical value		22957 4.71		

D()][⌀][[lny]]_t)]=2.435+0.172D(lnx_1t (-1))+0.090D(lnx_2t (-2))+e_t,-0.889y_(t-1)-0.243e_(t-1)-0.435e_(t-2) (6)

We substitute the ARIMA (1,1,2) model for the implicit error in the original regression model equation. As shown in Table 8, the MARMA model is a combination of the regression model and the time series model. The dependent variable,(y_t),and the independent variables are related whilst the error term that is partially "explained" by a time series model is estimated. Table 8 shows that the explanatory variables and the AR and MA parameters explain nearly 88% of the error term.

4.5.1. Diagnostic Tests: We Evaluate the Serial Correlation, Normality, Heteroscedasticity and Predictive Ability of the Composite Model by Performing Diagnostic Tests.

Table-9. Diagnostic test results.

Criterion		Criterion	
Durbin–Watson	1.98	Skewness	−0.259257
Mean	0.000419	Kurtosis	2.865634
Median	0.004609	Std. dev	0.036607
Maximum	0.079843	Jarque–Bera	1.063958 (0.587441)

Table (9), show the composite model passes all diagnostic tests, no autocorrelation is observed at 5% confidence level and the average and its standard deviation are 0.000419 and 0.036607. The error term is normally distributed based on the values of torsion, spacing in Jarque–Bera test.

We test the effect of heteroscedasticity by calculating the coefficients of the residual ACF and PACF for a certain number of time differences.

Table-10. ACF and PACF of the residuals.

Autocorrelation Function (ACF)			Patial Autocorrelation Function (PACF)		
Lag	**Autocorrelation**	**St. Error**	**Lag**	**Autocorrelation**	**St. Error**
1	0.085	0.091	1	.085	.091
2	0.046	0.092	2	.101	.091
3	.046	.092	3	.030	.091
3	.046	.092	4	.003	.091
4	.019	.092	5	.115	.091
5	.123	.092	6	.013	.091
6	.034	.094	7	-.165	.091
7	-.133	.094	8	.163	.091
8	.145	.095	9	-.087	.091
9	-.083	.097	10	.055	.091
10	.074	.098	11	.023	.091
11	.026	.098	12	.011	.091
12	-.009	.098	1	.085	.091

Table 10 shows that all ACF and PACF indicating the absence of correlation in the time series and heteroscedasticity in the error variances.

4.5.2. Assessing Predictive Ability: The difference between the adjusted-R^2 and predicted-R^2 must always be between 0 and 0.200 to ensure that the model has an adequate predictive ability. In our calculations, the difference between these values is 0.009, thereby indicating that both values are in good agreement and that CM-VECM has a high predictive ability.

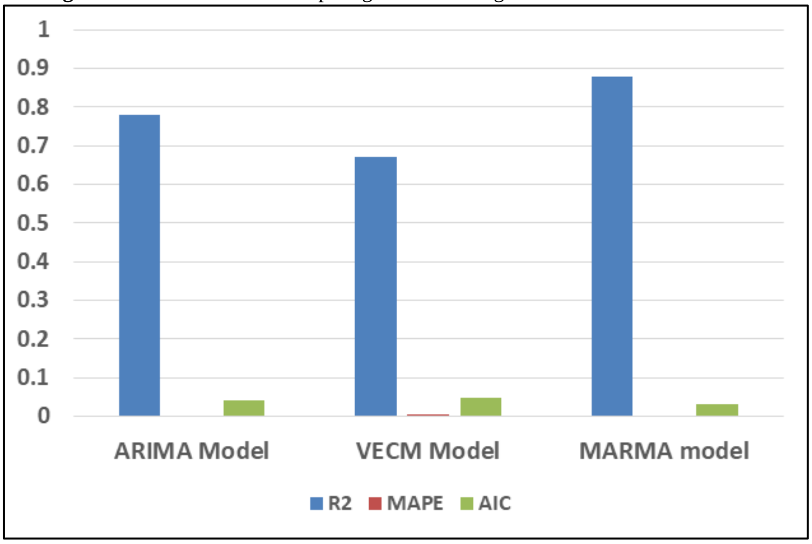
4.6. Analysis of the forecasting abilities of various models

The three models, the VECM model the ARIMA model, and composite model, are contrasted as seen in Table 11. These models were compared based on a range of error metrics. Table 11 and Figure 3 below provide summaries of the outcomes of the forecasting performance of these two models (5).

Table-11. Statistical measures of forecast error for Malaysia's imports.

Models	ARIMA Model	VECM Model	MARMA model
R^2	0.78	0.67	0.88
MAPE	0.002	0.006	0.001
AIC	0.042	0.047	0.031

Figure-3. The outcomes of comparing the forecasting abilities of the various models



The results shown in Table 11 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.

5. Discussion

The results presented in Table 11 revealed that the MAPE and AIC of composite model are 0.001, 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 composite 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

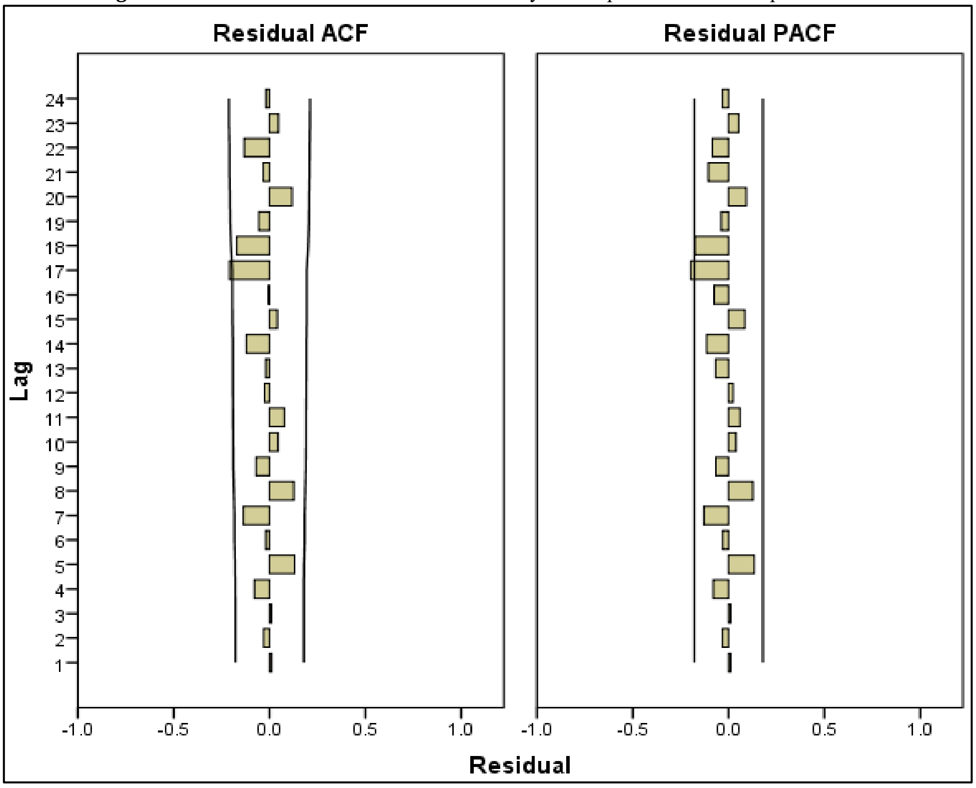


Figure (4) illustrates that the residual errors' ACF and PACF are insignificant, proving that the composite model is the best choice for projecting Malaysia's imports.

The selected model demonstrates excellent performance as reflected in its explained variability and predictive power. Therefore, the results of CO-VECM show that the dependent variable y (Malaysia's imports) and independent variables (GDP and exports) are related, the error term that is partially "explained" by a time series model is estimated and the explanatory variables as well as the AR and MA parameters explain nearly 0.88% of the error term. These findings are in line with those of Shamsudin and Arshad (1990), Shamsudin and Arshad (2000), Islam (2007), Khin (2008), Aye *et al.* (2011), Khin (2013). The composite model provides better forecasts than the regression equation or time series model alone because this model provides structural and time series explanations for those parts of the variance that can and cannot be explained structurally, respectively. This result supports the findings in Milad M. *et al.* (2017) Milad M. and Ross (2016).

6. Conclusion

The methods for predicting imports in Malaysia were suggested and assessed in this study. The proposed models, that are, VECM model, ARIMA model and composite 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 VECM model, ARIMA model and composite models. The achieved findings have proven the significance and worth of such composite 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 composite model is suitable for use it in forecasting Malaysian imports, the author recommends the proposed composite model is 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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