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Original article

Developing a Composite Model (Multiple Linear Regression and ARIMA Models) to Forecast Malaysian Imports

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Abstract
Forecast models have played a major role in many statistical applications for more than a century. When the error term follows a normal distribution, these models can yield highly accurate prediction results. The appropriate methodological framework for analysing time series data provides the theoretical basis for applying such models. This study, therefore, seeks to identify an appropriate statistical model that can better predict Malaysia's imports by evaluating several approaches, including the Autoregressive Distributed Lag (ARDL), the Autoregressive Integrated Moving Average (ARIMA), and a composite (a combined regression–ARIMA) model proposed in this research. The proposed model integrates insights from both regression and ARIMA approaches, thereby facilitating the development of a more effective statistical framework for forecasting the volume of Malaysia's imports and enhancing existing prediction methods. The prediction performance is assessed using the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The results show that the combined model outperforms all other models in terms of accuracy. Its primary strengths lie in its predictive power and its ability to address regression model issues such as residual autocorrelation. Model parameters and predictions were estimated using 54 observations. Future research may expand on these findings by exploring other approaches, such as combined models that account for autocorrelation or heterogeneity problems, or by applying larger datasets on Malaysia's imports and comparing the results with those of the present study.
Keywords. Composite Model, Multiple Linear Regression, ARIMA Models.

Introduction

Previous studies have confirmed the existence of a relationship between imports and economic growth, as they significantly facilitate a country's economic growth (Hashim & Masih, 2014). Several studies, including (Alias, 1978) and (Semudram, 1982) We have examined the behaviour of the import function. These studies estimated the import demand function using the traditional (OLS) method, treating import volume as the dependent variable and treating real income level and relative prices as explanatory variables. A study by (Rubinfeld, 1998) also constructed a composite model combining the regression equation and the ARIMA model and concluded that the composite model helps eliminate the problem of autocorrelation in the residuals. These studies were conducted on the assumption that the data were stationary, before cointegration (ECM) became a method for analysing time series. Instead, these studies used ordinary least squares (OLS) models and assumed a basic equilibrium relationship between import volume and the explanatory variables in their models. According to (Phillips, 1986), if the data are non-stationary, spurious regression can be observed. In this case, the usual statistical inferences from the least squares method are generally unreliable.

In (Aimer, 2019), an error correction model was used to estimate spurious regression. It was found that the time series of variables were non-stationary in their levels, contained a unit root, and were first-order integrated using the augmented Dickey-Fuller (ADF) test, which was significant at the 0.01 level. Researchers in (Cavusoglu & Alsabr, 2017) also aimed to identify the most important factors influencing the terms of trade during the study period (1980-2019), using the autoregressive distributed lag (ARDL) methodology and the bounds test for cointegration. It was shown that these series were first-order integrated and that the appropriate model for estimation was an error correction model. The study in (Albiman & Suleiman, 2016) focused on the relationship between imports, exports, and GDP in Malaysia, using 44 observations. The empirical analysis used the VAR algorithm, Granger causality tests, and the Johansen method, which indicated that the variables were not integrated and that a causal relationship existed between them. (Milad & Duzan, 2024; Milad & Ibrahim, 2016; Milad et al., 2015) They used a composite model to forecast future import volume and concluded that a composite model combining the regression equation and the ARIMA model yields more accurate results than using either model alone. They also concluded that the composite model helps eliminate the problem of autocorrelation and contributes to resolving the problem of heteroscedasticity in the residuals.

Although many studies have developed models for accurate import forecasting, several challenges need to be highlighted, such as the stability of time series data, the relationship between imports and their determinants in the short and long run, an appropriate methodological framework for analysing time series

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data, and finding an appropriate statistical model that can increase the accuracy of Malaysian import forecasting and improve current forecasting methods. Furthermore, the lack of an appropriate statistical model that can effectively predict the value of imports can negatively impact a country's future fiscal and economic policies. (Goyal et al., 2011; Kogid et al., 2011). They recommended that future research develop an effective statistical method for import forecasting to clearly determine countries' economic performance. Therefore, this study aims to re-examine Malaysia's imports by developing a composite model approach by combining the regression equation represented by the error correction model with the (ARIMA) model into a composite model to increase the accuracy of import forecasting and improve the current methods of import forecasting.

Materials and Methods

Materials

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's imports. Then, all study variables were analyzed based on time series characteristics using annual data for Malaysian imports (in Malaysian Ringgit), Malaysian exports (in Malaysian Ringgit), and GDP from 1970 to 2023 (a total of 54 observations) in this study. The data source is the Department of Statistics Malaysia. The following graph shows the time series of the variables and their trends from 1970 to 2023. The graphical plots of the series are presented in (Figure 1).

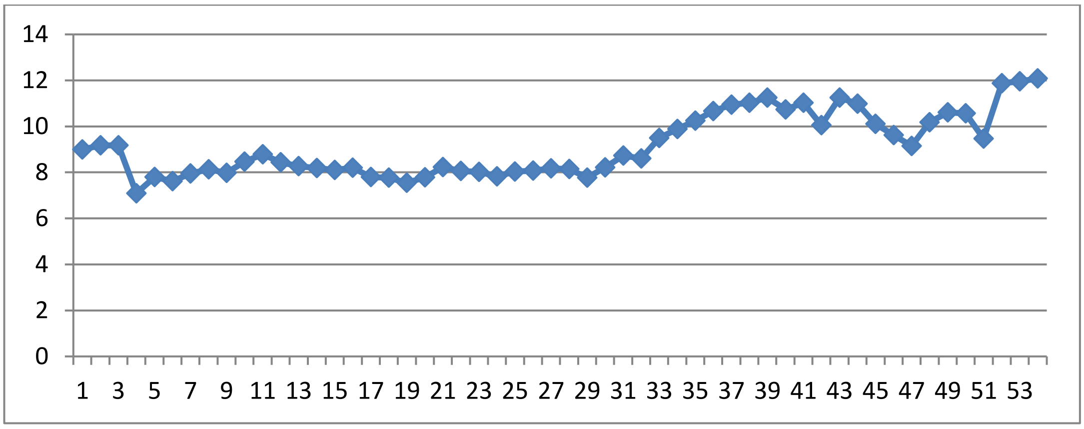

Figure 1. Time Series of Malaysia Imports

A very common accuracy measurement function is used to assess the performance of each model described below; these performance functions are root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD) (Milad; Milad, 2020).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \quad (1)$$

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

$$MAD = \frac{1}{n}\sum_{t=1}^{n} |e_t| \quad (3)$$

Methods

Stationarity test

The time series is a set of observations of a particular variable taken regularly over time at predetermined intervals. If the mean and variance of a time series are stationary and the variance depends on the lag and time interval between the two periods rather than the actual time at which the variance is calculated, the time series is also said to be stationary (simply stationary or weakly) (Brockwell & Davis, 2013; Chatfield, 2000; Enders, 2008). Time series modeling with exponential smoothing models, ARIMA models, and ARDL models should be stationary. In most studies, especially in the past, the parameters of the regression model are estimated using ordinary least squares (OLS). For the estimation to be correct, the stochastic process must be constant. Otherwise, it will lead to inaccurate estimates. These estimates are referred to by Granger (1981) referred to as "spurious regression" results since they have t-ratios and high R2 values but no discernible economic significance. In this study, unit root PP and ADF stationarity tests were conducted to rule out structural effects (autocorrelation) in the time series. In addition, the partial autocorrelation function (PACF) and the autocorrelation function (ACF) were used to assess the stationarity of the data. The PACF and ACF for non-stationary series show a pattern of gradually decreasing autocorrelation. (Figure 2) illustrates six cases of such series.

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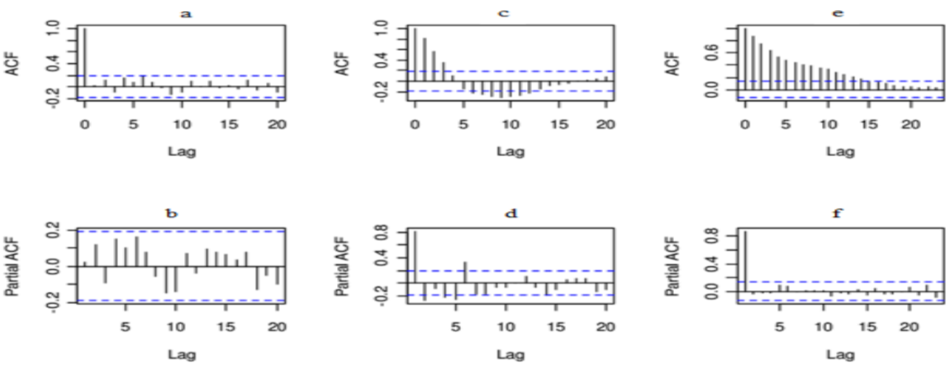

Figure 2. Time Series of Malaysian Imports (Salman & Kanigoro, 2021)

Composite Model

The composite model (combined regression and ARIMA) has proven its usefulness in many fields, such as business and economic forecasting. This method is based on excellent documentation (Pindyck & Rubinfeld, 1998) and has proven its computational efficiency. This model is expressed as follows:

$$Y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_p x_p + \emptyset^{-1}(B)\theta(B)\eta_t, \quad (4)$$

Whereas $x_1, x_2, x_3, \ldots\ldots, x_p$ are the independent variables, Y_t is the dependent variable. Parameters, $\emptyset$ and θ are the AR and MA parameters, respectively. $\beta_0, \beta_1, \beta_2, \beta_3, \ldots\ldots, \beta_p$ are the regression, and η_t is the residuals. The composite model can be used to eliminate the problem of autocorrelation in the residuals. Therefore, this study integrates CO-UECM into this model to improve its performance.

ARDL Model

The ARDL method is one of the best methods used recently to study co-integration, introduced by (Pasaran et al., 2001) Bazran (2001). This method relies on combining autoregressive models of the dependent variable with distributed lag models of the independent variable into a single model. According to this model, the time series of values of the dependent variable becomes a function of the value of the dependent variable and the independent variables, lags for a single time period. It also becomes a function of the mass of lags of the dependent and independent variables in the first difference.

Steps for applying the (ARDL):

Step 1: Cointegration is chosen within the unrestricted ECM regression framework, which takes the following form, assuming the relationship between the dependent variable and the independent variable or independent variables:

$$\Delta(y)_t = \beta_0 + \sum_{i=1}^{m} \beta_i \Delta(y)_{t-1} + \sum_{i=0}^{n} \emptyset_i \Delta(x_i)_{t-1} + \mu_1 y_{t-1} + \mu_2 y_{t-1} + e_t \quad (5)$$

For parameter μ_1, μ_2 denotes the coefficients of the long-run relationship. whilst for β_i, $\emptyset_i$ 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. e_t is the random error term.

The second step: The stage of verifying the existence of a long-term relationship between the variables using the limits test according to Pazran's procedure (Pasaran et al., 2001), which is based on the F test. Co-integration is tested in the equation above through the null hypothesis: no co-integration versus the alternative hypothesis: presence of co-integration. Therefore, rejecting the null hypothesis depends on comparing the calculated value of F with the table values within the proposed critical bounds. If the calculated value of F is greater than the table value, then in this case the null hypothesis is rejected, and the alternative hypothesis is accepted, and co-integration exists. If co-integration exists between the variables, the next step involves estimating the long-run equation with the following formula.

$$(y)_t = \beta_0 + \sum_{i=1}^{p} \beta_i (y)_{t-i} + \sum_{i=0}^{q} \emptyset_i (x)_{t-i} + e_t, \quad (6)$$

Where β_i and $\emptyset_i$ represent the coefficients of the variables, p and q indicate the lag times of those variables, and e_t represents the random error term.

Step 3: Build the following Unrestricted ECM regression (UECM) model:

$$\Delta(y)_t = c + \sum_{i=1}^{p} \beta_i \Delta(y)_{t-i} + \sum_{i=0}^{q} \emptyset_i \Delta(x)_{t-i} + \Psi ECT_{t-1} + e_t, \quad (7)$$

Where ECT_{t-1} is the error correction term, Ψ The error correction coefficient measures the speed of adjustment with which the disequilibrium in the short run is adjusted towards the equilibrium in the long run. Ψ is assumed to take a negative value and to be significant as a condition for accepting the model's estimates in the short run.

Results and Discussion

Stationarity Tests

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

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Table 1. Results of the ADF test for the linear variables

		Level	**First Difference**
		Constant and Trend	**Constant and Trend**
(lny_t)	*	-3.341	-11.437
	**	-4.438	-4.563
	***	Non-significant	Significant
(lnx_{1t})	*	-3.123	-8.653
	**	-5.319	-4.653
	***	Non-significant	Significant
(lnx_{2t})	*	-3.651	-8.986
	**	-5.432	-2.785
	***	Non-significant	Significant

** 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)	*	-3.654	-11.765
	**	-4.876	-4.765
	***	Non-significant	Significant
(lnx_{1t})	*	-4.675	-8.764
	**	-5.764	-4.764
	***	Non-Significant	Significant
(lnx_{2t})	*	-3.761	-10.653
	**	-4.567	-4.654
	***	Non-significant	Significant

The ADF and PP tests for stationarity show that all three logarithmic variables are non-stationary at the level data. The level series of imports, GDP, and exports becomes stationary at the first difference.

Lag Order Selection

The selection of the number of lags is critical in designing a VAR model. The length of the lag is often chosen using a fixed statistical criterion, such as LR, FPE, AIC, SC, and HQ.

Table 3. Specific data of Column/Row

VAR Lag Order Selection Criteria						
Lag	**HQC_p**	**SC**	**AIC**	**FPE**	**LR**	**Log L**
0	4.838	4.854	4.827	7.311	NA	-221.058
1	4.191	4.224*	4.169	3.788*	61.143	-189.806
2	4.082 *	4.131	4.049*	3.359	12.618*	-183.28*
3	4.115	4.180	4.071	3.432	0.0288	-183.269
4	4.145	4.227	4.090	3.498	0.2378	-183.144

The results of the AIC, LR, and HQ tests shown in (Table 3) show that the optimal number of delays in the model is 2. At the same time, the results of the SC and FPE tests indicate that the optimal number of delays is 1. By comparing these delays based on the accuracy of the model results, we find that the optimal number of delays in our models is 2.

(ARDL) Bound Testing Approach

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

Table 4. Co-integration test results

	10%		**5%**		**1%**		
Sample size	**I (0)**	**I (1)**	**I (0)**	**I (1)**	**I (0)**	**I (1)**	**17.55**
45	2.564	3.432	3.421	4.365	4.700	5.654	
50	2.564	3.432	3.421	4.254	4.548	5.574	
Asymptotic	2.472	3.234	3.211	3.275	4.120	5.342	

Source: Critical values for the bounds test; restricted intercept and no trend (Pesaran et al., 2001).

The table above shows the results of the F-test and the critical values. The F-test value is 16.43 with Lag (2) in the model, which is higher than the critical values for the upper bound for all significance levels, and

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therefore, our variables are complementary. Another study in Malaysian conducted by (Duasa, 2007) revealed a long-run equilibrium relationship between imports and their determinants.

Unrestricted Error Correction model (UECM)

The following table estimates an ECM model that captures the short-run dynamics (short-term relationship) between the explanatory variables and the dependent variable. Based on the estimation of the ECM model using the ARDL methodology, the short-run elasticities (coefficients) are obtained, as shown in (Table 5).

Table 5. UECM model results in the short run

Variable	Coefficient	St. Error		T-statistic	P-value
$Dlnx_{1t-2}$	-0.6432	0.0213		-6.5421	0.000
$Dlnx_{2t-2}$	0.6542	0.0342		3.7653	0.004
ECM (-1)	-0.8763	0.0432		-7.6531	0.000
Statistical analysis	Values	Statistical analysis		Values	
ARCH test P-value	0.0832 0.0243			R2	77%
Jarque-Bera P-value	5.452 0.231	D.W	1.21	Adjusted-R2	75%

$$lny_{t-2} = -0.6432 \ln x_{1t-2} + 0.6542 lnx_{2t-2} - 0.8763\ ecm_{t-2} + e_t, \quad (8)$$

From the table above, we note that the error correction coefficient has a negative sign (-0.8763), which is significant at a significance level of less than 0.01. The interpretation of this parameter is that if a deviation occurs in the short term from the long-term equilibrium relationship, this deviation will be corrected by (87.63%) per year. This finding is consistent with those of (Duasa, 2007), who considered the same restrictions for Malaysia's imports in his work. (Kotan & Saygılı, 1999) used the UECM model to check the relationship between imports and their determinants and found that exchange rates do not have a significant influence on Turkey's imports in the short run. These findings are consistent with the theoretical and empirical predictions.

(Table 5) shows that the D.W. test value indicates that the model suffers from the problem of serial autocorrelation of the residuals of the regression equation. The Jarque-Bera test confirms that the model does not suffer from the problem of non-normal distribution of the residuals of the regression equation. In addition, we confirm that the model also does not suffer from the problem of heteroskedasticity, as demonstrated by the results of the ARCH test, which indicates the stability of the variance of the random error term in the estimated model.

Composite Model

We develop a composite model that uses UECM to obtain short-term forecasts.

$$lny_{t-2} = -0.6432 \ln x_{1t-2} + 0.6542 lnx_{2t-2} - 0.8763\ ecm_{t-2} + e_t, \quad (9)$$

We construct an ARIMA model for the random error variable in UECM by performing a time series analysis. The residuals in this model, such as e_t, were analysed as follows by using the ARIMA model. The ARIMA model of the residual series is combined with UECM to develop the composite model (combined UECM-ARIMA) for forecasting Malaysia's imports. The results are presented in (Table 6).

Table 6. Results of the composite model

Variable	Coefficient	Std. Error	T. statistics	P-value
$Dlnx_{1t-2}$	-0.6432	0.0213	-6.5421	0.000
$Dlnx_{2t-2}$	0.6542	0.0342	3.7653	0.004
ECM (-1)	-0.8763	0.0432	-7.6531	0.000
MA(1)	0.842	0.075	11.126	0.000
Statistical analysis	Value		Statistical analysis	Value
R2	95%		F-statistic	234 0.00
Adjusted-R^2	94%		D.W	2.563
Predicted-R^2	96%			

$$lny_{t-2} = -0.6432 \ln x_{1t-2} + 0.6542 lnx_{2t-2} - 0.8763\ ecm_{t-2} - 0.842 e_{t-2} \quad (11)$$

We substitute the ARIMA (0,1,1) model for the implicit error in the original regression model equation. As shown in (Table 6), the composite model is a combination of the regression model and the time series model. The independent variables$(x)_{it}$, and the dependent variable,(y_t) are related whilst the error term that is partially "explained" by a time series model is estimated. (Table 6) shows that the explanatory variables and

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the AR and MA parameters explain nearly 95% of the error term. Diagnostic Tests: We evaluate the heteroscedasticity, normality, serial correlation, and predictive ability of the composite model by performing diagnostic tests.

Table 7. Diagnostic test results

Criterion		**Criterion**	
Durbin–Watson	2.563	Jarque–Bera	5.764(0.078)
Mean	0.045	Std. dev	0.011
Median	0.053		

(Table 7) shows that 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, it passes all diagnostic tests, no autocorrelation was observed at the 5% confidence level, and its mean and standard deviation are 0.023 and 0.054. The error term is normally distributed based on the kurtosis and skewness values in the 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.

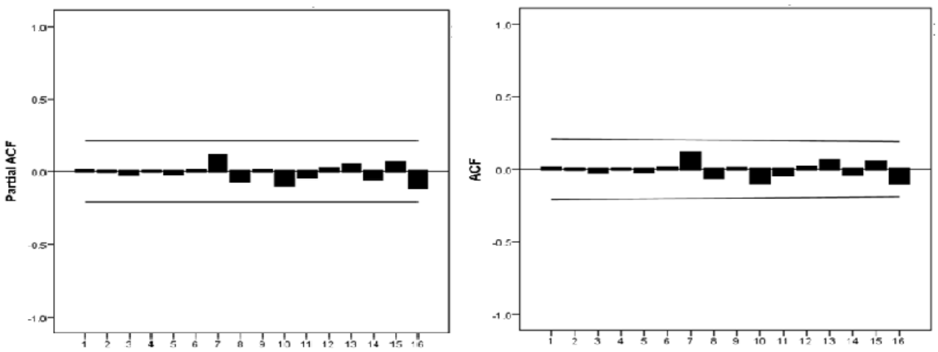

Figure 3. PACF and ACF of the residuals

(Figure 3) shows that all PACF and ACF coefficients are within the zero bound or have values close to zero, indicating the absence of correlation in the time series and heteroscedasticity of the error variances. Predictive Ability Assessment: For a model to have high predictive ability, the difference between the coefficient of determination and the adjusted coefficient of determination must always be between 0 and 0.2. The results from (Table 6) indicate that the difference is 0.01, indicating that the two values agree well, and the composite model has high predictive ability.

Analysis of the forecasting abilities of various models

The two models, the Composite model and the UECM model, are contrasted as seen in (Table 8). These models were compared based on a range of error metrics. (Table 8 and Figure 4) Below are summaries of the outcomes of the forecasting performance of these two models.

Table 8. Statistical measures of forecast error for Malaysia's imports

Models	**Composite Model**	**Regression Model**
MAE	0.412	0.521
RMSE	0.642	0.721
MAPE	5.124	5.564

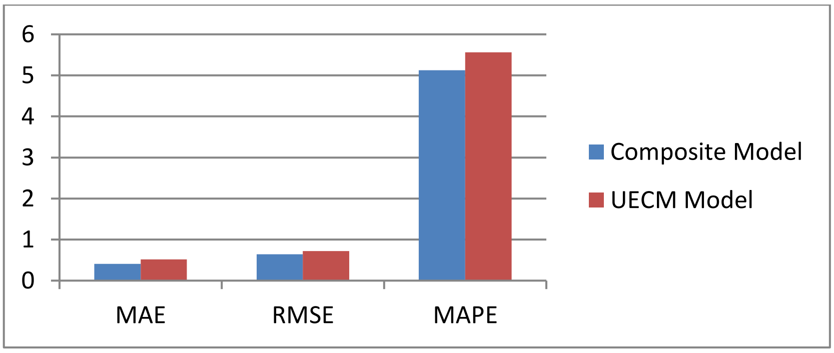

Figure 4. The outcomes of comparing the forecasting abilities of the various models

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The results shown in (Table 8 and Figure 5) 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. The results presented in (Table 8) revealed that the MSE, RMSE, and MAPE of the composite model are 0.412, 0.642, and 5.124, respectively, for the time series of Malaysia's imports. Such results clearly indicate that all results are lower than those of the other method. Based on that, since the composite model had the best match out of all the models, it performed the best. (Figure 5) 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.

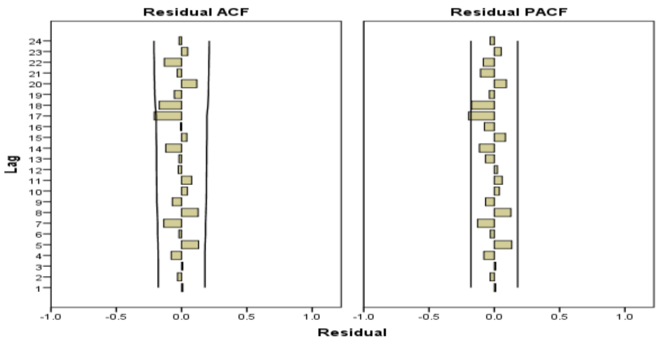

Figure 5. PACF and ACF of the residuals of Malaysia's imports from the composite model

(Figure 5) 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-UECM 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 0.95% of the error term. These findings are in line with those of (Shamsudin & Arshad, 1990) -(Khin et al., 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 et al., 2017; Milad & Ross, 2016).

Conclusion

Import forecasting methods for Malaysia were proposed and evaluated in this study. The proposed models, namely the composite model and the UECM, were evaluated by comparing them with each other using time series of Malaysian imports. This study makes a valuable contribution to the literature, as it is the first empirical study in this field comparing composite models and UECM models. The results obtained demonstrate the importance and value of these composite models as an effective forecasting technique that improves the accuracy of import forecasting and enhances forecasting techniques in the Malaysian context. As evident from the results, the composite model is suitable for use in forecasting Malaysia's imports, and the author recommends that the proposed composite model be a linear model based on feedback on Malaysia's imports. However, the non-linear models, such as neural networks, should provide a better description for future research. The same composite model used in this study could be used and compared with the nonlinear model in terms of prediction performance.

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