Journal of Science and Technology, Vol. 9 No. 3 (2017) p. 16-24

ARIMA and VAR Modeling to Forecast Malaysian Economic Growth

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Received 30 September 2017; accepted 4 December 2017; available online 12 December 2017

Abstract: This study presents a comparative study on univariate time series via Autoregressive Integrated Moving Average (ARIMA) model and multivariate time series via Vector Autoregressive (VAR) model in forecasting economic growth in Malaysia. This study used monthly economic indicators price from January 1998 to January 2016 and the economic indicators used to measure the economic growth are Currency in Circulation, Exchange Rate, External Reserve and Reserve Money. The aim is to evaluate a VAR and ARIMA model to forecast economic growth and to suggest the best time series model from existing model for forecasting economic growth in Malaysia. The forecast performances of these models were evaluated based on out-of-sample forecast procedure using an error measurement, Mean Absolute Percentage Error (MAPE). Results revealed that VAR model outperform ARIMA model in predicting the economic growth in term of lowest forecasting accuracy measurement.

Keyword: univariate, multivariate, growth, forecast, ARIMA, VAR, MAPE.

1. Introduction

Economy growth is an extension in the breaking point of an economy to make products and services, contrasted from one time frame with another. As demonstrated by [1], economy improvement accept as a basic piece of any country, including Malaysia as it prompts increase in the lifestyle, pay per capital, business circumstances, work level, financial security and other diverse things. Economic indicator measures how fiery an economy of a nation is. They can evaluate specific divisions of an economy, for instance, the cabin or retail division, or they give measurement or estimations of an economy in general, for example, Gross domestic product or unemployment.

Time series is a grouping of qualities measured after some time, in discrete or constant time units [2]. Time series models can be isolated into two which are univariate models where the perceptions are those of single variable recorded progressively over comparable isolated time intervals and multivariate models, where the perceptions are of different and numerous factors.

Univariate time series (UTS) alludes to a period arrangement that comprises of single perceptions recorded consecutively through time and is valuable for breaking down the dynamic properties of time series and forecasting. Meanwhile, multivariate time series (MTS) analysis is a vital factual instrument to study about the conduct of time dependent data and figure future qualities depending upon the historical backdrop of varieties on the information [3].

The UTS technique is an approach to manage forecast of a period plan on the premise of the historical behavior of the arrangement itself. This strategy is particularly useful in light of the way that it can give plausible precise short-to-medium term forecast moreover sparing to apply [4]. The inspiration for multivariate forecasting is that there is a data in multiple economic time series that can be utilized to enhance estimates of the variable or factors of interest [5].

This study aims to develop a model using UTS and MTS to forecast economic growth in Malaysia based on time series data collected from World Bank Development Indicators and Ministry of Finance Malaysia.

2. Materials and Methods

This study used a secondary economic data in its analysis from January 1998 to January 2016. Economic indicators used as the variable in this investigation are Currency in

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Circulation (CIC), Exchange Rate (EXC), External Trade (EXT) and Reserve Money (RM), refer [3] and [5]. The data dealt with would be analyzed both descriptively and quantitatively. Diagrams and tables were used to help in the clarifying examination. UTS focuses as a time series that includes single recognition recorded successively through time and MTS analysis is used to appear and clear up the relationship among a gathering of the economic indicators. In this way, this investigation concentrate on the UTS method by means of ARIMA model while MTS strategies by means of VAR. All estimations were completed using R and E views programming.

Correlation Test: The correlation test is used to legitimize whether the factors can be used for forecasting economic growth. To make sense of the relationship among variables do exist, the *p*-value is being compared to the significance level. A significance level, denoted as α or alpha of 0.05 functions well and the *p*-value tells whether the relationship coefficient is significantly different from 0.

Unit Root Test: Unit root test is done to check the data stationary position. The unit root test is conducted by applying the Augmented Dickey-Fuller (ADF) test strategy for testing Integrated order of *(1)* versus Integrated order of *(0)*. The ADF test:

$$\Delta Y_t = \alpha + \mathrm{B}_t + \gamma Y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta Y_{t-j} + \varepsilon_t \quad (1)$$

where, t is the time trend, α is an intercept constant, β is the coefficient on a time trend, γ is the coefficient presenting process root, p is the autoregressive process and ε_t is the white noise residual of zero mean and constant variance. The ADF unit root hypothesis test can be rejected if the *t*-test statistic is negatively less than the critical value. Meaning that, for the ADF test, a unit root presence in the series if the null hypothesis of equal to zero is not rejected.

2.1. Autoregressive Integrated Moving Average (ARIMA) modeling

ARIMA model was initially proposed by [6]. It forecast future estimations of a time series as a linear combination of its own past values and random shocks. ARIMA models are constantly applied in univariate situations where time series show confirmation of non-stationarity by utilizing an initial differencing step to evacuate the non-stationarity as stated in [7].

In ARIMA model, the future estimation of a variable is a direct blend of past qualities and past errors [30], communicated as takes after:

$$\begin{aligned} Y_t &= \phi_0 + \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} \\ &+ \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \end{aligned} \quad (2)$$

where Y_t is the actual value, $Ø_i$ and θ_j are the unknown coefficient, ε_t is the random error at t, p and q are integers that are often referred to as autoregressive (AR) and moving average (MA), respectively, as stated by [8].

Model identification consists of deciding the AR and MA order parts of the model. Potential model will be recognized and described. It will identify value whether the variable, which is being forecast, is stationary in time series or not. Number of differencing *(d)* and autoregressive *(p)* and moving average *(q)* terms are evaluated by using Autocorrelation function (ACF) and partial autocorrelation function (PACF). According to [9], caution to be taken in differencing as over differencing will incline to increment in the standard deviation. The best appropriate model for estimating, relatively small of AIC (Akaike Information Criterion) created by Hirotugu Akaike, [10] will be utilized as a part of this study to decide the best ARIMA model. The AIC lead gives the best lag number and parameters to be assessed in the models. Diagnostics is performed to check whether the fitted model is suitable or not and to analyze the validity of the fitted model. After all parameters have been assessed, it can be used to acquire forecasting model. The forecast model selected is:

$$Y_t = \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \varepsilon_t \quad (3)$$

where, $\varepsilon_t = y_t - \hat{y}_t$ is the difference between the actual value and the forecast value in the series.

2.2. Vector Autoregressive (VAR) Modeling

The VAR model, proposed by [11], is one of the well-known, adaptable and easy to utilize models for investigation of MTS. VAR models stretch the UTS model to dynamic MTS by considering for more than one developing variable. As indicated by [7] and [27], all factors in VAR model are managed symmetrically in an essential sense; every variable has a equation clarifying its advancement in light of its own lags and the lags of the other model variable.

Let $y_t = (y_{1t}, y_{2t}, ..., y_{nt})^T$ denote a $n\times 1$ vector of time series variables. A VAR model with p lags is shown as below:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + \varepsilon_t \quad (4)$$

where, c is a $k\times 1$ vector of constant, A_i is a time-invariant $k\times k$ matrix, and ε_t is a $k\times 1$ vector of error terms .

In model identification, criteria of lag length demonstrate the greatest lag to test for is shown. On the off chance that the lag length is too short, autocorrelation of the error terms could prompt evidently huge and weak estimators. Consequently, one would get mistaken outcomes. Hannan-Quinn Information Criterion (HQ) tests can be habituated to determine the optimal lag number models and given as:

$$HQ = -2L_{\max} + 2k \log n \quad (5)$$

where L_{max} is the log-likelihood, k is the number of parameters and n is the number of observations. Parameters of the VAR model should be assessed once the lag number in the model is resolved [11]. The most common method is Ordinary Least Square Estimator (OLS), [14]. The OLS method is used to estimate the parameters since it is the natural estimator as stated by [15]. The basic condition with OLS approach demonstrates that how each independent variable influenced the dependent variable and can be written as:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \quad (6)$$

where B_0 indicates drift component, Y_t is dependent value, X_t is independent value and ε_t is white noise error. The roots shows the converse underlying foundations of the AR characteristic polynomial. The roots may be appeared as a figure or as a table, see [16] and [29]. If all roots have modulus lying inside the unit circle, then the VAR model is said to be stable. In the event that the VAR is not stable, certain outcomes, for example, impulse response is not substantial. The VAR is regularly utilized for determining frameworks of interrelated time series and for separating the dynamic effect of random disturbances on the variables system [3]. For single lag determination, the underlying perception in the forecast sample will utilize the lagged Y actual value. In this manner, if S is the main observation in the forecast sample, it will compute:

$$y_s + \hat{c}_1 + \hat{c}_2 x_s + \hat{c}_2 z_s + \hat{c}_2 y_{s-1} \quad (7)$$

where y_{s-1} is the value of the lagged endogenous variable in the period prior to the start of the forecast sample and $\hat{c}$ is the coefficient value for each model. This is the one-step ahead forecast.

2.3. Measurement Forecast Accuracy

Forecast evaluation is important in deciding the model specification for subsequent use. The inclinations or misfortune capacity of the forecast user is key to the selection of the precision measure by referring to [21]. This study denotes the actual value of the variable of interest in time period t as y_t and the predicted value as $\hat{y}_t$. Then subtract the predicted value of $\hat{y}_t$ from the actual value y_t to obtain forecast error. The measurement of forecast accuracy, Mean Absolute Percentage Error (MAPE) will be employed in this study. It provides a measure of the distance of the true from the forecast value, see [22]. The forecast sample is $j = T+1, T+2, ..., T+h$, and y_t denote the actual and forecast value in period t as $\hat{y}_t$, respectively. The forecast evaluation measures are defined as:

$$MAPE = 100 * \sum_{t=T+1}^{T+h} \left| \frac{y_t - \hat{y}_t}{y_t} \right| / h \quad (8)$$

3. Results and Discussion

3.1. Correlation Test

Market analysts usually measure economic growth using gross domestic product (GDP). GDP is ascertained from a nation's national records which report a yearly data on incomes, consumption and expenditure for each area of the economy [28]. In this study, the significance correlation among the variables is inspected over the time of the year from 1990 to 2015. The motivation behind this correlation test is to confirm whether each variables that had been chosen for this study are related to GDP or not and hence can be utilized as the variables to forecast economic growth.

Table 1 Correlation Coefficient Analysis

Indicator	GDP	CIC	EXC	EXT	RM
GDP	1.00				
CIC	0.986 (0.00)*	1.00			
EXC	0.380 (0.06)**	0.370 (0.06)**	1.00		
EXT	0.971 (0.00)*	0.938 (0.00)*	0.319 (0.11)	1.00	
RM	0.881 (0.00)*	0.915 (0.00)*	0.324 (0.11)	0.800 (0.00)*	1.00

Table 1 demonstrates that CIC and EXT have a positive strong relationship with 0.9868 and 0.9717 at 1% significance level, individually. Moreover, RM likewise have a positive correlation with 0.8816 at 1% significance level. With respect to EXC, it shows a positive powerless correlation of 0.3806 and is significance at level of 5%. It can be summarized that Currency In Circulation, External Reserve, Reserve Money and Exchange Rate are correlated to Gross Domestic Product and can be utilized to estimate economic growth.

3.2. Unit Root test

The integration order of each variable is reviewed using the Augmented Dickey-Fuller (ADF) unit root test. The variables were transformed into log shape for completing the analysis. Data transformation are normally used tools that can serve many functions in quantitative analysis of data as applying the log transformation makes the data tend to be a normal distribution as expressed by [23]. Table 2 shows the results of the unit root tests for the four variables. The Null hypothesis is that series is non-stationary, or contain a unit root. The rejection of the null hypothesis based on the Mackinnon critical values. Note: ***, ** and * denotes significant at 1%, 5% and 10% significance level, respectively. It can be seen that all the variables (Currency In circulation, Exchange Rate, External Reserve and Reserve Money) exhibit non-stationary series which are integrated of first order. These result are consistent with the norm of macroeconomic series being *I(1)*.

Table 2 Result of unit root test using ADF test

	Augmented Dickey Fuller (ADF)
	Level
Variable	Constant
Log CIC	3.7415
Log EXC	-1.2673
Log EXT	-1.3326
Log RM	1.0471
	First Difference
Log CIC	-2.4268***
Log EXC	-6.1676***
Log EXT	-3.4606***
Log RM	-4.4321***

3.3. ARIMA Modeling

The model checking was finished with ADF unit root test on CIC, EXC, EXT and RM. Result affirms that the series ends up plainly stationary after first-difference in the series (Table 2). The *p* and *q* number is then characterized, where ARMA *(p, q)* model's order number can be determined by utilizing the cutoff property of the ACF and PACF sample model. All variables will be evaluated using ARIMA approach and is discussed in the next subsection below.

3.3.1. Model Identification

The lagging order number *p* and *q* is defined, where ARIMA *(p,d,q)* known as stationary ARMA *(p, q)* model's order number can be judged using the measurement of AIC value [24]. Table 3 shows the different parameters of *p* and *q* among the several ARIMA model experimental upon. The lowest model based on AIC is selected and experimental results for model selection of each CIC, EXC, EXT and RM are shown as below.

Table 3 Statistical Result of Different ARIMA Parameters for CIC, EXC, EXT and RM

Indicator	ARIMA Model *(p,d,q)*	AIC Value
CIC	ARIMA (4,1,2)	-3.4475
EXC	ARIMA (2,1,4)	-4.6573
EXT	ARIMA (3,1,0)	-3.7893
RM	ARIMA (3,1,3)	-2.9683

3.3.2. Parameter Estimation

From the Table 3, the fitted ARIMA model are as follows:

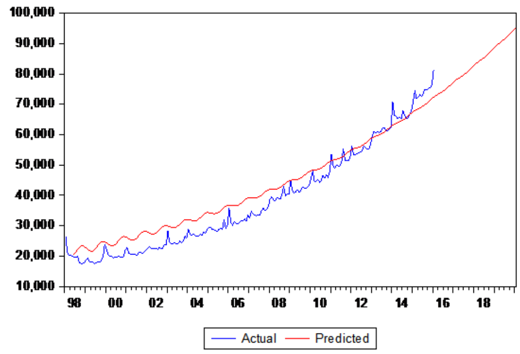
$$CIC = 257.48 - 0.12Y_{t-1} + \varepsilon_{t-1} - 0.03\varepsilon_{t-1} - 0.22\varepsilon_{t-2}$$
$$EXC = -0.02 - 0.75Y_{t-1} + \varepsilon_t + 0.08\varepsilon_{t-1}$$
$$EXT = 1633.12 + 0.25Y_{t-1} + \varepsilon_t$$
$$RM = 256.20 + 0.04Y_{t-1} - 0.99Y_{t-2} + \varepsilon_t - 0.04\varepsilon_{t-1} + 0.99\varepsilon_{t-2}$$

3.3.3. Model Diagnostic

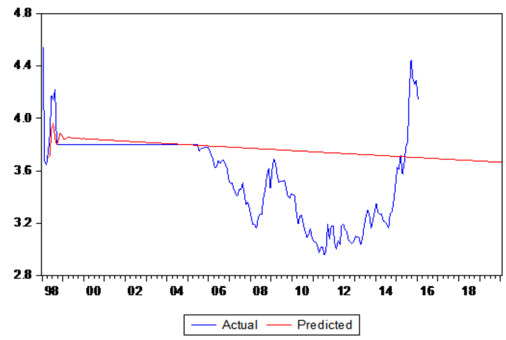
Under the null hypothesis of no serial correlation up to lag *k*, most of the *p*-values for the Q-stat are greater than α (0.01), thus we cannot reject the null hypothesis. This means that the residual of this selected ARIMA model are white noise.

3.3.4. Forecasting

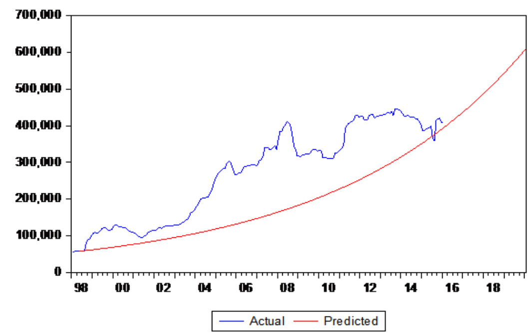
Fig.1 gives graphical illustration of the predicted values versus actual values to determine the execution of the selected ARIMA model. The predicted years begin from February 2016 until January 2020.



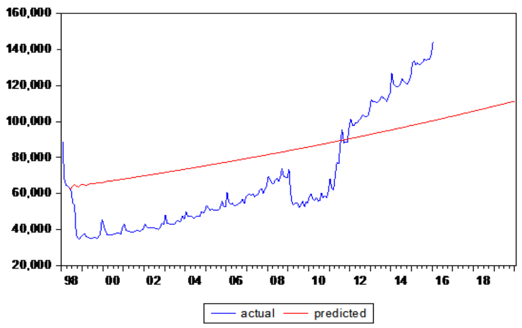
(a) ARIMA (4,1,2) for CIC



(b) ARIMA (2,1,4) for EXC



(c) ARIMA (3,1,0) for EXT



(d) ARIMA (3,1,3) for RM

Fig. 1 Forecast using ARIMA model

From the Fig.1, it shows that there is an upward trend for CIC, EXT and RM as the forecast values also increase. In the EXC graph, it can be seen that the predicted values show a downward trend and this is not surprising as the correlation coefficient values was considered low compared to other model.

3.4. VAR Modeling

As shown in the Table 2, all the Y_i time series are non-stationary. Here, again, the variables checking was done with Augmented Dickey-Fuller (ADF) unit root test. Results confirms that the series becomes stationary after the first-difference of the series as shown in Table 2.

3.4.1. Parameter Estimation

Based on HQ criteria, see [25], the chosen number of lags is 2. Then there are 36 parameters to be estimated. Therefore, the estimated VAR is shown as following:

$$\boldsymbol{CIC} = 0.4072*CIC_{t-1} + 0.5850*CIC_{t-2} - 411.5426*EXC_{t-1} + 1188.3076*EXC_{t-2} - 0.0187*EXT_{t-1} + 0.0219*EXT_{t-2} + 0.2139*RM_{t-1} - 0.2124*RM_{t-2} - 3049.3478$$

$$\boldsymbol{EXC} = 3.8432*CIC_{t-1} - 5.3831*CIC_{t-2} + 1.0281*EXC_{t-1} - 0.0840*EXC_{t-2} - 1.2573*EXT_{t-1} + 1.0765*EXT_{t-2} - 2.1541*RM_{t-1} + 1.73434*RM_{t-2} + 0.20911$$

$$\boldsymbol{EXT} = 0.00890*CIC_{t-1} + 0.1917*CIC_{t-2} + 5570.9826*EXC_{t-1} - 7822.5786*EXC_{t-2} + 1.2371*EXT_{t-1} - 0.2561*EXT_{t-2} - 0.1591*RM_{t-1} + 0.0801*RM_{t-2} + 12085.9240$$

$$\boldsymbol{RM} = -0.8554*CIC_{t-1} + 0.9010*CIC_{t-2} - 2636.0999*EXC_{t-1} + 2557.2739*EXC_{t-2} - 0.00830*EXT_{t-1} + 0.0131*EXT_{t-2} + 1.3044*RM_{t-1} - 0.3341*RM_{t-2} - 255.5732$$

3.4.2. Model Diagnostic

Result demonstrates that all the eigen values in modulus are lying inside the unit circle. Hence, the VAR model has the stability condition (Fig.2).

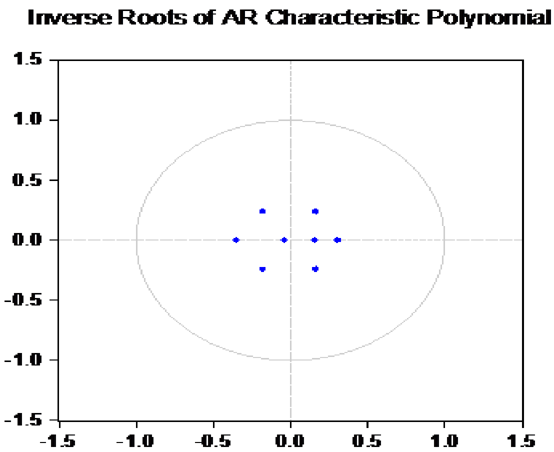
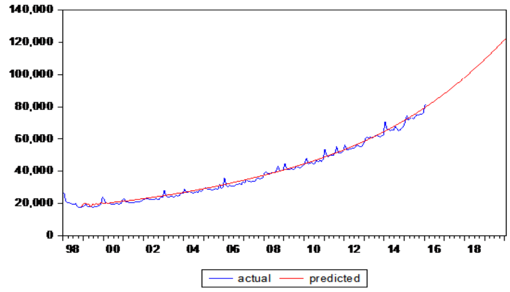


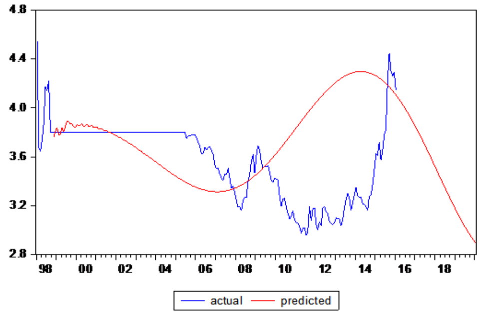
Fig. 2 Results of Polynomial Roots

3.4.3. Forecasting

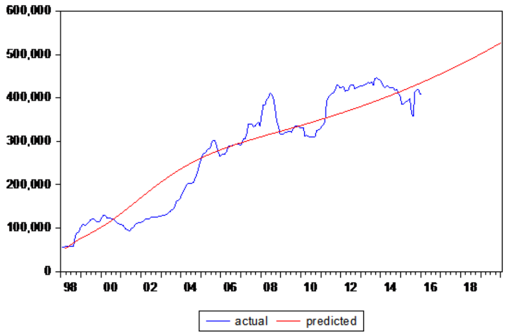
The VAR model above is employed to predict the economic growth in Malaysia amid February 2016 to December 2020. The forecasting results is presented in Fig. 3. From the figure, the predicted values of CIC, EXT and RM demonstrate an upward pattern as the predicted values are slowly increase followed the actual values. Meanwhile, in EXC, the chart demonstrates an inclination of increment years from 2004 to 2020 since the predicted has an inverse relationship with the actual value.



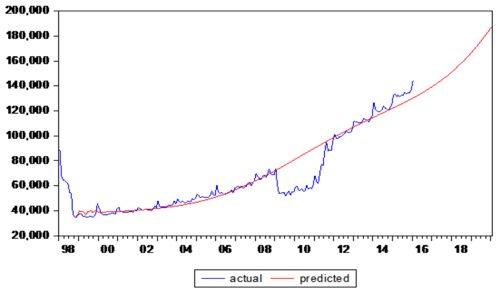
(a) VAR of CIC



(b) VAR of EXC



(c) VAR of EXT



(d) VAR of RM

Fig. 3 Forecast using VAR model

3.5. Comparative Study

Discussion in this section is about the comparative study of the model performance. The proposed models are VAR (2) for multivariate forecasting and ARIMA for univariate forecasting. ARIMA model that has been fitted are (1,1,2) for CIC, (1,1,1) for EXC, (1,1,0) for EXT and (2,1,2) for RM.

After estimation as specified in (8), the assessment of the forecast results created by time series ARIMA and VAR are presented in Table 4. The best model that can be used in forecasting CIC, EXC, EXT and RM price with a certain degree of accuracy is chosen.

Table 4 Accuracy Measurement for each model

Indicator	ARIMA	VAR
CIC	3.9567	3.7629
EXC	7.8894	7.8863
EXT	36.1147	14.8683
RM	44.2123	7.5041

From the Table 4, it is clearly seen that VAR give the best result for predicting CIC, EXC, EXT and RM in terms of less error.

4. Conclusion

The outcomes from the VAR models show that the estimation of MAPE is significantly smaller than the ARIMA model for forecasting CIC, EXC, EXT and RM. In conclusion, this study uncovers that the multivariate model beat univariate model in term of statistical results and forecasting values for predicting CIC, EXC, EXT and RM. Thus, it can be summarized that the proposed VAR model can increase the accuracy performance in predicting the economic growth in Malaysia.

Acknowledgment

The authors would like to express their appreciation for the support of the sponsors with Project Vote: U556 (contract grant) by Research, Innovation, Commercialization & Consultancy Office (ORICC) Universiti Tun Hussein Onn Malaysia.

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