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RESEARCH ARTICLE

Forecasting Loan Consented for Vehicle Purchase in Malaysia

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Abstract Banks are among the institutions that contribute significantly to the country's economic development. Thus, banking sectors play a critical role in the development of the country's economy. Providing credit or a loan is one of the most important services that any bank can do. In this study, a hybrid model was developed, and several existing time series models, such as the seasonal auto regressive integrated moving average (SARIMA), multilayer perceptron (MLP) neural network and a hybrid model were used to forecast the loans approved for purchase of vehicle in Malaysia. The hybrid model is a combination of linear and nonlinear model which is combination of Holt-Winter's and single exponential smoothing models. Mean absolute percentage error (MAPE) and root mean square error (RMSE) are used to assess the accuracy of the forecast. From the findings, the artificial neural network gives the best forecast compared to the other two models. In conclusion, the advanced model such as MLP gives better forecast compared to the SARIMA and hybrid model. This finding could help bank institution make decision for the future pattern of the loan consent for vehicle purchase.

Keywords: Loan forecast, Holt-Winter's, SARIMA, neural network, MLP, hybrid model.

Introduction

The main activity of almost bank in the world is loan distribution. Ke *et al.* [1] discovered that housing provident fund loans had lower interest rates than commercial bank loans, and provident fund contributions are currently regarded as regular employee perks by most businesses and governmental organisations. Due to the numerous applications that were received every day, which are challenging for bank staff to handle and provide a significant risk of error, loan approval has been a major problem for banks [2]. As a result, it is critical to create an effective and impartial system that may lead to more prudent and profitable loan decisions, resulting in significant savings for businesses and banks, as well as a more stable financial banking system, for financial stability and economic recovery [3] For banks to maximise profitability in the sale of personal loans, it must remove unnecessary operating costs during the target market selection phase [4].

Forecasting is widely recognized as the primary management activity in most of the governing and decision-making phases, as it contributes significantly to the process of producing economic value in enterprises and organizations [5]. Whether the borrower pays back the loan or not, the number of loans that influence a borrower's income or loss is large since the bank generates money by charging interest on the loans it makes.[6]. Furthermore, developing reliable forecasting for household credit loans would give useful information for reorganizing financial circumstances and related policies to keep the economy afloat [7]. To avoid dealing with a risky customer, the bank could reduce the loan's interest rate. In particular, prudent borrowers would pay off the mortgage before it matures or return the loan early within the contract period, as will the borrower who may potentially pay for their loan. This is done to prevent paying excessive loan interest. [1].

Numerous studies employing the time series model to forecast financial data also have been conducted in many nations. According to Özeroğlu [4], the utilisation of time series results in incredibly logical consequences for businesses. The Autoregressive Integrated Moving Average (ARIMA) model is a well-

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known and commonly used time series model. Kotillová [8] argued that, aside from the exponential smoothing approach, ARIMA is a highly prevalent time series forecasting model employed by decision makers and researchers in the last three decades. In a study done by Mondal, Shit *et al*. [9], the ARIMA model was chosen to anticipate stock values in India from various industries. The authors stated that the ARIMA model's accuracy in forecasting stock prices in India for seven distinct sectors is greater than 85%, thus it's no wonder that ARIMA is still in use throughout the world owing to its simplicity and superior forecasting ability.

Advanced models are largely based on computational intelligence, and they can capture aspects that traditional models cannot. Few sophisticated models, such as artificial neural networks, can capture nonlinear approximation, expert systems can make decisions when a human expert is unavailable, and fuzzy inference models can handle abrupt changes in data [10]. Zhang and Du [11] introduce the idea of algorithm fusion to increase prediction accuracy by combining machine learning and deep learning methodologies with data analysis and feature analysis. In this study, two types of neural network, the convolutional and the recurrent were used to obtain the fake user behaviour information feature, which was then matched with user data and rated. Using singular matrix decomposition, the characteristics of credit behaviour are then contrasted with those of fraud behaviour. The length of the feature data, or the actual length of the word sequences, word sequences, and phrase sequences in the representational process of the underlying feature, was discovered to be the most critical component impacting the ultimate accuracy.

According to Liang and Cai [12], the bulk of peer-to-peer (P2P) loans are granted based on borrowers' credit rather than mortgages. Due to a rise in loan requests from society, the author employed a deep learning strategy in this research, including an artificial neural network (ANN), a recurrent neural network (RNN), a long short-term memory (LSTM) model, and a gated recurrent unit (GRU). These models were compared to the standard time series model, ARIMA. The results reveal that the LSTM and GRU models outperform the other models. Weytjens *et al*. [13] also suggested using a machine learning approach to forecast cash flow. LSTM is compared against the ARIMA model, Facebook's TM Prophet, and multi-layered perceptron (MLP) in this study. Weytjens *et al*. [13] also recommended utilising a machine learning technique in estimating cash flow. With the goal of saving money, this study compared LSTM to the ARIMA model, Facebook's TM Prophet, and multi-layered perceptron (MLP). As a result, according to this study, LSTM and MLP perform better in projecting cash flow for this sort of data.

Other than machine learning, combination of models or also known as hybrid models have been widely used by many researchers. According to Merh, Saxena *et al*. [14] in their research, combining two or more computational models, will result in a better forecast than each model alone. Kotillová [8] also supported this idea, if a hybrid method is used, for example the ARIMA method is combined with a neural network, the forecasted outcomes will be highly preferable. Appiah [15] used a combination of regression analysis and the Box-Jenkins model in a study based on secondary data from the Minescho Credit Union to create a reliable prediction model for the trend of loan default. Since there is only one independent variable, they used simple linear regression in their regression analysis and hypothesis testing to evaluate their statistical hypotheses. The monthly loan default data from Minescho Credit Union shows a strong correlation and an upward trend.

But advanced models are not always better than conventional models. A study by Babu and Reddy [10] used a variety of methods to estimate the exchange rates of the Indian Rupee with few other countries by using ARIMA, Neural Network (NN), and Fuzzy Neuron models. In terms of learning skills, they claimed that NN is attempting to replace and work like the neurons in a real human brain, as well as building prototypes and models. But the ARIMA model outperformed more intricate and sophisticated models, according to the authors, when it came to predicting the Indian exchange rate market [10]. They further emphasized ARIMA's excellent performance when they discovered that the findings gained contradicted current research, which claimed that complicated nonlinear models outperform the standard time series forecasting technique.

In Malaysia, Bank Negara Malaysia (BNM) is the responsible body in endorsing budgetary and economic stability for country long-term economic growth. BNM acts as Malaysia's central bank governed by the Central Bank of Malaysia Act 2009. For the last two years, BNM has started to move towards on impacts of external risks such as climate, flood, and Covid-19 and preparing the Malaysian financial system to be more sustainable, climate-resistant, and ready for recovery plan [16]. Thus, it has become more important to study and forecast the financial growth of Malaysia considering the factors mentioned above.

Some of the study in Malaysia in financial is by Abdullah and Ling [17]. By testing the model on the Kuala Lumpur Composite Index, they have investigated the model despite the argument that the length of intervals effect predicting outcomes (KLCI). During the creation of experimental data sets using KLCI stock index data. The results show that the datasets examined were appropriate for the frequency density-based partitioning of the Chen model. This finding supports the importance of interval lengths in predicting success.

Eldersevi and Haron [18] study the decrees declared by the Shariah Advisory Council of Bank Negara Malaysia (SAC-BNM) based on conflicting perspectives of SAC-BNM and other entities of collective intelligence to determine the reason of rejection and overall effect on Islamic financing by using qualitative and comparative approach. Amanullah [19] emphasize the guidelines between two banks, Bangladesh Bank and BNM on the criteria whether they follow the Shariah rulings, compare them, and analyze them considering modern Muslim jurists' Shariah rules on these criteria.

There is not much study on analysis of BNM data has been done eventually, thus this study could add up more research on financial study especially related to loan forecasting in Malaysia. The objective of this research is to improve the forecasting for loans of transport vehicle purchase by develop a hybrid model and compare the performance with seasonal ARIMA (SARIMA), and ANN.

Methodology

Seasonal Auto Regressive Integrated Moving Average

ARIMA models can also be used to model seasonal variables. To generate a SARIMA model, additional seasonal components are introduced to the ARIMA model. A SARIMA model employs differencing with a latency equal to the number of seasons to eliminate additive seasonal effects. Just like to erase a trend, the lag 1 differencing is performed to the lag s differencing before inserts a moving average term. The seasonal ARIMA model comprises autoregressive and moving average components at lags. Thus the SARIMA (p,d,q) x $(P,D,Q)^S$ model is given by equation:

$$\emptyset_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D y_t = \theta_q(B)\vartheta_Q(B^S)u_t \tag{1}$$

where
B is the non-seasonal backward operators ,
B^S is seasonal backward operators,
$\emptyset_p$ and Φ_P is non-seasonal and seasonal AR component coefficients with order p and P,
θ_q and ϑ_Q is non-seasonal and seasonal MA component coefficients with order q and Q,
d is non-seasonal differencing order,
D is the seasonal differencing order,
y_t is the time series,
u_t is the white noise residuals.

The trend components can be selected by carefully examining the correlations of recent time steps in ACF and PACF plots. Similarly, by looking at correlation at seasonal lag time steps, ACF and PACF plots may be used to specify values for the seasonal model.

Multilayer Perceptron Neural Network

In this work, the multilayer perceptron (MLP) neural network has three layers: input, hidden, and output. In the hidden layer, the logistic function was utilized as a nonlinear activation function. All neurons are connected to each input, and the output is connected to the neurons. Each arrow has a matching weight or parameter to be estimated, and the source of the arrow is an argument of the function computed at the destination of the arrow. Constants or bias (in neural network language) are attached to each neuron and output, denoting 1 in each case. Figure 1 below is the architecture of MLP neural network model.

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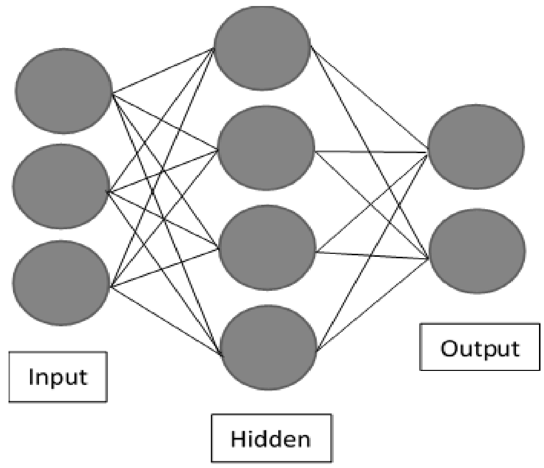

Figure 1. The architectural of multilayer perceptron neural network

MLPs are neural network models that can estimate any continuous function as universal approximators. MLPs are made from neurons known as perceptions. A perceptron takes n characteristics as input $(x = x_1, x_{2,\dots}, x_n)$, each of which has a weight assigned to it. To use a perceptron, Numeric input features are required therefore, for nonnumeric input characteristics must be transformed to numeric ones.

Hybrid Model

The hybrid forecasting approach incorporates the forecasting findings of both linear and nonlinear methods. In recent years, using a hybrid model to increase forecasting accuracy has been widespread practise. Zhang [20] list down three reasons why hybrid model is important for forecasting. To begin with, determining whether a time series is formed by a linear process or whether one approach is more efficient than another for time-series forecasting is tough. Second, few real-time series are exclusively linear or nonlinear processes, and many of them contain both. Finally, there is no one-size-fits-all approach that can be applied to all situations.

In this study, the hybrid model will be a mix of Holt-Winter's and single exponential smoothing (SES). The Holt-Winter's technique will be used in this study since the data shows a trend and seasonal pattern and in the second process of the hybrid model, the SES model was chosen to execute the hybrid model because the error yields from the forecast of the Holt-Winter's will usually generate a stationary pattern of residual. There will be three smoothing constants used: *α*, *β*, and *γ*. The general formula for the Holt-Winter's model is given as follows:

$$F_{t+m} = L_t + mb_t + S_{t+m-s}$$
$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$$
$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$$
$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s}$$

where
α is the smoothing constant for the level estimate
β is the smoothing constant for the trend estimate
γ is thesmoothing constant for the seasonality factor
S is the number of seasonality in a year
F_{t+m} is the m step ahead of forecast at time t.

The difference between the actual and predicted value of the in-sample forecasts can be used to compute the residuals. The in-sample residual will be used afterward to forecast the ε_t by using the SES model. The general formula for SES can be obtained below:

$$F_{t+1} = \alpha\varepsilon_t + (1-\alpha)F_t \qquad (2)$$

where,

F_{t+1} = forecast value for the next period t,
F_t = forecast value in period t,
α = smoothing constant $0 \leq \alpha \leq 1$,
ε_t = residual from the Holt-Winter's forecast in period *t*.

After this step, the out-sample forecasts of the residual generate by the SES and the out-sample forecast from the Holt-Winter's will be merged, resulting the forecast from the hybrid model. The following is a formula for a hybrid method:

$$z_t = \hat{y}_t + \hat{\varepsilon}_t \tag{3}$$

where z_t represents the out-sample forecast, $\hat{y}_t$ represents the out-sample forecast from the Holt-Winter's, and $\hat{\varepsilon}_t$ represents the out-sample forecast of the residual from the SES. The residual $\hat{\varepsilon}_t$ should be minimal if the forecasted value from the Holt-Winter's prediction $\hat{y}_t$ is close to the true value, and vice versa. This was also comparable to Zhang's approach, which views a time series to be a composite of a linear structure and a nonlinear component. The framework of the hybrid model can be seen as Figure 2 below.

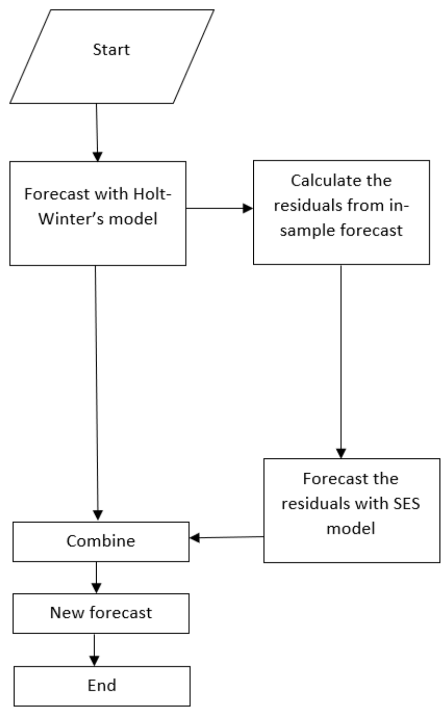

Figure 2. The framework of the hybrid Additive Holt-Winter's with SES

Result and Discussion

Loan application for vehicle purchase was obtained from Bank Negara Malaysia website. The data is recorded from January 2010 until November 2018. Data from January 2010 until December 2017 will be used as a training data and data from January 2018 until November 2018 will be used as a testing purpose. Do a time series plot for a data is an important step for us to determine whether the data has trend, cycle, seasonality, or irregular components. The time series plot of the data can be seen from Figure 3.

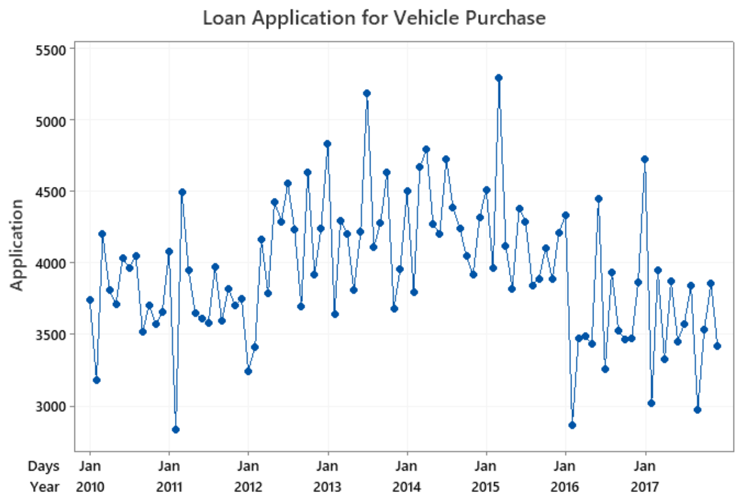

Figure 3. Time series plot of monthly loan approved for vehicle purchase in Malaysia from 2010 until December 2017

From the time series plot in Figure 3 above, we could see that the number of the application monthly is between 2800 to 5500. The first model to fit the data is SARIMA model. The SARIMA model is a good match for the stationary series. The Augmented Dickey-Fuller (ADF) unit root test can be used to do a formal stationary test [21]. If a series is non-stationary, we must first perform differencing before moving on to the next step. Because the p-value = 0.4964 > 0.05 in Figure 4 from RStudio indicates that the data is non-stationary, we accept H_0 and conclude that the series is non-stationary. Until the data becomes steady, data differencing is required.

```
> adf.test(TV)

        Augmented Dickey-Fuller Test

data:  TV
Dickey-Fuller = -2.1936, Lag order = 4, p-value = 0.4964
alternative hypothesis: stationary
```

Figure 4. ADF-test result for checking stationarity of the data

The stationarity of the data was verified again using the ADF test after regular differencing (d = 1) and seasonal differencing (D = 1) were completed. Consequently, we get the following result in Figure 5. Null hypothesis is rejected because p-value = 0.01 is less than α = 0.05. As a result, the model is stationary at the 0.05 level of significance.

```
> adf.test(seasonaldiffTV)

        Augmented Dickey-Fuller Test

data:  seasonaldiffTV
Dickey-Fuller = -7.027, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(seasonaldiffTV) : p-value smaller than printed p-value
```

Figure 5. ADF-test result after differencing the data to 1

To figure out how many orders there are in SARIMA model we may fill in the d and D with 1 because regular differencing and seasonal differencing were both done once earlier. There are no major spikes bigger than lag 2 as seen in the PACF from Figure 5. P has a substantial rise at lags 12 and 24, therefore the potential P is 2. The most notable spikes may be noticed on the ACF plot at lag 1. We use the ACF plot to estimate the value of Q, and we can see that the spike is only significant at lag 12, therefore Q is equal to 1.

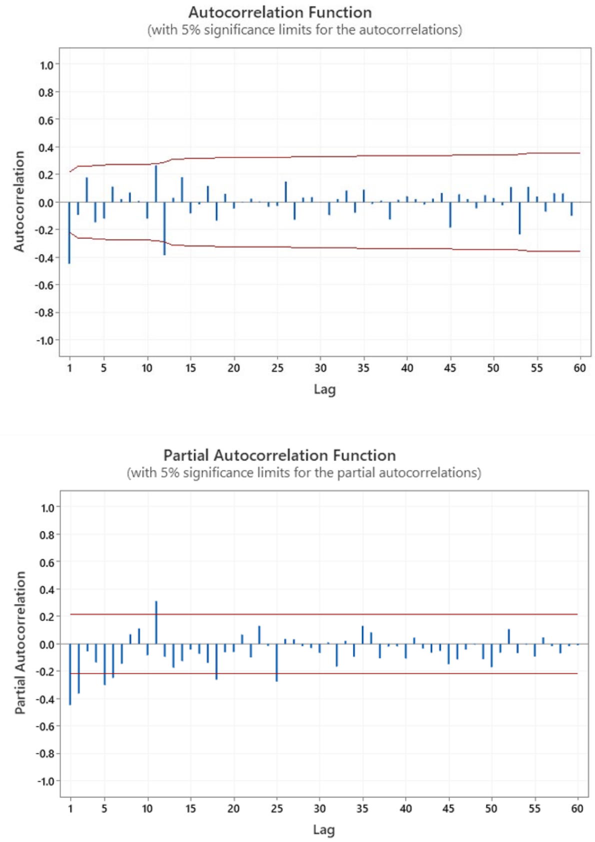

Figure 6. ACF and PACF plots for loan data after being difference to 1

From the ACF and PACF plots in Figure 6 by looking at the lags the ACF cuts off after lag 1 and PACF cuts off after lag 3 and as for the seasonal lag the ACF cuts off after lag 12 and the PACF dies down. Therefore, the possible model for SARIMA model is (2,1,1)(0,1,1)12. After fitting the SARIMA model with our data, the Ljung-Box statistics shows the values as in Table 1 below.

Table 1. Ljung-Box statistics to check the model adequacy

Lag	Chi-Square	DF	*p*-value
12	9.621	7	0.211
24	22.783	19	0.247
36	36.044	31	0.245
48	53.601	43	0.129

Since all the p-value are larger than 0.05. Therefore, this model is adequate to forecast the data. After fitting the data with SARIMA model, we then forecast the data with MLP. The data is set to 90% as training dataset and 10% as testing dataset. For the MLP, we analyse the training data with 10 hidden layers first, but the best three hidden layers with small error are 2, 3 and 5. Therefore, we used the 2, 3 and 5 for testing data afterward. The mean absolute percentage error (MAPE) and root mean square error (RMSE) of the hidden layer is shown in the Table 2 below.

Table 2. MAPE and RMSE for hidden layer of 2, 3 and 5 of MLP neural network model

Loan approved for purchase of transport	Hidden layer	MAPE	RMSE
Modelling (90% Training set)	2	7.467	392.415
	3	6.909	357.281
	5	**6.056**	**335.029**
Forecasting (10%Testing set)	**2**	**17.451**	**926.183**
	3	20.462	1063.294
	5	19.923	951.520

From Table 2, the training set shows that 5 hidden layer is a good fit but for testing set the hidden layer 2 is a good better for forecasting. Thus, we choose hidden layer 2 for the forecasting with MLR neural network. After being forecasted with MLR, the data is forecasted by using hybrid model a combination of additive Holt-Winter's and DES.

First, the data is being forecasted with Holt-Winter's model. For the Holt-Winter's model we set the values of the optimum parameters for the smoothing constant to $\alpha = 0.2$ and the smoothing constant for trend, $\beta = 0$, and smoothing constant for seasonality factor, $\gamma = 0.05$. These parameters value is chosen because it gives the smallest value of sum square error (SSE) when calculated by using the Solver tool in Microsoft Excel.

Then, we'll fit the data using the residual of the Holt-Winter's model, we plot the residual of the Holt-Winter's to see if there is a trend or seasonality contain in the residual. The residual of the Holt-Winter's technique is plotted as a time series in the image below in Figure 7. Looking at the plot below, the residual does not have trend and seasonality. Therefore, the SES model should be adequate to forecast the residual.

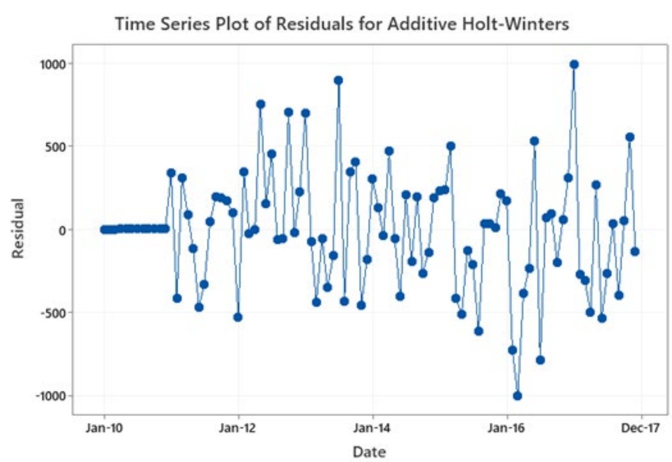

Figure 7. Time series plot of the residuals from additive Holt-Winter's model

After the residual is forecasted by using SES model, the SES and additive Holt-Winter's out-sample forecast is merged to create a new forecast. The new forecast is basically the forecast from the hybrid model which is a mix of the Holt-Winter's technique and its residuals, which were then predicted using SES. The smoothing constants of the SES model are set to a value between 0 and 1. The best smoothing parameter for minimizing the SSE is 0.10.

Then, in the next step, the prediction accuracy will be assessed by comparing all the models' forecasts with the actual data. Each model's predicting accuracy and performance will be evaluated by using two standard tools: the MAPE and RMSE. The out-sample loan data is used to assess the forecasting performance and accuracy of the models during a 12-month period from January to December 2018. The following Table 3 shows the result of the error assessment.

Table 3. MAPE and RMSE for model comparison between SARIMA, MLP and hybrid models

Forecasting model	MAPE	RMSE
SARIMA $(2,1,1)(0,1,1)_{12}$	16.51	1073.43
MLP	**10.88**	**547.92**
Hybrid	12.69	898.11

From the MAPE and RMSE values in Table 3, the MLP model gives the smallest values of MAPE and RMSE which indicate that it is the best model to forecast the loan approved for vehicle purchase in Malaysia. The MAPE value 10.88% indicate that the accuracy is acceptable although its quite low for accuracy [23]. The hybrid model gives the second best and SARIMA is the worst fit. MLP is known as a model that replicate the brain works and is suitable for a data that contain a sudden change or extreme value. Although SARIMA is known as one of the best conventional models for seasonal data and always being a benchmark model in forecasting, but since MLP and hybrid are more advanced than SARIMA, the SARIMA model gives the largest value of MAPE and RMSE in forecasting the data.

Even though the percentage error from the MAPE is not enormous, between 10% to 16% but looking at the RMSE value, the difference is quite big. But both error indicators give similar results, hence it can be concluded that the results are valid. We then plot the forecasts and compare with the real data to have a better understanding of the forecasting. The performance indicators might give idea on the goodness-of-fit of the models, but graphical plot can give better interpretation of the forecasting. The comparison plot can be seen in Figure 8 below.

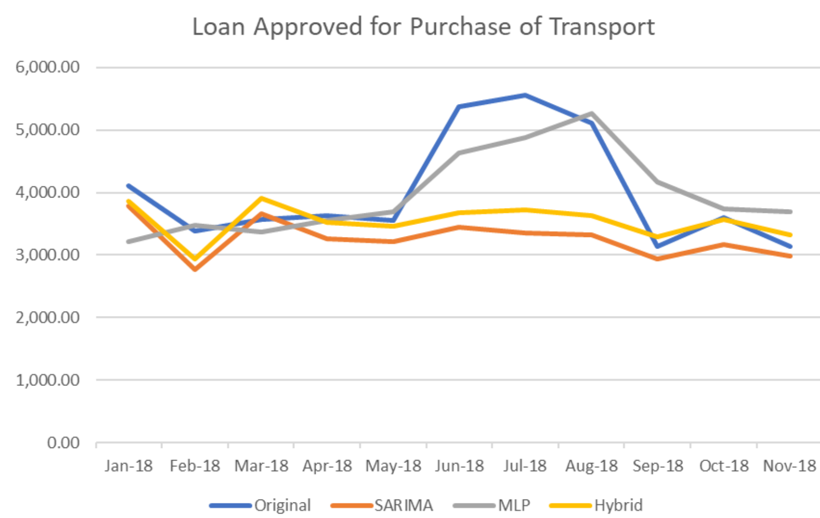

Figure 8. Comparison plot between actual data and selected time series models

As can be seen from Figure 8 above, compare to the hybrid and SARIMA models, the MLP can forecast the data better. It can even capture the extreme value in the data between June and August. In forecasting, it is very important to have a model that can capture an outlier or irregular pattern in the data. So, MLP is a good model in forecasting the loan approved for purchase of transport in Malaysia. This extreme value that is happening during that time can be investigated and can be concluded in the future analysis.

Although the hybrid model is a combination of two models which are the Holt-Winter's and SES models, but since both models used in this technique are conventional models, the hybrid does not outperform the MLP model. Therefore, it is important for analyst to consider the models that are going to be used in developing a hybrid model. As can be observed from this study, the MLP model which gives best forecast has simpler procedure compared to the hybrid model. The hybrid model is time consuming, and the procedure is also more complicated compared to the MLP.

Conclusions

In conclusion, the MLP outperform the hybrid and SARIMA models. This is due to the advantages the MLP haves that the conventional models do not have. A back propagation is used to train the neurons in the MLP. MLPs could tackle issues that are not linearly separable and are meant to estimate any continuous function. The hybrid model could not give a better fit compared to MLP because the hybrid model only used combination of conventional models. Conventional model is known to have a limitation in predicting an irregular or outlier contain in the data. Thus, it is important to consider models that can really improve the forecasting and improve the limitation of one model with another model. Therefore, it is recommended for analyst to consider advanced model such as neural network, artificial intelligence, machine learning and many more to be used in forecasting. Even when developing a hybrid model, it is important to make sure one of the models used is an advanced model. This concept could help improve the forecasting and furthermore help banks make strategy for future development of the country. The outcome of this study, could help the bank strategize the interest rate in a more manner way, assist the government to plan the budget and proper planning can be made by the economist.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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