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Research Article

Bootstrapping the Multilayer Feedforward Propagation System for Predicting the Arrival Guest in Malaysia

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Abstract

Predicting arrival guest is an essential step in estimating the Malaysia economic impact, particularly in short and long-term COVID-19 crisis. Neural Network family of models has been widely used in economic and tourism. Most of the study used single layer of fed forward propagation system, it is because of less sampling variation in Neural Network. However, apparently the multilayer provides a better predicting result but its disadvantage is to deal with high sampling variation. The motivation of this study is to enhance the ability of multilayer Neural Network in predicting the arrival guest. In this study, a hybrid model based on Bootstrapping the Neural Network proposed to predict the arrival guest of Singapore in Malaysia. The weights of variables to the first hidden layer nodes are bootstrapped. The subsequent hidden layer takes the bootstrapped weights in order to obtain the Neural Network output. The prediction obtained by hybrid model has been compared with conventional multilayer Neural Network in terms of small variation. The computational results shows that the hybrid model provides better performance in predicting the arrival guest.

Keywords

Neural Network, Sampling Variation, Bootstrap, Arrival Guest

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Introduction

Predicting arrival guest is an essential step in estimating the Malaysia economic impact, particularly in short and long-term COVID-19 crisis. Report from Malaysian Immigration stated that less than three thousand foreign guests transited with Malaysia authority permission during the Movement Control Order (MCO) phase (MYXpats Centre,2020; Shukri, 2020). Additionally, due to the defense action of closing national border made by Malaysia government, it has reported that there is no recorded foreign guest from neighboring countries, for example Singapore, visiting Malaysia during MCO (Shukri, 2020). Due to this pandemic crisis, Malaysia government designed a Standard Operating Procedure (SOP) structure for domestic tourism in order to regenerate the economic recovery (Shukri, 2020). These reports indicate that tourism plays a part to increase Malaysia's economy stability. Thus, it is important to study the prediction accuracy on foreign arrival guest especially neighboring country, i.e., Singapore, in order to help the government, design a new norm of policy-making that meet the foreign tourism demand.

Neural Network hybrid models has been widely used in predicting arrival guest volume domestically and internationally, see for example (Palmer et al., 2006; Hila et al.,2019; Höpken et al., 2020). Most of researcher used time series approach to predict the volume of guest and in order to generate the non-linearity component in time series, thus, neural network implemented on the hybrid procedure. For example, autoregressive family, Naive I, Markovian and exponential smoothing (Chu, 1998; Hyndman et al, 2002; Chandra et al., 2018; Yao et al., 2020). Most of previous studies used feedforward propagation system where the mapping structure is based on connecting function from input layer to a single hidden layer to output layer. The mapping is activated by an activation function.

Application of single hidden layer in neural network is widely used because it has provided significant small sampling variation (Law and Au, 1999; Constantino et al., 2016; Alamsyah et al., 2019). On the other hand, using multilayer feedforward neural network is reported to has better prediction compare to single layer, see for example (Chu et al, 2019; Pham et al., 2019), studied the double hidden layer recurrent structure and Yusoff et al. (2019) and Noori poor et al. (2020) studied the real application affection of using multilayer perceptron structure. However, unlike single layer, the multilayer often shows high variation of sampling either constructed in hidden layer or input layer (Yu et al., 2009; Zheng et al, 2018).

The high variation eventually could lead to underfitting neural network model. Even though applying the multi hidden layer neural network model onto arrival guest set data manage to analyse the nonlinearity characteristic, however, the underfitting problem eventually causing poor prediction estimator. In order to overcome this issue, some studies had embedded a hybrid or optimized method onto the neural network with another statistical approach. For example, Alameer et al. (2019) uses whale optimization algorithm in order to create learning system of multilayer perceptron neural network, Singh et al. (2019) used a hybrid namely multilayer convolutional neural to obtain accuracy classification result, and Tahir et al. (2016) developed optimization of neural network system and hybrid it with bootstrap method in order to analyze the data set characteristics.

Motivated by the high variation sampling inherit in multilayer neural network system which cause the underfitting model and with the result of previous studies on capability of hybrid the neural network and statistical method, this study proposed to use multilayer feedforward propagation system of neural network model to predict the volume of Singaporean arrival guest in Malaysia during COVID-19 crisis, and hybrid the model with non-parametric bootstrap method. The objective of this study is to reduce the variation sampling in the first hidden layer so that the prediction accuracy of Singaporean arrival guest can improved and eventually helps to predict the Singaporean guest in next two years.

In section 2, hybrid model of bootstrapping the multilayer feedforward propagation system is briefly discussed. The algorithm consists of three main steps which include the explanation of neural network and non-parametric bootstrap. In section 3, result discussion on applying the hybrid model using Singaporean arrival guest volume data set. Prediction accuracy is estimated and prediction of guest volume is shown for 2021- and 2022-time length. The last section is conclusion.

Methodology

Neural Network

Neural network is a machine learning system that has widely used in predicting, either as individual model or as part of hybrid modelling. Standard neural network consists of three layers of processing unit, i.e., input layer, single hidden layer that inherit bias nodes and an output layer that inherit output's bias node. Mapping each processing unit theoretically use many-to-one function to obtain connection line between input layer to hidden layer, and hidden layer to output layer (Kim, 2006; Yu et al., 2009; Hajizadeh et al., 2012).

Multilayer Feedforward Propagation System

In this study, multi hidden layer is considered where the additional connection line of first hidden layer and following hidden layer can be shown in Fig. 3. Based on the Fig. 3 it is a feedforward propagation algorithm where x_j is input variable of input layer with $j = 1, \ldots, n$. w_{jk}^{φ} is weight of φ input layer, j^{th} neuron node row and k^{th} neuron node column. w_{jk}^{l-1} and w_{jk}^{1} are weight of first hidden layer, $l-1$ and second hidden layer l. β_j^l is the weight of bias vector in each neuron in the l^{th} layer, i.e., first hidden layer, second hidden layer and output layer (Hirnik et al., 1989).

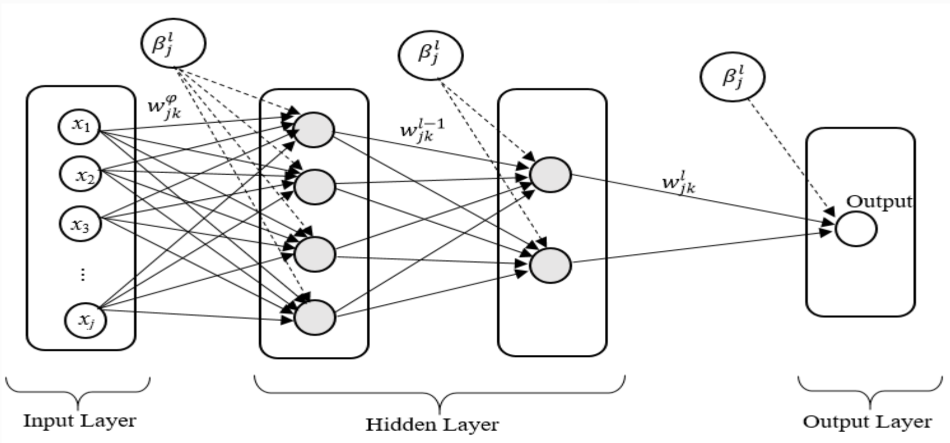

Figure 1. Mapping processing unit in neural network system

The activation function equation of Fig. 1 can be represented as follows:

$$G_j^l = \sum_k w_{jk}^l G_k^{l-1} + \beta_j^l \qquad (1)$$

where G_j^l is the activation function for neuron j in layer l where can be calculated using sigmoid function of following equation?

$$S_x = 1^{(1-e^{-X})} \qquad (2)$$

Considering the Equation (1), thus prediction of Fig. 1 can be represented as follows:

$$z_k = G_k^3\left(\sum_k w_{jk}^3 G_k^2\left(\sum_k w_{jk}^2 G_k^1\left(\sum_k w_{jk}^{\varphi} x_j + \beta_j^1\right) + \beta_j^2\right)\right) + \beta_j^3 \qquad (3)$$

where z_k is output. The $G_k^1\left(\sum_k w_{jk}^{\varphi} x_j + \beta_j^1\right)$ part represent the input layer, $G_k^2\left(\sum_k w_{jk}^2 G_k^1(\cdot) + \beta_j^2\right)$ and $G_k^3\left(\sum_k w_{jk}^3 G_k^2(\cdot)\right) + \beta_j^3$ are part represent the first and second hidden layer respectively. Equation (3) can also be rewrite in vector as follows:

$$z_k = f\left(x_1, \dots, y_j, \beta_j^l, w_{jk}^l\right) + e_k \qquad (4)$$

where β_j^l and w_{jk}^l are the vectors of parameters, f(.) is a function determinate by the network structure and the connection weights, and e_k is residual term of multilayer neural network structure.

Bootstrap

Bootstrap is a computational-persistent data random resampling methodology for assessing the accuracy of statistical estimates. Three particular accuracy indicators impute for bootstrap known as variance, confidence interval and bias. In the absence of any specified assumption distribution, the resampling is known as non-parametric bootstrap (Efron, 1979; Kunsch, 1989; Thompson et al., 2016; Berrar, 2019). Let a random sample, xi drawn from a population *P* with unknown probability function $\mathcal{F}$ that can be represent by following equation:

$$X_i = (x_i, y_i) \qquad (5)$$

is assumed to be independent and identically distributed (IID) with μ and σ^2, $X_i \sim IID(\mu, \sigma^2)$, with *i* = 1, …, *n*. x_i and y_i in Equation (5) are input vector and output vector of sample respectively. Applying the bootstrap to Xi, a set of bootstrap resamples T_n can be obtained and represents as follows:

$$\mathcal{R}_n = \{(x_i, y_i), \dots, (x_n, y_n)\} \qquad (6)$$

where *n* is the size of bootstrap sample $\hat{r}_i$ resulted from empirical distribution function $\hat{\mathcal{F}}$, by giving a mass of 1/*n* for each $r_1, \dots, r_n$ (Efron, 1979; Hila et al., 2016; Lola et al., 2017).

Bootstrap The Multilayer Feedforward Propagation System

The secondary data of monthly volume of Singaporean arrival guest in Malaysia generated in R-Language software in order to examine its statistical descriptive characteristic. Eight years of monthly generated data start from January 2012 until March 2020 are divided into training sample and test sample. Five years were selected as a training sample, while the remaining years is setting for test sample. The composition of neural network model is obtained from the data. In this study, the proposed hybrid model involves several steps:

Step 1: Compose a neural network model, $\mathbf{N}^{(\text{I-H-O})}$ by find the best fitting model that consist of input layer (I), hidden layer (H) and output layer (O). Separate the weight of variables, w_{jk}^2 and weight of bias, β_j^1 from the hidden layer.
Step 2: Implement bootstrap procedure on weights w_{jk}^2 . Resample the w_{jk}^2 using bootstrap size of 1000 to obtain bootstrap resample $\mathcal{R}_{1000} = \left(w_{jk_1}^2, w_{jk_2}^2, \dots, w_{jk_{1000}}^2\right)$. Note that, $\mathcal{R}_n$ is a matrix sample that consist columns of bootstrap size times *jk* rows. Obtain a bootstrap sample, $\widehat{w}_{jk\,i}^{2*}$ by calculating row mean, *jk of* $w_{jk_i}^2$. Replace the original weights variable with $\widehat{w}_{jk\,i}^{2*}$ at first hidden layer.
Step 3: Activate the activation function G_k^{2*} by mapping the $\widehat{w}_{jk\,i}^{2*}$ and β_j^2 to respective neuron nodes of second hidden layer. The activation function G_k^{2*} can be represented as $G_k^{2*} = \sum_k w_{jk}^{2*} G_k^{1*}\left(\sum_k w_{jk}^{\varphi*} x_j + \beta_j^{1*}\right) + \beta_j^2$ and calculated using Equation (2). Note that, implementing the bootstrap on w_{jk}^2 is an initiation to hybrid parameter. Through this, bootstrap weight of $\widehat{w}_{jk\,i}^{3*}$ obtained at second hidden layer. Apply the mapping $\widehat{w}_{jk\,i}^{3*}$ and β_j^3 to output layer can resulted activation function G_k^{3*} which can be represented as follows:

$$z_k^* = G_k^{3*}\left(\sum_k w_{jk}^{3*} G_k^{2*}\left(\sum_k w_{jk}^{2*} G_k^{1*}\left(\sum_k w_{jk}^{\varphi*} x_j + \beta_j^{1*}\right) + \beta_j^{2*}\right)\right) + \beta_j^{3*} \qquad (7)$$

where z_k^* is output for bootstrap neural network prediction model. Refers to Fig.2.

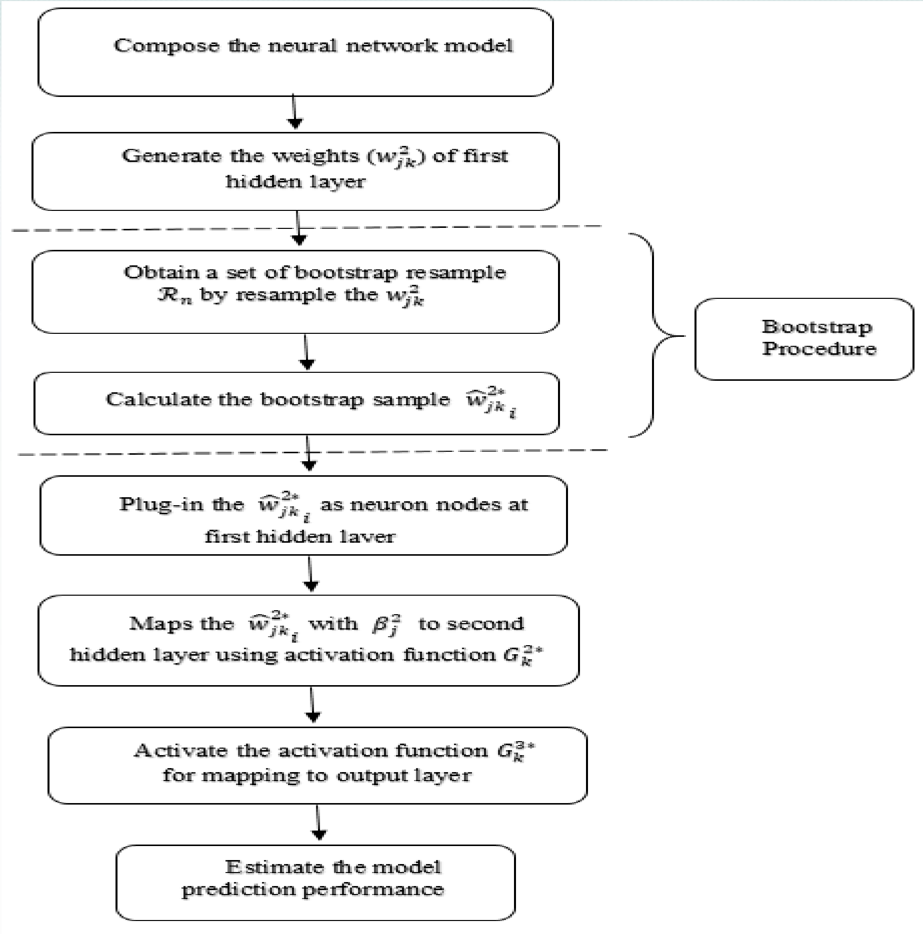

Figure 2. Bootstraping The Hidden Layer of Neural Network Prediction Model.

To evaluate predicting of hybrid model accuracy and its performance, the prediction output of hybrid model, z_k^* is compared with actual output, O_k. Consider that N is sample size which is equivalent to *jk*, thus four generalized error estimation is used. There is correlation coefficient (R), mean squared error (MSE), root mean squared error (RMSE) and mean absolute error (MAE) (Hajizadeh et al., 2012; Mohamed and Rosli, 2014; Hila et al.,2016; Lesnussa et al., 2016; Syed Ahmad et al., 2020) and can be refers as follows:

$$\mathrm{R} = \frac{\sum_{k=1}^{N}(O_k - \bar{O})\left(z_k^* - \overline{z_k^*}\right)}{\sqrt{\sum_{k=1}^{N}(O_k - \bar{O})^2 . \sum_{k=1}^{N}\left(z_k^* - \overline{z_k^*}\right)^2}} \quad (8)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}(O_k - z_k^*)^2 \quad (9)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(O_k - z_k^*)^2} \quad (10)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}|z_k^* - O_k| \quad (11)$$

Result and Discussion

The number of arrival guest of Singapore in Malaysia recorded by Malaysia Immigration Department. The eight years series data contain 99 monthly observations which are corresponding to January 2000 until March 2020. The observation is plotted in Figure 1. Inclusion of data set 2000 and 2018 could be a benchmark patterns of Malaysia having lowest Singapore guest volume in order to learn and restore the tourism sector after COVID-19 crisis. Due to the Malaysia statement of remain closing the national borders until 2021, thus there is no recorded arrival guest data from April until end of December 2020.

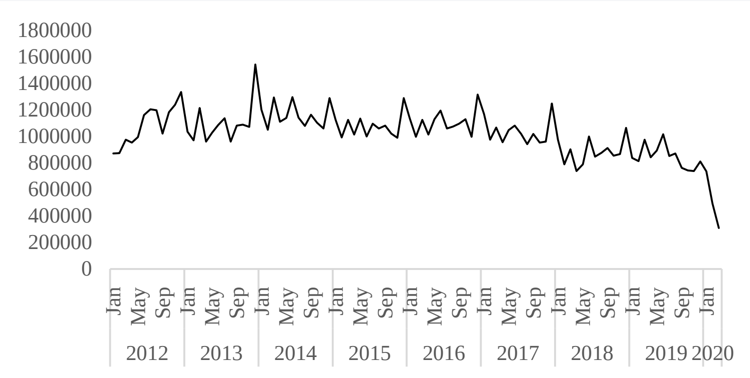

Figure 3. Monthly arrival guest in Malaysia (2012-2020)

Based on Fig. 3, the volume of Singapore guest recorded high peak recursively on each end of year and first quarter of respective year. It might due to the holiday months and festive event organised in Malaysia (Hila et al., 2019). Before COVID-19 crisis spread globally, the highest volume detected on December 2013 until February 2014 and the lowest volume is on April 2018. According to Azari (2019) decreasing volume of Singaporean guest in 2018 is due to traffic congestion at the Johor-Singapore cause- way and changing travel trends among Singaporeans. In 2019, the trends start to increase and fluctuate moderately. However, in first quarter of 2020, due to the Malaysia Movement Control Order and closing national borders, the recorded arrival guest of Singaporean shown the worst declining volume which is 309476 (March 2020). Despite of pandemic issue which cause a dramatic loss on tourism sector, Malaysia has the experience of handling the tourism changing trend in 2018 with dynamic policy-making. Thus, an accurate predicting statistical modelling for this unexpected historical data is important to be learned in the crisis of COVID-19 pandemic in order to well-structured the decision making for next uncertainty year ahead.
Table 1 shows the descriptive statistical of the Singapore arrival guest volume data. The kurtosis in arrival guest has thin-tailed distribution. When conducting the individual distribution identification test it was found that arrival guest series approximated to Weibull distribution with Anderson-Darling test = 0.815 and *p*-value = 0.014.

Table 1.
Data description of arrival guest of Singapore

N	**99**
Mean	1021140
Standard Deviation	175213
Median	1021447
Skewness	-0.67
Kurtosis	2.75
Minimum	309476
Maximum	1543174

In order to predict volume of Singaporean guest visiting Malaysia using the neural network model, the data from Figure 1 is separated to form a training set sample and testing set sample. The training data set contains 72 data and, the remaining 27 (test sample) data is used for validating process or so called as accuracy testing. To be specific, test sample is representing the data on period of January 2018 until March 2020. The best fitted neural network model is composed by **N** $^{(6\text{-}2\text{-}1)}$ where the layers are consists of six inputs, two hidden and one output. The composition of **N**

(6-2-1) can be referred on Figure 2. Based on Fig.2, x1 refers to the volume of each month of train sample and the output refers to the output of neural network model.

Based on the Fig. 4, the composition of neural network has two hidden layer that contain four nodes in first hidden layer and two nodes for second hidden layer. According to Makka and Kumar (2019) the multiple layers of hidden eventually effect the validity of neural network output due to increase number of weights of bias. With the **N** (6-2-1), it has found that seven of weight of bias within the algorithm and this might result of underfitting in neural network system. The underfitting eventually increase the poor predicting for test sample due to the high variance (Makka and Kumar, 2019; Zhang et al., 2019). In order to decrease the variance, this study proposed to use bootstrap method to resample the obtained weight at first hidden layer.

Fig. 5 illustrate the test sample of neural network model. The input variable is referring to x2018, x2019 and x2020. The second and third layer with the blue circle pointing at each node of these layer is a compilation of hidden layer. The last layer is representing by the output. Resampling the weight of each node in first hidden layer eventually result as shows in numerical value in Table 2. Based on Table 2, it shows that bootstrapping has decrease most of the mapping weights but unfortunately increase the second mapping weight value in each node. Interestingly, once the new weight, i.e., bootstrap weight, replace the actual weight in each node of first hidden layer, neural network algorithm produces new calculation and update the recent weights in all following nodes. Refers the differences illustrated in Fig. 6. Based on Fig. 6, the bw1, bw2, bw3 and bw4 refer to values of bootstrap weight, and boutput refers to update output of new neural network algorithm.

Table 2.
Numerical Mapping Weight of First Hidden Layer in Neural Network Algorithm

[a] **Conventional Model**				[b]**Hybrid Model**			
Node 1	Node 2	Node 3	Node 4	Node 1	Node 2	Node 3	Node 4
-0.6007	0.5975	-0.4447	0.4908	-0.9414	-0.9386	-0.9404	0.9588
-0.7924	-0.7877	-0.0294	0.2300	0.8269	0.8797	0.2246	0.2487
-1.3934	2.8053	1.1977	0.4522	0.2614	0.3970	0.3890	0.3938

[a] Conventional Model refers to neural network model without plug-in the bootstrap method
[b]Hybrid Model refers to neural network model hybrid with bootstrapping weight of first hidden layer

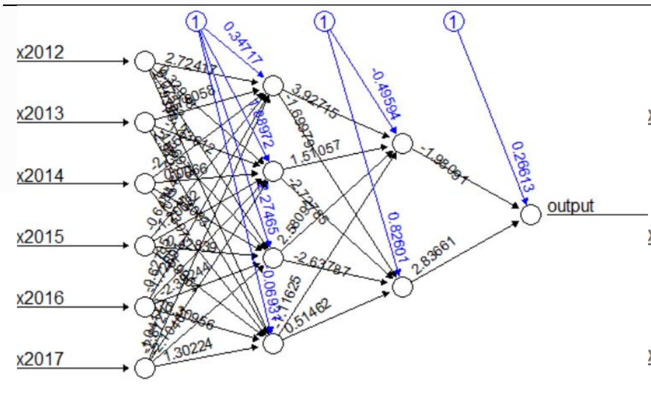

Figure 4. N (6-2-1) of neural network model for Singaporean guest visiting Malaysia

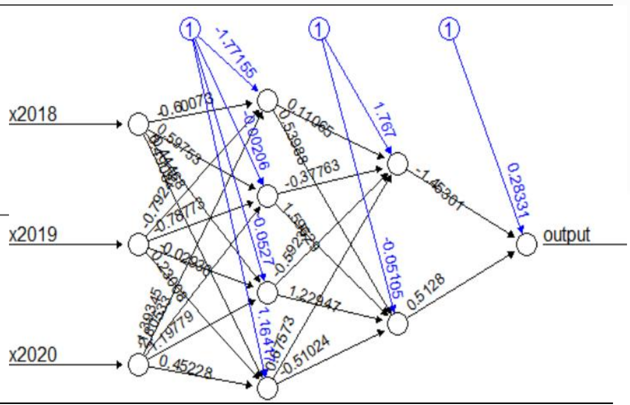

Figure 5. Neural network model for test sample of Singaporean guest visiting Malaysia

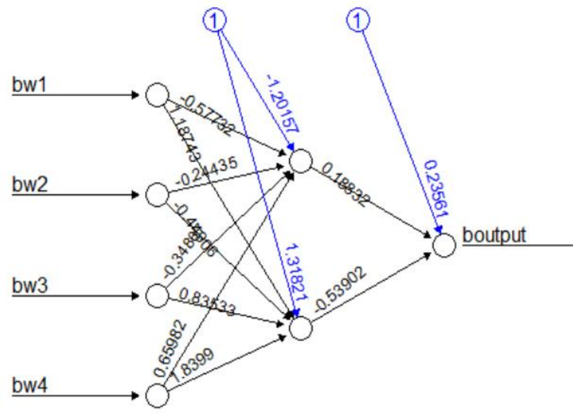

Figure 6. Bootstrap the weight of first hidden layer neural network

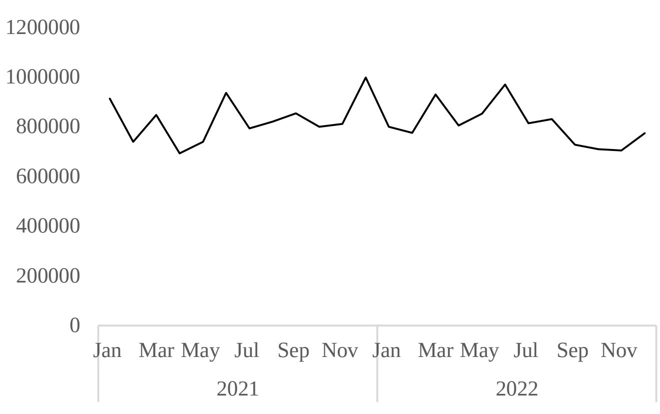

Figure 7. Predicting the Singaporean guest visiting Malaysia during COVID-19 crisis.

As indicated in Table 3, hybrid model gave a high correlation of observed and predicted values of testing data. Robustness of hybrid model is greater as compared to conventional model where it gave greater value of MAE estimation. Despite of having more robust, bootstrapping the hidden layer managed to reduce the variance where the generated error of MSE and RMSE estimation is smaller as compared to the conventional model. Thus, in term of accuracy performance, the designed hybrid model has better performance in predicting the volume of Singaporean guest visiting Malaysia during the pandemic crisis.

During the monthly observation, starting 2018 until 2019, the thousand Singaporean guests. By considering this fluctuation trend, the proposed model is applied to predict the arrival of thousand Singaporean guests. By considering this fluctuation trend, the proposed model is applied to predict the arrival of Singaporean guest for visiting Malaysia in 2021 and 2022.

Table 3.

Comparison Performance of Predicting Using Multilayer Neural Network Model

	R	MSE	RMSE	MAE
[a]Conventional Model	0.99735	0.01186	0.10892	0.09345
[b]Hybrid Model	0.99967	0.01012	0.10062	0.09359

[a and b]Refers to the abbreviation at Table 2.

The predicting plot can be referred in Fig. 7. Based on the figure, it is predicted that a starting volume on January 2021 is 913,049 guests which it is predicable if Malaysia preciously open its national border during COVID-19 crisis. Furthermore, by learning from previous trend of fluctuation, using the hybrid model of neural network, it is predicted that large volume of Singaporean guest visit Malaysia on March, June and December.

Conclusion

This paper has designated the process of predict the volume of Singaporean arrival guest in Malaysia during the COVID-19 crisis, using a proposed hybrid model of bootstrapping hidden layer of neural network. Data applied to construct the hybrid model were obtained from Ministry of Tourism Malaysia. The main focus on bootstrapping the hidden layer because of multilayer eventually resulted the underfitting neural network model. Resample the neuron nodes of first hidden layer could decrease the variation and gave more accuracy on neural network predicting procedure. Thus, the arrival guest data were separated into a training sample and a testing sample in order to construct a composition neural network and examine the variation of predicting accuracy. Experimental results showed that the application of hybrid model has small variation estimation and gave a high correlation between observed and predicted value. This indicate that bootstrapping the hidden layer improve the inherit issue of underfitting neural network model. Also, the hybrid model has better predicting accuracy and reliable to predict the fluctuation trends of Singaporean guest in 2021 and 2022.

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