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# The Effect of Aggregating Bootstrap on the Accuracy of Neural Network System for Islamic Investment Prediction

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**Abstract** Accurate prediction of the stock price is necessary for efficient financial decision making and reconstruction planning, especially during the COVID-19 crisis. Meanwhile, the ARIMA model with neural network approach is a hybrid statistical model that has been used widely in finance and statistics. It could solve the non-linearity problem in ARIMA. However, based on the unreliable sampling variation, the unbalance between the linearity and nonlinearity parts in the hybrid model could lead to inaccurate prediction. This matter motivates the purpose of this study, where the authors aim to balance the linearity and nonlinearity of the hybrid model towards predicting the Islamic investment during the Malaysia Movement Control Order (MCO). In this study, Islamic investment is analyzed using statistical based model of ARIMA. In order to balance linearity and nonlinearity parts of ARIMA which is outperforming the unreliable sampling variation, the aggregating bootstrap approach is used on ARIMA. The resampled linearity and nonlinearity parts will be declared as inputs of neural network system in order to predict the Islamic investment. Resampled nonlinearity part will be generated in this system and its sampling variation is examined. In addition, the performance of model procedure is estimated. It shows that the aggregating bootstrap gives smaller bias values and generates small weights in neural network system. In terms of prediction, applying the resampled procedure in neural network system eventually increases the precision of prediction estimation where it reduces the error estimation of MAE and MSE. Also, the prediction values continually align with actual values of investment at MCO phase. Balancing the linearity and nonlinearity part using the aggregating bootstrap in major procedure of prediction field contributes to high precise prediction of Islamic investment return estimation. The uncertainty of investment returns during MCO phase is a challenging phase and affects Malaysia financial trading. By considering using alternative procedure proposed in this study, i.e. helps in providing accuracy of investment prediction returns, a well-construct financial decisions and plans could be structured during MCO. However, this study limits to examine the effect of aggregating bootstrap. For further research, it is suggested to apply prediction on 10 years returns of Islamic investment using the proposed method.

**Keywords** Aggregating Bootstrap, Neural Network, Islamic Investment, COVID-19

# 1. Introduction

Financial investment is an important sector in Malaysia. During the widespread of COVID-19, Malaysia has announced the first phase of Movement Control Order (MCO) starting from 18th March 2020. Since then, the trading activities at Bursa Malaysia were reported to decline, especially after the ramification of MCO extension. For example, FBM KLCI decreased until 0.74% in April 2020 Murugiah [1]. However, the trading is reported to show active trading after the Recovery Movement Control Order (RMCO) announcement on 40th June 2020. This matter gives positive effect on economic growth Surendran [2]. In addition, the Islamic stock trading is said to have moderately fluctuate compared to the conventional stock [3] and it might affect badly during the MCO phase. These reports indicate that during the global pandemic crisis, the financial investment sector is part of Malaysia economic contributor. Thus, the precise prediction of the stock returns for the investment decision is needed since the investment decision solely depends on the accurate expected returns.

There are many studies that have proved that the hybrid time series model with machine learning such as Autoregressive Integrated Moving Average (ARIMA) Neural Network models is more accurate than single application model [4,5,6]. The nonlinear mapping structure of the neural network could overcome the nonlinear component in ARIMA. In this case, the nonlinear relationship structure and random characteristic of the stock prices [4,5,8] contribute to this matter. However, nonlinear mapping structure in neural network system inherent generated bias within each hidden layer and output layer [9,10,11]. It could lead to underfitting and overfitting problems in learning train and test, respectively. In such case, theoretically, neural network ARIMA model is not an appropriate tool for the stock return prediction.

Motivated by generated bias that leads to underfitting and overfitting hybrid model, this study proposes aggregating bootstrap to be plugged-in on ARIMA prediction estimation. As stated by [12-15], the effect of sampling variation, i.e. reducing bias, can be assessed by resampling the prediction variable, for example stock returns. Plug-in the aggregate bootstrap, theoretically, reducing the inherent bias of nonlinear component of ARIMA. Generating the unbiased nonlinear component of bootstrap ARIMA eventually overcomes the inherent bias in mapping structure in neural network system.

The objective of this study is to examine whether generating unbiased nonlinear component of bootstrapping ARIMA model can improve the accuracy of neural network system in predicting the stock returns. In Section 2, proposed model of aggregating bootstrap for neural network is briefly discussed. In Section 3, the proposed model is applied on selected conventional stock and Islamic stock. The proposed model performance also discuss in this section. In the last section, i.e. Section 4, provides the conclusion remarks.

# 2. Methodology

This study applies Autoregressive Integrated Moving Average (ARIMA) of time series model. The ARIMA was introduced by Box and Jenkins [16,17]. It is acknowledged as the practically prediction method for univariate time series trends data. In the study, log returns of Islamic s tock from MCO phase period will be used to show the trends. Let say the ARIMA model is denoted as ARIMA($p$,$d$,$q$), where it is a combination of number of autoregressive parameter ($p$), number of integration parameter ($d$) and number of moving average parameter ($q$) terms .

Let

$$\epsilon_t \sim NID(\mu, \sigma^2) \tag{1}$$

where $\epsilon_t$ is a noise and it is assumed to normal and independent and identically distributed with $\mu = 0$. By considering the noise in (1), the ARIMA($p$,$d$,$q$) model can be referred as follows :

$$\varphi_p(L)\nabla^d y_t = \theta_q(B)\epsilon_t \tag{2}$$

where $y_t$ refers to the observed value at time $t$, $\varphi$ is the parameter weights of the autoregressive, $\theta$ is the parameter weight of moving average, and $\nabla^d$ is differencing operator. Once all parameters of $(\varphi, \nabla^d, \theta)$ are s elected and fitted to the ARIMA model, the past observation data can be treated as a linear function.

The ARIMA model is ascertained as the best fits if the model could minimize three criteria of Information Criterion, i.e. i) Akaike Information Criterion (AIC), ii) small-sample corrected Akaike Information Criterion (AICc) and iii) Bayesian Information Criterion (BIC)[16,18]. These Information Criterions can be formulated as follows:

$$\text{AIC} = 2k - 2\ln(\hat{L}) \tag{3}$$

$$\text{AICc} = \text{AIC} + \{(2k^2 + 2k\,)/(n - k - 1\,)\} \tag{4}$$

$$\text{BIC} = \ln(n)k - 2\ln(\hat{L}) \tag{5}$$

where $k$ iindicates the number of estimated parameters in ARIMA model in (1), $\hat{L}$ indicates the maximum value of the likelihood function for (1), and $n$ is sample size for time series information data.

Linear and nonlinear components of ARIMA model eventually will go through the resampling procedure of aggregating bootstrap. Generally, aggregating bootstrap is a data-driven simulation method that has been used extensively to determinate the variance and biasness. According to [12], bootstrap samples obtained through resampling a sample data with replacement procedure. By the resampling, it provides a statistical information regarding the average and variability of actual, unknown distribution that yield to resolve the biasness associated with the estimate [10,14,15].

Let $T$ be a population with unknown probability function $F$ where each sample, $t_i$ drawn from this population is assumed to be independently and identically distributed:

$$t_i = (x_i, y_i) \text{ and } t_i \sim IID(\mu, \sigma^2) \tag{9}$$

where $x_i$ refers to a input vector and $y_i$ refers to corresponding output vector.

Let $T_n$ is a bootstrap resample of (9) which can be represented as follows:

$$T_n = \{(x_i, y_i), \dots, (x_n, y_n)\} \tag{10}$$

where $n$ is the size of sample $\hat{t}_i$. It is obtained from empirical distribution function $\hat{F}$ by putting a mass of $1/n$ for each $t_1, \dots, t_n$. Therefore, a set of bootstrap samples can be obtained. The set samples could be denoted as $T^1, \dots, T^S$, where S refers to the sample size of bootstrap samples [12,21].

By reducing the inherent variance and bias of nonlinear component, the neural network system will be affected. Neural network is known as a part of machine learning families. It has been widely used for prediction in the time series modelling. A neural network system is based on a nonlinear model which encompasses a structural mapping procedure. It starts from the input layer into the hidden layer and lastly into the output layer [19,20]. The mapping procedure can be referred to Fig. 1.

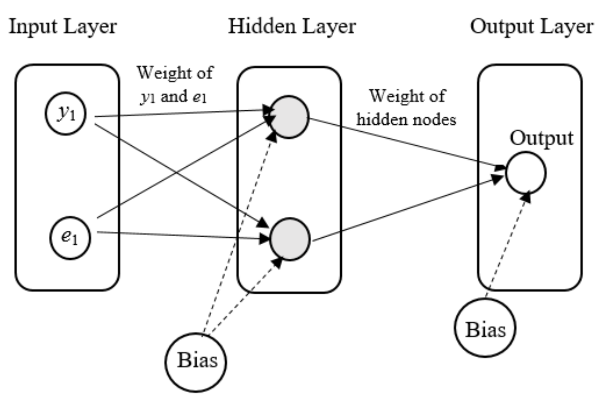


**Figure 1.** A complete structural mapping procedure of a neural network system

Based on Fig. 1, it shows that the neural network system involves three layers, i.e. input layer, hidden layer and output layer. Fig. 1 shows a single layer mapping procedure. However, in some cases, the neural network system works with multilayer mapping where the hidden layer contains more than one layer. For example, [19] highlight on multihidden layer in his research. The input layer contains with nodes for input variable, which is $y1$ and $e1$. Both nodes carry particular weights which map to nodes of hidden layer. Each node in the hidden layer contains bias value and particular weights. These nodes map for output (as viewed by the grey circle) and have their own calculated bias value.

Interestingly, the structural procedure in Fig. 1 is also recognized as feedforward propagation learning algorithm. The propagation contains a single input layer ($y_i = y_t, e_t$), one hidden layer and one output layer. Within the hidden layer, it contains two neuron nodes, and a neuron node at the output layer. A significant bias node ($\gamma$) estimated within both hidden layer and output layer. The neural network prediction from the mapping procedure can be simplified as follows:

$$z_{t+1} = \gamma_0 + F\left(\sum_{j=1}^{M} \omega_j G\left(\gamma_j + \sum_{i=t-(p-1)}^{t} \omega_i y_i\right)\right) + \varepsilon_t \tag{6}$$

where "$t$ +1" represents the one step ahead prediction of neural network, $\left(\gamma_j + \sum_{i=t-(p-1)}^{t} \omega_i y_i\right)$denotes the input layer that contains input variables $y_i$, an activation function $G$ and connection weights $\omega_i$ ($i$ = 0, 1, 2, …, $t$). The $\mathrm{F}\left(\sum_{j=1}^{M} \omega_j \mathrm{G}(\cdot)\right)$ denotes the hidden layer that comprises of a new activation function, $F$ and another connection weights, $\omega_j$ ($j$ = 0, 1, 2,…, $M$). Meanwhile, $\gamma_j$ and $\gamma_0$ denotes as bias nodes values of hidden layer and output layer, respectively. In this notation, $\varepsilon_t$ is the residual term of neural network system.

In this study, the sigmoid function is selected to be an activation function. It can be written as follows:

$$\mathrm{Sig}(x) = 1^{-(1-e^{-X})} \tag{7}$$

Therefore, (6) performs a nonlinear component that mapped the past observation into the predicted value such that:

$$z_{t+1} = f\left(y_{t-(p-1)}, \dots, \gamma, \omega\right) + \varepsilon_t \tag{8}$$

where $\gamma$ and $\omega$ denote as the vectors of parameters and $f(.)$ is a function defined by the network structure and the connection weights.

In general, the application of log returns of Islamic stock during the MCO phase has linear and nonlinear components. Some researchers reported that embedded the time series model into neural network system eventually combined both components [14,15]. Furthermore, the nonlinear component fits the weight of bias definition in the neural network system. Thus, it can be used for imprecision estimation. Therefore, in order to reduce the variation and biasness of both components for better prediction of Islamic stock investment, the aggregating bootstrap was applied in this study.

In order to generate the linear component, the returns of conventional and Islamic stock investment data were fitted by ARIMA model. The generated fitted stocks data were divided into train sample and test sample. The selected data for the train sample starts from the first wave of the MCO phase in Malaysia (from 18 March 2020) until the middle of the RMCO phase (which is 28 August 2020). Meanwhile, the range of test sample is within the RMCO phase (1 September 2020 until 5 October 2020).

The test sample from the RMCO phase data is fitted to ARIMA model which comprises of linear and nonlinear component parameters. It is denoted as $x_t$ and $k_t$, respectively. It can be written as follows:

$$Y_t = x_t + k_t \tag{11}$$

where $Y_t$ is actual value. The aggregating bootstrap applied on $x_t$, so (11) can be rewrite as follows:

$$Y_t^b = x_t^b + k_t^b \tag{12}$$

From (12), a residual of aggregating bootstrap of RMCO phase denotes as $e_t^b$, where it can be obtained as follows:

$$e_t^b = Y_t^b - \hat{x}_t^b \tag{13}$$

In (13), $\hat{x}_t^b$ is the prediction data. By (13), the nonlinear relationship is defined as $f(\cdot)$ in the neural network, such that:

$$\hat{e}_{t+k}^b = f\left(e_t^b, e_{t-k}^b, \dots\right) + \varepsilon_t^b \tag{14}$$

where $\hat{e}_{t+k}^b$ is the prediction of nonlinear component at time $t + k$ (or one step ahead, i.e. $t + k$) and $\varepsilon_t^b$ is residual of neural network at time $t$. Therefore, the combination of linear and nonlinear components can be calculated using the following prediction equation:

$$\hat{Y}_{t+k}^b = \hat{x}_{t+k}^b + \hat{e}_{t+k}^b \tag{15}$$

The function in (15) also represents the proposed model as follows:

$$Y_t^b = f(x_t^b, e_t^b) \tag{16}$$

The (16) can also be used for train data (from MCO until the middle of RMCO phase data).

# 3. Result and Discussion

In this section, the data sets of Malaysia Government Securities Long Term investment-Islamic GO180002 data and conventional stock price-MT180003 data are used in order to obtain the objective, i.e. the effectiveness of the proposed hybrid model during the Covid-19 crisis. Both data sets and its returns activities are compared. Several times series from different phase of Malaysia Movement Control Order (MCO), i.e. first MCO, Enhanced Movement Control Order (EMCO), Conditional Movement Control Order (CMCO), Semi Enhanced Movement Control Order (SEMCO) and Recovery Movement Control Order (RMCO) also will be considered. Both conventional and proposed models have been applied to the Government MGS Long Term investment data set. The study considers the one step ahead forecasting. Moreover, in order to evaluate the prediction performance of the models, four performance estimations such as MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error) are considered [23-26].

Log returns predictions of an investment are an essential task in financial field. The application of neural networks helps to improve the nonlinear theoretical component in the financial model. The data applied in this study are focusing on daily return from previous investment activities, starting from 18 March 2020 until 5 October 2020. During this period, the Islamic stock of GO180002 and conventional stock of MT180003 give 101 and 103 data points, respectively. The continuous daily price is used to calculate the logarithmic returns. The data points plot are shown as Fig. 2 and Fig. 3.

Based on Fig. 2 and Fig. 3, both stocks have a stable increasing price and moderate fluctuations of returns. However, during the early phase of MCO declaration, the conventional stock has dropped down to the lowest return, but managed to increase and stable the returns during the inter-phase of EMCO (refer Fig. 3b). Interestingly, the conventional s tock has a dramatic fluctuation within two weeks of July (during the RMCO).

It started with slight decreasing value on the first of July until seventh of July, and eventually gave the highest returns in the following week. Meanwhile, the history of Islamic stock returns shows stable fluctuation. By referring to Fig.1b, it shows active fluctuation points from MCO until EMCO period. The lowest return value was detected in EMCO phase, but started to stable from CMCO until RMCO phase.

Table 1 shows the basic statistical characteristic of the returns series data for both stocks. It shows negative estimation of skewness, which means that both stocks characterized as leftward asymmetry or approximate to half-normal distribution. Based on vaulting or eccentricity coefficient (i.e. greater than 3 value estimation), it is found that both stocks are more arching during the MCO phases. The kurtosis in conventional stock and Islamic stock advocate that the daily returns have fat-tailed distribution. By individual distribution identification test, it was found that the return series for both stocks are approximated to Weibull distribution. The study of daily returns activity has an important role for investors, statisticians and social economic scientists especially during the MCO phase.

The conventional and Islamic stock data have been widely studied with enormous concepts of linear and nonlinear time series models, including family of ARIMA and neural network [5,8]. In order to apply the ARIMA model in these two stock data, the daily returns are tested for best-fitted estimation. Table 2 shows the selection of ARIMA models for conventional and Islamic stock based in-sample prediction error of AIC, AICc and BIC. From the table, the information loses by ARIMA(1,0,2), ARIMA(2,0,1) and ARIMA(1,0,1) obtain small results as compare to other models. But, interestingly, for auto-correlation function estimation, the variation of residual found to be constant and lack of correlation when applying the ARIMA(2,0,1) on both stocks (refer Fig. 4). This matter shows that this model is the best fitted in predicting the stock returns activity for conventional and Islamic stocks during the MCO phase.

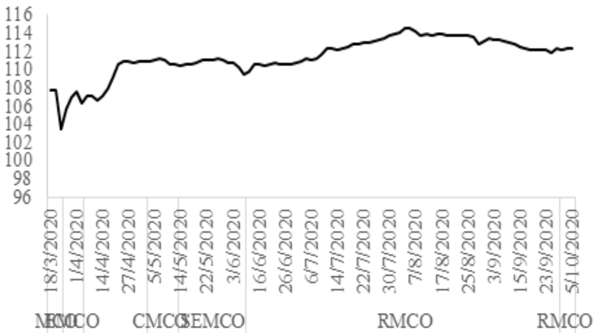


**Figure 2a.** Islamic stock daily price


**Figure 2b.** Islamic stock logarithmic return

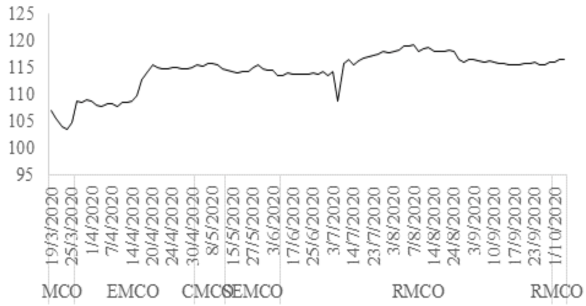


**Figure 3a.** Conventional stock daily price

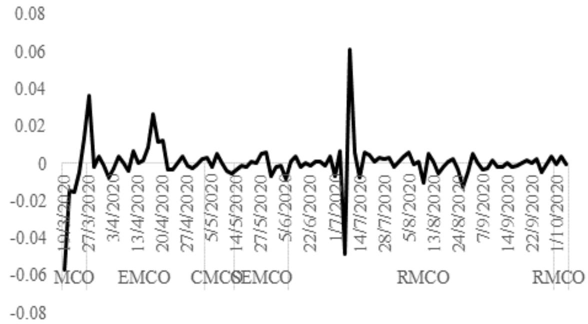


**Figure 3b.** Conventional stock logarithmic return

**Table 1.** Data description of daily returns of Islamic stock (GO180002) and conventional stock (MT180003)

| | Islamic Stock | Conventional Stock |
|---|---|---|
| N | 101 | 103 |
| Mean | 0.00047 | 0.00025 |
| S.D. | 0.00587 | 0.01159 |
| Median | 0.00031 | 0.00047 |
| Skewness | -3.13 | -0.08 |
| Kurtosis | 27.74 | 15.68 |
| Minimum | -0.04167 | -0.05684 |
| Maximum | 0.02157 | 0.06139 |

S.D is standard deviation

**Table 2**. Result of best-fitted ARIMA models applying for stock returns.

| Models | Islamic stock GO180002 | | | Conventional stock MT180003 | | |
|---|---|---|---|---|---|---|
| | AIC[a] | AICc[b] | BIC[c] | AIC | AICc | BIC |
| ARIMA (2,1,2) | -734.94 | -734.30 | -721.91 | -606.08 | -605.45 | -592.95 |
| ARIMA (2,1,1) | -736.29 | -735.87 | -725.87 | -608.07 | -607.66 | -597.57 |
| ARIMA (1,1,1) | -734.33 | -734.08 | -726.52 | -609.56 | -609.31 | -601.68 |
| ARIMA (1,0,2) | -747.84 | -747.21 | -734.76 | -617.95 | -617.33 | -604.77 |
| ARIMA (2,0,1) | -748.69 | -748.05 | -735.61 | -617.77 | -617.15 | -604.60 |
| ARIMA (1,0,1) | -748.67 | -748.25 | -738.21 | -623.40 | -622.99 | -612.86 |

[a]Refers to Akaike Information Criterion. [b]Refers to small-sample corrected Akaike Information Criterion. [c]Refers to Bayesian Information Criterion.

Eventually, linear and nonlinear component created from ARIMA (2,0,1) were applied in neural network system's model. In order to obtain prediction performance in neural network model, the data set of stocks returns are divided into two samples, i.e. train sample and test sample. The train sample is used to construct the formulation of a neural network model while the train sample is specifically used to investigate the model performance. The training data set contains 82 data and the remaining 21 and 19 data from conventional stock and Islamic stock, respectively, were used for test sample. In line with the Covid-19 situation, the train sample is selected within the MCO, EMCO, SEMCO, CMCO and middle phase of RMCO. Meanwhile, the remaining RMCO phase period data are used as test sample data.

By using the *neuralnet* algorithms in R-Language software, the best fitted neural network model is selected for conventional stock and Islamic stock. The model is composed by N(2-1-1) where the layers consist of two inputs, one hidden and one output. By referring to Fig. 5 and Fig. 6 of N(2-1-1) neural network system, yt1 and et1 are referring to the linear component of y1 and nonlinear component of e1, while output and output1 represent the output of the neural network and aggregating bootstrap neural network, respectively.

Based on the Fig. 5 and Fig. 6, by applying the proposed model, the aggregating bootstrap could decrease the bias value. For example, during the MCO phase, the bias value of the Islamic stock decreases at the second nodes of the hidden and output layer. Additionally, some weights value for both stock also decreases.

The prediction for estimated values of Neural Network and proposed model by using the stock test sample data (for RMCO phase) are plotted as Fig. 7a and Fig. 7b. In these figures, it appears that the prediction values from both models continuously align with actual values of return for conventional and Islamic stock. However, both models predict a high return over a loss for actual value on 11th until 13th day of RMCO phase for Islamic stock and 15th day of RMCO phase for conventional stock. Thus, the proposed model is shown to outperformed neural network as the predicted returns are consistently resemble the values of actual return.

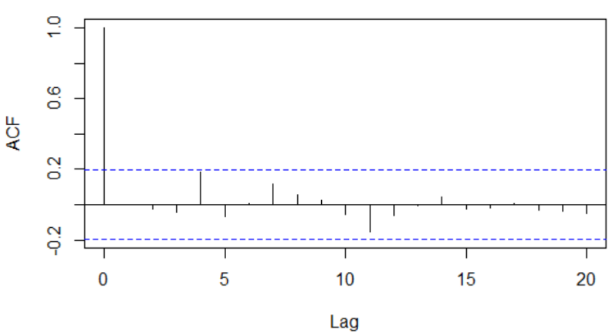


**Figure 4a.** ACF of residuals from ARIMA (2,0,1) applied to Islamic stock

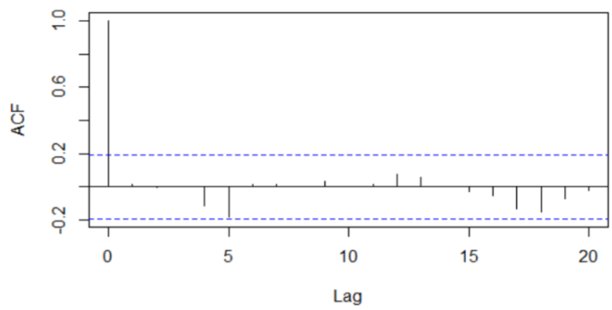


**Figure 4b.** ACF of residuals from ARIMA (2,0,1) applied to conventional stock

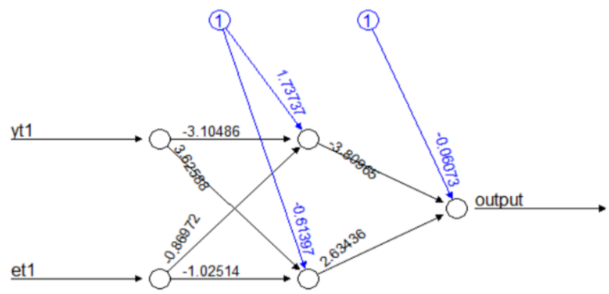


**Figure 5a.** Neural network system for Islamic stock data during MCO phase

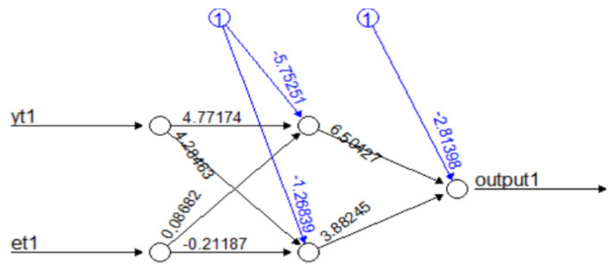


**Figure 5b.** Aggregating Bootstrap for Neural network system for Islamic stock data during MCO phase.

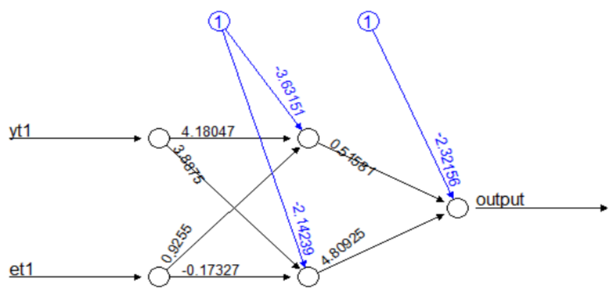


**Figure 6a.** Neural network system for conventional stock data during MCO phase

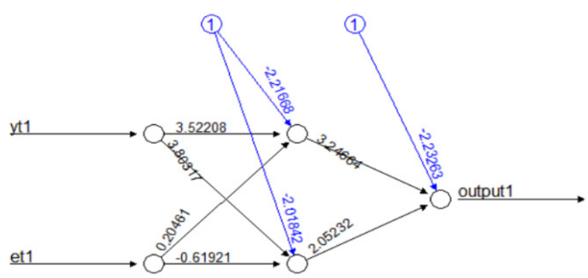


**Figure 6b.** Aggregating Bootstrap for Neural network system for conventional stock data during MCO phase

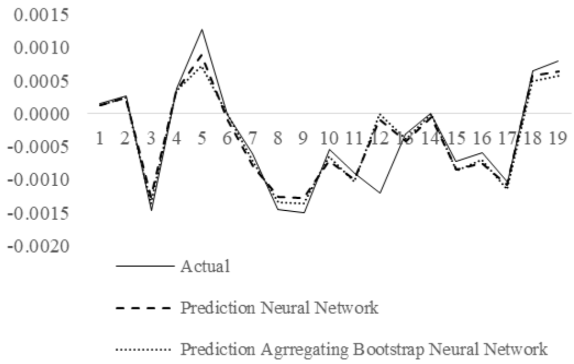


**Figure 7a.** Estimated prediction of Islamic data

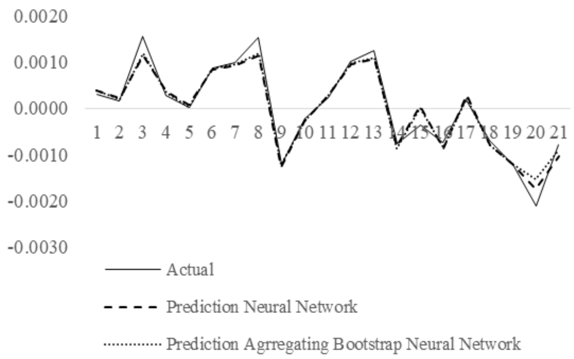


**Figure 7b.** Estimated prediction of conventional data

In order to validate the significance of the outperform performance for the proposed model, the MASE and MAE estimation for the train sample (MCO phase) are measured. Meanwhile, for the test sample (RMCO phase), the MSE, RMSE, MAPE, VAF and MAE estimation are measured. The performance measure results are reported in Table 3. According to the measurement values, the proposed model shows small errors. Moreover, the VAF is found to be greater than 80%. Eventually, the proposed model could be categorized as full mediation [22, 27]. The mediation effect in time series data prediction supports the opinion of [5], where there is full mediation effect whenever a neural network algorithm is involved in calculation.

Moreover, in order to validate the proposed model, comparison prediction by using the MAE and MSE indicators are considered. The detail results are reported in Table 4. It shows that by applying the neural network, the prediction of s tock returns could be improved. Interestingly, consistent with the result in Table 4, the aggregating bootstrap reduced the error of estimation for the neural network in both conventional and Islamic stock returns data. This may suggest that aggregate bootstrap outperformed the neural network model in terms precision prediction of the volatility returns during the RMCO phase.

**Table 3.** Performance measures of the proposed model for both stock data

| | Train (MCO phase) | | Test (RMCO phase) | | | | |
|---|---|---|---|---|---|---|---|
| | MSE | MAE | MSE | RMSE | MAPE | VAF | MAE |
| Islamic | 1.32E-07 | 2.01E-04 | 9.87E-08 | 3.14E-04 | 54.45 | 84.31 | 1.85E-04 |
| Conventional | 1.14E-07 | 1.46E-04 | 3.98E-08 | 2.00E-04 | 42.79 | 95.71 | 1.53E-04 |

**Table 4.** Comparison of the performance of the prediction proposed model with single neural network model

| Model | Islamic data | | Conventional data | |
|---|---|---|---|---|
| | MAE | MSE | MAE | MSE |
| Neural Network | 0.00019 | 9.49E-08 | 0.000161 | 4.33E-08 |
| Aggregating Bootstrap Neural Network | 0.00018 | 9.31E-08 | 0.000158 | 4.16E-08 |

# 4. Conclusions

Improving precision of statistical model estimation is an essential resolution in time series prediction. Numerous hybrid models were proposed in previous studies, and one of them is embedded neural network system in time series model. This hybrid model manages to solve the nonlinearity component and improve the precision prediction. Aggregating bootstrap is also shown to be an effective method in decreasing the bias in a neural network system that eventually increases the prediction precision. Therefore, the main contribution of this study is the development of aggregating boots trap hybrid onto a neural network with the application of Malaysia stock returns data during the Malaysia Movement Control Order phase.

The hybrid model generates unbiased nonlinear component and provides accurate predictions for Islamic stock returns during Malaysia Movement Control Order. Malaysia has experienced uncertainty in financial trading activities impact during the early period of COVID-19 pandemic. The agreement termination, consumer confidence and disclosure of business risk have been burdened the listed companies in Bursa Saham Malaysia. As a result of this matter, trading activities declined excessively due to MCO extension. In order to overcome this predicament, financial decision and economic reconstruction plan need to be addressed. For example, rebate decision given on annual listing issuer, so that the market participants will be flexile. The proposed hybrid model in this study predicts the both stock returns precisely, as the MSE is decreased up to 1.8% and 1.7% for Islamic and conventional investment, respectively. Thus, the hybrid model is recommended as an alternative prediction estimator for time series investment.

However, the hybrid model estimation in this study can be extended on relevant issues. For example, i)large scale of simulation studies on overfitting problem in neural network system by using time series approximate distribution, ii)despite linear model consideration in neural network system and without loss of generality, threshold regression can be replaced for the mapping procedure, and iii)apply the proposed hybrid model to predict 10 years returns of large scale Islamic and conventional investments issued in Malaysia.


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