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COMPARISON OF ARIMA MODEL AND ARTIFICIAL NEURAL NETWORK IN FORECASTING GOLD PRICE

(Perbandingan Model ARIMA dan Rangkaian Neural Buatan dalam Peramalan Harga Emas)

UH BING HONG & NORIZA MAJID

ABSTRACT

Developing an accurate model of gold price is crucial as gold price have a great effect on the investment decisions of individuals, corporations and countries. The purpose of this study is to compare the performance of model Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) in gold price forecasting based on the value of root mean squared error (RMSE). Daily gold price data collected from World Gold Council dated from 3 September 2018 to 30 October 2020 is used in this study. ARIMA (4,1,0) is chosen as the best model for the time series model based on Akaike Information Criterion (AIC). Long short-term memory (LSTM) has been chosen as artificial neural network's method to forecast the gold price. After comparing multiple step forecasting and one step ahead forecasting using ARIMA and LSTM, it is found that LSTM has smaller RMSE as compared to ARIMA. The result in this paper show that the ANN model outperforms ARIMA model in forecasting gold price.

Keywords: gold price; ARIMA; artificial neural network

ABSTRAK

Pembinaan model peramalan harga emas yang tepat adalah penting kerana harganya mempunyai kesan yang mendalam terhadap keputusan pelaburan yang dibuat oleh individu, korporat atau negara. Kajian ini bertujuan untuk membanding prestasi model integrasi purata bergerak autoregresif (ARIMA) dan rangkaian neural buatan (ANN) dalam meramal harga emas berdasarkan punca ralat kuasa dua (RMSE). Data harga emas harian untuk tempoh 3 September 2018 hingga 30 Oktober 2020 yang diperoleh daripada World Gold Council telah digunakan dalam kajian ini. ARIMA(4,1,0) merupakan model terbaik antara model siri masa berdasarkan nilai Kriterion Informasi Akaike (AIC). Dalam kajian ini, memori jangka pendek yang panjang (LSTM) telah dipilih sebagai model ANN. Selepas membandingkan hasil peramalan pelbagai langkah dan satu langkah ke hadapan, model LSTM mempunyai RMSE yang lebih kecil berbanding ARIMA(4,1,0). Hasil kajian ini telah menunjukkan model ANN adalah model yang lebih baik berbanding model ARIMA dalam meramal harga emas.

Kata kunci: harga emas; ARIMA; rangkaian neural buatan

1. Introduction

Gold has intrinsic value which is the value that it has due to its own property and characteristics. According to Sullivan (2020), more people are buying up gold, silver, and other precious metals during the economic crisis. Gold has gained 12.5% in year 2020, beating out most other assets. Gold is a hedge against stocks on average and a safe haven in extreme stock market condition (Baur & Lucey 2010). Based on study done by Ibrahim *et al*. (2014) as mentioned in Gokmenoglu and Fazlollahi (2015), oil and gold prices have extensive economic impacts on financial activities where the volatilities of oil and gold influence the stock price, and create some implications in the capital market of the US and indirectly exhibit itself in inflation and unemployment. Therefore, the gold price and its trend is important for the investors to make their investment decision.

Zhang (2003) stated that artificial neural networks (ANNs) have been extensively studied and used in time series forecasting. The major advantage of neural networks is their flexible nonlinear modelling capability. Hochreiter and Schmidhuber (1997) introduced the long short-term memory (LSTM) which can be applied in time series foreacasting, music composition, speech recognition and so forth. LSTM has sets of gates which can control the flow of information. LSTM has the capabilities to study the long term dependencies in sequence data with memory cell.

Various study on gold price forecasting has been done by many researchers (Okezie *et al*. 2020; Yang 2019; Yaziz *et al*. 2016). Box and Jenkins' state that ARIMA model appears to be one of the broadly applied models in forecasting gold price (Yang 2019). Based on the study by Yang (2019), ARIMA(3,1,2) appears to be the best model for predicting daily gold price by using the international gold closing prices from July 1, 2013 to July 29, 2018. Ping *et al*. (2013) uses ARIMA and GARCH model to predict gold price of Malaysia by using daily data from 18 July to 25 September 2012. Based on lower value of maximum absolute percentage error (MAPE) indicates that GARCH(1,1) is a better model in forecasting the change of the volatility in gold price compared to ARIMA(1,1,1). Besides, Yaziz *et al*. (2016) examines the performances of ARIMA-TGARCH with Gaussian, Student's-*t*, skewed Student's-*t*, generalized error distribution and skewed generalized error distribution in modeling and forecasting gold prices.. Using daily gold price data from the years 2003 to 2014, their study concluded that a hybrid ARIMA(0,1,0)-TGARCH(1,1) with *t*-innovation was the best model due to the existence of leverage effect and heavier tail characteristics in the data.

Mombeini and Yazdani-Chamzini (2015) develop an artificial neural network model which includes seven input parameters, which are USD Index, inflation rate, oil price, interest rate, stock market index ,silver price and world gold production. maximum absolute error (MAE), R^2 and RMSE were used to evaluate the forecasting performance. They conclude that ANN is a powerful tool to model the gold price and can give better forecasting performance than the ARIMA method. Okezie *et al*. (2020) use the monthly data from October 2014 to February 2020 to forecast the gold price using ANN. The ANN [2,6,1] is chosen as the best model as it has a lower value of mean squared error (MSE) and RMSE.

This study has two main objectives. First, to develop gold price forecasting model using ARIMA model and artificial neural network (ANN) and forecast with the model built. Second, to compare the performance of ARIMA model and ANN in order to determine the best model in forecasting daily gold price.

2. Materials and Method

A total of 565 daily gold prices from 3 September 2018 to 30 October 2020 have been obtained from World Gold Council. The data used in this study consists of the historical daily gold price only which is time series data. The data are then splited into 90 percents for training the model and ten percents to test the model trained.

First, to ensure that the time series data is stationary before fitting into the ARIMA model, Augmented Dickey Fuller Test (Dickey & Fuller 1979) is used to test for the existance of unit root. The significance level used in this study is 0.05. If the data is stationary, the data will be fitted into ARIMA model and the model with the lowest Akaike information criterion (AIC) will be chosen as the best model. Ljung Box test (Ljung & Box 1978) will be used to test the residuals of the ARIMA model. The *p*-value of greater than 0.05 will imply that there is not enough evidence to reject the hipothesis null which is the residuals are independently distributed. If the residuals of the ARIMA model is independent, it indicates that the model is adeqaute.

Next, ANN is chosen in this study due to its flexibliliy and capability in modelling. The ANN that will be used is a LSTM model, which is a recurrent neural network (RNN). LSTM has input gate, forget gate and output gate in hidden layer. Input gate controls the update of information in the cell, forget gate controls the reset of the information and output gate controls the information added in hidden layer. These gates help LSTM to learn long term dependencies in sequence data. Thus, LSTM can be used in time series forecasting. In this study, LSTM is built by refering to the website of Mathworks (2020). The process of building LSTM starts with data normalization to ensure that the data is in the range of zero and one which helps to speed up the training process. The numbers of epochs and hidden units will be determined by trial and error method. The performace will be evaluated by comparing the RMSE of the ARIMA model and LSTM.

3. Results and Discussions

Table 1 presents the results of ADF test after differencing once. Therefore, the parameter d in ARIMA(p,d,q) is one as the stationarity is obtained after differencing once.

Table 1: Result of ADF test after differencing once

Test	Statistic value	p value
ADF	-9.1136	< 0.01

Based on the results shown in Table 2, the best arima model is ARIMA(4,1,0) as it has the lowest AIC value. The equations for the ARIMA (4,1,0) is shown as below:

$$y_t = 1.4745 - 0.004 y_{t-1} + 0.1771 y_{t-2} - 0.0459 y_{t-3} - 0.2262 y_{t-4} + \varepsilon_t \quad (1)$$

Table 2: List of AIC values for ARIMA model

Model	Nilai *AIC*
ARIMA (0,1,0)	4180.02
ARIMA (0,1,0) with drift	4177.256
ARIMA (0,1,1)	4182.01
ARIMA (0,1,1) with drift	4179.279
ARIMA (0,1,2)	4165.592
ARIMA (0,1,2) with drift	4164.649
ARIMA (0,1,3)	4167.054
ARIMA (0,1,3) with drift	4165.713
ARIMA (0,1,4)	4159.851
ARIMA (0,1,4) with drift	4155.891
ARIMA (0,1,5)	4161.588
ARIMA (0,1,5) with drift	4157.896
ARIMA (1,1,0)	4182.002
ARIMA (1,1,0) with drift	4179.279
ARIMA (1,1,1)	4183.025
ARIMA (1,1,1) with drift	4180.269
ARIMA (1,1,2)	4167.392

Table 2 (*Continued*)

ARIMA (1,1,2) with drift	4166.331
ARIMA (1,1,3)	4163.079
ARIMA (1,1,3) with drift	4157.458
ARIMA (1,1,4)	4157.004
ARIMA (1,1,4) with drift	4154.438
ARIMA (2,1,0)	4171.981
ARIMA (2,1,0) with drift	4170.77
ARIMA (2,1,1)	4173.813
ARIMA (2,1,1) with drift	4171.536
ARIMA (2,1,2)	4165.688
ARIMA (2,1,2) with drift	4164.088
ARIMA (2,1,3)	4162.338
ARIMA (2,1,3) with drift	4157.175
ARIMA (3,1,0)	4173.28
ARIMA (3,1,0) with drift	4171.716
ARIMA (3,1,1)	4167.087
ARIMA (3,1,1) with drift	4161.674
ARIMA (3,1,2)	4163.438
ARIMA (3,1,2) with drift	4159.725
ARIMA (4,1,0)	4154.062
ARIMA (4,1,0) with drift	4149.974
ARIMA (4,1,1)	4153.005
ARIMA (4,1,1) with drift	4150.284
ARIMA (5,1,0)	4155.746
ARIMA (5,1,0) with drift	4151.948

Table 3 shows the results of Ljung-Box test. The *p*-value of greater than 0.05 indicates that there is not enough evidence that the residuals produced from ARIMA (4,1,0) are correlated. Therefore, ARIMA(4,1,0) is adequate to model the gold price.

Table 3: Result of Ljung-Box test

Degree freedom	Statistic value	*p*-value
5	8.1473	0.1483

Figure 1 shows the forecast value and actual value of gold price from 13 August 2020 until 30 October 2020. Blue line represents the forecast price of ARIMA model and the orange line represents the actual price. The forecast from ARIMA model is far apart from the actual value because of predicting in a long time horizon which has 57 time steps. By using deep learning toolbox in Matlab R2020b software, LSTM which consists of one input layer, hidden layer and output layer is built. LSTM with 72 hidden unit and 100 epochs is chosen to forecast the gold price as it has the lowest error by using trial and error method. Figure 2 shows the prediction value of LSTM. Figure 3 shows that the prediction values are only close to the actual value at a few early time steps and the error increases in the subsequent time steps.

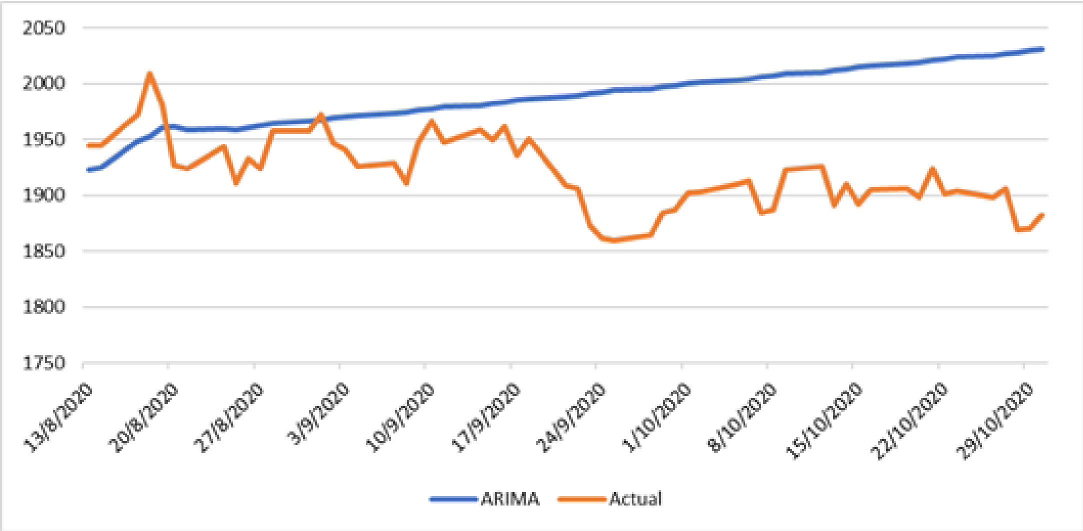

Figure 1: Gold price forecasting using ARIMA model

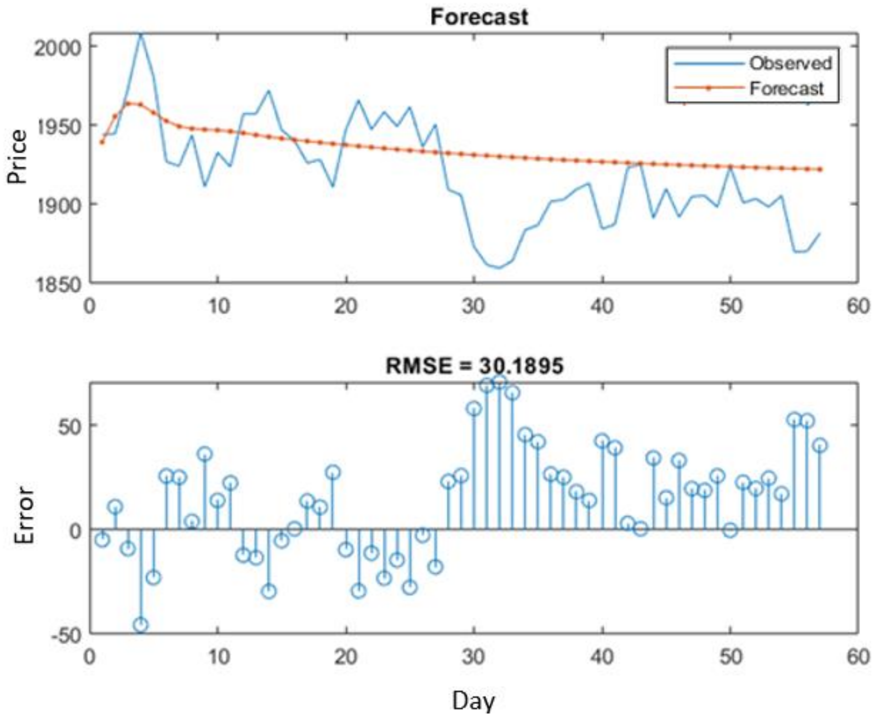

Figure 2: Gold price forecasting using LSTM

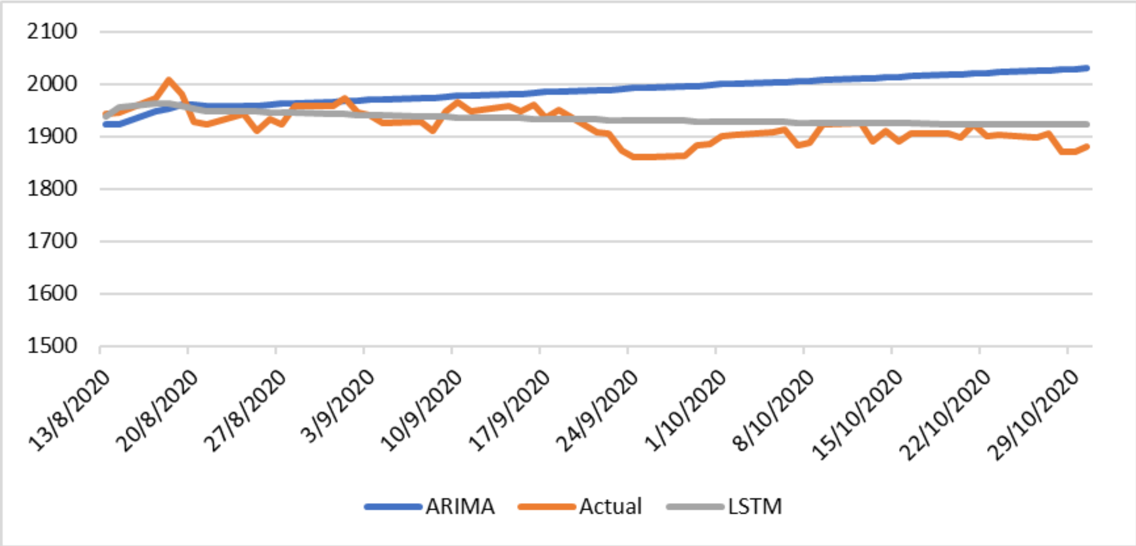

Figure 3: Gold price forecasting in testing set

To further evaluate and compare both the models, one step ahead forecasting is used. Figure 4 and 5 show the results of one step ahead forecasting. The forecasting performance for both models improve a lot as the gap between predicted value and actual value is getting smaller if compared to the previous prediction in testing set.

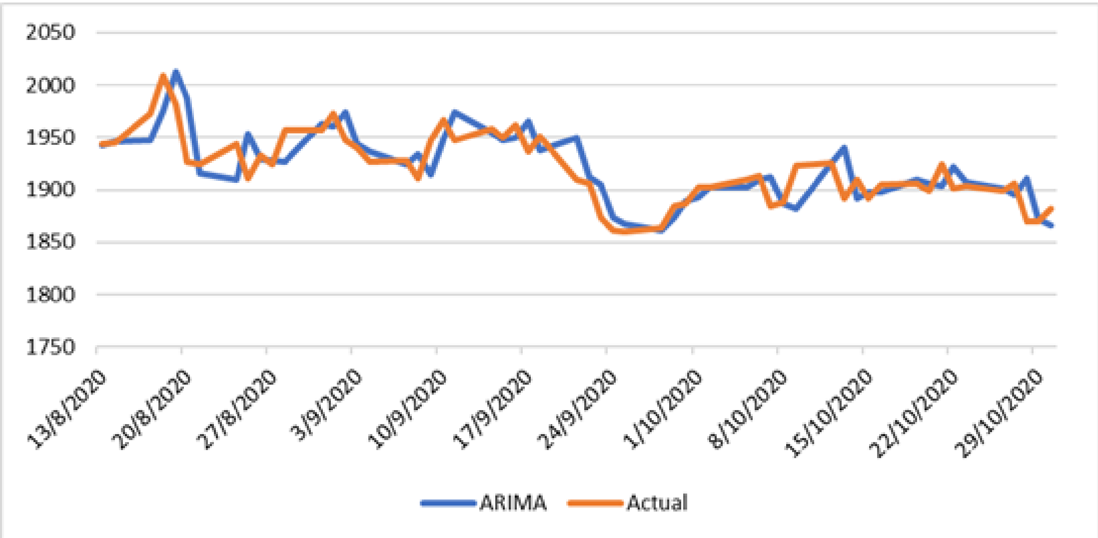

Figure 4: One step ahead forecasting using ARIMA model

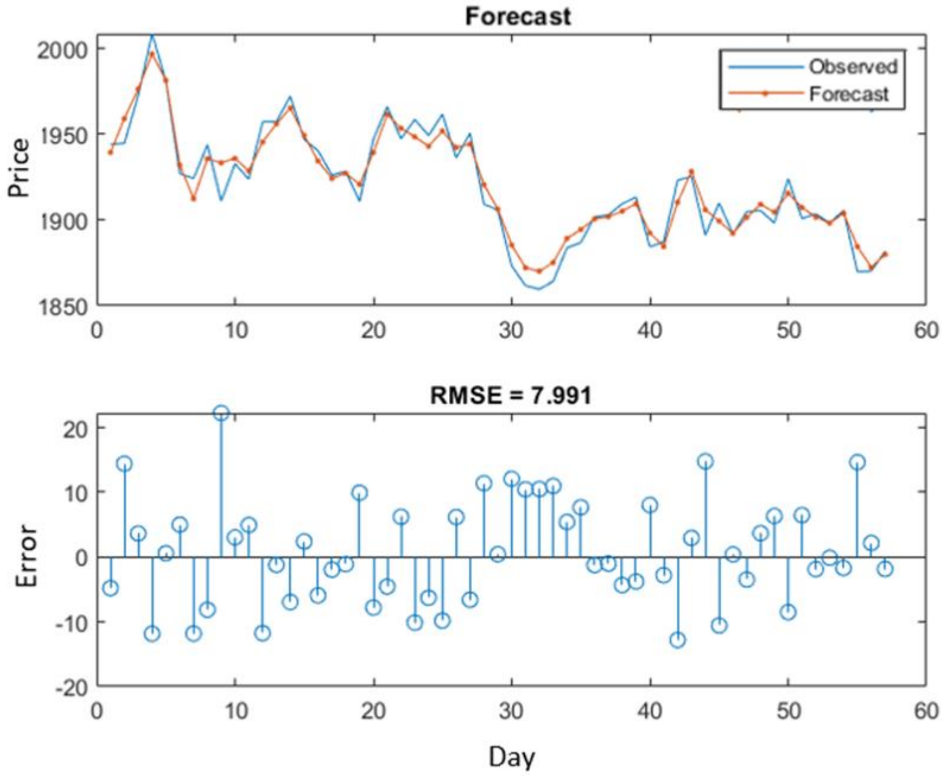

Figure 5: One step ahead forecasting using LSTM

Figure 6 shows the plot of gold price prediction with one step ahead forecasting for both models. Prediction of LSTM is closer to the actual value. Table 4 presents the RMSE of the ARIMA model and LSTM in forecasting gold price. LSTM has lower RMSE in both testing set and one step ahead forecasting if compared to ARIMA model.

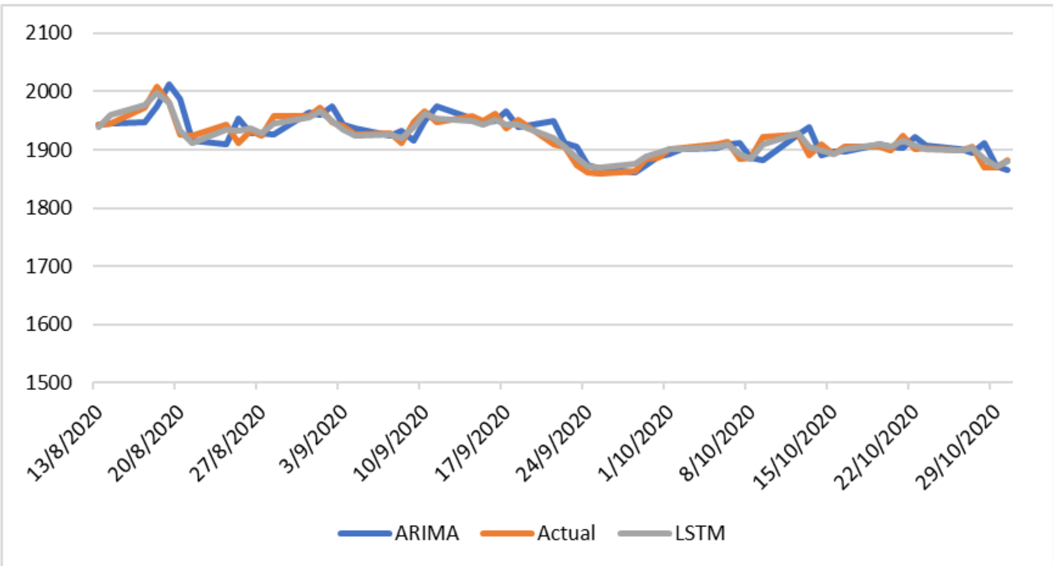

Figure 6: Gold price forecast with one step ahead forecasting

Table 4: RMSE of ARIMA and LSTM

Model	RMSE	
	Testing set	One step ahead forecasting
ARIMA(4,1,0)	87.2472	21.6919
LSTM	30.1895	7.991

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4. Conclusions

The study aims to forecast gold price using ARIMA model and ANN and compare the their performance. LSTM appears to be a better model than ARIMA (4,1,0) based on the value of RMSE. LSTM is able to capture the trend of gold price in one step ahead forecasting. Therefore, ANN is better than ARIMA model in forecasting gold price.

This study has similar result with the research done by Mombeini and Yazdani-Chamzini (2015) where ANN has the lower RMSE when comparing to ARIMA model. NARX was used as the model of ANN in their study which took account of exogenous inputs. Other than that, in the study done by He *et al*. (2019), an integration of LSTM and CNN neural networks with Attention Mechanism was proposed to predict the tendency of daily gold price. The results showed that the proposed model outperforms conventional methods such as ARIMA, deep regression, Support Vector Machine (SVR) and convolutional neural network (CNN). In their study, the vanilla LSTM model, a simple LSTM model without any extra hyrid model was also used. Based on the table which presents the forecasting perforamces of various models, LSTM had a lower RMSE compared to ARIMA model although the LSTM-Attention-CNN had the lowest RMSE. The result where LSTM having a lower RMSE than the ARIMA model is similar to the result of this study.

This vanilla LSTM which only uses the historical gold price as input has its own limitation because there could be various factors that can affect the gold price so there exists a gap between the real value and the forecasted value. The factors that are related to gold price can be included in future study. Extra RNN components can also be added into the network as He *et al*. (2019) suggested to lower the RMSE.

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School of Mathematical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor DE, MALAYSIA
E-mail: nm@ukm.edu.my, bing_hong_uh@hotmail.com*

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*Corresponding author