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COMPARISON BETWEEN ARTIFICIAL NEURAL NETWORK AND AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL IN BITCOIN PRICE FORECASTING

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

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ABSTRACT

In this era of globalization, cryptocurrency is being created as one of the modern investment instruments and an alternative payment method. Many cryptocurrency has been created since the last decade, for examples Bitcoin, Litecoin, Peercoin, Auroracoin, Dogecoin and Ripple. The investment and usage of cryptocurrency is getting popular among the investors and consumers. Bitcoin is one of the most popular cryptocurrencies due to the low-cost-guaranteed transactions and its skyrocketed price. However, the price of Bitcoin depends on the consumers' and investors' speculation. The price volatility has caused losses to many investors. Two forecasting models, which are artificial neural network and the autoregressive integrated moving average (ARIMA) model will be used to forecast the price of Bitcoin. Comparison between the two models will be made and the most accurate model will be selected. Bitcoin price data dated from 1 January 2012 to 28 February 2018 is being used to build the forecasting models. The models will be used to forecast the price of Bitcoin in March 2018, and the predicted values will be used to compare with the actual values. Model building methods, pros and cons of the two models in forecasting will be discussed. Long-term and short-term forecasting will be carried out by using the two models. The suitability of each model in long-term and short-term forecasting will be discussed.

Keywords: cryptocurrency; non-linear autoregressive model; volatility

ABSTRAK

Dalam era globalisasi ini, mata wang digital telah muncul sebagai suatu instrumen pelaburan dan kaedah pembayaran moden. Pelbagai mata wang digital telah diwujudkan sejak sedekad yang lepas, antaranya Bitcoin, Litecoin, Peercoin, Auroracoin, Dogecoin dan Ripple. Pelaburan dan penggunaan mata wang digital semakin mendapat sambutan daripada para pelabur dan pengguna. Bitcoin adalah antara mata wang digital yang paling mendapat sambutan. Keadaan ini adalah disebabkan jaminan kos transaksi yang lebih rendah dan kenaikan nilai Bitcoin secara mendadak. Walau bagaimanapun, harga Bitcoin adalah bergantung pada spekulasi para pengguna dan pelabur. Ketidakstabilan harga Bitcoin juga merugikan banyak pelabur. Dua model peramalan, rangkaian neural buatan dan model autoregresi bersepadu purata bergerak (ARIMA) telah diperkenalkan untuk meramal harga Bitcoin. Perbandingan antara kedua-dua model peramalan dilakukan dan model yang paling tepat dalam peramalan harga Bitcoin telah ditentukan. Data harga Bitcoin dari 1 Januari 2012 hingga 28 Februari 2018 telah digunakan untuk membina model peramalan dalam kajian ini. Selepas model peramalan dibina, peramalan harga Bitcoin untuk bulan Mac 2018 dilakukan dan nilai peramalan akan dibandingkan dengan nilai sebenar. Kaedah pembinaan, kebaikan dan keburukan kedua-dua model dalam konteks peramalan juga dibincangkan dalam kajian ini. Dua jenis peramalan yang berbeza, iaitu, peramalan jangka masa panjang dan peramalan jangka masa pendek dijalankan dengan rangkaian neural buatan dan model ARIMA. Kesesuaian model dalam jenis peramalan yang berbeza turut dibincangkan

Kata kunci: mata wang digital; model autoregresif tak linear; kemeruapan

1. Introduction

In this era of globalization, cryptocurrency is being created as one of the modern investment instruments and an alternative payment method. Many cryptocurrencies have been created since the last decade, for example Bitcoin, Litecoin, Peercoin, Auroracoin, Dogecoin and Ripple. Bitcoin is the most popular and valuable cryptocurrency compared to the others. This is due to its price development and volatility (Ciaian *et al.* 2016).

Bitcoin uses peer-to-peer network as the transaction platform which allows transactions to be done without involving third party or any authorized party. Bitcoin supporters believe Bitcoin can benefit consumers in a few ways, such as it is not manipulated by any institution or any authority, thus it is relatively less prone to exploitation. Besides, users do not need to provide his or her real information to trade Bitcoin. Apart from that, Bitcoin charges lower transaction fee.

From economists' point of view, Bitcoin could function as the alternative payment method if it can serve as a unit of account, a store of value and a medium of exchange (Lo & Wang 2014). Bitcoin failed to operate as real money due to its value which depends entirely on the investors' speculation and its price volatility.

Bitcoin price recorded a significant increase from USD 980 on the 1st of January 2017 to USD 19,182 on the 17th of December 2017, an increase of 1857.34 percent within a year. This situation has attracted many investors to invest in this digital currency. However, Bitcoin price is quite volatile and has dropped from USD 19,182 on the 17th of December 2017 to USD 6,993 on the 5th of February 2018, a sharp decrease of 63.54 percent within 2 months. Bitcoin price volatility and high daily price movements have increased the risk to invest in Bitcoin. This has caused many investors to lose money and shows the importance of Bitcoin pricing forecasting models.

There are several studies which compare between artificial neural network and ARIMA model in forecasting problems. Artificial neural network and ARIMA model are used to predict the number of babies born every month in 2013 in Gaza-Strip (Baker 2015). Bitcoin price forecasting model has been constructed with the reversed Bayesian neural network, long-short term memory network and ARIMA model (McNally 2016). Both studies have shown that artificial neural network's forecasting performance is better than the ARIMA model. Torres and Qiu (2018) have shown that ARIMA model performs better than artificial neural network in One step ahead (OSA) prediction, but the performance of artificial neural networks is better in forecasting for longer periods.

This study has two main objectives, firstly, to develop Bitcoin price forecasting model using artificial neural network (ANN) and ARIMA model. Secondly is to identify the best model in Bitcoin price forecasting. A non-linear autoregressive model with exogenous inputs (NARX) based on multi-layer perceptron (MLP) has been built, the autocorrelation analysis, residual histogram test and cross correlation analysis have shown that the model is a valid model (Indera *et al.* 2018). OSA prediction and regression test have proved that the model can provide a good fit. Studies showed that the ARIMA model (2,1,2) can forecast Bitcoin price accurately (Bakar & Rosbi 2017).

2. Materials and Methods

2.1. *Data*

Price and transaction volume of Bitcoin from January 1, 2012 to April 1, 2018 have been taken from Investing.com. This study uses the Bitcoin price data for the latest five-year period as input data because the Bitcoin price before year 2012 is very low and difficult to obtain.

Besides that, there are 2283 data for the specified time period and this number meets data requirement by time series analysis. Moving average of Bitcoin price for 5 days, 10 days, 20 days, 50 days and 100 days is calculated by using the daily Bitcoin closing price to include trend of Bitcoin price in the short and long run. The formula for calculating the moving average is as shown in (1):

$$MA_n = \frac{\sum_{i=1}^{n} P_i}{n} \tag{1}$$

where MA_n is the moving average for n days, P_i is the Bitcoin price on the day i in the n time period.

2.2. *Development of artificial neural network*

Planning the structure of a neural network is a crucial step before developing it. The process is divided into several parts as follows:

2.2.1. *Data normalization*

This study uses two different data normalization method which are log-transformation followed by differencing and min-max scaling. The formula for log-transformation followed by differencing is as shown in (2):

$$x_i^* = \log_{10}(x_i) - \log_{10}(x_{i-1}) \tag{2}$$

where x_i is the Bitcoin price on day i, while x_i^* is the log-transformed and differenced data. The formula for min-max scaling is as shown in (3):

$$x_{\text{scale}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

where x is the Bitcoin price, while x_{scale} is the value after scaling which will be used as the input data for the neural network.

2.2.2. *Data distribution*

Data will be divided into three parts namely data to train the neural network, data for model validation and data to test model accuracy with ratio 70:15:15.

2.2.3. *Determining the neural network structure*

The price movement of Bitcoin is a time series model. Many factors that cause the price of Bitcoin to change. Based on the research by Ciaian *et al*. 2016, the main factors in determining the price of Bitcoin includes its supply and demand, the effect of latest news on Bitcoin and investors' speculation about Bitcoin. Almeida *et al.* (2015) built four models of single layer feed-forward neural network to predict the changes in price of Bitcoin. The findings suggested that the model that includes the historical price, price trend and trading volume would give more accurate prediction.

Indera *et al.* (2018) has developed NARX model to forecast the closing price of Bitcoin for the next day. A few validation tests including autocorrelation analysis, residual histogram plot, cross correlation analysis has been done and the model is proved to be unbiased. Thus, this non-linear autoregressive model with exogenous input (NARX) is selected. Factors other than the closing price of Bitcoin are considered as the exogenous input to the model. The number of input nodes is the same as the number of variables in the input data. There are 10 variables in the input data, thus there will be 10 input nodes. The number of output nodes depends on the duration of the forecast. 1 output node will be used for OSA forecasting while 31 output nodes will be used for 31-steps forecasting. The NARX model is being set up in a way that every output node equals to the closing price forecast of a day. We only need to forecast the closing price of the next day in OSA forecasting, thus only one output node is being used. As for 31-steps forecasting, we need to forecast the closing price for the next 31 days, thus we will need 31 output nodes. The number of hidden nodes is determined by using rule of thumb followed by trial and error. According to the rule of thumb, the number of hidden nodes has to be the number between the number of input and output nodes. Trial and error is done by changing the number of hidden nodes to look for the model with lowest mean squared error (MSE) and mean absolute error (MAE). The resulting best model is being tabulated in Table 1.

Table 1: Number of hidden nodes in the best NARX model for different data normalization and types of forecasting

Data normalization	Type of forecasting	Number of hidden nodes in NARX model with lowest MSE and MAE
Log-transformed followed by differencing	OSA forecasting	5
Log-transformed followed by differencing	31-steps forecasting	31
Min-max scaling	OSA forecasting	4
Min-max scaling	31-steps forecasting	18

2.3. *Development of ARIMA model*

Stationarity of time series data have to be tested by using Augmented Dickey–Fuller (ADF) test, Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and Phillips–Perron (PP) test. If the time series is not stationary, log transformation and data differencing have to be done. The optimal parameter for ARIMA model have to be determined by using the autocorrelation function (ACF) and partial autocorrelation function (PACF) plot. The Akaike information criterion (AIC) of the ARIMA models should be calculated and the model with the lowest AIC value is the best model for forecasting. The best ARIMA model can be further confirmed by using the `auto.arima()` function in R software.

2.4. *Model validation test*

The model validation tests for NARX model include residual histogram, regression analysis, ACF and PACF plots while the model validation tests for ARIMA model include residual histogram, ACF and PACF plots only. The model is unbiased if the residual histogram shows a Gaussian bell-shaped curve, proving the residuals are randomly distributed. Regression analysis measure the relationship between target and desired output where value which is higher than 0.95 indicates that the model is a good fit. For ACF and PACF plots, most of the correlation coefficient in between the 95% confidence limit indicating that the model can be accepted and the error occurs randomly.

2.5. *Model accuracy test*

Model accuracy test include mean squared error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

3. Results and Discussion

3.1. *Bitcoin price forecasting with ARIMA model*

There are three parameters required by an ARIMA (p,d,q) model. The optimal value for parameter d is 1 as the data of the time series is only being differenced once to obtain a discrete white noise series. To determine the optimal parameter p and q, ACF and PACF plots are needed. ACF plot of the log-differenced time series enter the significant zone at the second stroke, thus the parameter q most probably will be 1 or 2. PACF plot of the log-differenced time series enter the significant zone at the third stroke, thus the parameter p most probably will be 2 or 3. The model with the lowest AIC value is the best model as shown in Table 2.

Table 2: AIC Values

ARIMA model	AIC value
(2, 1, 1)	-9842.82
(2, 1, 2)	-9897.13
(3, 1, 1)	-9866.42
(3, 1, 2)	-9933.53

Table 3 shows the MSE, MAE and MAPE value of the OSA and 31-steps forecasting with ARIMA (3, 1, 2), which is the best fit ARIMA model for Bitcoin price since it has the lowest AIC value.

Table 3: MSE, MAE and MAPE value of Bitcoin price forecasting for ARIMA (3, 1, 2)

Type of forecast	MSE	MAE	MAPE
OSA	223677.6000	368.3578	4.1981
31-steps	11035195.0000	2952.5800	36.4006

Figure 1 and 2 show the forecast value and actual value of Bitcoin price from 2 March 2018 until 1 April 2018. Dotted line showing the forecast value while the blue line showing the actual value of Bitcoin price. The results show that ARIMA model is more accurate in OSA forecasting, while the 31-steps forecasting of ARIMA model produces unacceptable results, where the MAPE value is higher than 5. The output of ARIMA model depends linearly on its own previous values and on a stochastics term, thus it will become less accurate when it is use for long-term forecasting.

3.2. *Bitcoin price forecasting with NARX model using log-transformed and differenced input data*

Table 4 shows the MSE, MAE and MAPE value of the OSA and 31-steps forecasting with NARX model using log-transformed and differenced input data. The results show that this model is quite accurate in OSA forecasting, but the resuts of 31-steps forecasting, which is the longer term forecasting is not acceptable where the MAPE value is higher than 5.

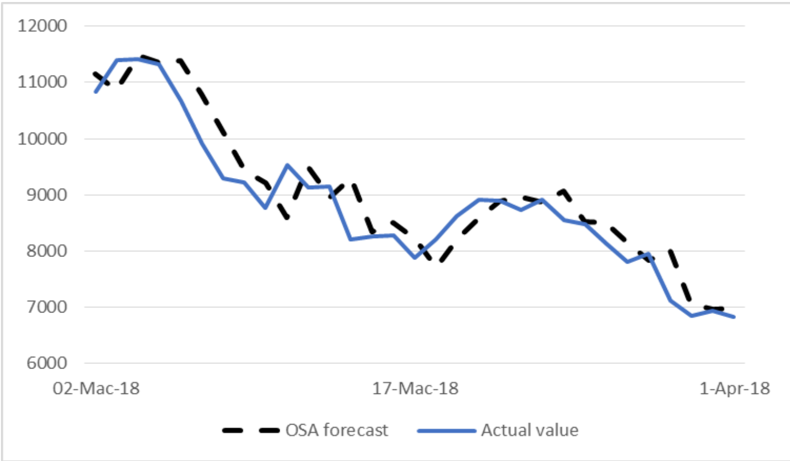

Figure 1: OSA forecast value using ARIMA model and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

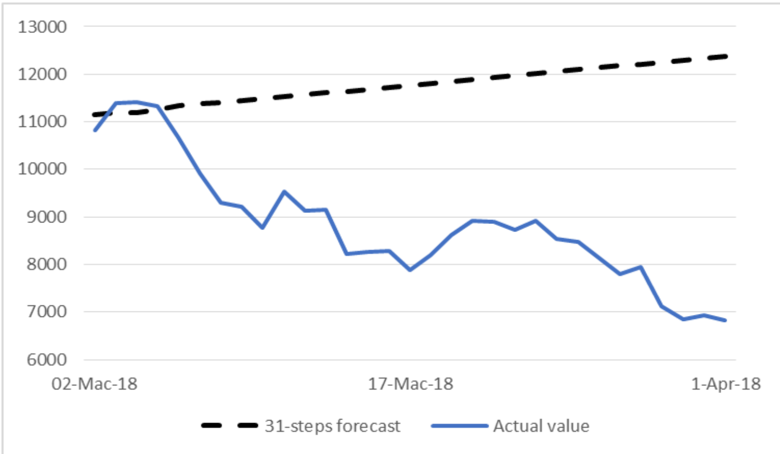

Figure 2: 31-steps forecast value using ARIMA model and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

Table 4: MSE, MAE and MAPE value of Bitcoin price forecasting with NARX model

Type of forecast	MSE	MAE	MAPE
OSA	168176.0000	323.2193	3.6745
31-steps	4501840.0000	1922.4190	23.5379

Figures 3 and 4 show the forecast value and actual value of Bitcoin price from 2 March 2018 until 1 April 2018. Dotted line showing the forecast value while the blue line showing the actual value of Bitcoin price.

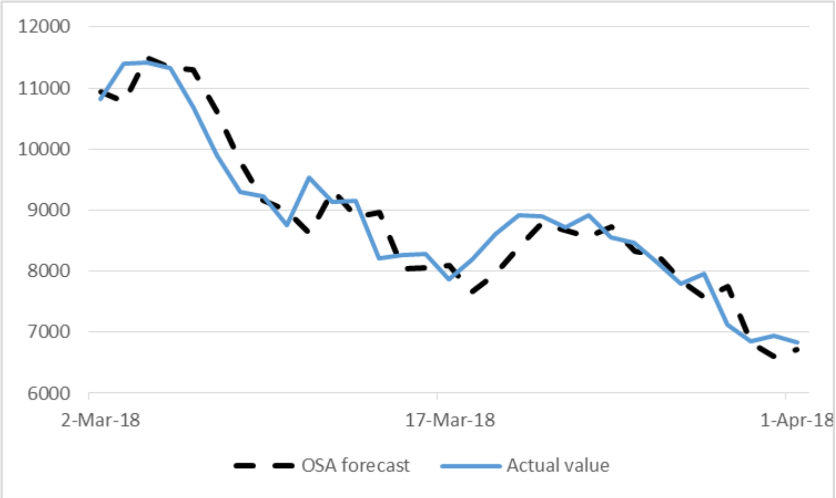

Figure 3: OSA forecast value using NARX model (with log-transformed and differenced input data) and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

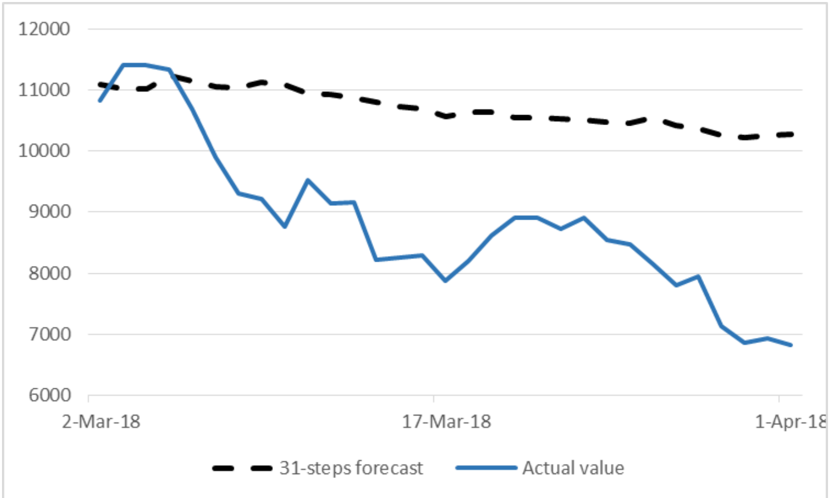

Figure 4: 31-steps forecast value using NARX model (with log-transformed and differenced input data) and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

3.3. *Bitcoin price forecasting with NARX model using min-max scaled input data*

Table 5 shows the MSE, MAE and MAPE value of the OSA and 31-steps forecasting with NARX model using min-max scaled input data. Both OSA and 31-steps forecasting show acceptable and accurate results where the MAPE value is less than 5. This model is suitable to be used for both long and short term Bitcoin price forecasting.

Table 5: MSE, MAE and MAPE value of Bitcoin price forecasting with NARX model

Type of forecast	MSE	MAE	MAPE
OSA	197619.7000	349.2068	4.0556
31-steps	237446.5000	363.9348	4.2780

Figure 5 and 6 show the forecast value and actual value of Bitcoin price from 2 March 2018 until 1 April 2018. Dotted line showing the forecast value while the blue line showing the actual value of Bitcoin price.

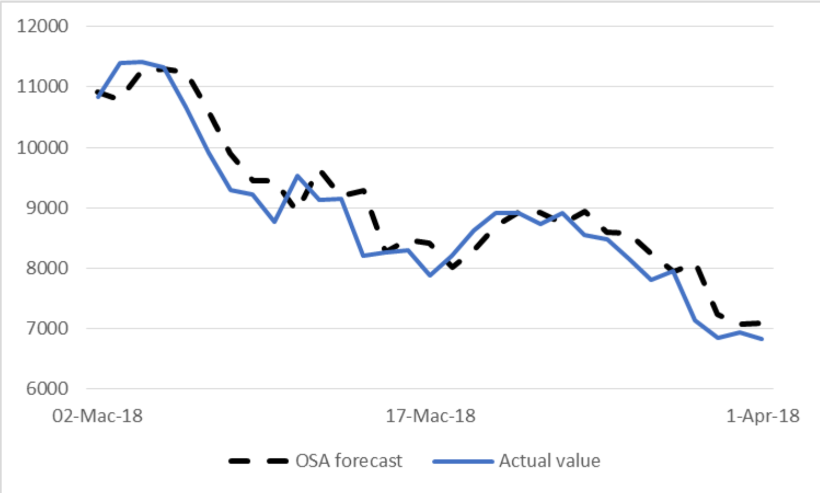

Figure 5: OSA forecast value using NARX model (with min-max scaled input data) and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

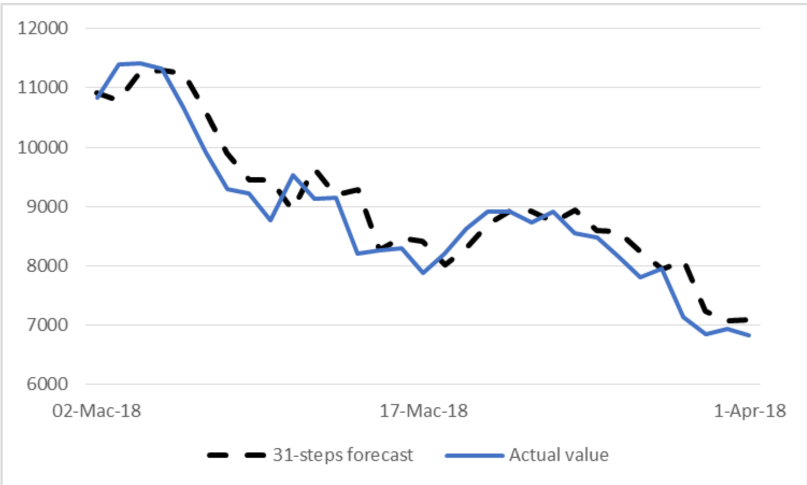

Figure 6: 31-steps forecast value using NARX model (with min-max scaled input data) and actual value of Bitcoin price from 2 March 2018 until 1 April 2018

4. Conclusions

NARX model is more accurate as it has lower MAPE value in both OSA and 31-steps forecast. In OSA forecast, NARX model using log-transformed and differenced input data is the most accurate, as it has the lowest MAPE value but the difference between the 3 models are not significant. Both ARIMA and NARX model can be used for OSA forecast. In 31-steps forecast, NARX model using min-max scaled input data outperform the other two models as it has a much lower MAPE value compared to the other models. However, we suggest that ARIMA model is more suitable for OSA forecast since ARIMA model require less data. Hence, it is more cost-efficient. For NARX model using min-max scaled input data, we suggest that it is more suitable for long-term forecast as it has a much lower MAPE value compared to the other two models.

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