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Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Cryptocurrency Exchange Rate in High Volatility Environment: A New Insight of Bitcoin Transaction

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***Abstract*— *The cryptocurrency is a decentralized digital money. Bitcoin is a digital asset designed to work as a medium of exchange using cryptography to secure the transactions, to control the creation of additional units, and to verify the transfer of assets. The objective of this study is to forecast Bitcoin exchange rate in high volatility environment. Methodology implemented in this study is forecasting using autoregressive integrated moving average (ARIMA). This study performed autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis in determining the parameter of ARIMA model. Result shows the first difference of Bitcoin exchange rate is a stationary data series. The forecast model implemented in this study is ARIMA (2, 1, 2). This model shows the value of R-squared is 0.444432. This value indicates the model explains 44.44% from all the variability of the response data around its mean. The Akaike information criterion is 13.7805. This model is considered a model with good fitness. The error analysis between forecasting value and actual data was performed and mean absolute percentage error for ex-post forecasting is 5.36%. The findings of this study are important to predict the Bitcoin exchange rate in high volatility environment. This information will help investors to predict the future exchange rate of Bitcoin and in the same time volatility need to be monitor closely. This action will help investors to gain better profit and reduce loss in investment decision.*

Keywords*— *Cryptocurrency, Bitcoin, ARIMA model, Volatility, Error diagnostics.

I. INTRODUCTION

Technology is being presented as something new as it drives change at an ever-increasing rate (Chaharbaghi and Willis, 2000). The accelerating of technology give an impact on pervades aspect of human life. Technology is convergence of computing, telecommunications and imaging technologies has had radical impacts on IT users, their work, and their working environments. In its various manifestations, IT processes data, gathers information, stores collected materials, accumulates knowledge, and expedites communication (Chan, 2000), plays an important role in many aspects of the everyday operations of today's business world.

In response to a new technological shift, criminals and consumers alike are increasingly finding new ways to evolve (Reynolds and Irwin, 2017). Therefore, accelerating technology was introduced many financial mechanisms such as bitcoin cryptocurrency.

A bitcoin cryptocurrency transaction is a new mechanism in digital currency. A bitcoin transaction was introduced based on cryptographic, allowing two parties to transact directly with each other without the need for a trusted third party. This transaction are computationally impractical to reverse would protect sellers from fraud, and routine escrow mechanisms could easily be implemented to protect buyers (Nakamoto, 2009). Blockchains are a software protocol that underlie bitcoin cryptocurrency in one sense, are nothing more than a modernizing information technology, but in another sense, are novel and disruptive (Yeoh, 2017). Cryptocurrencies, such as Bitcoin, rely on a de-centralised system based on peer-to-peer public key addresses, rather than having a central regulating body, such as a financial institution or bank, which reviews and monitors transactions. This allows potential criminal transactions to be processed through cryptocurrencies, as the process of moving money is quicker and more efficient due to the bypassing of the regulatory controls that third-party institutions, such as banks, are legally bound to perform.

This situation makes a bitcoin transaction faced with high volatility due to uncontrolled by professional body.

Volatility is a statistical measure of the dispersion of returns for a stock market. Volatility of stock markets has created much attention among investors because high volatility can bring high returns or losses to investors (Abu Bakar and Rosbi, 2017). This situation creates a risk to investors, because a rational investor always makes an investment decision based on risk and return (Lee, et al., 2016). Even there are many study focus on the volatility but no previous study are examine the volatility of bitcoin cyptocurrency using ARIMA model. Therefore this study try to fulfil this gap by investigates the volatility of bitcoin cryptocurrency using ARIMA model. According to Brailsford and Faff (1996) identify the best volatility forecasting technique is a critical job because a best predict volatility forecasting techniques not only depends on data availability and predefined assumption but also depends on the quality of data (Lee, et al., 2016; Abraham et al, 2007).

II. LITERATURE REVIEW

A number of studies have been undertaken on how the volatility is reflecting on the real returns that investors earn. Most of the previous study are investigates the performance of stock market. Study from Faff and McKenziet (2007) concluded that low or even negative return autocorrelations are more likely in situations where: return volatility is high; price falls by a large amount; traded stock volumes are high; and the economy is in a recessionary phase.

While, Abu Bakar and Rosbi (2017) investigate the reliability of Box–Jenkins statistical method to forecast the share price performance for Oil and Gas sector in Malaysia Stock found that the performance of Gas Malaysia Berhad can be forecast accurately using Autoregressive integrated moving average (ARIMA) model of (5,1,5). Similar to Malaysia, Balli and Elsamadisy, (2012) compare the linear methods, the seasonal ARIMA model provides better estimates for short-term forecasts in the State of Qatar. The range of forecast errors for the seasonal ARIMA model forecasts are less than 100 million Qatar Riyadh for the short-term currency in circulation (CIC) forecasts.

The significance of forecasting method in the stock market is also presented by Stevenson (2007), examines issues relating to the application of forecasting method. The results highlight the limitations in using the conventional approach in order to identify the best-specified ARIMA model in sample, when the purpose of the analysis is to provide forecasts. The results show that the ARIMA models can be useful in anticipating broad market trends; there are substantial differences in the forecasts obtained using alternative specifications.

Although study from Jadevicius and Huston (2015) suggests that ARIMA is a useful technique to assess broad market price changes. Government and central bank can use ARIMA modelling approach to forecast national house price inflation. Developers can employ this methodology to drive successful house-building programme. Investor can incorporate forecasts from ARIMA models into investment strategy for timing purposes. If this player can predict the future changes in investment, they can modify future investment and reorganize strategic planning (Abu Bakar and Rosbi, 2017)

A more recent study, Coskun and Ertugrul, (2016) suggest several points. First, city/country-level house price return volatility series display volatility clustering pattern and therefore volatilities in house price returns are time varying. Second, it seems that there were high (excess) and stable volatility periods during observation term. Third, a significant economic event may change country/city-level volatilities. In this context, the biggest and relatively persistent shock was the lagged negative shocks of global financial crisis. More importantly, short-lived political/economic shocks have not significant impacts on house price return volatilities. Fourth, however, house price return volatilities differ across geographic areas, volatility series may show some co-movement pattern.

El-Masry and Abdel-Salam (2007) examine the effect of firm size and foreign operations on the exchange rate exposure of UK non-financial companies. They found that a higher percentage of UK firms are exposed to contemporaneous exchange rate changes than those reported in previous studies. In summary, while there has been a multitude of literature in the stock market literature concerned with the performance of stock market determinants, little attention has been placed on the forecasting of bitcoin cryptocurrency volatility.

III. RESEARCH METHODOLOGY

This section describes the forecasting procedure involving Bitcoin exchange rate. The process starting with data selection process then followed by forecasting process using autoregressive integrated moving average (ARIMA) method.

3.1 Data selection process

This study selects monthly data for Bitcoin exchange rate starting from January 2013 until October 2017. The data are collected from *https://www.coindesk.com*.

3.2 Forecasting procedure

This study forecast the performance of Bitcoin exchange rate using the statistical procedure as shown in Fig. 1. The

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forecasting process is start with the identification of the data model using autoregressive integrated moving average (ARIMA). In developing ARIMA model, analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF) need to be performed. Then, this research need to develop estimation of the parameter for chosen ARIMA model. In validating the model, diagnostics checking need to be developed. The residual is the difference between the observed value and the estimated value of the quantity of interest (sample mean). The residual should be uncorrelated, zero mean and zero variance. Then, forecasting and error checking stage can be performed.

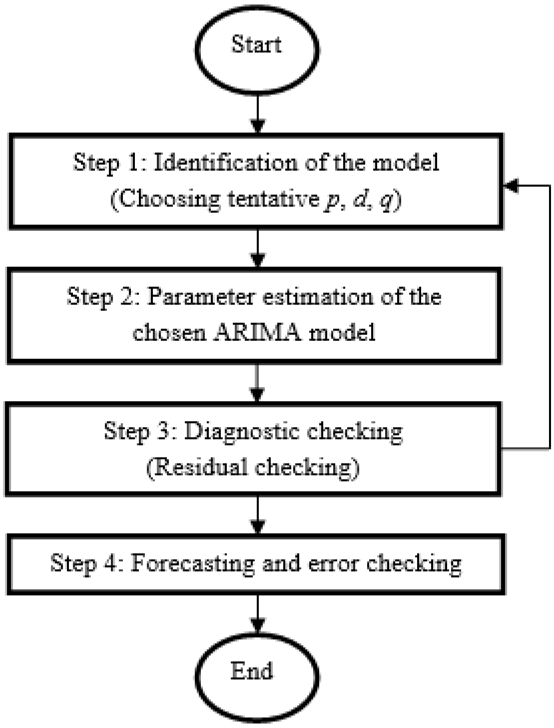

Fig. 1: Statistical forecasting procedure

3.3 Mathematical derivation of ARIMA model

This section describes mathematical derivation of autoregressive integrated moving average (ARIMA). This method is combining autoregressive (AR) with moving average (MA) method. Then, this hybrid method is integrated with data of difference process. The difference process is important to make sure data involved in this analysis can be represented as data with stationary characteristics. Therefore, the combination of this method is called as autoregressive integrated moving average.

Firstly, this study describes the derivation of autoregressive (AR) method. An autoregressive (AR) model is a representation of a type of random process. It is used to describe certain time-varying processes in time series data. The autoregressive model specifies that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term). Thus, the model is in the form of a stochastic difference equation.

The notation AR (*p*) indicates an autoregressive model of order *p*. The AR (*p*) model is defined as:

$$X_t = c + \varphi_1 X_{t-1} + \ldots + \varphi_p X_{t-p} + \varepsilon_t$$

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \text{ ……………………………... (1)}$$

where $\varphi_i, \ldots, \varphi_p$ the parameters of the model, c is constant, and ε_t is white noise.

Then, this study derived the equation for moving average (MA). The moving-average model specifies that the output variable depends linearly on the current and various past values of a stochastic (imperfectly predictable) term. MA of current deviation from mean depends on previous deviations.

The notation MA *(q)* refers to the moving average model of order *q*:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{ …………………..…………. (2)}$$

where μ is the mean of the series, $\theta_1, \ldots, \theta_q$ are the parameters of the model, and $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are white noise error terms. The value of *q* is called the order of the MA model.

Then, this study developed the mathematical derivation for autoregressive–moving-average (ARMA) models. In the statistical analysis of time series, autoregressive–moving-average (ARMA) models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials, one for the autoregression and the second for the moving average.

Given a time series of data X_t the ARMA model is a tool for understanding and predicting future values in this series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The AR part involves regress the variable on its own lagged values. The MA part involves modeling the error term as a linear combination of error terms occurring contemporaneously and at various times in the past.

The notation ARMA (*p, q*) refers to the model with *p* autoregressive terms and *q* moving-average terms. This model contains the AR (*p*) and MA (*q*) models. Equation (3) is an equation from adding the left term of Equation (1) and Equation (2).

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t + \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{ ……..…... (3)}$$

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where μ is the mean of the series is expected as zero.Then, this study re-arranged the equation (3) to become Equation (4).

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{ .... (4)}$$

where $\varphi_i,...,\varphi_p$ the parameters of the AR model, $\theta_1,...,\theta_q$ are the parameters of the MA model, c is constant, and ε_t is white noise. The white noise ε_t is independent and has identical probability normal distribution. The model is usually referred to as the ARMA (p,q) model where p is the order of the autoregressive (AR) part and q is the order of the moving average (MA) part.

The error terms ε_t are generally assumed to be independent identically distributed random variables (i.i.d.) sampled from a normal distribution with zero mean: $\varepsilon_t \approx N(0,\sigma^2)$ where σ^2 is the variance.

Then, this study performed the derivation of autoregressive integrated moving average (ARIMA). Given a time series of data X_t where t is an integer index and the X_t are real numbers. An ARMA (p', q) model is given by Equation (4). Then, this study re-arranged to become Equation (5).

$$X_t - \alpha_1 X_{t-1} - ... - \alpha_{p'} X_{t-p'} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q}$$

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \quad \text{.................. (5)}$$

where L is the lag operator, α_i are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and ε_t are error terms. The error terms ε_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

In time series analysis, the lag operator, L or backshift operator operates on an element of a time series to produce the previous element. For example, given some time series:

$$X = \{X_1, X_2, ...\}$$

Then, $LX_t = X_{t-1}$ for all $t > 1$.

where L is the lag operator.

Note that the lag operator can be raised to arbitrary integer powers so that:

$$L^k X_t = X_{t-k}$$

Referring to Equation (5), assume now that the polynomial $\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right)$ has a unit root (a factor $(1-L)$) of multiplicity d. Then it can be rewritten as:

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) = \left(1 - \sum_{i=1}^{p'-d} \alpha_i L^i\right)(1-L)^d \text{ .... (6)}$$

An ARIMA (p,d,q) process expresses this polynomial factorization property with $p = p' - d$, and is given by:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \text{ .... (7)}$$

The Equation (7) can be generalized as follows,

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \delta + \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \text{ .... (8)}$$

This defines equation for an ARIMA (p,d,q) process with drift $\delta/(1 - \Sigma\varphi i)$.

IV. RESULT AND DISCUSSIONS

This section describes the result for autoregressive integrated moving average (ARIMA) model for forecasting the Bitcoin exchange rate.

4.1 Dynamic behavior of Bitcoin exchange rate

This section describes characteristics of the data that involved in this study. Figure 1 shows the dynamic behavior of Bitcoin exchange rate. The observation data are selected from January 2013 until October 2017. The total number of observations is 58. In January 2013, the value of 1 Bitcoin is 15.6 USD. Meanwhile, the value of exchange rate increased to 5350.5 USD in October 2017. The increment is 5334.9 USD.

Then, this study performed the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis. There is slow decay in autocorrelation analysis. Therefore, exchange rate data is a non-stationary data.

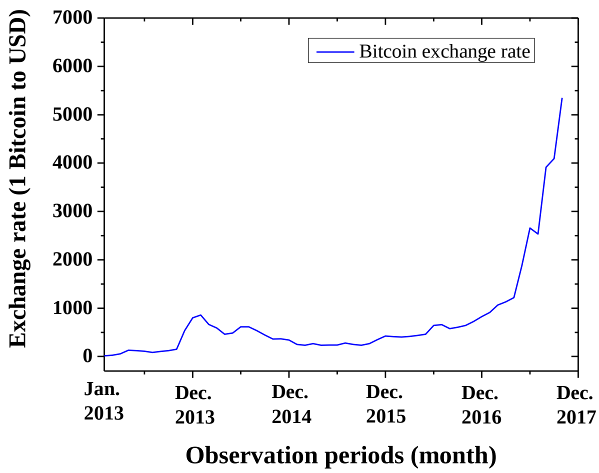

Fig. 1: Bitcoin exchange rate

Table 1: Correlogram for Bitcoin exchange rate

Sample: 2013M01 2017M10
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.775	0.775	36.707	0.000
		2	0.632	0.076	61.494	0.000
		3	0.454	-0.144	74.550	0.000
		4	0.368	0.094	83.295	0.000
		5	0.251	-0.090	87.419	0.000
		6	0.175	-0.020	89.459	0.000
		7	0.141	0.096	90.810	0.000
		8	0.107	-0.038	91.602	0.000
		9	0.071	-0.037	91.956	0.000
		10	0.043	0.017	92.092	0.000
		11	0.026	-0.013	92.143	0.000
		12	0.015	0.003	92.161	0.000
		13	0.010	0.020	92.169	0.000
		14	0.005	-0.014	92.172	0.000
		15	-0.001	-0.013	92.172	0.000

4.2 Stationary transformation using first difference

Figure 2 shows the first difference of Bitcoin exchange rate. The first difference results are calculated from February 2013 until October 2017. Figure 2 shows high volatility of exchange rate stating from May 2017 until October 2017.

Then, this study evaluated the stationarity characteristics for first difference of Bitcoin exchange rate. Table 2 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis for first difference of Bitcoin exchange rate. Autocorrelation function (ACF) shows a significant spike on order of two with value of 0.539. This indicates the moving average is represented by order of two. In the same time, partial autocorrelation function (PACF) shows a significant spike on second order with value of 0.531. This indicates the autoregressive part can be represented by order of two. Therefore, the first difference of Bitcoin exchange rate can be represented by ARIMA (2, 1, 2).

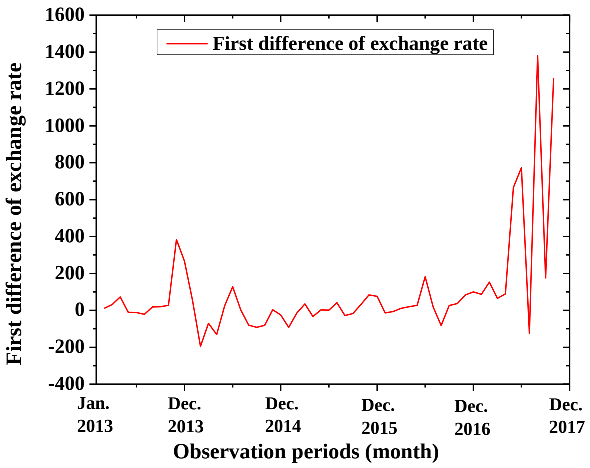

Fig. 2: First difference of Bitcoin exchange rate

Table 2: Correlogram for first difference of Bitcoin exchange rate

Sample: 2013M01 2017M10
Included observations: 57

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.133	0.133	1.0581	0.304
		2	0.539	0.531	18.844	0.000
		3	0.156	0.074	20.362	0.000
		4	0.231	-0.094	23.755	0.000
		5	0.187	0.088	26.007	0.000
		6	0.085	-0.025	26.480	0.000
		7	0.059	-0.127	26.716	0.000
		8	0.062	0.042	26.979	0.001
		9	0.009	0.029	26.985	0.001
		10	-0.006	-0.088	26.987	0.003
		11	0.040	0.072	27.105	0.004
		12	0.000	0.070	27.105	0.007
		13	-0.020	-0.120	27.135	0.012
		14	0.004	-0.006	27.137	0.018
		15	-0.011	0.085	27.147	0.028

4.3 Parameters estimation for ARIMA (*2, 1, 2*)

This section describes the estimation of parameters for ARIMA (2, 1, 2) model. This section starts with the derivation of ARIMA (*p, d, q*). In this study the value of p is set as 2; d is set as 1 and q is set as 2. Therefore, this study derived equation for ARIMA (2, 1, 2).

ARIMA (p, d, q) is represented by:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_t = c+\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

Then, this study derived equation for ARIMA (2, 1, 2).

$$\left(1-\sum_{i=1}^{2}\phi_i L^i\right)(1-L)^1 X_t = c+\left(1+\sum_{i=1}^{2}\theta_i L^i\right)\varepsilon_t$$

Then, this study expended the equation as below procedure.

$$\left(1-\phi_1 L^1-\phi_2 L^2\right)(1-L)^1 x_t = c+\left(1+\theta_1 L^1+\theta_2 L^2\right)\varepsilon_t$$

$$\left(1-\phi_1 L^1-\phi_2 L^2\right)(x_t - x_{t-1}) = c+\left(1+\theta_1 L^1+\theta_2 L^2\right)\varepsilon_t$$

$$\left(1-\phi_1 L^1-\phi_2 L^2\right)\Delta x_t = c+\left(1+\theta_1 L^1+\theta_2 L^2\right)\varepsilon_t$$

$$\Delta x_t - \phi_1 L^1 \Delta x_t - \phi_2 L^2 \Delta x_t = c+\varepsilon_t+\theta_1 L^1\varepsilon_t+\theta_2 L^2\varepsilon_t$$

$$\Delta x_t - \phi_1 \Delta x_{t-1} - \phi_2 \Delta x_{t-2} = c+\varepsilon_t+\theta_1\varepsilon_{t-1}+\theta_2\varepsilon_{t-2}$$

Therefore, ARIMA (*2, 1, 2*) can be represented as below equation:

$$\Delta x_t = c + \phi_1 \Delta x_{t-1} + \phi_2 \Delta x_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t \quad ..(9)$$

Table 3 shows parameter estimation for ARIMA (2, 1, 2). Therefore, historical data of Bitcoin exchange rate can be represented by below equation of ARIMA (2, 1, 2).

$$\Delta x_t = 218 + 0.237084 \Delta x_{t-1} + 0.687976 \Delta x_{t-2} - 0.281149 \varepsilon_{t-1} - 0.024093 \varepsilon_{t-2} + \varepsilon_t \quad ...(10)$$

R-squared is a statistical measure of how close the data are to the fitted regression line. R-squared is represented by the percentage of the response variable variation that is explained by a linear model. This model shows the value of R-squared is 0.444432. This value indicates the model explains 44.44% from all the variability of the response data around its mean. The Akaike information criterion is 13.7805. This model is considered a model with good fitness.

Table 3: Parameter estimation for ARIMA (2,1,2)

Sample: 2013M02 2017M10
Included observations: 57
Convergence achieved after 92 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	218.8310	381.8171	0.573130	0.5691
AR(1)	0.237084	0.277129	0.855501	0.3963
AR(2)	0.687976	0.208808	3.294773	0.0018
MA(1)	-0.281149	0.230441	-1.220046	0.2281
MA(2)	-0.024093	0.185385	-0.129961	0.8971
SIGMASQ	44301.25	5707.468	7.761980	0.0000

R-squared	0.444432	Mean dependent var	93.59530
Adjusted R-squared	0.389964	S.D. dependent var	284.8936
S.E. of regression	222.5155	Akaike info criterion	13.78035
Sum squared resid	2525171.	Schwarz criterion	13.99541
Log likelihood	-386.7400	Hannan-Quinn criter.	13.86393
F-statistic	8.159581	Durbin-Watson stat	1.968995
Prob(F-statistic)	0.000010		

Inverted AR Roots	.96	-.72
Inverted MA Roots	.35	-.07

4.4 Diagnostics checking for ARIMA (*2, 1, 2*)

Diagnostics checking process is to prove this model adequately describes the time series under consideration by subjecting the calibrated model to a range of statistical tests. For the diagnostic checks in this paper, it is assumed that a maximum likelihood estimator is used to estimate the model parameters. A random pattern of residuals supports a linear model. In discrete time, white noise is a discrete signal whose samples are regarded as a sequence of serially uncorrelated random variables with zero mean and finite variance. Table 4 shows the residual for the first difference of Bitcoin exchange rate is not significant. Therefore, the residual is considered as white noise.

Table 4: Residual diagnostics of ARIMA (2,1,2)

Sample: 2013M01 2017M10
Included observations: 57
Q-statistic probabilities adjusted for 4 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.008	-0.008	0.0039	
		2	0.009	0.009	0.0093	
		3	0.004	0.004	0.0103	
		4	0.024	0.024	0.0483	
		5	0.047	0.048	0.1937	0.660
		6	0.107	0.108	0.9468	0.623
		7	0.116	0.120	1.8571	0.603
		8	0.049	0.053	2.0215	0.732
		9	-0.110	-0.115	2.8749	0.719
		10	-0.078	-0.097	3.3128	0.769
		11	0.109	0.093	4.1812	0.759
		12	0.038	0.024	4.2877	0.830
		13	-0.051	-0.079	4.4857	0.877
		14	-0.002	-0.020	4.4859	0.923
		15	-0.014	0.005	4.5012	0.953

4.5 Ex-post forecasting using ARIMA (*2, 1, 2*) model

In validating the prediction model of ARIMA (2, 1, 2), an ex-post analysis is needed. Firstly, this study started with calculated the parameters for ARIMA (2, 1, 2). The selected data for developing parameters are started from January 2013 until August 2017. Table 5 shows the parameters for ARIMA (2, 1, 2). Therefore, the equation for ex-post forecasting validation is represented by:

$$\Delta x_t = 148.984 + 0.593 \Delta x_{t-1} + 0.302 \Delta x_{t-2} - 0.603 \varepsilon_{t-1} - 0.166 \varepsilon_{t-2} + \varepsilon_t \quad .... (11)$$

Next, this study plotted the forecasted value using Equation (11). Figure 3 shows the ex-post forecasting validation. Figure 3 shows the actual value for September and October 2017 are in the range of 2 standard errors from the forecasted value. Therefore, ARIMA (2, 1, 2) is a reliable forecasting model.

Table 5: Correlogram for first difference of Bitcoin exchange rate

Included observations: 55
Convergence achieved after 130 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	148.9841	289.6027	0.514443	0.6093
AR(1)	0.592845	0.767750	0.772185	0.4437
AR(2)	0.301765	0.764740	0.394598	0.6949
MA(1)	-0.603318	0.679653	-0.887684	0.3790
MA(2)	0.166194	0.615973	0.269808	0.7884
SIGMASQ	43375.50	6130.310	7.075579	0.0000

R-squared	0.242640	Mean dependent var	70.89276
Adjusted R-squared	0.165359	S.D. dependent var	241.5214
S.E. of regression	220.6508	Akaike info criterion	13.75470
Sum squared resid	2385652.	Schwarz criterion	13.97368
Log likelihood	-372.2542	Hannan-Quinn criter.	13.83938
F-statistic	3.139687	Durbin-Watson stat	1.741713
Prob(F-statistic)	0.015481		

Inverted AR Roots	.92	-.33
Inverted MA Roots	.30-.27i	.30+.27i

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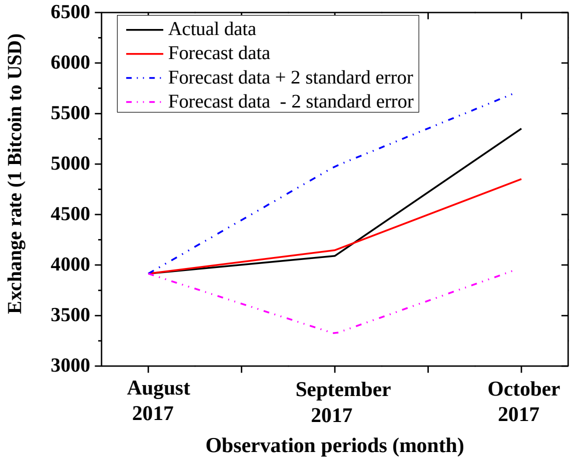

Fig. 3: Ex-post forecasting validation

Then, this study also checked the mean absolute percentage error (MAPE) between forecast value and actual value. Equation (12) shows the equation for calculating mean absolute percentage error (MAPE).

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(12)}$$

where A_t is the actual value , F_t is the forecast value and n is number of fitted.

Table 6 shows the error analysis between forecasting value and actual data. The mean absolute percentage error for ex-post forecasting is 5.36%.

Table 6: Error analysis between forecasting value and actual data

Observation periods (Month)	Forecast data	Actual data	Absolute percentage error
September 2017	4147.7	4090.7	1.4%
October 2017	4851.8	5350.5	9.3%
Mean absolute percentage error (MAPE)			**5.36%**

4.6 Ex-ante forecasting using ARIMA (*2, 1, 2*) model

This study performed ex-ante forecasting using ARIMA (2,1,2) model for November and December 2017. Figure 4 shows ex-ante forecasting of Bitcoin exchange rate. Forecast value in November 2017 is 5700, and December 2017 is 6659. Forecast value is represented by red line. Upper limit of forecast value is forecast value add with 2 standard errors. Meanwhile, lower limit is forecast value minus with 2 standard errors.

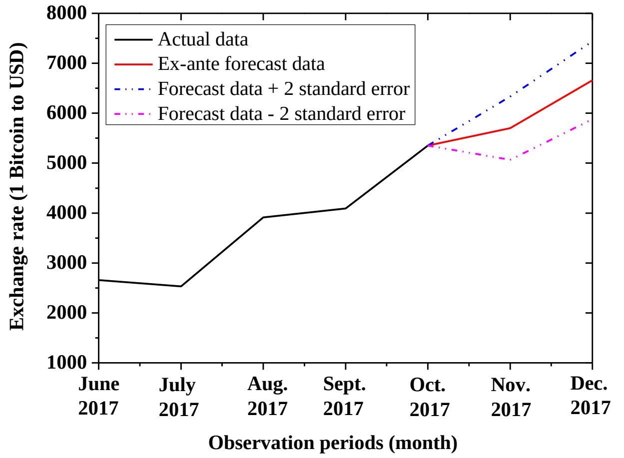

Fig. 4: Ex-ante forecasting of Bitcoin exchange rate

V. CONCLUSION

The objective of this paper is to forecast cryptocurrency exchange rate. In this study, we focus on value of 1 Bitcoin to United States Dollar (USD). The data selected for this study are started from January 2013 until October 2017.We performed the forecasting approach using autoregressive integrated moving average (ARIMA) method. The main findings from this study are:

(a) In January 2013, the value of 1 Bitcoin is 15.6 USD. Meanwhile, the value of exchange rate increased to 5350.5 USD in October 2017. The increment is 5334.9 USD.

(b) This study performed the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis for Bitcoin exchange rate. There is slow decay in autocorrelation analysis. Therefore, exchange rate data is a non-stationary data

(c) Then, this study performed stationary transformation method with finding the correlogram analysis for first difference of Bitcoin exchange rate. Autocorrelation function (ACF) shows a significant spike on order of two with value of 0.539. This indicates the moving average is represented by order of two. In the same time, partial autocorrelation function (PACF) shows a significant spike on second order with value of 0.531. This indicates the autoregressive part can be represented by order of two. Therefore, the first difference of Bitcoin exchange rate can be represented by ARIMA (2, 1, 2).

(d) Therefore, historical data of Bitcoin exchange rate can be represented by below equation of ARIMA (2, 1, 2).

$$\Delta x_t = 218 + 0.237084\Delta x_{t-1} + 0.687976\Delta x_{t-2} - 0.281149\varepsilon_{t-1} - 0.024093\varepsilon_{t-2} + \varepsilon_t$$

(e) The error analysis is calculated between forecasting value and actual data. The mean absolute percentage error for ex-post forecasting is 5.36%.

(f) This study performed ex-ante forecasting using ARIMA (2,1,2) model for November and December 2017. Forecast value in November 2017 is 5700, and December 2017 is 6659

As a conclusion, forecasting approach using autoregressive integrated moving average (ARIMA) method produce a reliable forecasting model. However, high volatility environment creates larger error. Therefore, Forecasting in high volatility environment need special consideration of error diagnostics.

The findings of this study are important to predict the Bitcoin exchange rate in high volatility environment. This information will help investors to predict the future exchange rate of Bitcoin and in the same time volatility need to be monitor closely. This action will help investors to gain better profit and reduce loss in investment decision.

VI. FURTHER RESEARCH

This research can be extending to discover the factors that contribute to the volatility of Bitcoin exchange rate. In the same time, the correlation of Bitcoin with other currency also is another area that can be analyze

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