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A comparative study for Bitcoin cryptocurrency forecasting in period 2017-2019

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Abstract. The objective of this study were (i) to construct the classical statistic and artificial intelligent model for predicting bitcoin cryptocurrency, and (ii) to compare the predicting performance by using root mean square error (RMSE) and mean square error (MSE) as forecasting evaluation tool. The observation data used in this study were collected during January, 5 2017 to October, 1 2019 (in total 1,000 daily observation data). The statistical method used in this study were ARIMA (Autoregressive Moving Average) and Exponential Smoothing. The artificial intelligent model were used in this study were fuzzy time series and ANFIS (Adaptive Neuro Fuzzy Inference System). The partitions data set were of 75%-25% of training and testing, respectively. The cryptocurrency investigated was bitcoin (BTC) which is the top three of most widely traded cryptocurrency. The forecasting results show that the classical method has the smallest value of RMSE and MSE which is exponential smoothing with 9749.81 for MSE and 98.74 for RMSE. However, the performance of forecasting method cannot be guaranteed from either classical or modern forecasting method. Analyzing with different method can be considered for future study, for example machine learning, neural network, modified fuzzy time series, etc.

1. Introduction

Cryptocurrency is a kind of digital currency. According to [1], a kind of optional tools of exchange consisting of through 1441 (since January 2018) which especially crypto coin types is named as cryptocurrency. There are several types of cryptocurrency such as Bitcoin, Litecoin, Ethereum, Nem, Ripple, Iota, Stellar and etc. A bitcoin cryptocurrency transaction is a new mechanism in digital currency. Bitcoin is the first decentralized cryptocurrency created in 2009 and documented in [2]. Since its introduction, it has enhanced a consideration from the media, academics, and finance industry. The transaction of bitcoin had been introduced according to cryptographic which is through two parties to transfer the transaction without asking permission for a trusted third party. This transaction are computationally theoretical to be opposite would secure sellers from cheat, and common secret message procedures could easily be applied to defend buyers [2].

Forecasting of experimental time series has an important duty in various social and science fields of study [3]. According to [4], the forecasting of future event was needed in planning and decision making processes. Nowadays, forecasting in finance field is the fascinating topic in time series analysis. Forecasting is very helpful for investor, stock holder and another people who are interested in financial. Because they can use it for decision maker in future time. According to [5], technical analysis in finance forecasting gave effect in future evolution of market. Time series are set of well-defined data compiled at sequential points with steady time intervals [6]. The vital part in statistics analysis which has purpose to gain some knowledge on the data characteristics and to help in estimating future values of the time series according to data characteristic is called time series analysis. Inflation forecasting has critical role to consider the monetary policy, as central banks aims to propose forecast as regards monetary policy.

However, cryptocurrency forecasting has been considered as research in numerous model. The researcher are competing to optimize their model performance. There are various methods which have been utilized to this fields in order to be more helpful in financial time series predicting. [7] had applied machine learning and artificial intelligent method to analyze the cryptocurrency market. Still in the same method, the comparative study of machine learning for cryptocurrency forecasting had been proposed by [1]. According to [8], ARIMA had been implemented to predict exchange rate of cryptocurrency in strong volatility of bitcoin transaction surrounding. They had been applied the deep learning chaotic neural networks to predict the three most extensively traded digital currencies i.e., Bitcoin, Digital Cash, and Ripple [9]. According to [10], they had compared the several method of univariate and multivariate models of four most capitalized series: Bitcoin, Litecoin, Ripple, and Ethereum.

However, there were competitions among researcher to forecast cryptocurrency. According to [11], it can be challenge for considering the competitive performance in cryptocurrency forecasting. But, it is quite hard to seek comparative study about comparison cryptocurrency forecasting method in classical and artificial intelligent. Since 1993, fuzzy time series became popular technique in artificial intelligent or soft computing area. This study presented a comparative study to forecast bitcoin cryptocurrency. And root mean square error (RMSE) and mean square error (MSE) will be applied as evaluation tools.

2. Background theory

2.1. ARIMA (Autoregressive Integrated Moving Average)

ARIMA has been established by Box and Jenkins in 1970. According to [12], the ARIMA model is the famous linear forecasting models during these three decades. [13] presented that the future value is assumed as linear combination of past value and error. It can be written as follow:

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}, \qquad (1)$$

where
y_t is defined as the real value,
ε_t is defined as the error at time t,
ϕ_i and θ_j are defined as the coefficient,
p and q are defined as integers that can be order of model and reflected to as autoregressive and moving average polynomials, respectively.

[14] stated that there are three basic steps to construct ARIMA model as follow:

1. Identification
   In this step, the autocorrelation and the partial autocorrelation function is applied to identify the ARIMA order number. Data transformation is applied in order to get stationary series. Since the stationary time series has stable mean and variance thus it is useful for forecasting process.
2. Parameter estimation
   A nonlinear estimation procedure will deal parameter such that it can minimize the error.
3. Diagnostic checking
   It will be checked error assumptions whether satisfy or not. Plot of residual is used to examine the fitness of model.

2.2. Exponential smoothing

According to [4], a data set consists of two components such as signal and noise. Smoothing can be described as a way to separate signal (data set) and noise as smooth as possible in order to obtain signal estimation. A simple exponential weight smoother can be used to achieve smoother separation by applying discount factor θ. It can be expressed as:

$$\tilde{y}_T = (1-\theta)y_T + \theta\tilde{y}_{T-1}, \quad (2)$$

Where
$\tilde{y}_T$ is defined as the fitted value of y_T,
θ is defined as the discount factor,
y_T is defined as the observation value.
The simple exponential smoothing also can be represented in other equation by defined $\alpha = 1-\theta$,

$$\tilde{y}_T = \alpha\, y_T + (1-\alpha)\tilde{y}_{T-1}, \quad (3)$$

where α as the weight place on the end observation and $(1-\alpha)$ represents the weight place on the smoothed value of the previous observation $(0 \le \alpha \le 1)$.

2.3. Fuzzy time series

The stepwise procedure of fuzzy time series [15] is presented as:
1. Determine the universal set,
2. Separate the universe set into same lengths,
3. Define the fuzzy sets with triangular membership function,
4. Fuzzification and construct the fuzzy logical relationships,
5. Forecasting.

2.4. *ANFIS (Adaptive Network-Fuzzy Inference System)*

ANFIS is modified neural network which has algorithm as the mix of fuzzy system and neural network especially as multilayer feedforward network [16-17]. ANFIS is proposed as fuzzy inference system (FIS) which has optimized membership function. According to Tarno *et al.* [17], ANFIS consider four kinds of membership function, i.e. triangular, trapezoidal, Generalized Bell, and Gaussian membership function. The learning algorithm which is used in ANFIS are either a backpropagation algorithm, or the combination with least squares which is a hybrid algorithm.

3. Methodology

3.1. Data management

The data were obtained from www.coinmarketcap.com, The observation data used in this study were collected during January, 5 2017 to October, 1 2019 (in total 1,000 daily observation data). Figure 1 showed the plot of time series of the observation daily data cryptocurrency. Figure 1 had been captured the trend of 1,000 daily observation data. The observation data seems not constant then it is required to make it stationary. In order to get the optimal forecasting result, the data were divided into two groups which are training and testing. According to [18], the optimal proportion of training and testing dataset is 75%-25%.

Stationary data will be required in this study. Differencing is being as tool to get stationary data. Stationary process is the main thing in traditional time series particularly in forecasting model such as ARIMA, moving average, exponential smoothing, etc. Stationary defined as a kind of time series data which has constant statistical properties such as means, variance, autocorrelation, etc. [13]. The stationary time series data of bitcoin is showed in Figure 2. Figure 2 as stationary time series data seems more stable than the original observation data in Figure 1. Thus, it is very useful in forecasting.

Figure 3 shows the ACF plot for data before differencing. In stationary data, the ACF plot will decrease to zero quickly. Actually, there is no exact stationary time series. The researcher was trying to approach in stationary. As seen in Figure 4, ACF plot for bitcoin cryptocurrency shows the stationary data that has been differenced. The ACF showed few lag come out from the horizontal line.

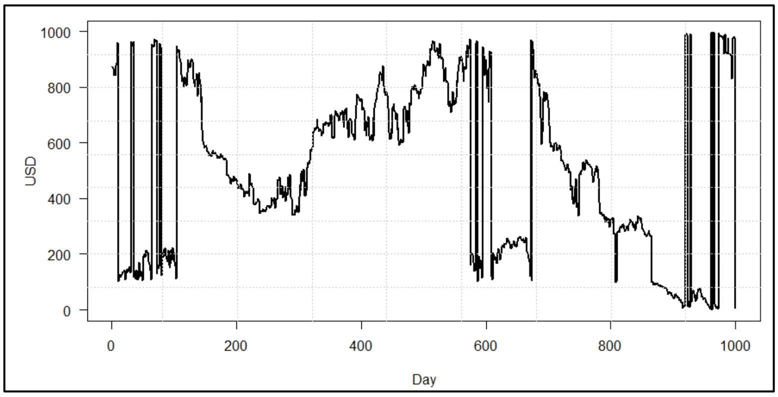

Figure 1. The plot of time series daily BTC cryptocurrency.

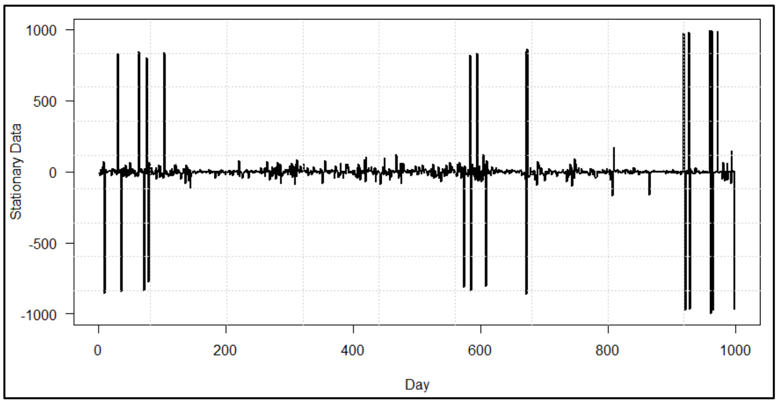

Figure 2. The plot of time series BTC cryptocurrency after differencing.

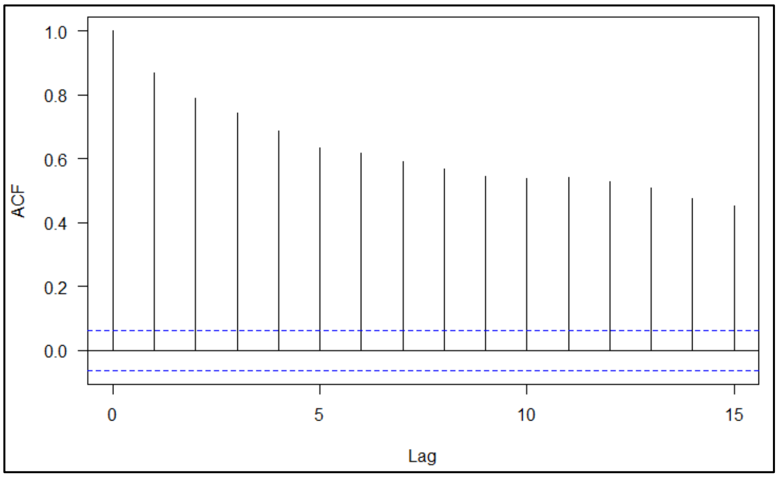

Figure 3 The ACF plot of BTC cryptocurrency before differencing process.

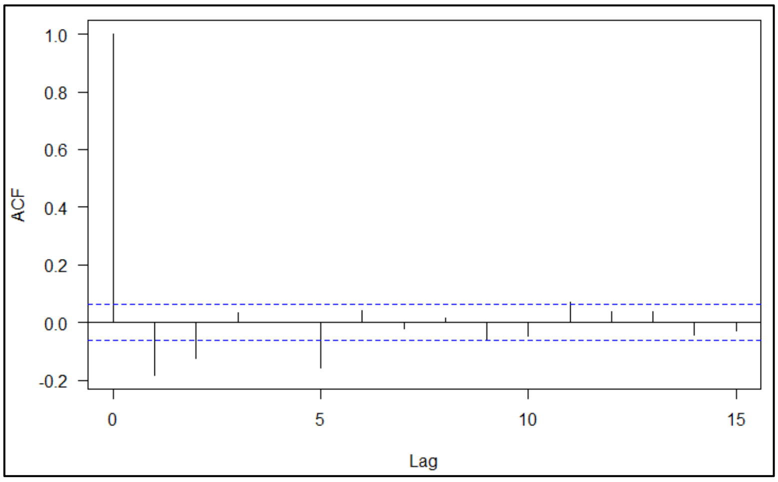

Figure 4. The ACF plot of BTC cryptocurrency after differencing process.

3.2. Method

3.2.1. Implementation of ARIMA

According to [14], there are three basic steps to construct ARIMA model as follow:

1. Identification
   In this step, it will identify the ACF plot and the PACF plot.
2. Parameter estimation
   The parameter estimation of ARIMA for each time series data has been executed by R program.
3. Diagnostic checking
   After estimating the parameter, it will be checked whether the forecast error correlated by using ACF plot and the Ljung-Box test and whether they are normally distributed which has mean zero and stable variance by using plot of time series and histogram of the forecast error s. The diagnostic checking deal for 245 predicted values.

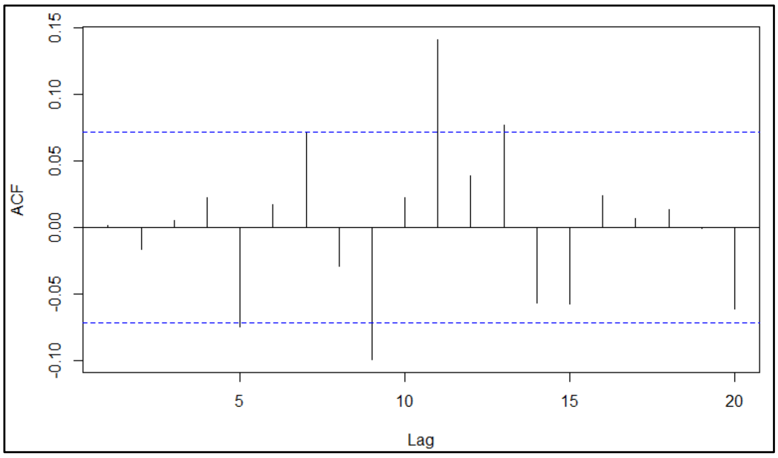

Figure 5. The ACF plot of the forecast error.

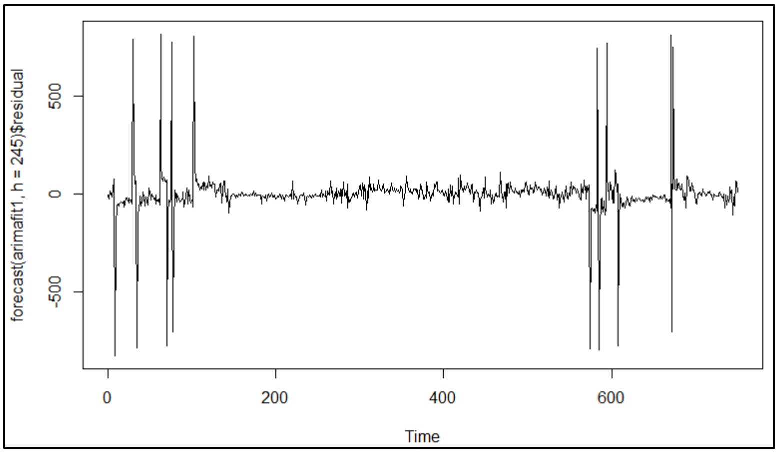

Figure 6. The time series plot of forecast error.

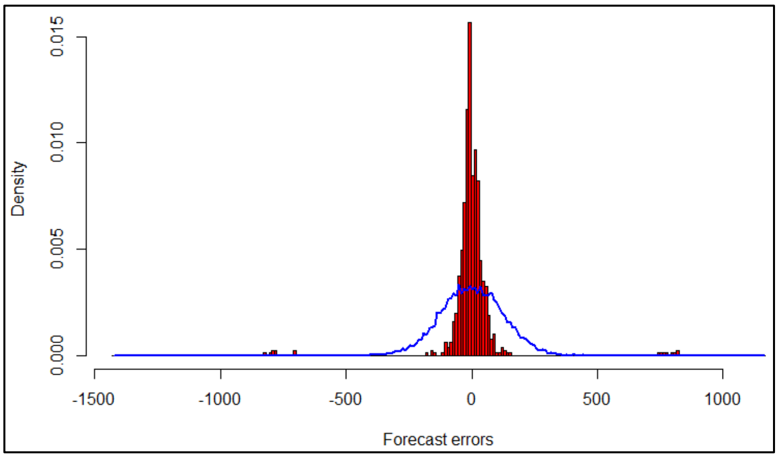

Figure 7. The histogram plot of forecast error.

The ACF plot in Figure 5 captures the sample of autocorrelation of forecast error at lag 20 which passes the significance bounds for 245 predicted values of stationary time series data. Moreover, the p-value of the Ljung-Box test is 0.0006624, suggesting that there is small proof for non-zero autocorrelations in the forecast errors. In Figure 6, the plot of time series of the forecast errors for 245 predicted values of stationary time series data presents that the constant variance over time. The histogram for 245 predicted values captures the forecast errors which are hard normally distributed and the mean looks to be going to zero, as shown in Figure 7. Figure 7 reported that the forecast errors seems follow normally distributed since the red histogram has the highest part in the middle and in the mean is around zero. Therefore, it gives evidence which the forecast errors of 245 predicted values of stationary data are normally distributed with mean zero and stable variance.

Since auspiciously forecast errors do not look to be associated, and the forecast errors look to be normally distributed with mean zero and stable variance, the constructed ARIMA provide a predictive model for all of predicted values.

3.2.2. Implementation of exponential smoothing

Simple exponential smoothing is a classical forecasting model which has a simple process as its name. According to equation

$$\tilde{y}_T = \alpha\, y_T + (1-\alpha)\tilde{y}_{T-1}, \tag{4}$$

it is necessary to estimate a parameter (α) for 75% training data. The examining simple exponential smoothing model which has aim to obtain the smallest RMSE has been done by R program.

3.2.3. Implementation of fuzzy time series
The stepwise procedure of fuzzy time series [15] to forecast cryptocurrency is presented as:

1. Determine the universal set into same intervals
   Divide the universal set U into three equal intervals.
2. Construct the fuzzy sets with the triangular membership function
   The triangular membership function has been constructed to get degree of the membership function.
3. Fuzzify and construct the fuzzy logical relationships (fuzzy rules)
   The data is fuzzified to establish the fuzzy rules.
4. Forecasting
   Singh's model consider of three order, as $F(t+1)$ is caused by $F(t-2), F(t-1)$ and $F(t)$. $F(t+1)$ is obtained by using equation as follow

$$F(t+1) = F(t-1) * R(t, t-1, t-2), \quad (5)$$

here " $*$ " is defined as max-min composition operator and the relation R is defined as a numeric value of the difference between the consecutive value of time t with $t-1$ and value of $t-1$ with $t-2$. The difference between of the past 3 times t data are calculated as follows

$$R(t, t-1, t-2) = \left| |E_i - E_{i-1}| - |E_{i-1} - E_{i-2}| \right|, \quad (6)$$

where E_i, E_{i-1}, and E_{i-2} are the actual data of time $i, i-1$, and $i-2$, respectively.

3.2.4. Implementation of ANFIS
According to Tarno *et al.* [17], preprocessing data, constructing the rules, and evaluating the model are the algorithm ANFIS. The application of ANFIS to forecast cryptocurrency can be described as follows:

1. Input selection
   According to the ACF plot as shown in Figure 4, five inputs were considered in this study to process in examining step.
2. Establishing the membership function
   ANFIS model was constructed which has three of generalized bell functions (gbellmf) with constant outputs. The membership function for all input were shown in Figure 8. There are three membership function which are MF1, MF2, and MF3. Membership function is applied in fuzzification process which is the transformation from crisp set into fuzzy sets.

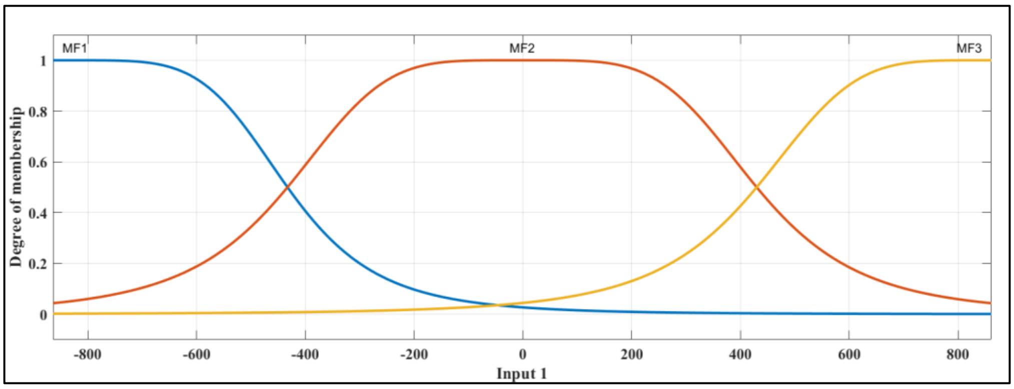

Figure 8. The membership function.

3. Generating fuzzy rules
   There are 243 of the fuzzy rules which were generated from the system. The number of fuzzy set output equals to the rule numbers.

4. Selecting the learning algorithm
   In this study, ANFIS model selected the hybrid method as learning algorithm. Figure 9 showed the ANFIS model architecture in this research. Based on to the architecture of ANFIS, the model is consist of 3 membership function in each input to get 1 output in the end of process.

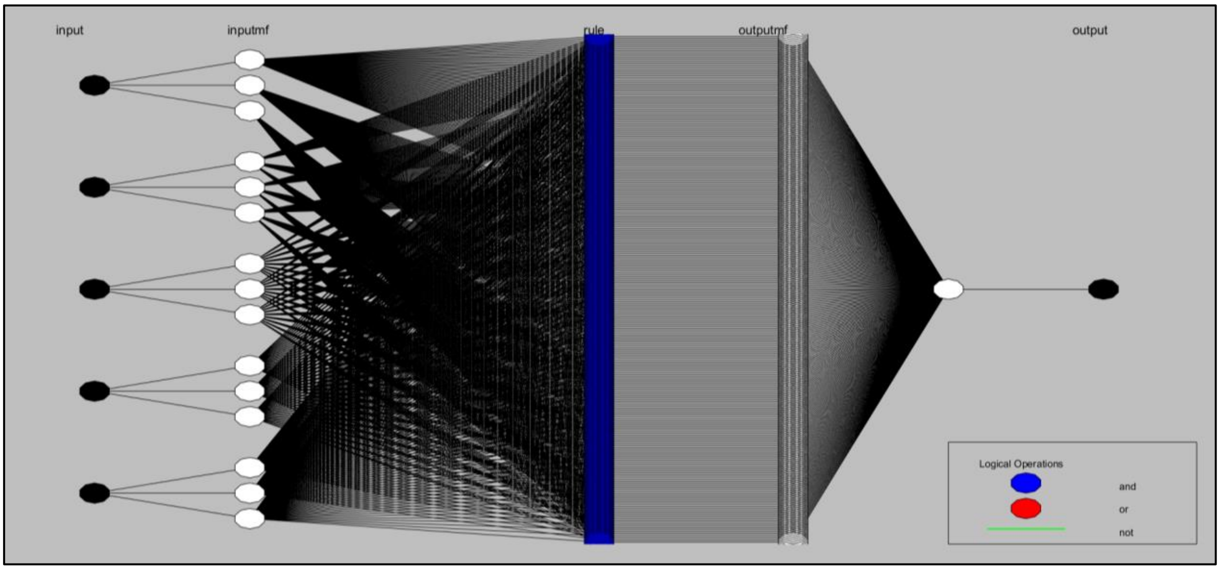

Figure 9. The ANFIS architecture

5. Tuning parameters of the fuzzy inference system (FIS)
   In this step determined the FIS parameters. FIS was applied to reason the fuzzy relationship to gain the output of fuzzy system. It has been trained until 100 epochs to obtain the optimal solution. The training error plots for all data proportions are shown in Figure 10. It had been treated such as the training error decreasing along the epoch time step. The training error plots in 100 epoch is going down or decreasing from 106.5 until 99. It means that the tuning parameter process is successful since the training error is not enhancing.

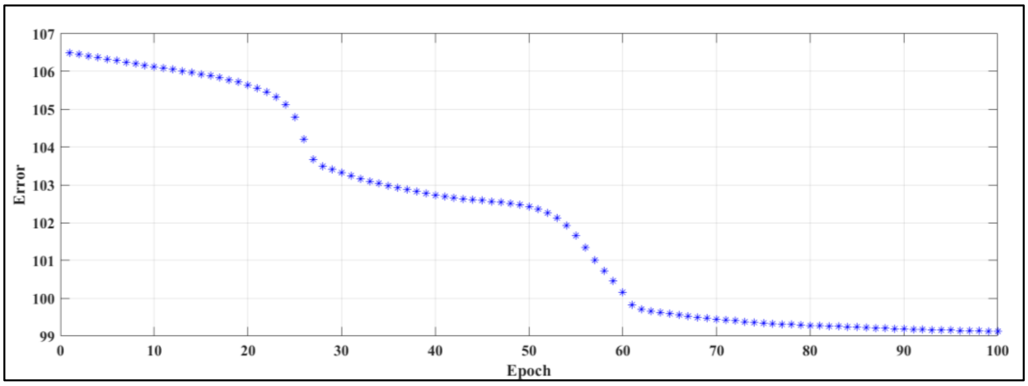

Figure 10. The training error plot.

4. Results and discussions

In this study, four model had been implemented to forecast Bitcoin cryptocurrency. The observation values has been divided into training and testing data set such that 75%-25%, respectively. ANFIS and fuzzy time series are being representative as artificial intelligent model. Thus, exponential smoothing and ARIMA are being representative as statistical model. The forecasting results had been evaluated by using RMSE and MSE.

Table 1 shows the MSE and RMSE values for testing data of all models. According the evaluation value, the exponential smoothing model had the smallest evaluation value. The evaluation value can give evidence that exponential smoothing is a sufficient predictive model. Yet, the evaluation value of ANFIS model is quite different with others model. It means that the modern model cannot guarantee to produce the better result in forecasting model. Since the data characteristic is unique in each case study.

Table 1. The MSE and RMSE value for testing data.

	ANFIS	FTS	ES	ARIMA
MSE	14243316.35	9767.19	9749.81	9805.09
RMSE	3774.03	98.83	98.74	99.02

Figure 11 show the time series plot of the forecasting results. Figure 11 contains 4 sub-figure for ANFIS, fuzzy time series, exponential smoothing, and ARIMA forecasted. The black line represented for the actual value of bitcoin cryptocurrency, red line as bitcoin cryptocurrency forecasting result with ANFIS, green as bitcoin cryptocurrency forecasting result with fuzzy time series, blue as bitcoin cryptocurrency forecasting result with exponential smoothing, and cyan as bitcoin cryptocurrency forecasting result with ARIMA. From the time series plot, it can be seen that the difference of bitcoin cryptocurrency forecasting result is quite small for fuzzy time series, exponential smoothing, and ARIMA. Yet, bitcoin cryptocurrency forecasting result with ANFIS has bigger difference than others method.

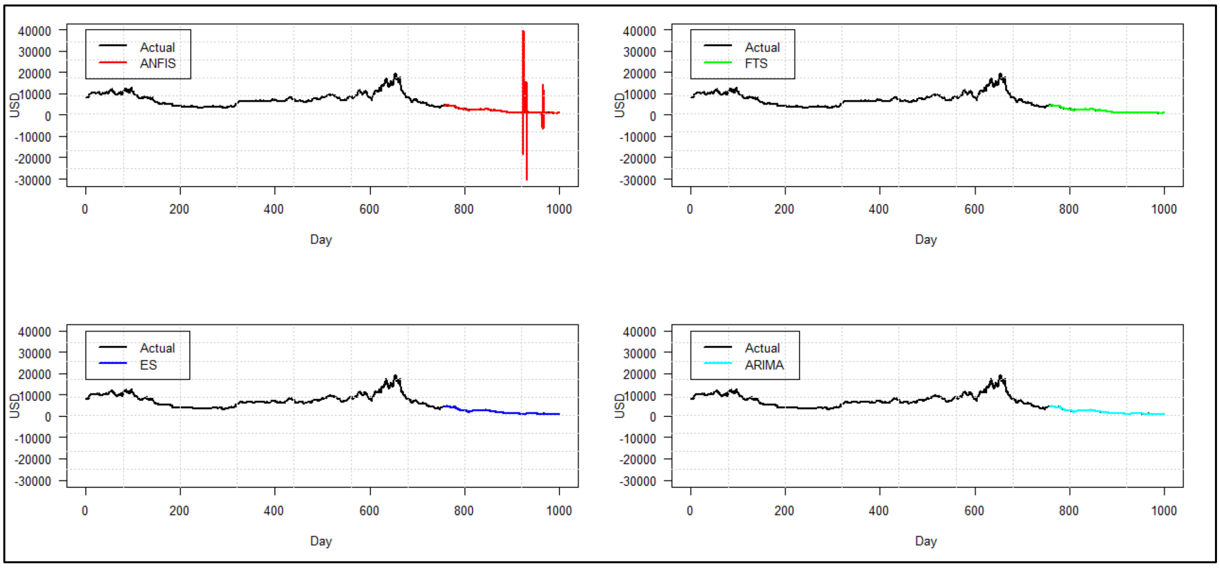

Figure 11. Time series plot of forecasting results for all models.

5. Conclusions

The aims of this study are to construct the classical statistic and artificial intelligent model for predicting bitcoin cryptocurrency, and to compare the predicting performance by RMSE and MSE as forecasting evaluation tool. In this research, the observation values has been divided into two dataset which are 75% training and 25% testing dataset. According to the result of this study, statistical method can perform better than artificial intelligent model. Yet, each time series data has unique characteristic which need to analyze. It can be considered with other method to analyze bitcoin cryptocurrency, for example machine learning, neural network, etc. Also, it can be analyzed by using different parameter in the type of membership function, the number of membership function, the number of epoch, the type of output, etc. Thus, it can be applied in future study.

References

[1] Hitam N A and Ismail A R 2018 Comparative performance of machine learning algorithms for cryptocurrency forecasting *Ind. J. Electr. Eng. Comput. Sci* **11** 1121-1128
[2] Nakamoto S 2008 Bitcoin: A peer-to-peer electronic cash system
[3] Bontempi G, Taieb S B and Borgne L 2013 Machine Learning Strategies for Time Series Forecasting Machine learning strategies for time series forecasting *InEuropean business intelligence summer school 2012 Jul 15* (Berlin, Heidelberg/ Springer) pp 62-77
[4] Montgomery D C, Jennings C L and Kulahci M 2015 *Introduction to Time Series Analysis and Forecasting*. (Inc Hoboken. New Jersey- John Wiley & Sons)
[5] Grigoryan H 2015 Stock Market Prediction using Artificial Neural Networks. Case Study of TAL1T, Nasdaq OMX Baltic Stock *Database Systems Journal* **6** 14-23
[6] Mondal P, Shit L and Goswami S 2014 Study of effectiveness of time series modeling (ARIMA) in forecasting stock prices *International Journal of Computer Science, Engineering and Applications* **4** 13–29
[7] Alessandretti L, Elbahrawy A, Aiello L M and Baronchelli A 2018 Anticipating Cryptocurrency Prices Using Machine Learning *Complexity* **2018**
[8] Bakar N A and Rosbi S 2017 Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction *International Journal of Advanced Engineering Research and Science* **4** 130-137
[9] Lahmiri S and Bekiros S 2019 Cryptocurrency forecasting with deep learning chaotic neural networks *Chaos, Solitons Fractals Interdiscip. J. Nonlinear Sci. Nonequilibrium Complex Phenom* **118** 35–40
[10] Catania L, Grassi S and Ravazzolo F 2018 Forecasting Cryptocurrencies Financial Time Series (*Preprint*)
[11] Rebane J and Karlsson I 2018 Seq2Seq RNNs and ARIMA models for Cryptocurrency Prediction : A Comparative Study *SIGKDD Fintech* **18** 2–6
[12] Pai P and Lin C 2005 A hybrid ARIMA and support vector machines model in stock price forecasting *Omega* **33** 497–505
[13] Zhang G P 2003 Time series forecasting using a hybrid ARIMA and neural network model *Neurocomputing* **50** 159–175
[14] Box G E P and Jenkins G M 1970 *Time series analysis: forecasting and control* (San Frasisco, USA-Holden-Day)
[15] Singh S R 2008 A computational method of forecasting based on fuzzy time series *Mathematics and Computers in Simulation* **79** 539–554
[16] Wang J S and Ning C X 2015 ANFIS Based time series prediction method of bank cash flow optimized by adaptive population activity PSO algorithm *Information* **6** 300-313
[17] Tarno, Subanar D R and Suhartono 2013 Analysis of financial ttime series data using Adaptive Neuro Fuzzy Inference System (ANFIS) *International Journal of Computer Science Issues* **10** 491–496
[18] Septiarini T W and Musikasuwan S 2018 Adaptive Neuro Fuzzy Inference System (ANFIS) for Predicting the Hourly Temperature in Pattani, Thailand *Journal of Physics: Conference Series* **1097** 24–26