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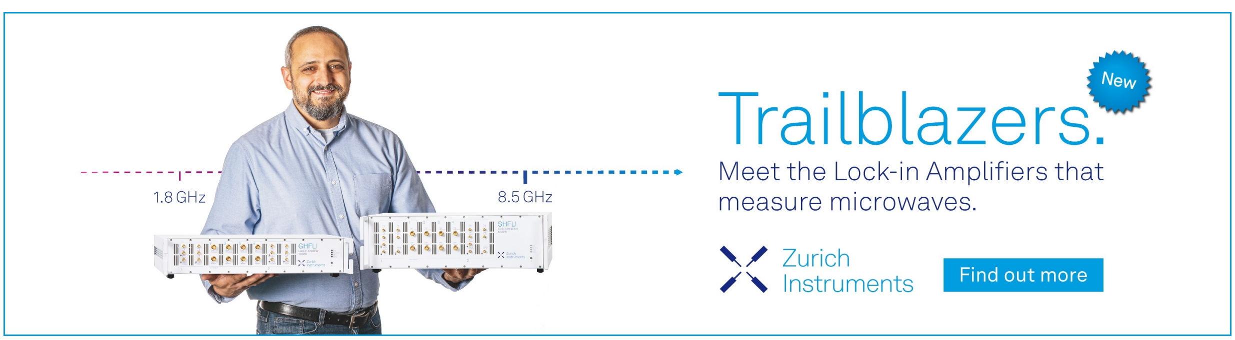

The Forecasting Model of Bitcoin Price with Fuzzy Time Series Markov Chain and Chen Logical Method

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Abstract. Bitcoin is electronic money that can be used as an alternative for investment. Investors will get benefit buying bitcoin when the price of bitcoin is down and reselling it when bitcoin prices are increasing. The fluctuating bitcoin prices cause forecasting as a basis for investors to make decisions, where the time series method is used as a forecasting model, then a pattern can be found to predict future events. The classical time series methods are often violating the statistical assumptions. To face these problems, then it is used free assumptions methods, the method with the Fuzzy Time Series Markov Chain, the Chen Logical Method, and its segmented methods due to unbalancing forecasting results. This study is built the forecasting model of the price of bitcoin for the coming period based on the data from 2010 to 2020. The proposed methods have a better fit for bitcoin time series data prices. Besides, the Fuzzy Time Series Markov Chain method has the slightly smallest accuracy error based on Mean Absolute Percentage Error (MAPE) comparing to the Fuzzy Time Series Segmented Chen Logical Method and Fuzzy Time Series Chen Logical Method.

INTRODUCTION

Bitcoin is electronic money that uses peer-to-peer technology. Bitcoin can be sent over the internet to other bitcoin address holders, and bitcoin is stored in a wallet file format on a personal computer [1]. The price is fluctuating, it causing bitcoin can be used as an alternative in investing. Investors will get benefits buying when bitcoinprices are down and resell when bitcoin prices have risen [2].

The changes in the bitcoin price data form a repeating pattern in which the past period will be repeated in the present (time series data). The purpose of the time series model analysis is to find an order that can be used in forecasting future events and identify factors that can affect the value in time series [3]. Forecasting is usually classified based on the future time it covers, namely the short-term, long-term, and medium-term. The short-term forecasting is forecasting to predict events in daily, weekly, and monthly periods. The medium-term forecasting is forecasting from one to two years into the future. The long-term forecasting covers more than two years [4].

Time series data can be modeled by the classic time series method and the Fuzzy Time Series method. The classic method, for example, the Autoregressive Integrated Moving Average (ARIMA) method. In addition, the neural network method [5] can be used to model the back propagation method in the artificial neural network until the error is obtained in small issue weights. Multivariate Adaptive Regression Spline (MARS) nonparametric regression methods can model data without regard to classical statistical assumptions for specific time series data such as [6] giving slightly better results than the Artificial Neural Network (ANN) method.

In addition, time series data analysis can be approached with sample distribution. Some papers are using exponential distribution in research, such as on its convolution in Devianto et al. [7] and Levy measure property in exponential distribution [8]. Besides that, the Levy measure property can also be used on the generalized exponential distribution as gamma distribution [9]. In another study, Devianto et al. [10] using the new Poisson

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compound distribution was introduced randomly identical variables and the number of independent from the variational Cauchy distribution with the number of random variables having a Poisson distribution.

The suitable method often used to predict short and medium term is the ARIMA model and its variations [11]. The accurate short-term forecasting can be determined from past and present values of the dependent variable. Usually, the forecast value will tend to be flat for a fairly long period [12]. In a previous study, Azari [13] forecasted using bitcoin price change data every day for two years to see how bitcoin prices would be in the future. While long-term forecasting can use the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model, especially for conventional macroeconomic approaches [14]. However, this proposed research has been done forecasting with bitcoin price data every month from 2010 to 2020 by using a method that is free from assumptions, namely the Fuzzy Time Series method.

In the 1960s, a professor named Lotfi A. Zadeh discovered a theory known as fuzzy logic [15]. Then, in 1993, Song and Chissom developed fuzzy logic into a method that was used to do forecasting [16]. Fuzzy Time Series (FTS) method is a new approach that combines linguistic variables with the process of analyzing the application of fuzzy logic into time-series data to overcome data obscurity [17]. This method was developed to overcome the shortcomings of the classic time series method. In 1996, the FTS method was re-developed by Chen using simple arithmetic operations for forecasting at the University of Alabama [18]. Furthermore, the FTS Markov Chain method was first proposed by Tsaur [19], which combines the Fuzzy Time Series method and the Markov Chain to obtain the greatest probability using the transition probability matrix. Markov Chains can also be used to model other time-series data [20].

In investing, of course, there are risks that must be accepted. Because every day, the price can change according to market conditions [21]. The FTS Chen Logical method, the FTS Segmented Chen Logical method, and the FTS Markov Chain method are used to forecasting the bitcoin price in the next few periods. There are three methods that will be investigated that produces the best forecast value to predict the price of bitcoin in the future period.

MATERIALS AND METHODS

The main difference between the Fuzzy Time Series and conventional time series is the value used in forecasting, which is the fuzzy set of real numbers for a given set of universes. Fuzzy sets can be interpreted as a number class with the same boundaries. If the set U is the set of universes $U = \{u_1, u_{2,}, \dots, u_n\}$, then a fuzzy set A_i of the set U is defined as [14]:

$$A_i = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \dots + \frac{\mu_{A_i}(u_n)}{u_n}, \tag{1}$$

where $\mu_{A_i}(u_j)$ is the degree of membership u_j of the fuzzy set A_i, with $i, j = 1,2, \dots, n$ are many linguistic intervals. Here are some rules:

1. If the observation data X_t is u_1, then the degree of membership u_1 is 1, u_2 is 0.5, and the other is 0.
2. If the observation data (X_t) is u_j; $1 < j < n$, then the degree of membership u_j is 1, u_{j+1} and u_{j-1} are 0.5, and the other is 0.
3. If the observation data (X_t) is u_n, then the degree of membership u_n is 1, u_{n-1} is 0.5, and the other is 0.

Fuzzy Time Series Chen Logical Method (FTS-CLM)

There are several stages in determining to forecast using the Fuzzy Time Series Chen Logical Method (FTS-CLM). The stages of forecasting are as follows [18]:

1. **Step 1**: Defining the universal set U.

   In this section, the maximum (D_{max}) and minimum (D_{min}) values of historical data are determined. The value of D_1 and D_2 can be determined freely as long as the two values are still real positive. Following is the formula for the formation set of universes U:

$$U = [D_{\min} - D_1, D_{\max} + D_2]. \tag{2}$$

2. **Step 2**: Determination of the length and number of intervals.

In this section, the set of universes U is partitioned into several parts with the same interval (n) as the following Sturges formula [22]:

$$n = 1 + 3{,}322 \log N, \tag{3}$$

with N is many of historical data. Then, the length of the interval can be determined by:

$$l = \frac{[D_{\min} - D_1, D_{\max} + D_2]}{n}, \tag{4}$$

with l is the length of the interval, and n is the number of intervals. Where each interval can be determined by using the formula:

$$u_n = [D_{\min} - D_1 + (n-1)l; D_{\min} - D_1 + nl]. \tag{5}$$

3. **Step 3**: Defining fuzzy sets for each linguistic interval.

The determination of the fuzzy set can be determined as follows:

$$A_i = \sum_{j=1}^{n} \frac{\mu_{ij}}{u_{ij}}, \tag{6}$$

provided that the degree value of membership u_i is $\mu_{ij} = 1$, if $i = j, \mu_{ij} = 0.5$, if $j = i - 1$ or $i = j - 1$, and $\mu_{ij} = 0$ for others.

4. **Step 4**: Perform the fuzzification of observational data.

The fuzzification process is the process of changing numerical values into fuzzy variables.

5. **Step 5**: Determination of Fuzzy Logic Relations (FLR) and Fuzzy Logic Relations Group (FLRG).

Definition 1.[19]. *Let the universe of discourse* $X(t)$ $(t = \cdots, 0,1,2, \dots n, \dots)$ *be a subset of R defined by the fuzzy set* A_i*. If F(t) consists of* $A_i(i = 1,2,,,,n)$*, than F(t) is defined as a fuzzy time series on* $X(t)$ $(t = \dots, 0,1,2, \dots n, \dots)$.

Definition 2.[19]. *Suppose* $F(t) = A_i$ *is caused by* $F(t-1) = A_j$*, then the fuzzy logical relationship is defined as* $A_i \rightarrow A_j$*.*

This relationship can be stated by $A_i \rightarrow A_j$, which A_i is called the left-hand side (LHS), and A_j is called the right-hand side (RHS) of the FLR. If there are two FLR that have the same fuzzy set (LHS $A_i \rightarrow A_{j1}$, $A_i \rightarrow A_{j2}$), they can be grouped into fuzzy logical relationship groups (FLRG) $A_i \rightarrow A_{j1}, A_{j2}$.

6. **Step 6**: Determination of forecasting.

If $F(t-1) = A_i$, then the forecast to $F(t)$ comply with the following rules:

a. If the FLR of A_i is empty $(A_i \rightarrow \emptyset)$, the forecasting of $F(t) = m_i$, which m_i is the midpoint of interval u_i.

b. If the FLR is one-to-one FLR $(A_i \rightarrow A_j)$, then the forecasting of $F(t) = m_j$, which m_j is the midpoint of interval u_j.

c. If the FLRG$(A_i \rightarrow A_{1,}A_2, A_3)$, then the forecasting of $F(t) = (m_1 + m_2 + m_3)/3$, which m_1, m_2, m_3 are the midpoint of interval u_1, u_2, u_3.

7. **Step 7**: Perform the defuzzification process.

The defuzzification process is the process of returning each linguistic variable to a real number obtained from forecasting results. The result of the defuzzification process in the form of real numbers is the forecast value. For example, $F(t) = (A_{j1,}A_{j2}, \ldots, A_{jk})$, the defuzzification for $F(t)$ is

$$\hat{X}_t = \frac{\sum_{p=1}^{k} m_{jp}}{k} \tag{7}$$

With $\hat{X}_t$ is defuzzification, and m_{jp} is the middle value of A_{jp}.

Fuzzy Time Series Segmented Chen Logical Method (FTS-SCLM)

It is determining the forecasting for the Fuzzy Time Series Segmented Chen Logical method, segment a time series data that has a small range. Then after it is divided into several segments, the steps are the same as in the Fuzzy Time Series Chen Logical method**.**

Fuzzy Time Series Markov Chain (FTS-MC)

The forecasting steps in the Fuzzy Time Series Markov Chain model are the same as the first step to the fifth step in the Fuzzy Time Series Chen Logical method. The difference between these two methods lies in the forecasting of the FTS-MC method, which starts from the following steps [19]:

6. **Step 6**: Create a Markov transition probability matrix. Transitional probabilities can be written as follows,

$$P_{ij} = \frac{M_{ij}}{M_i},\ i, j = 1,2,3,\ldots,n\,. \tag{8}$$

The transitional probability from the state to one step is P_{ij}. The amount of data from the state is M_i. The transitional time from the state to one step is M_{ij}. The transition probability matrix R of the state is written as follows:

$$R = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}$$

7. **Step 7**: Calculate the results of the initial forecasting.

The initial forecast value is calculated based on the probability matrix obtained in the previous step, which is the rule as follows:

Rule 1. If the FLRG A_i is one to one $A_i \rightarrow A_k$ with $P_i = 0$ and, $P_{ik} = 1, j \neq k$, then the forecasting result $F(t)$ is m_k, which m_k is the midpoint of u_k, it given by the equation:

$$F(t) = m_i P_{ik} = m_k \tag{9}$$

Rule 2. If the FLRG A_j from is one too many $(A_i \rightarrow A_1, A_2, \ldots, A_n, J = 1,2, \ldots, n)$ when collected data $X(t-1)$ at the time $t-1$ is in the state A_j, the forecasting of $F(t)$ is equal as:

$$F(t) = m_1 P_{j1} + m_2 P_{j2} + .. + m_{j-1} P_{j(j-1)} + X(t-1) P_{jj} + m_{j+1} P_{j(j+1)} + .. + m_n P_{jn} , \tag{10}$$

where $m_1, m_2, .., m_{j-1}, m_{j+1}, .., m_n$ are the midpoint of $u_1, u_2, .., u_{j-1}, u_{j+1}, .., u_n$ and, m_j is substituted for $X(t-1)$ in order to take more information from the state A_j at the time $t-1$.

8. Step 8: The purpose of this step is to correct forecasting errors caused by the Markov Chain matrix.

This is due to the relatively small sample size used to model. The values of the adjustment are:

a. The state A_i is related with A_i, if it starts in the state A_i, as $F(t-1) = A_i$, at the time $t-1$, and at time *t*, $(i < j)$ makes an increasing transition into state A_j, then the adjusting trend value D_t is defined as $D_{tI} = (l/2)$.
b. The state A_i is related with A_i, if it starts in the state A_i, as $F(t-1) = A_i$, at the time $t-1$, and at time *t*, $(i > j)$, makes a decreasing transition into state A_j, then the adjusting trend value D_t is defined as $D_{tI} = -(l/2)$.
c. The current state is in the state A_i, as $F(t-1) = A_i$, at the time $t-1$, and at time *t*, $(1 \leq s \leq n-i)$ makes a jump-forward transition into state A_{i+s}, then the adjustment trend value D_t is defined as $D_{t2} = (l/2)s$, with $(1 \leq s \leq n-i)$, and *l* is the length of the universal discourse *U* partitioned into as *n* equal intervals.
d. The process is defined to be in the state A_i, as $F(t-1) = A_i$, at the time $t-1$, and time *t*, $1 \leq v \leq i$ makes a jump-backward transition into the state A_{i-v}, the adjusting trend value D_t is defined as $D_{t2} = (l/2)v$, $1 \leq v \leq i$.

9. Step 9: Determination of the final forecasting results.

The general form for forecasting result $F'(t)$ can be obtained as,

$$F'(t) = F(t) \pm D_{t1} \pm D_{t2} . \tag{11}$$

Forecasting Accuracy

Error calculation is a way to determine the accuracy of the model that has been obtained. Error calculation can be seen how accurate the forecasting data from the model that has been obtained with actual data. The smaller the value generated from MAPE, MSE, and RMSE, the better the forecasting model used. The accuracy of each forecasting methods used are:

1. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{\left| X_t - \hat{X}_t \right|}{X_t} \times 100\% \tag{12}$$

MAPE accuracy criteria [23]:

a. The forecasting accuracy is perfect when the MAPE value of <10%
b. The forecasting accuracy is good when the MAPE value of 10% -20%
c. The forecasting accuracy is good enough when the MAPE value of 20% -50%
d. The forecasting accuracy is not accurate when the MAPE value of > 50%.

2. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (X_t - \hat{X}_t)^2} \tag{13}$$

3. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|X_t - \hat{X}_t\right| \quad (14)$$

where X_t is actual data, and $\hat{X}_t$ is forecast data.

RESULTS AND DISCUSSIONS

In this section, we will discuss data forecasting methods, the Fuzzy Time Series method. Bitcoin prices will be processed using the Fuzzy Time Series Chen Logical method, the Fuzzy Time Series Segmented Chen Logical method, and the Fuzzy Time Series Markov Chain.

1. Fuzzy Time Series Chen Logical Method (FTS-CLM).

The data used in this forecasting is bitcoin price data, which is calculated every month from August 2010 to February 2020. The data is expressed in USD. The first step is defining the set of universes then they are obtained: $u_1 = [0; 1731.42]$, $u_2 = [1731.42; 3462.79]$, $u_3 = [3462.79; 5194.16], u_4 = [5194.16; 6925.53], u_5 = [6925.53; 8656.89], u_6 = [8656.89; 10388.26], u_7 = [10388.26; 12119.63], u_8 = [12119.63; 13851.00]$.

The next stage determines the fuzzy set for each linguistic variable obtained as follows:

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7} + \frac{0}{u_8}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7} + \frac{0.5}{u_8}$$
$$A_8 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0.5}{u_7} + \frac{1}{u_8}$$

After the linguistic variable is defined, the next step is the fuzzification process. This process is carried out to determine the linguistic interval ofactual data, then the linguistic variable is determined. For example, it is known that the actual value of the bitcoin price in August 2010 was USD 0.1. This means that the data is at linguistic interval u_1. The linguistic variable is A_1. Then the fuzzification process is carried out as in TABLE 1.

TABLE 1. Fuzzification Data

t	Period	Actual Data	Fuzzy Data	t	Period	Actual Data	Fuzzy Data
1	Aug 10	0.10	A_1	64	Nov 15	378.00	A_1
2	Sep 10	0.10	A_1	65	Dec 15	430.00	A_1
3	Oct 10	0.20	A_1	66	Jan 16	369.80	A_1
...	...	...	...	...	...	...	...
61	Aug 15	229.50	A_1	113	Dec 19	7196.40	A_5
62	Sep 15	235.90	A_1	114	Jan 20	9349.10	A_6
63	Oct 15	311.20	A_1	115	Feb 20	9644.70	A_6

Linguistic variables have been determined in each table for the actual data, which means that the actual data is in the fuzzy set. The next stage is determining how the relationship between the fuzzy set by determining the Fuzzy Logic Relations (FLR) and the Fuzzy Logic Relations Group (FLRG) according to Definition 2. The results are obtained based on TABLE 2 and TABLE 3.

TABLE 2. Fuzzy Logic Relations (FLR)

t	Period	FLR	t	Period	FLR
1	Aug 10 → Sep 10	$A_1 \rightarrow A_1$	64	Nov 15 → Dec 15	$A_1 \rightarrow A_1$
2	Sep 10 → Oct 10	$A_1 \rightarrow A_1$	65	Dec 15 → Jan 16	$A_1 \rightarrow A_1$
3	Oct 10 → Nov 10	$A_1 \rightarrow A_1$	66	Jan 16 → Feb 16	$A_1 \rightarrow A_1$
...	...	...	...	...	...
61	Aug 15 → Sep 15	$A_1 \rightarrow A_1$	113	Dec 19 → Jan 20	$A_5 \rightarrow A_6$
62	Sep 15 → Oct 15	$A_1 \rightarrow A_1$	114	Jan 20 → Feb 20	$A_6 \rightarrow A_6$
63	Oct 15 → Nov 15	$A_1 \rightarrow A_1$	115	Feb 20 → Mar 20	$A_6 \rightarrow A_6$

From TABLE 2, it can be observed how the fuzzy set relationship from month to month. This relationship can be stated by $A_i \rightarrow A_j$, which A_i is called the left-hand side (LHS), and A_j is called the right-hand side (RHS) of the FLR.

TABLE 3. The Fuzzy Logic Relations Group (FLRG)

No	FLRG
1	$A_1 \rightarrow A_1, A_2$
2	$A_2 \rightarrow A_2, A_3$
3	$A_3 \rightarrow A_2, A_3, A_4$
4	$A_4 \rightarrow A_3, A_4, A_5, A_6$
5	$A_5 \rightarrow A_4, A_5, A_6, A_7$
6	$A_6 \rightarrow A_5, A_6, A_8$
7	$A_7 \rightarrow A_6$
8	$A_8 \rightarrow A_8$

The fuzzy set relation above shows that the FLR relationship is in a group. The purpose of the relation states that the fuzzy set on the left side only has a relation with the fuzzy set on the right side.

The next step is to predict the price of bitcoin and do the defuzzification process. The value of $X(t)$ is actual data, and $\hat{X}(t)$ is the result of defuzzification in the form of real numbers that are used as the value of forecasting results.

TABLE 4. Forecasting Results by Fuzzy Time Series Chen Logical Method (FTS-CLM)

t	Period	Actual Data	FTS-CLM	t	Period	Actual Data	FTS-CLM
1	Aug 10	0.10	0.00	64	Nov 15	378.00	1731.41
2	Sep 10	0.10	1731.41	65	Dec 15	430.00	1731.41
3	Oct 10	0.20	1731.41	66	Jan 16	369.80	1731.41
...	...	...	...	...	...	...	...
61	Aug 15	229.50	1731.41	113	Dec 19	7196.40	8656.90
62	Sep 15	235.90	1731.41	114	Jan 20	9349.10	10099.70
63	Oct 15	311.20	1731.41	115	Feb 20	9644.70	10099.70

According to TABLE 4, it appears that the forecast data has a large difference with the actual data. The table shows that for bitcoin forecasting values from period 2 to period 66, the forecasting data is constant because the data have the same linguistic variables. Because since the beginning of the emergence of bitcoin, the price of bitcoin experienced high fluctuations resulting in large data ranges, then the early years resulted in poor forecasting results.

2. Fuzzy Time Series Segmented Chen Logical Method (FTS-SCLM)

In forecasting with the Fuzzy Time Series Chen Logical method, in the initial period, the forecasting results obtained have far different from the actual data. The segment is carried out, which is dividing the data into two segments. The first segment of the data is 1-80, and the second is 81-115. The two segments are carried out again in the same steps in the Fuzzy Time Series Chen Logical method. We get the final result in the form of the Fuzzy Time Series Segmented Chen Logical method in TABLE 5.

TABLE 5. Forecasting Results by The Fuzzy Time Series Segmented Chen Logical Method (FTS-SCLM)

t	Period	Actual Data	FTS-SCLM	t	Period	Actual Data	FTS-SCLM
1	Aug 10	0.10	0	64	Nov 15	378	376.90
2	Sep 10	0.10	150.79	65	Dec 15	430	376.90
3	Oct 10	0.20	150.79	66	Jan 16	369.8	376.90
...	...	...	...	...	...	...	...
61	Aug 15	229.50	577.89	113	Dec 19	7196.4	7600.99
62	Sep 15	235.90	577.89	114	Jan 20	9349.1	8779.57
63	Oct 15	311.20	577.89	115	Feb 20	9644.7	8779.57

In TABLE 5, it can be seen that the result of forecasting has a better difference than the Fuzzy Time Series Chen Logical method.

3. Fuzzy Time Series Markov Chain (FTS-MC)

The steps to determine the forecasting with Fuzzy Time Series Markov Chain are the same as steps 1-5 on the Fuzzy Time Series Chen Logical method. For the next step, we start from equation 8. It using the fuzzy logical relationship group in TABLE 3, the transition probability matrix R may be obtained,

$$R = \begin{bmatrix} \frac{80}{81} & \frac{1}{81} & \ldots & 0 \\ 0 & \frac{2}{4} & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & 1 \end{bmatrix}$$

Calculate the forecasted outputs. For examples, the forecasting value of $t = 2$ is, $F(2) = \frac{80}{81} * X(1) + \frac{1}{81} * m_2 = \frac{80}{81} * 0.1 + \frac{1}{81} * 2597.1 = 32.18.$

They are using the same method, the initial forecasting results obtained for some bitcoin price data. After getting all, the initial forecast data, proceed with calculating the forecast adjustment. The adjusted forecasting value for t = 114 is $F'(114) = F(114) + 865.71 = 8969{,}68$. The forecasting data using the Fuzzy Time Series Markov Chain method as in TABLE 6.

TABLE 6. The Forecasting with The Fuzzy Time Series Markov Chain Method

t	Period	Actual Data	FTS-MC	t	Period	Actual Data	FTS-MC
1	Aug 10	0.10	0	64	Nov 15	378.00	339.42
2	Sep 10	0.10	32.17	65	Dec 15	430.00	405.39
3	Oct 10	0.20	32.17	66	Jan 16	369.80	456.75
...	...	...	...	...	...	...	...
61	Aug 15	229.50	312.26	113	Dec 19	7196.40	8379.32
62	Sep 15	235.90	258.73	114	Jan 20	9349.10	8969.68
63	Oct 15	311.20	265.05	115	Feb 20	9644.70	9060.73

From TABLE 6, it can be seen that the results of the forecast using the Fuzzy FTS-MC are almost close to the actual data. The difference between actual data and forecast data is not so far. Overall, the data from the FTS-MC forecast results can be said to be good.

The following graph has presented a comparison between the actual data and the forecasting value using the Fuzzy Time Series Chen Logical method, Fuzzy Time Series Segmented Chen Logical method, and Fuzzy Time Series Markov Chain method can be seen in FIGURE 1.

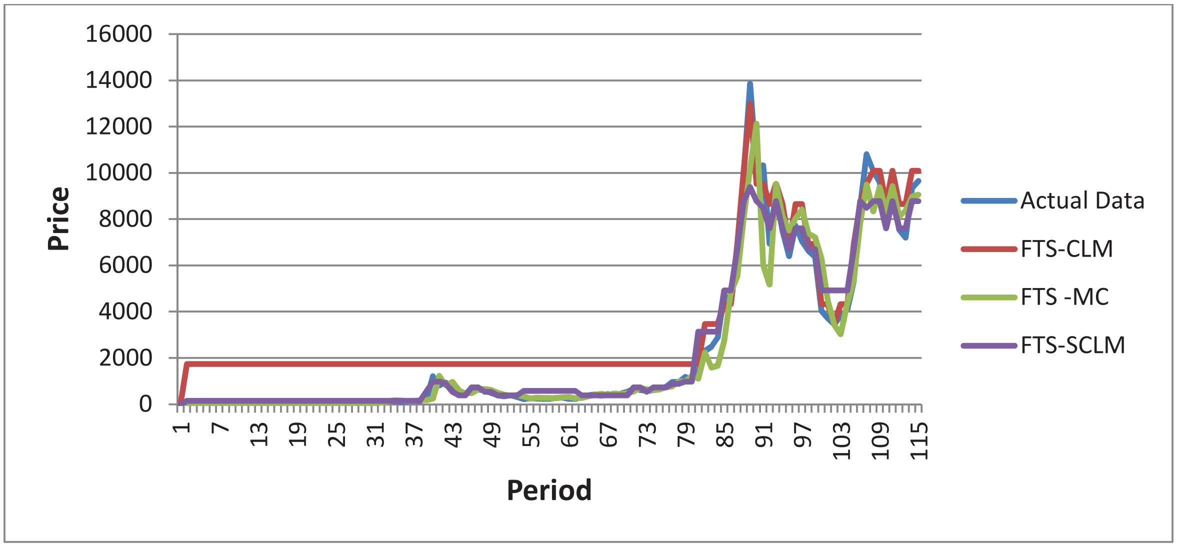

FIGURE 1. Comparisons Among The Fuzzy Time Series Methods and Actual Data

Based on FIGURE 1, it can be seen that the Fuzzy Time Series Chen Logical method is not good enough in predicting in the initial period until the 80 periods. Then from the initial period, Fuzzy Time Series Markov Chain and Fuzzy Time Series Segmented Chen Logical method are good in predicting data because forecasting data approaches the actual data. However, it can be seen that the Fuzzy Time Series Markov Chain method is closer to actual data after the initial period than the Fuzzy Time Series Segmented Chen Logical method. Therefore, both of the Fuzzy Time Series Markov Chain method and the Fuzzy Time Series Segmented Chen Logical method have good enough performance in forecasting bitcoin prices.

Forecasting Accuracy

Forecasting accuracy is done to find out which forecasting method is better and accurate enough to predict bitcoin price data. The forecast accuracy value for each method uses the equation (12), (13), and (14). The accuracy is presented in TABLE 7.

TABLE 7. Forecasting Accuracy

Methods	MAPE	MAE	RMSE
FTS Markov Chain	8.80%	359.38	782.39
FTS Chen Logical Method	470.65%	1197.02	1304.79
FTS Segmented Chen Logical Method	40.80%	355.51	678.01

Based on TABLE 7, it can be seen that the Fuzzy Time Series Markov Chain method has a MAPE value <10%, which means that this method is very good. Then, the Fuzzy Time Series Chen Logical method has a MAPE value> 50%, which means the forecast results are not accurate. The resulting data range is too large. Therefore the Segmented Chen Logical method starts in order to predict the data forecasting good enough. This can be seen in the MAPE value, which is between 20% -50%. However, based on the criteria of MAE and RMSE values, it is seen that forecasting results in the Fuzzy Time Series Segmented Chen Logical method is better than the Fuzzy Time Series Chen Logical method and the Fuzzy Time Series Markov Chain because it has the smallest MAE and RMSE.

CONCLUSION

Based on data analysis techniques that have been done, it can be predicted that the price of bitcoin for the next period will increase. Fuzzy Time Series methods can model various types of time series data patterns because this method is free from classical assumptions. Based on forecasting results obtained through a good method seen from the level of forecasting using MAPE is a Fuzzy Time Series Markov Chain. Because in this method, the MAPE value <10% means that the results of forecasting data are very good. However, when viewed based on the accuracy of the MAE and RMSE forecasting results obtained by the Fuzzy Time Series Segmented Chen Logical method is better than the Fuzzy Time Series Chen Logical method and the Fuzzy Time Series Markov Chain because it has the smallest MAE and RMSE values among the three methods.

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