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Prediction of IDR-USD Exchange Rate using the Cheng Fuzzy Time Series Method with Particle Swarm Optimization

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ABSTRACT

Currently, much research on machine learning about prediction has been carried out. For example, to predict the exchange rate of the rupiah against the United States currency, namely the United States Dollar (USD). The continuing trend of USD depreciation has attracted many researchers to explore currency trading, especially in establishing an efficient method for predicting fluctuating exchange rates. The rapid development of time series prediction methods has resulted in many methods that can predict data according to needs. In this study, we apply the Fuzzy Time Series Cheng method with Particle Swarm Optimization (PSO) to predict the IDR exchange rate against USD. The data used in this research is sourced from Bank Indonesia in the form of time series data on the selling and buying exchange rate. The FTS Cheng method forecasts the IDR exchange rate against USD. In contrast, the PSO algorithm optimizes the interval parameter to increase the forecasting accuracy. Based on the implementation and the results of the tests, the results show that using the PSO algorithm can produce the best optimization interval parameters and increase the accuracy value. From the results of 10 trials with training data, testing data, and different iterations, it was obtained that the MAPE test for predicting the rupiah exchange rate against the US dollar using FTS Cheng with 60% training data and 40% testing data resulted in the lowest MAPE of 0.610145%. Furthermore, 70% of the training and 30% of the testing data resulted in the lowest MAPE of 0.313388%. Then the FTS Cheng and PSO testing with 60% training data and 40% testing data, and an iteration value of 200 resulted in the lowest MAPE of 0.394707%. Furthermore, 70% of training data and 30% of testing data and an iteration value of 90 resulted in the lowest MAPE of 0.263666%.

Keywords: Prediction; Exchange Rate; Fuzzy Time Series Cheng; Particle Swarm Optimization; Optimization; Parameter Interval.

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I. INTRODUCTION

The need to make predictions is vital in stock predictions, sales of goods, as well as weather forecasting, and currency rates. In predicting the rupiah exchange rate, the United States Dollar (USD) is the international reference currency. The trend of USD fluctuations attracts many researchers to know the pattern, especially in establishing an efficient method for exchange rate prediction. The rapid development of time series prediction methods has resulted in many methods that can predict data according to needs. Many methods have been proposed ranging from linear and non-linear regression to artificial intelligence algorithms [1].

Research related to currency exchange rate prediction using the Arima Box-Jenkins method produces the best model, ARIMA (13, 1, 13). Still, the ARIMA method has a complicated process to identify the appropriate model. [2]. The data will be transformed into stationery data, not original data that can be directly processed. The Fuzzy Mamdani method used to predict the exchange rate produces a MAPE value of 9.35%[3]. Machine learning with the Support Vector Regression (SVR) method with training modeling as much as 415 data with an R^2 value of 0.9223 and an RMSE of 54.3156. The 30 data testing also shows quite good results with an R^2 value of 0.5397 and an RMSE of 66.8015[4]. Predicting the Malaysian Ringgit (MYR) exchange rate against the Singapore Dollar (SGD) using the Fuzzy Time Series Markov Chain and Fuzzy Time Series Chen & Hsu methods produces a MAPE for Fuzzy Time Series (FTS) Markov Chain of 0.9895%. While the MAPE value for FTS Chen & Hsu is 3,4306%[5].

The fuzzy time series algorithm is one of the computational intelligence methods that is attracting much attention today. Fuzzy Time Series (FTS) modeling through fuzzy relational equations and approaching reasoning [6]. One of the advantages of the fuzzy time series approach is that theoretical assumptions do not need to be checked compared to conventional time series methods, where various theoretical assumptions have to be considered. The fuzzy time series approach can handle minimal data sets, and

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the assumption of linearity does not need to be considered [7]. Many FTS methods have been developed, for example, the Chen FTS method and the Cheng FTS method. The research by [8] compared both methods and found that the Cheng method had a lower error rate. However, there are still weaknesses in FTS, namely the lack of consideration in determining the universe of speech and the optimal length of the interval [8]. An optimization algorithm is needed to find the optimal value of the FTS interval, and the optimization algorithm used is Particle Swarm Optimization (PSO) to overcome these weaknesses [9].

Particle Swarm Optimization (PSO) is a PSO optimization strategy that performs well in many function and parameter optimization problems [10]. Many studies using PSO have been shown to increase the performance percentage in research [11], [12]. The advantage of the PSO algorithm is that it has high decentralization with a simple implementation to solve optimization problems efficiently [13]. Another advantage of PSO is that the PSO algorithm can quickly achieve convergence values and is not sensitive to population size [10], [14], [15]. In this study, PSO will be applied to solve problems that occur in FTS Cheng by changing the pattern of the parameter intervals of the universe of speech to maximize the performance of the resulting model by achieving more accurate accuracy values.

Based on the problems and research references described, this study proposes the Fuzzy Time Series Cheng method with Particle Swarm Optimization (PSO) to predict the IDR exchange rate against USD. The data used in this study is sourced from Bank Indonesia in the form of time series data on the selling and buying rates. The FTS Cheng method forecasts the IDR exchange rate against USD, while the PSO algorithm is used to optimize the interval parameter so that the prediction accuracy level increases. This study is expected to determine the accuracy performance of the Cheng FTS method by optimizing the PSO interval parameter in predicting the rupiah exchange rate against the US dollar.

II. METHOD

The research methodology used for data collection in this study is quantitative. The quantitative research method is used if the data collected is quantitative or other data types that can be quantified and processed using statistical techniques. The research method in Fig. 1 contains the stages of planning that will be carried out while conducting this research. There are four stages to be carried out: data collection, particle swarm optimization algorithm, fuzzy time series Cheng algorithm, and error calculation.

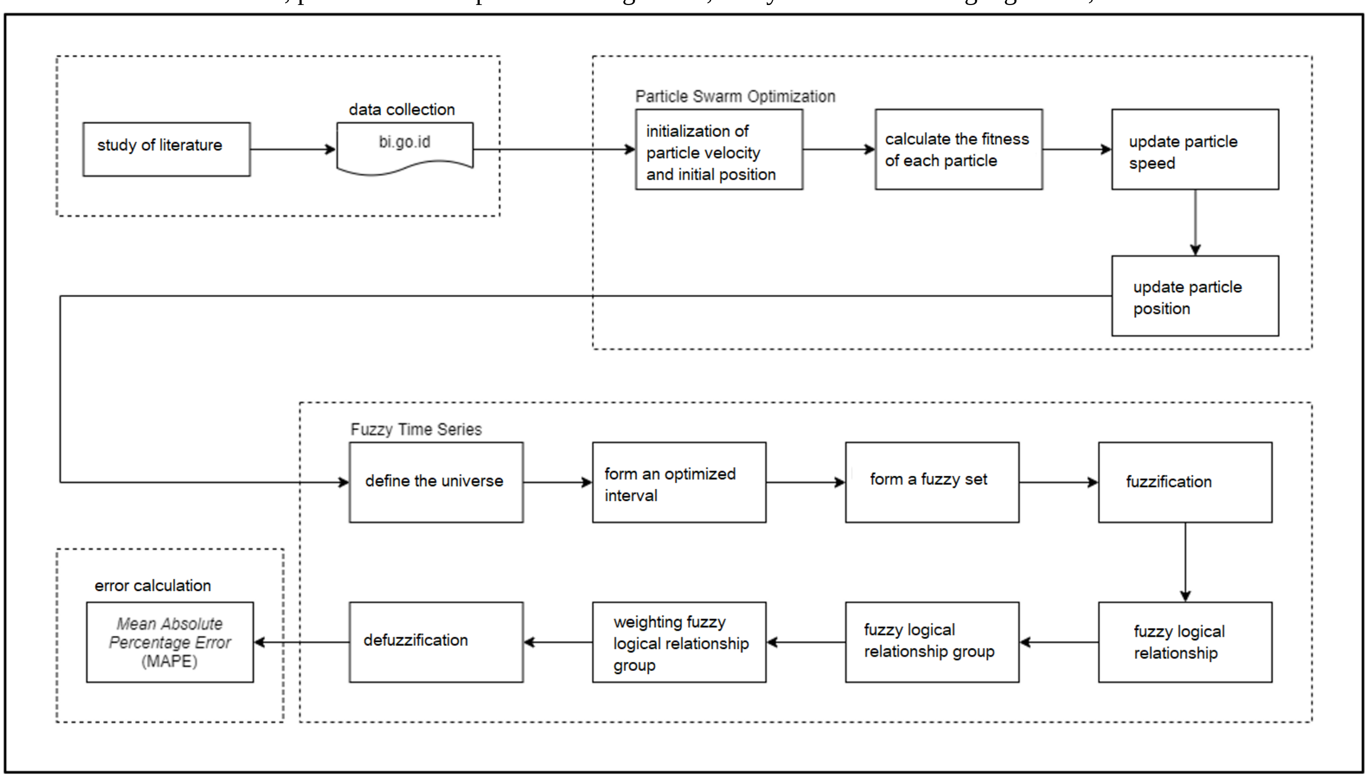

Fig 1. Research methods

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A. Data Collection

The data collection process is carried out by taking data from the Bank Indonesia website at the address http://www.bi.go.id/id/statistik/information-kurs/transaksi-bi/default.aspx. The data used is data on the exchange rate of the rupiah (IDR) against the US dollar (USD) in the form of selling and buying rates from 2 January 2018 to 9 July 2021

B. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization technique. There are three basic principles in PSO as an algorithm based on cognitive and social behavior: evaluation, comparison, and imitation.[10]. PSO is a population-based evolutionary computing technique inspired by the social behavior of animals, such as flocks of birds, fish flocks, and swarming theory. PSO can solve many problems, such as Genetic Algorithms [16].

This kind of swarm intelligence-based optimization method is called a behaviorally inspired algorithm, which has a different approach from genetic algorithms. Genetic algorithms are usually considered by the method of evolution-based producers. It is assumed that the swarm on each particle has a specific or fixed size, and its initial position is random in multidimensional space. Each particle is assumed to have two characteristics: position and velocity. Each particle moves in a particular space and remembers the best position ever traversed or found concerning the food source or the value of the objective function. The particle conveys each particle's best position, adjusting the position and speed according to the information received regarding the best position.
There are several steps or stages of learning in Particle Swarm Optimization (PSO), which are as follows: [17]:

- Initialization of the velocity and initial position of the particle. The initial particle velocity is symbolized by v_i, while the particle's initial position is symbolized by x_i, for $1 \leq i \leq N$, N is the number of particles.
- Calculate the fitness value for each particle. The fitness value calculation is carried out for each particle i as well as the best position P_{best} of each particle and its fitness value. The best position P_{best} with the best fitness value is stored as G_{best}.
- Update particle speed. Particle velocity updates are carried out to determine the direction of displacement of particles in the population [10]. Equation (1) calculates the new particle velocity based on the previous velocity, the distance between the current position and $P_{best,}$ and between the current position and the best position G_{best}.

$$v_j(i) = v_j(i-1) + c_1 r_1 \left[P_{best,j} - x_j(i-1)\right] + c_2 r_2 [G_{best,j} - x_j(i-1)] \tag{1}$$

  Where the j variable is 1 , 2, … ,n represents the number of particles; the $v_j(i)$ variable is a particle velocity j in the iteration i; the c_1,c_2 variable the cognitive and social particle coefficient; the r_1,r_2 variable is the random numbers in the range [1,10]; the $P_{best,j}$ variable is the P_{best} value represents the personal best of the particle j; and the $G_{best,j}$ variable is the the G_{best} value represents the global best of the entire population.
- Update particle position. Particle position updates are carried out to find the latest position on each particle i based on Equation (2).

$$x_j(i) = v_j(i) + x_j(i-1) \tag{2}$$

  Equation (2) is simulated in a space with a particular dimension with many iterations. In each iteration, the particle's position will increasingly lead to the intended target (minimizing or maximizing the value of the function). The iteration is done until the maximum iteration is reached or other stopping criteria are met.

C. Fuzzy time series Cheng

The Cheng method has a slightly different way of determining intervals, using a Fuzzy Logical Relationship (FLR) by including all relationships and assigning weights based on the same FLR sequence and iteration. [18]. The stages in making predictions using Cheng fuzzy time series are:

- Determining the Universe of Discourse using Equation (3). Where d_{min} and $d_{\max}$ are the smallest and largest data from data, and d_1 and d_2 are positive numbers.

$$U = [d_{min} - d_1 \, , d_{max} + d_2] \tag{3}$$

- Determining the interval width using the frequency distribution based on Equation (4).

$$R = (d_{max} + d_2) - (d_{min} - d_1) \tag{4}$$

- Determine the number of class intervals using the Sturges based on Equation (5).

$$K = 1 + 3{,}322 \times \log n \tag{5}$$

  Specify the width of the interval using Equation (6).

$$I = \ Range\ Data/Number\ of\ class\ interval\ (K) \tag{6}$$

Finding the middle value using Equation (7). Where, the i variable is the number of fuzzy sets.

$$m_i = (lower\ limit + upper\ limit)/2 \tag{7}$$

- Define fuzzy sets and form fuzzification, fuzzy sets A_1, A_2, ... A_p can be formed based on pre-formed intervals.
- Create a Fuzzy Logical Relationship (FLR) table based on actual data. FLR can be denoted by $A_i \longrightarrow A_j$ where A_i is called the current state and A_j is called the next state.
- Determine the weight of the FLR relationship into a Fuzzy Logical Relationship Group (FLRG) by including all relationships (all relationships) and assigning weights based on the same sequence and iteration. FLRs that have the same current state (Ai) are combined into one group in the form of a weighting matrix. Suppose there is a sequence of the same FLR.
  (t = 1) $A_1 \rightarrow A_1$, given weight 1
  (t = 2) $A_2 \rightarrow A_1$, given weight 1
  (t = 3) $A_1 \rightarrow A_1$, given weight 2
  (t = 4) $A_1 \rightarrow A_1$, given weight 3
  Where t denotes time, the weights obtained in the FLR relation are entered as a weighting matrix using the matrix in Equation (8). Where wi is the weight of the matrix in the i-th row and j-th column with i = 1, 2,…, p ; j = 1, 2,…, p.

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1p} \\ W_{21} & W_{22} & \cdots & W_{2p} \\ \vdots & \vdots & W_{ij} & \vdots \\ W_{p1} & W_{p2} & \cdots & W_{pp} \end{bmatrix} \tag{8}$$

- Transforming the FLRG weights into a normalized weighting matrix (***W****) using a matrix on Equation (9). where ***W**** is a weighted matrix that has been normalized with Equation (10).

$$W^* = \begin{bmatrix} {W_{11}}^* & {W_{12}}^* & \cdots & {W_{1p}}^* \\ {W_{21}}^* & {W_{22}}^* & \cdots & {W_{2p}}^* \\ \vdots & \vdots & {W_{ij}}^* & \vdots \\ {W_{p1}}^* & {W_{p2}}^* & \cdots & {W_{pp}}^* \end{bmatrix} \tag{9}$$

$$w_i * = \frac{w_i}{\sum_{j=1}^{p} w_i} \tag{10}$$

- Determine the Defuzzification of the predicted value. The normalized weighting matrix (***W****)* is multiplied by m_i, the median value on the fuzzy set interval, and the prediction calculation using Equation (11) where F_i is the result of weight prediction calculated using Equation (12).

$$F_i = \ w_{i1} * (m_1) + \ w_{i2} * (m_2) + \cdots + w_{ip} * (m_p) \tag{11}$$

$$w_i * = \frac{w_i}{\sum_{j=1}^{p} w_i} \tag{12}$$

If the result of the fuzzification i-th period is A_i, and A_i do not have FLR on FLRG with condition $Ai \rightarrow \emptyset$, where the maximum value of the degree of membership is at u_i, then the predicted value (Fi) is the median value of u_i, defined by m_i [19].

D. Error Calculation

Error calculation is performed to compare the predicted results with the actual data. In this study, the method used to calculate the error is the Mean Absolute Percentage Error (MAPE). Mean Absolute Percentage Error (MAPE) is a method used to measure and evaluate the predicted value generated [17]. MAPE values are displayed as a percentage using Equation (13).

$$MAPE = \frac{\sum \frac{|Ai - Fi|}{Ai}}{n} \times 100\% \tag{13}$$

Where, the A_i variable is actual data i, the F_i variable is the prediction result value for data i, and the N *variable* is the amount of data. Table I shows the quality of a prediction value calculated using the MAPE value can be determined based on the MAPE value criteria.

TABLE I
CRITERIA OF MAPE VALUE

MAPE	Criteria
<10%	Very Good
10% - 20%	Good
20% - 50%	Good Enough
>50%	Poor

III. RESULT AND DISCUSSION

A. Data Collection

The data used is data on the exchange rate of the rupiah against the US Dollar in the form of selling rates and buying rates from 2 January 2018 to 9 July 2021, with a total of 872 data. The data is copied to Microsoft Excel with file format .csv and then imported into a MySQL database. However, for the exchange rate data sample based on the values in Table II, 50 selling rate data were used from 2 January 2018 to 13 March 2018. There are 30 data samples used for data training from 2 January 2018 to 12 February 2018. There are 20 data samples used for data testing from 13 February 2018 to 13 March 2018 in Table III, which is an example of exchange rate data for testing.

TABLE II
EXCHANGE RATE DATA SAMPLE FOR TRAINING

Date	selling rates	Date	selling rates	Date	selling rates
02-01- 2018	13610	16-01- 2018	13400	30-01- 2018	13465
03-01- 2018	13565	17-01- 2018	13390	31-01- 2018	13480
04 -01- 2018	13541	18 -01- 2018	13432	01 -02- 2018	13469
05 -01- 2018	13472	19 -01- 2018	13398	02 -02- 2018	13495
08-01- 2018	13464	22-01- 2018	13401	05-02 - 2018	13565
09 -01- 2018	13495	23 -01-2018	13385	06 -02 -2018	13646
10 -01- 2018	13516	24 -01- 2018	13388	07 -02- 2018	13601
11 -01-2018	13494	25 -01-2018	13356	08 -02 -2018	13670
12 -01-2018	13429	26 -01-2018	13370	09 -02- 2018	13711
15 -01-2018	13397	29 -01-2018	13394	12 -02-2018	13677

TABLE III
EXCHANGE RATE DATA SAMPLE FOR TESTING

Date	selling rates	Date	selling rates	Date	selling rates
13-02- 2018	13712	23-02- 2018	13738	06 -03- 2018	13819
14 -02- 2018	13725	26-02- 2018	13727	07-03- 2018	13832
15 -02- 2018	13638	27 -02- 2018	13718	08-03 - 2018	13843
19 -02- 2018	13609	28 -02- 2018	13776	09 -03- 2018	13863
20 -02- 2018	13641	01 -03- 2018	13862	12-03 - 2018	13837
21 -02- 2018	13650	02 -03-2018	13815	13 -03 -2018	13826
22 -02- 2018	13733	05 -03- 2018	13809		

B. Particle Swarm Optimization

Parameter interval optimization aims to find the best FTS interval parameters that can provide better results. The Particle Swarm Optimization (PSO) algorithm has several stages: initializing the initial particle velocity and particle position, calculating the fitness value, updating the speed and position of the particle, updating for the personal best value P_{best}, and the global best G_{best}. After the number of iterations is reached. The slightest error value and the best interval will be obtained, where the interval will then be used in calculating the exchange rate prediction with FTS Cheng.

- Initialization of Particle Position and Initial Velocity. Initialization of the particle's initial position based on in the value in Table IV is done to generate a solution in the problem space of a predetermined number of particles. The initialization process for the initial position in this problem is carried out randomly.
-

TABLE IV
INITIALIZATION OF PARTICLE POSITION

Particle	Value
X1	6
X2	15
X3	3
X4	18

- Calculate Fitness Value. After the initial position and velocity of the particles are formed, the next step is to calculate the fitness value for each particle. The fitness value is obtained from MAPE (Mean Absolute Percentage Error), which is the result of calculating the level of forecasting error generated by FTS Cheng using interval optimization results with actual data related to the results in Table V.

TABLE V
CALCULATE FITNESS VALUE

Particle	Result
1	0.0024662247403721
2	0.0017976700736430
3	0.0034692927113368
4	0.0015139978715540

- Update P_{best}. Personal best P_{best} is the best position of the particle during iteration. The P_{best} value is obtained from the comparison of the current position of the particle with the previous. At the time of the first iteration, the particle does not have a position that can be compared with the current position. In this case, the particle's current position will be used as P_{best} based on the value in Table VI.

TABLE VI
UPDATE P_{BEST}

Particle	Value
Pbest1	6
Pbest2	15
Pbest3	3
Pbest4	18

- Update G_{best}. Global best G_{best} is the best position of the particle. The G_{best} value is the P_{best} value which has the lowest fitness value. G_{best} value constantly changes in each iteration. In this example problem, the P_{best} with the lowest fitness value is owned by the 4-th particle. $G_{best} = 18$.
- Update Particle Speed. After obtaining P_{best} and G_{best} from the four particles. The particle velocity will be updated based on the value of both based on Equation (1). Next, to initialize the initial velocity, because new particles are generated, the initial velocity value for each particle position is 0.
- Update Particle Position. After getting the latest velocity, the particle position is updated according to Equation (2), and we get the latest particle position, as seen in the results of Table VII. The second iteration with the same steps as the previous iteration until the results are obtained, as seen in the results of Table VIII.

TABLE VII
UPDATE PARTICLE POSITION

Particle	Value
X1	10
X2	16
X3	8
X4	18

TABLE VIII
PSO PARAMETER AND RESULT INTERVAL

No	PSO Parameter	Value	No	PSO Parameter	Value
1	Number of Particles	4	7	The initial speed of a particle	Random
2	Learning factor 1 (c1)	1	8	Number of iterations	4
3	Learning factor 2 (c2)	1	9	Result Interval	16
4	The initial position of a particle	Random			
5	r1	0,921823			
6	r2	0,986884			

C. *Fuzzy time series*

The Fuzzy Time Series Cheng method with Particle Swarm Optimization (PSO) was applied to predict the rupiah exchange rate against the USD based on the values in Table III.

- *Universal Set (U)*. After sorting the exchange rate sample data, the smallest and largest values from the data are obtained: $d_{min} = 13609$, $d_{max} = 13863$, $d_1=9$, and $d_2=7$. Based on Equation (3), then the universal set is $U = [13600, 13870]$
- The length of the interval using the frequency distribution has the following steps:
    1) Calculating range using Equation (4). The results obtained $R = (13870 – 13600) = 270$.
    2) Calculating class Intervals using Equation (5). The results obtained $K = 1 + 3{,}322 \times \log (20) = 5$.

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The weakness of FTS Cheng is that the determination of intervals is less than optimal. So that the interval needs to be optimized, with the PSO playing a role in optimizing the interval so that it will affect the following calculation process. Because optimization will be carried out with PSO. The interval above will be replaced with the results carried out by PSO, which produces K_{new}=16.

3) Calculate the width of the interval using Equation (6). The results obtained $I = R/K_{new} = 270/16 = 16{,}88$.

- Fuzzy set. Calculating the frequency of exchange rate data with results in Table IX.

TABLE IX
FREQUENCY OF EXCHANGE RATE DATA

U_i	Upper limit	Lower Limit	Middle value	Class Conversion	Total
u_1	13600	13616,88	13608,44	A1	1
u_2	13616,88	13633,75	13625,31	A2	0
u_3	13633,75	13650,63	13642,19	A3	3
u_4	13650,63	13667,5	13659,06	A4	0
u_5	13667,5	13684,38	13675,94	A5	0
u_6	13684,38	13701,25	13692,81	A6	0
u_7	13701,25	13718,13	13709,69	A7	2
u_8	13718,13	13735	13726,56	A8	3
u_9	13735	13751,88	13743,44	A9	1
u_{10}	13751,88	13768,75	13760,31	A10	0
u_{11}	13768,75	13785,63	13777,19	A11	1
u_{12}	13785,63	13802,5	13794,06	A12	0
u_{13}	13802,5	13819,38	13810,94	A13	3
u_{14}	13819,38	13836,25	13827,81	A14	2
u_{15}	13836,25	13853,13	13844,69	A15	2
u_{16}	13853,13	13870	13861,56	A16	2

- Fuzzification and Fuzzy Logical Relationship (FLR). The fuzzification stage is based on the number of intervals formed, and there are 13 fuzzy sets, namely A_1, A_2, A_3, ...,A_{13}. In the fuzzification process, data will be checked at a particular time, whether the data is included in a specific interval. If data is contained in an interval, then the data is included in the set associated with that interval. Suppose the exchange rate data is 13712; then the data is included in the fuzzy set A_7 because the data is between 13701.25 and 13718.13, which is the limit of interval 7 based on Table X.

TABLE X
FUZZIFICATION

Fi	Date	Exchange Rate	Fuzzification
F_1	13-02- 2018	13712	A7
F_2	14 -02- 2018	13725	A8
F_3	15 -02- 2018	13638	A3
F_4	19 -02- 2018	13609	A1
u_5	20 -02- 2018	13641	A3
F_6	21 -02- 2018	13650	A3
F_7	22 -02- 2018	13733	A8
F_8	23-02- 2018	13738	A9
F_9	26-02- 2018	13727	A8
F_{10}	27 -02- 2018	13718	A7
F_{11}	28 -02- 2018	13776	A11
F_{12}	01 -03- 2018	13862	A16
F_{13}	02 -03-2018	13815	A13
F_{14}	05 -03- 2018	13809	A13
F_{15}	06 -03- 2018	13819	A13
F_{16}	07- 03- 2018	13870	A14
F_{17}	08-03 - 2018	13843	A15
F_{18}	09 -03- 2018	13863	A16
F_{19}	12-03 - 2018	13837	A15
F_{20}	13 -03 -2018	13826	A14

The FLR is arranged by first-order rule, where the fuzzy logical relationship is based on two consecutive fuzzy sets. The FLR can be arranged as follows: $FLR(i) = F(i-1) \rightarrow F(i)$. For example, the results of the fuzzification of exchange rate data on 13, 14, 15, and 19 February 2018 are A_7, A_8, A_3, and A_1, respectively. The FLR compiled from the fuzzification results are $A_7 \rightarrow A_8$, $A_8 \rightarrow A_3$, dan $A_3 \rightarrow A_1$ based on Table XI.

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TABLE XI
FUZZIFICATION AND FLR

Date	Exchange Rate	Fuzzification	FLR
13-02- 2018	13712	A7	-
14 -02- 2018	13725	A8	A7→A8
15 -02- 2018	13638	A3	A8→A3
19 -02- 2018	13609	A1	A3→A1
20 -02- 2018	13641	A3	A1→A3
21 -02- 2018	13650	A3	A3→A3
22 -02- 2018	13733	A8	A3→A8
23-02- 2018	13738	A9	A8→A9
26-02- 2018	13727	A8	A9→A8
27 -02- 2018	13718	A7	A8→A7
28 -02- 2018	13776	A11	A7→A11
01 -03- 2018	13862	A16	A11→A16
02 -03-2018	13815	A13	A16→A13
05 -03- 2018	13809	A13	A13→A13
06 -03- 2018	13819	A13	A13→13
07-03- 2018	13870	A14	A13→A14
08-03 - 2018	13843	A15	A14→A15
09 -03- 2018	13863	A16	A15→A16
12-03 - 2018	13837	A15	A16→A15
13 -03 -2018	13826	A14	A15→A14

- Fuzzy Logical Relationship Group (FLRG). After the FLR is formed, the next step is to form the FLR by grouping the FLRs with the same current state (left side) based on Table XII.

TABLE XII
THE FUZZY LOGICAL RELATIONSHIP GROUP

Group	FLRG
G1	A1→A3
G3	A3→A1, A3→A3, A3→A4
G7	A7→A8, A7→A11
G8	A8→A3, A8→A7, A8→A9
G9	A9→A8, A9→A11
G11	A11→A16
G13	A13→A13, A13→A14
G14	A14→A15
G15	A15→A14, A15→A16
G16	A16→A13, A16→A15

Then the weights obtained in the FLR relation are entered as a weighting matrix (*W*). The following is based on Equation (8) and Equation (14).

$$W = \begin{array}{c c} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix} & \begin{matrix} A_1 \\ A_3 \\ A_7 \\ A_8 \\ A_9 \\ A_{11} \\ A_{13} \\ A_{14} \\ A_{15} \\ A_{16} \end{matrix} \\ \begin{matrix} A_1 & A_3 & A_7 & A_8 & A_9 & A_{11} & A_{13} & A_{14} & A_{15} & A_{16} \end{matrix} & \end{array} \quad (14)$$

- The results of the standardized weighting matrix (*W**) based on Equation (8) are as follows in Equation (15).

$$W^* = \begin{array}{c} \begin{bmatrix} 0 & 0 & 1/1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1/3 & 1/3 & 0 & 0 & 0 & 1/3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/2 & 0 & 1/2 & 0 & 0 & 0 & 0 \\ 0 & 1/3 & 1/3 & 0 & 1/3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2/3 & 1/3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1/2 & 0 & 1/2 & 0 \end{bmatrix} \begin{matrix} A_1 \\ A_3 \\ A_7 \\ A_8 \\ A_9 \\ A_{11} \\ A_{13} \\ A_{14} \\ A_{15} \\ A_{16} \end{matrix} \\ \begin{matrix} A_1 & A_3 & A_7 & A_8 & A_9 & A_{11} & A_{13} & A_{14} & A_{15} & A_{16} \end{matrix} \end{array} \tag{15}$$

- Defuzzification Process. The defuzzification process calculates the predicted value based on Equation (11). If the result of fuzzification period i is A_i and A_i does not have FLR on FLRG with condition $A_i \rightarrow \emptyset$, then the predicted value is the mean value of A_i. The results of the Defuzzification of FLRG are obtained in Table XIII.

TABLE XIII
THE FLRG WEIGHT AND DEFUZZIFICATION

Current State (A_i)	Next State (A_j)	Prediction
A1	A3	13642,19
A2	-	13625,31
A3	A1, A3, A4	13659,06
A4	-	13659,06
A5	-	13675,94
A6	-	13692,81
A7	A8, A11	13751,88
A8	A3, A7, A9	13698,44
A9	A8, A11	13726,56
A10	-	13760,31
A11	A16	13861,56
A12	-	13794,06
A13	A13, A14	13816,56
A14	A15	13844,69
A15	A14, A16	13844,69
A16	A13, A15	13827,81

The predicted value obtained is based on the fuzzy set in the period i for each $F(i)$. Table XIV shows exchange rate prediction results from 13 February 2018 to 14 March 2018.

TABLE XIV
EXCHANGE RATE PREDICTION RESULTS

Date	Exchange Rate	Fuzzification	Prediction
13 -02- 2018	13712	A7	-
14 -02- 2018	13725	A8	13751,88
15 -02- 2018	13638	A3	13698,44
19 -02- 2018	13609	A1	13659,06
20 -02- 2018	13641	A3	13642,19
21 -02- 2018	13650	A3	13659,06
22 -02- 2018	13733	A8	13659,06
23-02- 2018	13738	A9	13698,44
26-02- 2018	13727	A8	13726,56
27 -02- 2018	13718	A7	13698,44
28 -02- 2018	13776	A11	13751,88
01 -03- 2018	13862	A16	13861,56
02 -03-2018	13815	A13	13827,81
05 -03- 2018	13809	A13	13816,56
06 -03- 2018	13819	A13	13816,56
07-03- 2018	13870	A14	13816,56
08-03 - 2018	13843	A15	13844,69
09 -03- 2018	13863	A16	13844,69
12-03 - 2018	13837	A15	13827,81
13 -03 -2018	13826	A14	13844,69
14 -03 -2018	-	-	13844,69

The prediction on the FTS Cheng method looks at the fuzzification of the previous data, so the exchange rate prediction for 14 March 2018 uses the fuzzification of 13 March 2018, namely $A_{14,}$ with a prediction result of 13844.69 points

D. Error Calculation

The Mean Absolute Percentage Error (MAPE) obtained based on Equation (13) is 0.150265% for the prediction of Cheng's Fuzzy Time Series optimization using PSO. Based on Table I, predictions using the FTS Cheng and PSO methods include having excellent performance because they have a MAPE value below 10%

E. Error Calculation

In this study, predictions of the IDR exchange rate against the US dollar have been made using the Fuzzy Time Series Cheng with Particle Swarm Optimization. The dataset is obtained from the official website of Bank Indonesia, namely daily data on selling rates and buying rates. Then the dataset is entered into the database to be used in the prediction process. The process starts from the PSO algorithm initializing the particles obtained from the FTS Cheng process until the output is obtained, namely the interval parameter, which will be the interval in the FTS Cheng prediction process. After obtaining the optimization interval, the FTS Cheng algorithm will conduct the prediction process and find the prediction error rate using MAPE.

Based on the implementation and the results of the tests, the results show that using the PSO algorithm can produce the best optimization interval parameters and increase the accuracy value. From the results of 10 trials with training data, testing data, and different iterations, it was obtained that the MAPE test for predicting the rupiah exchange rate against the US dollar using FTS Cheng with 60% training data and 40% testing data resulted in the lowest MAPE of 0.610145%. Furthermore, 70% of the training and 30% of the testing data resulted in the lowest MAPE of 0.313388%. Then the FTS Cheng and PSO testing with 60% training data and 40% testing data, and an iteration value of 200 resulted in the lowest MAPE of 0.394707%. Furthermore, 70% of training data and 30% of testing data and an iteration value of 90 resulted in the lowest MAPE of 0.263666%.

Based on the MAPE value criteria, the Fuzzy Time Series Cheng algorithm with Particle Swarm Optimization can predict the rupiah exchange rate against the US dollar with excellent prediction results. The test results also showed that the weighting value affects the level of accuracy with the result in Table XV.

TABLE XV
TESTING RESULTS OF FTS AND FTS-PSO

No	Data		Parameter FTS Cheng	Parameter PSO		MAPE	
	Training	Testing	Interval FTS Cheng	Iteration	Interval Optimization PSO	FTS Cheng	FTS Cheng-PSO
1	60%	40%	10	190	19	0.610145%	0.431483%
2	60%	40%	10	200	28	0.610145%	0.394707%
3	60%	40%	10	10	13	0.610145%	0.518461%
4	60%	40%	10	100	18	0.610145%	0.450217%
5	60%	40%	10	150	22	0.610145%	0.403492%
6	70%	30%	9	190	19	0.313388%	0.279702%
7	70%	30%	9	10	17	0.313388%	0.284368%
8	70%	30%	9	30	27	0.313388%	0.264429%
9	70%	30%	9	90	30	0.313388%	0.263666%
10	70%	30%	9	5	15	0.313388%	0.291571%

In this case, the FTS Cheng algorithm with PSO gives a better partition than the partition obtained from the FTS Cheng only. Thus, PSO performance increases with a small MAPE. The impact of these results is that iterations are also getting smaller MAPE because convergence will be achieved more quickly.

IV. CONCLUSION

Optimizing the PSO interval parameter on predicting the rupiah exchange rate against the US dollar using the FTS Cheng method affects the results, namely reducing the MAPE results. From the results of 10 trials with training data, testing data, and different iterations, it was obtained that the MAPE test predicts the rupiah exchange rate against the US dollar. The most optimal accuracy obtained by the FTS Cheng algorithm produces a MAPE value of 0.313388%, while the FTS Cheng and PSO algorithms obtain a MAPE of 0.263666%. In the FTS Cheng algorithm, many intervals affect the fuzzy set, subsequent stages, and the obtained MAPE value. The more intervals, the smaller the MAPE value obtained. The PSO algorithm's number of iterations affects the interval value obtained. Thus, the interval obtained by PSO improves the FTS Cheng interval and reduces the MAPE value. From various experiments on several FTS Cheng and PSO parameters, the MAPE produced by the FTS Cheng and PSO algorithms is relatively smaller than FTS Cheng alone, proving that PSO can optimize the FTS Cheng algorithm well. In future research, it would be better if the Fuzzy Cheng could be tested with other metaheuristic algorithms, such as Evolutionary algorithms, physics-based algorithms, or bio-inspired algorithms.

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