

Comparison of Chen and Cheng Fuzzy Time Series Methods for Forecasting BBKA Closing Prices

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Keywords: BBKA, Forecasting, Fuzzy Time Series Chen, Fuzzy Time Series Cheng, MAPE

Abstract:

Stock price forecasting helps investors make investment decisions. This study compares the accuracy of the Chen and Cheng Fuzzy Time Series methods in forecasting the closing price of PT Bank Central Asia Tbk (BBKA) shares. The data are 566 weekly closing prices from January 2014 to December 2024. Forecasting follows four stages: fuzzification, fuzzy logical relationship (FLR) formation, FLR grouping (FLRG), and defuzzification. The Mean Absolute Percentage Error (MAPE) measures accuracy. The Chen method forecasts Rp9,440.75 for the first week of January 2025 with a MAPE of 6.32%. The Cheng method forecasts Rp9,441 with a MAPE of 5.74%. The Cheng method is more accurate, which shows that weighting fuzzy relations improves forecasting accuracy.

1. Introduction

Forecasting estimates future values from historical data. Researchers use it for inventories, commodity production, prices, and macroeconomic indicators. Andini and Auristandi (2016) used double exponential smoothing for office stationery stocks, and Ariza Siregar and Puspitasari (2023) used Holt-Winters exponential smoothing for palm oil production. Muthahharah et al. (2025) applied Holt's exponential smoothing to the wholesale price index. Fahmuddin and Rais (2021) combined decomposition with ARIMA to forecast inflation in Makassar, and Qadrini et al. (2020) compared ARIMA, time series regression, ARIMAX, and neural network approaches for currency inflow and outflow. Mar'ah et al. (2024) modeled the Composite Stock Price Index with multivariate adaptive regression splines.

Stock prices fluctuate and carry high uncertainty, so forecasting them needs methods that handle that uncertainty. Wibowo and Cahyono (2025) compared linear regression and neural network algorithms for stock price prediction. Fuzzy Time Series (FTS), introduced by Song and Chissom (1993) on the basis of fuzzy logic, is another option. FTS does not require stationary data, which makes it more flexible than conventional time series methods. Nugroho (2016) built a prediction model with FTS, Vivianti et al. (2020) used FTS to forecast visitors at Fort Rotterdam, and Tricahya and Rustam (2019) used a weighted high order FTS for pneumonia patients in Jakarta. Virgianti et al. (2021) applied Chen average based FTS to rainfall, Indah Nabila and Sukarsih (2023) applied average-based FTS Lee to cooking oil prices, and Ramoza (2023) compared FTS with triple exponential smoothing for palm oil fresh fruit bunches. Pratiwi et al. (2023) used a fuzzy set model to set the optimal selling price of beef.

Chen (1996) and Cheng et al. (2008) developed two FTS methods. The Chen method is simple, while the Cheng method also weights fuzzy relations and should produce higher accuracy. Wirawan et al. (2021) compared the two methods on

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chili prices, and Khanifah and Hendikawati (2024) compared them with ANN and Markov chain FTS models on the closing price of Zoom Video Communication stocks.

PT Bank Central Asia Tbk (BBCA) is one of Indonesia's leading stocks. Its price moves relatively steadily but still fluctuates in the short term. Liantoni and Simanjuntak (2025) forecast BBCA share prices with exponential smoothing, and Arum et al. (2023) compared FTS with FTS optimized by particle swarm optimization on daily BBCA closing prices from January 2022 to May 2023. None of the studies cited here compares the Chen and Cheng methods on a long weekly series of BBCA closing prices.

This study compares the accuracy of the Chen and Cheng Fuzzy Time Series methods in forecasting the closing price of BBCA shares. It uses 566 weekly closing prices from January 2014 to December 2024 and measures accuracy with the Mean Absolute Percentage Error (MAPE). The novelty is a direct comparison of the two methods on a ten-year weekly BBCA series, which shows whether weighting fuzzy relations improves forecast accuracy for this stock.

2. Literature Review

2.1. Time Series

Time Series is an approach used to predict future events by paying attention to related historical data over a certain time period (Hyndman & Athanasopoulos, 2021).

2.2. Fuzzy Logic

Fuzzy describes something vague or unclear. Therefore, fuzzy logic can be defined as logic that is uncertain or contains ambiguity (Pratiwi et al., 2023). Fuzzy logic is a method of calculating using linguistic variables, instead of calculating using numbers. The term "fuzzy" means vague or unclear, but the fuzzy system built to model forecasting still has a clear working method and description based on fuzzy logic theory (Virgianti et al., 2021).

2.3. Fuzzy Time Series

Fuzzy Time Series (FTS) is a fuzzy logic-based forecasting method used to model time series data containing high uncertainty or instability. FTS integrates the concepts of data fuzzification and fuzzy logic relations in predicting future values. In FTS, historical data is converted into fuzzy sets, and relationships between time periods are analyzed using fuzzy logic-based rules (Indah Nabila & Sukarsih, 2023). The forecasting steps using Fuzzy Time Series (Chen, 1996) are:

a. Determining the Universal Set (U)

The universal set, which is the entire set of possible values, is determined using the formula:

$$U = [D_{min} - D_1, D_{max} + D_2]$$

Where:

U = Universal set

D_1 = The first positive value determined by the researcher

D_2 = The second positive value determined by the researcher

D_{min} = Minimum value of the data

D_{max} = Maximum value of the data

b. Interval Formation

Next, determine the number of intervals using the Sturges formula (Sturges, 1926):

$$k = 1 + 3.322 \log(n)$$

Where:

k = Number of interval classes

n = Amount of data

Next, calculate the length of the interval (l) using the formula:

$$l = \frac{[(D_{\max} + D_2 - (D_{\min} - D_1))]}{k}$$

Each interval is obtained by the equation:

$$\begin{aligned} u_1 &= [D_{\min} - D_1 ; D_{\min} - D_1 + l] \\ u_2 &= [D_{\min} - D_1 + l ; D_{\min} - D_1 + 2l] \\ &\vdots \\ u_p &= [D_{\min} - D_1 + (n - 1) ; D_{\min} - D_1 + nl] \end{aligned}$$

Then to calculate the mean value (m_i) from an interval in a fuzzy set, the formula is used:

$$m_i = \frac{(\text{batas atas} + \text{batas bawah})}{2}$$

where = 1, 2, ..., k_i

c. Defining fuzzy sets in the universal set

Suppose the universe of discourse consists of elements (U) $U = [u_1, u_2, \dots, u_p]$ where every u_i is a possible value of, then the linguistic variable can be formulated as: $UA_i U$

$$A_i = \frac{\mu_{Ai}}{u_1} + \dots + \frac{\mu_{Ai}(u_p)}{u_p}$$

Where μ_{Ai} is the membership function of fuzzy, which is a mapping of the universal set into an interval or written as. The value of the degree of membership of is determined based on these rules: $A_i U [0,1] \mu_{Ai} \rightarrow [0,1] \mu_{Ai}(u_i)$

- 1) If the actual data D_t included in, then the degree of membership for is 1, and is and $u_i u_t u_{t+1} 0,5$ if not and, it means it is declared zero. $u_i u_{t+1}$
- 2) If the actual data D_t included in, then the degree of membership for is 1, for and is and if not, and means it is declared zero. $u_i 1 \leq i \leq p u_i u_{i-1} u_{i+1} 0,5 u_i u_{i-1} u_{i+1}$
- 3) If the actual data is included in, then the degree of membership for is 1, and for is and if not and means it is declared zero. $D_t u_i u_{i-1} 0,5 u_i u_{i-1}$ (Virgianti et al., 2021).

Based on these definitions and rules, fuzzy sets can be defined as:

$$\begin{aligned} A_1 &= \frac{1}{u_1} + \frac{0,5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ A_2 &= \frac{0,5}{u_1} + \frac{1}{u_2} + \frac{0,5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ A_3 &= \frac{0}{u_1} + \frac{0,5}{u_2} + \frac{1}{u_3} + \frac{0,5}{u_4} + \frac{0}{u_5} + \dots + \frac{0}{u_p} \\ &\vdots \\ A_p &= \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \dots + \frac{0,5}{u_{p-1}} + \frac{1}{u_p} \end{aligned}$$

d. Perform fuzzification

Fuzzification is the process of converting historical numerical data into fuzzy form. Each data item will be associated with a fuzzy set based on a predetermined interval. If the dataIf the historical data obtained is in the interval , then the data will be expressed in fuzzy form as $.u_i A_i$

2.4. Fuzzy Time Series Chen

To perform fuzzy time series forecasting, the next step is to determine the Fuzzy Logical Relationships (FLR) and group these relationships into Fuzzy Logical Relationship Groups (FLRG). The steps are:

- a. Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG)

The formation of Fuzzy Logical Relationship (FLR) in Fuzzy Time Series is based on actual historical data expressed as where describes the current state and describes the future state. For example, if there are relations such as and , then the Fuzzy Logical Relationships Group (FLRG) formed from is $A_1 \rightarrow A_2, A_1 \rightarrow A_1, A_1 \rightarrow A_3, A_1 \rightarrow A_1, A_1 \rightarrow A_1, A_2, A_3$ (Virgianti et al., 2021).

- b. Performing defuzzification and Chen forecasting calculations

Defuzzification In the Fuzzy Time Series method, Chen follows several specific provisions that must be considered, namely:

- 1) If the fuzzification results in the t th week are and there is a fuzzy set that does not have a fuzzy logic relation, for example if , where the maximum value of the membership function is att $A_j A_i \rightarrow \emptyset A_i$ the interval and the mean value are , then the forecast result is $.u_i u_i m_i F_{t+1} m_i$
- 2) If the fuzzification result in the t th week is and there is only one FLR relationship in FLRG, for example where and are fuzzy sets and the maximum value of the membership function of is in the interval and the middle value of is , then the forecasting result is $.t A_i A_i \rightarrow A_j A_i A_j u_j u_j m_j F_{t+1} m_j$
- 3) If the fuzzification result in the t th week is and has some FLR on FLRG, for example where is a fuzzy set and the maximum value of the membership function of is in the interval , and , then the forecasting result is: $t A_j A_j A_i \rightarrow A_{j1}, A_{j2}, \dots, A_{jk} A_i, A_{j1}, A_{j2}, \dots, A_{jk} A_{j1}, A_{j2}, \dots, A_{jk} u_{j1} u_{j2}, \dots, u_{jk} m_{j1} m_{j2}, \dots, m_{jk} F_{t+1}$

$$F_{t+1} = \frac{m_{j1}, m_{j2}, \dots, m_{jk}}{k}$$

where k is the number of middle values. $k(m_i)$

2.5. Fuzzy Time Series Cheng

The Cheng algorithm is an improved version of the Chen model, which previously had several weaknesses. One of the main weaknesses of the Chen model is its lack of emphasis on repetition and its inability to assign lower weights to more common observations (Cheng et al., 2008). This method uses these steps:

- a. Assigning weights to FLRG

For example, if there is a sequence of the same FLR,

- () , given a weight of $1t = 1A_i \rightarrow A_1$
- () , given a weight of $2t = 2A_i \rightarrow A_2$
- () , given a weight of $3t = 3A_i \rightarrow A_3$
- () , given a weight of $4t = 4A_i \rightarrow A_4$
- () , given a weight of $5t = 5A_i \rightarrow A_5$

where t represents time.

Then the weights obtained in the FLR relation are entered into the form of a weighting matrix (W) whose equation is written as:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix}$$

inwhere is the weight of the matrix in the i th row and j th column with and $w_{ij} \ i = 1, 2, \dots, m \ j = 1, 2, \dots, n$

b. Normalization of weighting matrix

Transferring the weights into a normalized weighting matrix () whose equation is written as: w_{ij}^*

$$w_{ij}^* = \frac{w_{ij}}{\sum_{j=1}^n w_{ij}}$$

c. Cheng's Forecasting Calculation

To obtain the forecast value, the normalized weight matrix is multiplied by , which is the midpoint of each interval. The forecast value is calculated as: $(F_t)(W)(W^*)m_i m_i$

$$F_t = w_{i1}^*(m_1) + \dots + w_{ij}^*(m_n)$$

where states time and $.tt = i$

2.6. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error(MAPE) is one of the most commonly used metrics to evaluate forecast accuracy. MAPE measures the average absolute percentage error between the actual value and the predicted value, making it intuitive and easy to understand, especially since the result is expressed as a percentage. The MAPE value can be calculated using the equation (Nabillah & Ranggadara, 2020):

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|X_t - F_t|}{X_t} \times 100$$

Where:

n =time period value

X_t =actual value at period t

F_t =forecast value in period t

2.7. Shares

Stocks are one of the most popular financial instruments for investors in the capital market. Investing in stocks is an effective way to invest long-term. The advantage of investing in stocks is that investors will receive profits in the form of capital gains or dividends. Investors benefit from company profits, known as dividends, while investors receive capital gains from the difference between the selling price and the purchase price. Investing in stocks means investors have ownership rights in the company (Sukartaatmadja et al., 2023). Namirah and Nur (2023) analyzed the value of LQ45 bank stocks in relation to macro indicators.

2.8. PT Bank Central Asia Tbk (BBCA)

PT Bank Central Asia Tbk (BBCA) is one of the largest private banks in Indonesia, founded on February 21, 1957. Since then, BBCA has grown into a leading financial institution with an extensive service network throughout Indonesia. Liantoni and Simanjuntak (2025) forecast its share prices with exponential smoothing.

3. Research Methods

3.1. Types of Research

The type of research used is applied research with a quantitative approach, namely a type of research that aims to apply scientific theories, concepts, or methods in real situations to solve a problem practically using numerical data and statistical analysis.

3.2. Types and Sources of Data

This study used secondary data as a source of information. Secondary data is readily available and was obtained by the researcher from <https://www.marketwatch.com>. The data used is weekly closing stock prices of PT Bank Central Asia Tbk (BBCA) from January 2014 to December 2024. A total of 566 data sets were used in the study.

3.3. Operational Definition of Variables

The variable used in this study is the closing price of PT Bank Central Asia Tbk (BBCA) shares, which is the last price recorded at the close of trading for PT Bank Central Asia Tbk (BBCA) shares within a week. This price serves as the primary reference for forecasting because it reflects the final value of weekly transactions.

3.4. Data Analysis Techniques

The data analysis steps used are:

1. Carrying out the stages of the Fuzzy Time Series method, namely:
 - a. Determine the universal set.
 - b. Formation of the number and length of classes.
 - c. Determine the fuzzy set for the entire universe set.
 - d. Perform fuzzification on historical data.
2. Carrying out the stages of the Chen Fuzzy Time Series method, namely:
 - a. Determining Fuzzy Logical Relationships (FLR) and Fuzzy Relationships Group (FLRG).
 - b. Perform defuzzification and calculate forecast values using Chen's Fuzzy Time Series method.
 - c. View the results of prediction accuracy with MAPE calculations.
3. Carrying out the stages of Cheng's Fuzzy Time Series method, namely:
 - a. Determining Fuzzy Logical Relationships (FLR) and Fuzzy Relationships Group (FLRG).
 - b. Performing the matrix weighting process.
 - c. Perform the matrix weighting normalization process.
 - d. Perform defuzzification and calculate forecast values using Cheng's Fuzzy Time Series method.
 - e. View the results of prediction accuracy with MAPE calculations.
4. Comparing the accuracy of forecasting results from the two methods using the MAPE value.
5. Draw a conclusion.

4. Results and Discussion

4.1. Descriptive Analysis

Descriptive analysis was used to obtain an overview of the research data. Descriptive statistics included minimum, maximum, average (mean), and standard deviation values. The results of the descriptive analysis are shown in Table 1.

Table 1. Descriptive Analysis

Descriptive Statistics	Mark
Minimum	1,880.00
Maximum	10,775.00
Mean	5,601.00
Standard Deviation	2,544.56

4.2. Fuzzy Time Series Analysis

In the fuzzy time series analysis method, there are several steps taken, namely:

- a. Determining the Universal Set

$$\begin{aligned}
 U &= [D_{min} - D_1, D_{max} + D_2] \\
 &= [1880 - 0, 10775 + 0]
 \end{aligned}$$

$$= [1880, 10775]$$

So we get a universal set= [1880, 10775]

b. Interval Formation

$$k = 1 + 3,322 \log(n)$$

$$= 1 + 3,322 \log(566)$$

$$= 10$$

Based on these results, the number of interval classes is 10. After the number of interval classes is obtained, the next step is to determine the length of each interval using the equation.

$$l = \frac{[(D_{max} + D_2 - (D_{min} - D_1))]}{k}$$

$$= \frac{[10.775 + 0 - 1.880 - 0]}{10}$$

$$= 889,5$$

Thus, 10 intervals are obtained based on the class length, which can be expressed using the equation.

$$u_1 = [D_{min} - D_1 ; D_{min} - D_1 + l]$$

$$= [1880,0 - 0 ; 1880,0 - 0 + 889,5]$$

$$= [1880,0 ; 2769,5]$$

$$u_2 = [D_{min} - D_1 + l ; D_{min} - D_1 + 2l]$$

$$= [1880,0 - 0 + 889,5 ; 1880,0 - 0 + 1779,0]$$

$$= [2769,5 ; 3659,0]$$

$$\vdots$$

$$u_{10} = [D_{min} - D_1 + (n - 1)l ; D_{min} - D_1 + nl]$$

$$= [1880,0 - 0 + (9)889,5 ; 1880,0 - 0 + 10(889,5)]$$

$$= [9885,5 ; 10775,0]$$

The intervals of the universal set and the mean value in each interval are presented in Table 2.

Table 2. Intervals and Midpoints of the Universal Set

No	Interval	Middle Value(<i>m</i>)
1	$u_1 = [1880,0 ; 2769,5]$	$m_1 = 2324.75$
2	$u_2 = [2769,5 ; 3659,0]$	$m_2 = 3214.25$
3	$u_3 = [3659,0 ; 4548,5]$	$m_3 = 4103.75$
4	$u_4 = [4548,5 ; 5438,0]$	$m_4 = 4993.25$
5	$u_5 = [5438,0 ; 6327,5]$	$m_5 = 5882.75$
6	$u_6 = [6327,5 ; 7217,0]$	$m_6 = 6772.25$
7	$u_7 = [7217,0 ; 8106,5]$	$m_7 = 7661.75$
8	$u_8 = [8106,5 ; 8996,0]$	$m_8 = 8551.25$
9	$u_9 = [8996,0 ; 9885,5]$	$m_9 = 9440.75$
10	$u_{10} = [9885,5 ; 10775,0]$	$m_{10} = 10330.25$

c. Defining Fuzzy Sets in the Universal Set

After 10 fuzzy sets are formed based on the predetermined intervals, we obtain , which can be denoted as . These fuzzy sets represent the linguistic values of the linguistic variables used. Each fuzzy set has a degree of membership ranging from 0 to 1, with the condition that , where 10 indicates the number of interval classes. $u_1, u_2, u_3, \dots, u_{10}$ $A_1, A_2, A_3, \dots, A_{10}$ $1 \leq i \leq 10$ At this stage each fuzzy set has a full membership value (1) in its central interval and a partial membership value (0.5) in the adjacent intervals.

d. Determining Linguistic Values

Determining linguistic values aims to transform quantitative data into qualitative form, making it easier to interpret linguistically. The determination of linguistic values is presented in Table 3.

Table 3. Determination of Linguistic Values

Fuzzy	Interval	Linguistic Values
A_1	$u_1 = [1880,0 ; 2769,5]$	The lowest
A_2	$u_2 = [2769,5 ; 3659,0]$	Very Low
A_3	$u_3 = [3659,0 ; 4548,5]$	Fairly Low
A_4	$u_4 = [4548,5 ; 5438,0]$	Low
A_5	$u_5 = [5438,0 ; 6327,5]$	Quite Low
A_6	$u_6 = [6327,5 ; 7217,0]$	High enough
A_7	$u_7 = [7217,0 ; 8106,5]$	Tall
A_8	$u_8 = [8106,5 ; 8996,0]$	Quite High
A_9	$u_9 = [8996,0 ; 9885,5]$	Very high
A_{10}	$u_{10} = [9885,5 ; 10775,0]$	The tallest

e. Performing Fuzzification

The fuzzification results are presented in Table 4.

Table 4. Data Fuzzification Results

No	Period	Closing Stock Price (Rupiah)	Fuzzification
1	January 3, 2014	1900	A_1
2	January 10, 2014	1880	A_1
3	January 17, 2014	1980	A_1
4	January 24, 2014	2035	A_1
5	January 30, 2014	1985	A_1
⋮	⋮	⋮	⋮
562	December 6, 2024	10075	A_{10}
563	December 13, 2024	10050	A_{10}
564	December 20, 2024	9650	A_9
565	December 27, 2024	9800	A_9
566	December 30, 2024	9675	A_9

4.3. Fuzzy Time Series Analysis Chen

To perform fuzzy time series forecasting, the next step is to determine the Fuzzy Logical Relationship (FLR) and group the relationships into Fuzzy Logical Relationship Groups (FLRG).

Table 5. Fuzzy Logical Relationship (FLR)

No	Time Period	FLR
1	January 3, 2014 January 10, 2014 →	$A_1 \rightarrow A_1$
2	January 10, 2014 January 17, 2014 →	$A_1 \rightarrow A_1$
3	January 17, 2014 January 24, 2014 →	$A_1 \rightarrow A_1$
4	January 24, 2014 January 30, 2014 →	$A_1 \rightarrow A_1$
5	January 30, 2014 February 7, 2014 →	$A_1 \rightarrow A_1$
⋮	⋮	⋮
565	December 27, 2024 December 30, 2024 →	$A_9 \rightarrow A_9$

a. Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG)

The FLR and FLRG results formed from actual BBKA stock closing data are presented in Tables 5 and 6.

After the FLR for each data point in Table 5 is determined, the next step is to form a Fuzzy Logical Relationship Group (FLRG). FLRG grouping is based on the transition between states, namely the current state and the next state. Fuzzy sets that have the same current state will be combined into one group.

Table 6. Fuzzy Logical Relationship Group (Chen)

Group	FLRG
1	$A_1 \rightarrow A_1, A_2$
2	$A_2 \rightarrow A_1, A_2, A_3$
3	$A_3 \rightarrow A_2, A_3, A_4$
4	$A_4 \rightarrow A_3, A_4, A_5$
5	$A_5 \rightarrow A_4, A_5, A_6$
6	$A_6 \rightarrow A_5, A_6, A_7$
7	$A_7 \rightarrow A_6, A_7, A_8$
8	$A_8 \rightarrow A_7, A_8, A_9$
9	$A_9 \rightarrow A_8, A_9, A_{10}$
10	$A_{10} \rightarrow A_9, A_{10}$

Based on the grouping results presented in Table 6, it can be seen that each fuzzy set has one or more relationships with other fuzzy sets.

b. Performing Defuzzification and Forecasting Calculations

The results of defuzzification and forecasting calculations using the Chen method are presented in Tables 7 and 8.

Table 7. Chen's Defuzzification

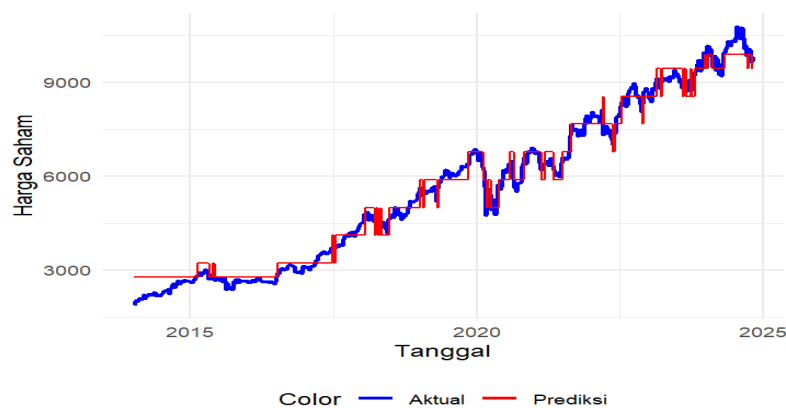
No	FLRG	Calculation of F(t)	Forecast Value (Rupiah)
1	$A_1 \rightarrow A_1, A_2$	$\frac{(m_1 + m_2)}{2}$	2769.5
2	$A_2 \rightarrow A_1, A_2, A_3$	$\frac{(m_1 + m_2 + m_3)}{3}$	3214.25
3	$A_3 \rightarrow A_2, A_3, A_4$	$\frac{(m_2 + m_3 + m_4)}{3}$	4103.75
4	$A_4 \rightarrow A_3, A_4, A_5$	$\frac{(m_3 + m_4 + m_5)}{3}$	4993.25
5	$A_5 \rightarrow A_4, A_5, A_6$	$\frac{(m_4 + m_5 + m_6)}{3}$	5882.75
6	$A_6 \rightarrow A_5, A_6, A_7$	$\frac{(m_5 + m_6 + m_7)}{3}$	6772.25
7	$A_7 \rightarrow A_6, A_7, A_8$	$\frac{(m_6 + m_7 + m_8)}{3}$	7661.75
8	$A_8 \rightarrow A_7, A_8, A_9$	$\frac{(m_7 + m_8 + m_9)}{3}$	8551.25
9	$A_9 \rightarrow A_8, A_9, A_{10}$	$\frac{(m_8 + m_9 + m_{10})}{3}$	9440.75
10	$A_{10} \rightarrow A_9, A_{10}$	$\frac{(m_9 + m_{10})}{2}$	9885.50

This defuzzification stage aims to change the linguistic value of the fuzzy results into a numerical form, so that it can be used to estimate the closing price of shares.

Table 8. Chen Method Forecasting Results

Period	Closing Stock Price (Rupiah)	Forecast Results(F_t)
January 3, 2014	1900	-
January 10, 2014	1880	2769.50
January 17, 2014	1980	2769.50
January 24, 2014	2035	2769.50
January 30, 2014	1985	2769.50
⋮	⋮	⋮
December 6, 2024	10075	9885.50
December 13, 2024	10050	9885.50
December 20, 2024	9650	9885.50
December 27, 2024	9800	9440.75
December 30, 2024	9675	9440.75
First Week of January 2025	-	9440.75

Thus, the predicted closing price for BBCA shares in the first week of January 2025 is Rp9,440.75. A comparison of actual data and predicted results can be seen in Figure 1.

**Figure 1. Comparison of Actual Data and Prediction Results Using the Chen Method**

In general, Chen's model is able to follow the main trend of stock price movements, both during periods of upswing and downswing. This indicates that Chen's method is quite effective in capturing historical patterns in fluctuating stock data.

c. Calculating MAPE

The results of the calculation of the accuracy of the forecasting model using MAPE are presented in Table 9.

Table 9. Mean Absolute Percentage Error (MAPE) Chen Method

Period	Closing Stock Price (Rupiah)	Error
January 3, 2014	1900	-
January 10, 2014	1880	47,313
January 17, 2014	1980	39,873
January 24, 2014	2035	36,093
January 30, 2014	1985	39,521
⋮	⋮	⋮
December 6, 2024	10075	1,880

Period	Closing Stock Price (Rupiah)	Error
December 13, 2024	10050	1,636
December 20, 2024	9650	2,440
December 27, 2024	9800	3,665
December 30, 2024	9675	2,421
MAPE		6.32

Based on Table 9, the calculation results *Mean Absolute Percentage Error*(MAPE) for the Fuzzy Time Series Chen method was obtained at 6.32%, where this value is classified as very good because it is below the 10% limit. With a relatively small MAPE value, it can be concluded that the Chen method has a high level of accuracy and good performance in predicting the closing price of BBKA shares.

4.4. Cheng's Fuzzy Time Series Analysis

The initial steps in Cheng's Fuzzy Time Series analysis are essentially similar to Chen's, but there are differences in the forecasting calculation stage. The Cheng model considers the weighting of each fuzzy relation to obtain more accurate forecast values. The analysis stages using this method include forming a universe set, determining the interval length using the Sturges formula, fuzzification, forming Fuzzy Logical Relationships (FLR) and their grouping (FLRG), assigning weights, and defuzzification to obtain forecast values.

a. Weighting

The FLRG results formed from actual BBKA stock closing data are presented in Table 10.

Table 10. Fuzzy Logic Relationship Group (Cheng)

Group	FLRG
1	$A_1 \rightarrow A_1(115), A_2(3)$
2	$A_2 \rightarrow A_1(2), A_2(60), A_3(2)$
3	$A_3 \rightarrow A_2(1), A_3(34), A_4(4)$
4	$A_4 \rightarrow A_3(3), A_4(42), A_5(5)$
5	$A_5 \rightarrow A_4(4), A_5(69), A_6(5)$
6	$A_6 \rightarrow A_5(4), A_6(45), A_7(2)$
7	$A_7 \rightarrow A_6(1), A_7(40), A_8(3)$
8	$A_8 \rightarrow A_7(2), A_8(34), A_9(5)$
9	$A_9 \rightarrow A_8(4), A_9(43), A_{10}(4)$
10	$A_{10} \rightarrow A_9(4), A_{10}(25)$

Based on Table 10, it can be seen that each Fuzzy Logic Relationship Group (FLRG) in Cheng's method has one or more fuzzy logic relations that show the relationship between fuzzy sets over time. Compared to Chen's method, in Cheng's method each relation in FLRG is given a weight based on its frequency of occurrence.

b. Cheng's Weighting Matrix

Based on FLRG, the Cheng weighting matrix is:

$$W = \begin{bmatrix} 115 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 60 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 34 & 4 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 42 & 5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4 & 69 & 5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 4 & 45 & 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 40 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & 34 & 5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4 & 43 & 4 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4 & 25 \end{bmatrix}$$

c. Normalization of Weighting Matrix

The normalization of the Cheng weighting matrix is:

$$W^* = \begin{bmatrix} 0,97 & 0,03 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 \\ 0,03 & 0,94 & 0,03 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 \\ 0,00 & 0,03 & 0,87 & 0,10 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 \\ 0,00 & 0,00 & 0,06 & 0,84 & 0,10 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 \\ 0,00 & 0,00 & 0,00 & 0,05 & 0,89 & 0,06 & 0,00 & 0,00 & 0,00 & 0,00 \\ 0,00 & 0,00 & 0,00 & 0,00 & 0,08 & 0,88 & 0,04 & 0,00 & 0,00 & 0,00 \\ 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,02 & 0,91 & 0,07 & 0,00 & 0,00 \\ 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,05 & 0,83 & 0,12 & 0,00 \\ 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,08 & 0,84 & 0,08 \\ 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,00 & 0,14 & 0,86 \end{bmatrix}$$

Based on the normalized weighting matrix, each element in the matrix represents the relative weighting of the relationships between fuzzy sets. The values in this matrix are obtained by dividing each element of the weighting matrix by the total weight in the corresponding row. Thus, the total weight in each row is 1, meaning all relations in a fuzzy set are A_i have been normalized based on their frequency of occurrence.

d. Defuzzification and Cheng's Forecast

The results of defuzzification and forecasting for the Cheng method can be seen in Tables 11 and 12.

Table 11. Cheng's Defuzzification

No	FLRG	Forecast Value (Rupiah)
1	$A_1 \rightarrow A_1(115), A_2(3)$	2347
2	$A_2 \rightarrow A_1(2), A_2(60), A_3(2)$	3214
3	$A_3 \rightarrow A_2(1), A_3(34), A_4(4)$	4172
4	$A_4 \rightarrow A_3(3), A_4(42), A_5(5)$	5029
5	$A_5 \rightarrow A_4(4), A_5(69), A_6(5)$	5894
6	$A_6 \rightarrow A_5(4), A_6(45), A_7(2)$	6737
7	$A_7 \rightarrow A_6(1), A_7(40), A_8(3)$	7702
8	$A_8 \rightarrow A_7(2), A_8(34), A_9(5)$	8616
9	$A_9 \rightarrow A_8(4), A_9(43), A_{10}(4)$	9441
10	$A_{10} \rightarrow A_9(4), A_{10}(25)$	10208

This defuzzification value represents the forecasting results that have been converted from linguistic form to numerical values through the matrix weighting and normalization process in the previous stage.

Table 12. Cheng Method Forecasting Results

Period	Closing Stock Price (Rupiah)	Forecast Results(F_t)
January 3, 2014	1900	-
January 10, 2014	1880	2374
January 17, 2014	1980	2374

Period	Closing Stock Price (Rupiah)	Forecast Results(F_t)
January 24, 2014	2035	2374
January 30, 2014	1985	2374
⋮	⋮	⋮
December 6, 2024	10075	10208
December 13, 2024	10050	10208
December 20, 2024	9650	10208
December 27, 2024	9800	9441
December 30, 2024	9675	9441
First Week of January 2025	-	9441

Thus, the predicted closing price of BBKA shares in the first week of January 2025 is IDR 9,441. A comparison of actual data and predicted results can be seen in Figure 2.

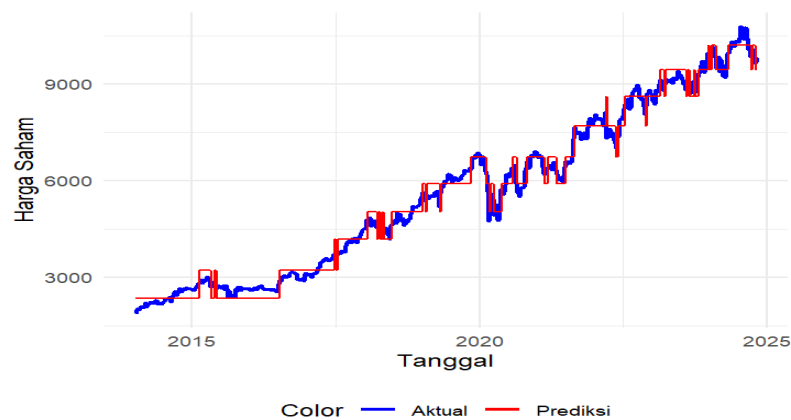


Figure 2. Comparison of Actual Data and Prediction Results Using the Cheng Method

In general, the Cheng model is able to follow the main pattern of stock price movements more stably than the Chen model, both during periods of upswing and downswing. Thus, it can be concluded that the Cheng Fuzzy Time Series method successfully describes the BBKA stock price movement pattern more smoothly and stably than the Chen method.

e. Calculating MAPE Value

The results of the calculation of the accuracy of the forecasting model using MAPE are presented in Table 13.

Table 13. Mean Absolute Percentage Error (MAPE) Cheng Method

Period	Closing Stock Price (Rupiah)	Error
January 3, 2014	1900	-
January 10, 2014	1880	24,840
January 17, 2014	1980	18,535
January 24, 2014	2035	15,331
January 30, 2014	1985	18,236
⋮	⋮	⋮
December 6, 2024	10075	1,320
December 13, 2024	10050	1,572

Period	Closing Stock Price (Rupiah)	Error
December 20, 2024	9650	5,782
December 27, 2024	9800	3,663
December 30, 2024	9675	2,418
MAPE		5.74

Based on Table 13, the MAPE value is 5.74%, which is below 10%, which means that the forecasting ability of the Cheng Fuzzy Time Series method in the case of BBCA stock closing prices is very good.

4.5. Comparison of MAPE Values in the Chen and Cheng Models

After conducting fuzzy time series analysis with two models, namely Chen and Cheng, the MAPE values from each model can be compared. This comparison is presented in Table 14.

Table 14. Comparison of MAPE Values and Forecasting Results

Fuzzy Time Series	MAPE Value	Forecast Results for the First Week of January 2025
Chen	6.32%	9440.75
Cheng	5.74%	9441.00

Based on the comparison in Table 14, the Cheng model obtained the smallest MAPE value. This indicates that the Cheng method forecast results are closer to the actual data. The forecast result for the first week of January 2025 was Rp9,441.

4.6. Discussion

The Cheng method (MAPE 5.74%) forecast the weekly closing price of BBCA shares more accurately than the Chen method (MAPE 6.32%), a gap of 0.58 percentage points. Both values fall below the 10% limit used in this study, so both methods rate as very good, and their forecasts for the first week of January 2025 are almost the same (Rp9,440.75 and Rp9,441). The Cheng method gains its advantage by following the historical data more closely, not by producing a different forecast.

The two methods treat fuzzy relations differently. The Chen method does not emphasize relations that occur repeatedly, while the Cheng method gives them larger weights (Cheng et al., 2008). When some transitions between fuzzy sets occur far more often than others, weighting lets those transitions shape the defuzzified forecast more strongly. This probably explains the lower MAPE of the Cheng method.

Compare earlier work with care. Arum et al. (2023) forecast BBCA daily closing prices from January 2022 to May 2023. They reported symmetric MAPE (sMAPE) of 1.4701% for FTS and 1.3678% for FTS optimized with particle swarm optimization (PSO), and PSO was more accurate. Those errors are smaller than the MAPE values here (5.74% and 6.32%), but the studies differ in data frequency (daily versus weekly), number of observations (328 versus 566), and error measure (sMAPE versus MAPE), so the values cannot be compared directly. The two studies agree on one point: refining basic FTS gave a modest gain in accuracy, through interval optimization in their case and relation weighting in ours, and every method scored below 10% error.

Wirawan et al. (2021) compared the Chen and Cheng methods on chili prices, and Khanifah and Hendikawati (2024) compared them with ANN and Markov chain FTS models on Zoom Video Communication stock prices. This study adds a ten-year weekly series of an Indonesian bank stock. The Markov chain approach of Khanifah and Hendikawati (2024) and the interval optimization of Arum et al. (2023) are candidates for further comparison with the Cheng method on the same data.

This study has limits. It covers one stock, one accuracy measure (MAPE), and a fixed 10 intervals from the Sturges formula, and it does not test whether the 0.58-point gap is statistically significant. Future work could add measures such as RMSE, try other interval partitions, and include more stocks.

5. Conclusion

The Cheng Fuzzy Time Series method forecasts the closing price of BBKA shares more accurately than the Chen method, with a lower MAPE. Both methods stay below 10% MAPE, which rates them very good, and both forecast about Rp9,441 for the first week of January 2025. Weighting fuzzy logical relationships improves forecast accuracy for this series.

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