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# Stock Price Forecasting Model Using Short Cross Association of Logical Fuzzy Relations in Fuzzy Time Series

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**Abstract**: Forecasting stock prices plays a crucial role in financial engineering and data-driven decision-making systems in the industrial world. The accuracy of stock price predictions is essential for investors, financial analysts, and infrastructure project managers to mitigate investment risks and optimize business strategies. Fuzzy Time Series (FTS) has become one of the popular methods for time series forecasting due to its ability to handle uncertainty and nonlinear patterns that often arise in financial and engineering systems. However, conventional FTS methods still face challenges in forming Fuzzy Logical Relationships (FLR), which can affect the accuracy of prediction results. This study proposes the Short Cross-Association Fuzzy Logical Relationship (SCA-FLR) approach to improve forecasting accuracy by considering influential factors in FLR formation. This method is applied to stock price data of PT Wijaya Karya (Persero) Tbk (WIKA.JK), using the stock closing price as the main factor and the highest stock price as the influencing factor. The forecasting results show an Average Forecasting Error Rate (AFER) of 2.97%, indicating excellent prediction accuracy. The findings of this study contribute to the development of forecasting systems in financial engineering, risk management, and industrial decision-making optimization. The application of this method can be extended to various engineering fields involving time series analysis.

**Keywords:** Fuzzy time series, Short cross-association, Stock price forecasting, Financial engineering, Data-driven prediction system

## Introduction

Forecasting concepts in mathematics are used to predict future conditions. This concept is applied in various aspects of human life, as it aids in preparing policies that need to be implemented in the future. One crucial aspect that requires forecasting is the financial sector. Stock prices in the construction sector fluctuate due to global economic factors, government policies, and market conditions (Indonesia Stock Exchange, 2023). This instability creates uncertainty for investors, necessitating accurate forecasting methods to understand stock price movement patterns.

Fuzzy Time Series (FTS) is a forecasting method introduced by Song and Chissom (1993) that is used to predict problems where actual data is represented in linguistic values (Husain et al., 2021). The fuzzy time series forecasting method has become widely used by researchers as an extension of traditional time series forecasting. Several fuzzy time series forecasting methods include frequency density-based partitioning (Jilani & Burney, 2008)and percentage change from year to year as the universe of discourse (Husain et al., 2021).

In this study, the fuzzy time series forecasting method is modified into a multi-factor fuzzy time series forecasting approach, which predicts data based on multiple variables, namely the main factor and the influence factor. In multi-factor fuzzy time series forecasting, the predicted data is the main factor. Previous studies on multi-factor fuzzy time series forecasting have been conducted by several researchers, including Tsai et al. (2019), who used this method to forecast stock indices. Dong et al., (2019)applied multi-factor fuzzy time series forecasting by constructing fuzzy logical relationships and cloud models to predict aircraft surface control failures. Furthermore, Li & Yu (2020) employed first-order multi-factor fuzzy time series forecasting using cross-association of fuzzy logical relationships in the formation stage.

In multi-factor fuzzy time series forecasting, the formation of Fuzzy Logical Relationships (FLR) requires further development. In the existing multi-factor fuzzy time series models, the FLR formation often results in multiple premises being matched, leading to cases where no FLR exists, making prediction values indeterminate. Therefore, constructing FLR based on the short cross-association of fuzzy logical relationships, as proposed by Li and Yu, can help address this issue. This study explores a modified multi-factor fuzzy time series forecasting method using the short cross-association approach in the formation stage of fuzzy logical relationships. Additionally, the defuzzification process follows the method used by Li et al., with the universe of discourse divided into ten intervals. The subinterval determination is based on frequency density-based partitioning. The membership function used in this study is the triangular membership function, while forecasting accuracy is evaluated using the Average Forecasting Error Rate (AFER).

This method is applied to forecast the closing stock price of PT Wijaya Karya (Persero) Tbk, which serves as the main factor, while the highest stock price is used as the influence factor (referred to as the second factor). PT Wijaya Karya (Persero) Tbk is one of Indonesia's largest construction companies, engaged in construction services, engineering, investment, energy, and property. The company has an extensive track record in national infrastructure development, including toll roads, bridges, and energy projects that contribute to Indonesia's economic growth.

**Fuzzy Time Series**

Definition 1 (Guler Dincer & Akkus, 2018)

Given $Y(t)(t = 1,2, \dots)$, which is a subset of the set of all real numbers, it represents the universal set defined by the fuzzy set $f_i(t)(i = 1,2, \dots)$. If $F(t)$ is the universe of discourse for $f_i(t)(i = 1,2, \dots)$ then $F(t)$ is refrred to as a fuzzy time series on $Y(t)$.

Definition 2 (Jilani & Burney, 2008)

If given $A_{j_1}, A_{j_2}, A_{j_3}, \dots, A_{j_m} \in F(t)$ and $A_i \in F(t-1)$ such that the following fuzzy logical relationships (FLR) are formed :

$$\begin{gathered} A_i \to A_{j_1} \\ A_i \to A_{j_2} \\ A_i \to A_{j_3} \\ \dots \\ A_i \to A_{j_m} \end{gathered}$$

From these FLR, a fuzzy logical relationship group (FLRG) can be constructed as follows: $A_i \to A_{j_1}, A_{j_2}, A_{j_3}, \dots, A_{j_m}$

*Multi-Factor Fuzzy Time Series*

Definition 3 (Guler Dincer & Akkus, 2018)

Let $F(t)$ be a fuzzy time series where $t = 1,2,3, \dots, n$ and $F(t)$ is a fuzzy set. If $F(t)$ is obtained from $F(t-1), F(t-2), \dots., F(t-n)$, then fuzzy logical relationship (FLR) can be represented as

$$(F_1(t-n), \ldots, F_1(t-2), F_1(t-1)) \rightarrow F(t)$$

Which is referred to as an n-th order one-factor fuzzy time series. Here, $F(t)$ is called the next state, while $F_1(t-n), \ldots, F_1(t-2), F_1(t-1)$ are called the current state.

Definition 4 (Efendi et al., 2015)

Let $F(t)$ be a fuzzy time series where $(t = 1,2,3, \ldots, n)$. The value of $F(t)$ is a fuzzy set. If $F_1(t)$ is obtained from $(F_1(t-n), F_2(t-n), F_3(t-n), \ldots, F_k(t-n))$,…, $(F_1(t-1), F_2(t-1), F_3(t-1), \ldots, F_k(t-1))$, then $F_1(t)$ can be represented as $\big(F_1(t-n), \ldots, F_k(t-n)\big), \ldots, (F_1(t-1), \ldots, F_k(t-1)) \rightarrow F_1(t)$ which is called a multi-factor fuzzy time series of order-n.

Definition 5 (Li & Yu, 2020)

In 1-order multi-factor fuzzy time series forecasting, there are two defuzzifiction rules as follows:

Rule 1**:** If $N \neq 0$, meaning that there exists a fuzzy logical relationship (FLR) in the forecasting process, the forecasted value can be determined using equation (1).

$$x(a) = \begin{cases} \dfrac{0{,}5m(1) + Q(1)}{1{,}5}, & \text{if } a = 1 \\ \dfrac{0{,}5m(a-1) + Q(a) + 0{,}5m(a+1)}{2}, & \text{if } 2 \leq a \leq k \\ \dfrac{0{,}5m(a-1) + Q(a-1) + q}{1{,}5}, & \text{if } a = k+1 \end{cases} \tag{1}$$

$$x' = \frac{v_1 \times \bar{x}(l_1) + v_2 \times \bar{x}(l_2) + v_3 \times \bar{x}(l_3) + \cdots + v_N \times \bar{x}(l_N)}{v_1 + v_2 + \cdots + v_N} \tag{2}$$

where:
$m(a)$ represents the midpoint of the fuzzy interval $u_a$
$Q(a)$ denotes the lower bound of the fuzzy interval $u_a$
q is the distance between $m(a)$ and $Q(a)$ within the fuzzy interval $u_a$
$\bar{x}(l_r)$ $(r = 1,2,3, \ldots, N)$ refers to the forecasted values obtained using equation 1. $v_r$ $(r = 1,2,3, \ldots, N)$ represents the number of next states corresponding to the same current state in the fuzzy logical relationship (FLR).

Thus, the forecasted value at time $x_t^*$ can be computed using:

$$x_t^* = 0{,}5(\bar{x}(p) + x') \tag{3}$$

where $\bar{x}(p)$ represents the forecasted value at $a = k + 1$

Rule 2**:** If $N = 0$, meaning that no fuzzy logical relationship (FLR) is present in the forecasting process, the forecasted value at the next time step is given by:

$$x_t^* = \bar{x}(p) \tag{4}$$

Definition 6 (Vamitha & Vanitha, 2022)

The forecasting error or deviation can be measured using AFER (Average Forecast Error Rate) (Vamitha & Vanitha, 2022):

$$AFER = \frac{\sum_{i=1}^{n}\left(\frac{|X_i - Y_i|}{X_i}\right)}{n} x100\% \tag{5}$$

where:
$X_i$ represents the actual value at time $i$
$Y_i$ represents the forecasted value at time $i$
$n$ is the number of forecasting time periods involved.
The AFER value can be used as an indicator for determining the performance criteria of the forecasting method employed. The following are AFER values along with their corresponding forecasting performance criteria (Irawanto et al., 2019)

Table 1. Forecasting criteria based on AFER values

| AFER Value | Forecasting Performance Criteria |
|---|---|
| <10% | Excellent |
| 10% - 20% | Good |
| 20% - 50% | Fair |
| >50% | Poor |

## Method

Determining the forecasted value using short cross-association of fuzzy logical relationships consists of three parts, as follows:

*Part 1: Fuzzification Process for the Main Factor*

The steps are as follows:
Step 1: Determine the universe of discourse U based on the historical data of the main factor.
Step 2: Partition the universe into ten intervals (Li et al., 2021) and further divide the intervals into subintervals using frequency density-based partitioning (Jilani & Burney, 2008).
Step 3: Define fuzzy sets based on the determined intervals and input the data according to the fuzzy sets.

*Part 2: Fuzzification Process for the Second Factor*

The steps are as follows:
Step 1: Determine the universe of discourse V based on the historical data of the second factor.
Step 2: Partition the universe into ten intervals (Li et al., 2021) and further divide the intervals into subintervals using frequency density-based partitioning (Jilani & Burney, 2008).
Step 3: Define fuzzy sets based on the determined intervals and input the data according to the fuzzy sets.

*Part 3: Defuzzification Process for the Main Factor and Second Factor*

The steps are as follows:
Step 1: Construct the Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG).
Step 2: Determine the forecasted value based on defuzzification rules and calculate the error usning AFER.

## Results and Discussion

The stock price of PT Wijaya Karya (Persero) Tbk exhibits unstable movements due to fluctuations in stock prices across different periods. In this study, the author utilizes closing price data and highest price data of PT Wijaya Karya (Persero) Tbk, comprising 41 data points collected from May 3, 2024, to February 7, 2025, with a weekly period. As shown in Figure 1, the data is non-stationary with respect to the mean due to the presence of a trend in the data pattern itself. Therefore, stationarization is necessary for further analysis.

Using the short cross-association of fuzzy logical relationships method in the fuzzy logical relationship (FLR) formation stage, the predicted closing stock price for the following week, with the closing stock price as the main factor, is 226,091 IDR. This forecast indicates an increase of 10.8% compared to the closing stock price in the last observed week.


Figure 1. Stock price of PT Wijaya Karya (Persero) Tbk

**Short Cross Association Fuzzy Logical Relationship Simulation**

The method for forecasting the closing stock price of PT Wijaya Karya (Persero) Tbk using short cross-association in the defuzzification stage of the closing stock price data of PT Wijaya Karya (Persero) Tbk will be explained below.

*Part 1: Fuzzification Process for the Main Factor*

[Step 1] : The universal set $(U)$ is defined as equal to $U = [D_{min} - c_1, D_{max} + c_2]$ (Bose & Mali, 2018). $c_1$ and $c_2$ are corresponding positive numbers. We know that based on the maximum and minimum available data, to obtain integers, $c_1 = 6$ and $c_2 = 10$ are used so that the universal set is obtained $U = [460 - 80]$.

[Step 2] : The universe set $U$ is initially partitioned into 10 equal-length intervals $u_1, u_2, \dots, u_{10}$. These intervals are then further subdivided using frequency density-based partitioning. The three intervals with the highest frequencies are divided into four, three, and two subintervals, respectively. Intervals with zero frequency are removed. As a result, a total of 17 final intervals is obtained.

[Step 3] : Defining real data into fuzzy sets $A_1, A_2, A_3, \dots, A_n$. Next, find the membership value using a triangular membership function as in (Stevenson & Porter, 2009).

*Part 2: Fuzzification Process for the Second Factor*

[Step 1] : The universal set $(V)$ is defined as equal to $V = [D_{min} - c_1, D_{max} + c_2]$ (Bose & Mali, 2018). $c_1$ and $c_2$ are corresponding positive numbers. We know that based on the maximum and minimum available data, to obtain integers, $c_1 = 9$ and $c_2 = 10$ are used so that the universal set is obtained $U = [490 - 80]$.

[Step 2] : The universe set $V$ is initially partitioned into 10 equal-length intervals $v, v_2, \dots, v_{10}$. These intervals are then further subdivided using frequency density-based partitioning. The three intervals with the highest frequencies are divided into four, three, and two subintervals, respectively. Intervals with zero frequency are removed. As a result, a total of 20 final intervals is obtained.

[Step 3] : Defining real data into fuzzy sets $B_1, B_2, B_3, \dots, B_n$. This step is called fuzzification. Next, find the membership value using a triangular membership function as in (Stevenson & Porter, 2009)

Table 2. The result of part 1 and part 2

| Week | Actual data of main factor | Fuzzification | Actual data of second factor | Fuzzification |
|---|---|---|---|---|
| 1 | 158 | A4 | 200 | B6 |
| 2 | 145 | A3 | 158 | B5 |
| 3 | 133 | A3 | 145 | B4 |
| 4 | 113 | A2 | 135 | B4 |
| 5 | 112 | A2 | 132 | B3 |
| 6 | 111 | A2 | 118 | B2 |
| 7 | 88 | A1 | 113 | B2 |
| 8 | 86 | A1 | 89 | B1 |
| 9 | 86 | A1 | 90 | B1 |
| 10 | 141 | A3 | 160 | B5 |
| 11 | 236 | A8 | 238 | B9 |
| 12 | 226 | A7 | 250 | B10 |
| 13 | 204 | A5 | 236 | B9 |
| 14 | 208 | A5 | 226 | B8 |
| 15 | 212 | A5 | 220 | B7 |
| 16 | 338 | A12 | 380 | B16 |
| 17 | 332 | A12 | 364 | B15 |
| 18 | 390 | A14 | 390 | B17 |
| 19 | 450 | A17 | 480 | B20 |
| 20 | 402 | A15 | 474 | B20 |
| 21 | 388 | A14 | 410 | B19 |
| 22 | 384 | A13 | 406 | B18 |
| 23 | 370 | A13 | 394 | B17 |
| 24 | 398 | A15 | 426 | B19 |
| 25 | 412 | A16 | 424 | B19 |
| 26 | 372 | A13 | 420 | B19 |
| 27 | 386 | A14 | 404 | B18 |
| 28 | 320 | A11 | 390 | B17 |
| 29 | 290 | A10 | 328 | B14 |
| 30 | 314 | A11 | 358 | B15 |
| 31 | 294 | A10 | 328 | B14 |
| 32 | 296 | A10 | 312 | B13 |
| 33 | 292 | A10 | 322 | B13 |
| 34 | 250 | A9 | 298 | B13 |
| 35 | 246 | A9 | 258 | B11 |
| 36 | 248 | A9 | 268 | B12 |
| 37 | 224 | A7 | 260 | B11 |
| 38 | 242 | A8 | 268 | B12 |
| 39 | 234 | A8 | 256 | B11 |
| 40 | 220 | A6 | 240 | B9 |
| 41 | 204 | A5 | 228 | B8 |

*Part 3: Defuzzification Process for the Main Factor and Second Factor*

[Step 1]: Construct the Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG). According to the obtained Fuzzy Logical Relationship (FLR), Fuzzy Logical Relationship Groups (FLRG) can also be formed according to the concept of short cross-association in fuzzy logical relationships. That is, current states and next states that are the same in the previously established FLR can be grouped together.The result of the FLR and FLRG is shown in Table 3.

[Step 2] : Due to the fact that there exists a Fuzzy Logical Relationship (FLR) $(N \neq 0)$ , the forecasted data values can be determined based on Rule 1 of defuzzification in multi-factor fuzzy time series forecasting using Equation (1). The forecasted data values for future time periods can be calculated using Equation (3), and the error can be computed using Equation (5). As a result, the defuzzification values for each fuzzy set are obtained, as presented in Table 4.

Table 3. FLR and FLRG

| | FLR and FLRG | | | |
|---|---|---|---|---|
| FLR | B6 → A3 | B9 → A7 | B19 → A13 | B14 → A10 |
| | B5 → A3 | B10 → A5 | B18 → A13 | B13 → A10 |
| | B4 → A2 | B9 → A5 | B17 → A15 | B13 → A9 |
| | B4 → A2 | B8 → A5 | B19 → A16 | B13 → A9 |
| | B3 → A2 | B7 → A12 | B19 → A13 | B11 → A9 |
| | B2 → A1 | B16 → A12 | B19 → A14 | B12 → A7 |
| | B2 → A1 | B15 → A14 | B18 → A11 | B11 → A8 |
| | B1 → A1 | B17 → A17 | B17 → A10 | B12 → A8 |
| | B1 → A3 | B20 → A15 | B14 → A11 | B11 → A6 |
| | B5 → A8 | B20 → A14 | B15 → A10 | B9 → A5 |
| FLRG | B1 → A1 (1) | B9 → A5 (1) | B13 → A10 (1) | |
| | B1 → A3 (1) | B9 → A7 (1) | B14 → A10 (1) | B18 → A11 (1) |
| | B2 → A1 (2) | B9 → A5 (1) | B14 → A11 (1) | B18 → A13 (1) |
| | B3 → A2 (1) | B10 → A5 (1) | B15 → A10 (1) | B19 → A13 (1) |
| | B4 → A2 (2) | B11 → A6 (1) | B15 → A14 (1) | B19 → A14 (1) |
| | B5 → A3 (1) | B11 → A8 (1) | B16 → A12 (1) | B19 → A16 (1) |
| | B5 → A8 (1) | B11 → A9 (1) | B17 → A10 (1) | B19 → A13 (1) |
| | B6 → A3 (1) | B12 → A7 (1) | B17 → A17 (1) | B20 → A14 (1) |
| | B7 → A12 (1) | B12 → A8 (1) | B17 → A15 (1) | B20 → A15 (1) |
| | B8 → A5 (1) | B13 → A9 (2) | | |

Table 4. Forecasting result and AFER value

| Week | Actual data ($X_i$) | Forecasting data ($Y_i$) | $\lvert X_i - Y_i \rvert / X_i$ |
|---|---|---|---|
| 1 | 158 | 164.3125 | 0.03995253165 |
| 2 | 145 | 130.6666667 | 0.09885057471 |
| 3 | 133 | 130.6666667 | 0.01754385965 |
| 4 | 113 | 108.5 | 0.03982300885 |
| 5 | 112 | 108.5 | 0.03125 |
| 6 | 111 | 108.5 | 0.02252252252 |
| 7 | 88 | 82.11111111 | 0.06691919192 |
| 8 | 86 | 82.11111111 | 0.04521963824 |
| 9 | 86 | 82.11111111 | 0.04521963824 |
| 10 | 141 | 130.6666667 | 0.07328605201 |
| 11 | 236 | 235.5625 | 0.001853813559 |
| 12 | 226 | 225.2708333 | 0.00322640118 |
| 13 | 204 | 199.9375 | 0.01991421569 |
| 14 | 208 | 199.9375 | 0.03876201923 |
| 15 | 212 | 199.9375 | 0.05689858491 |
| 16 | 338 | 334.125 | 0.01146449704 |
| 17 | 332 | 334.125 | 0.00640060241 |
| 18 | 390 | 382.8125 | 0.01842948718 |
| 19 | 450 | 417.25 | 0.07277777778 |
| 20 | 402 | 395.875 | 0.01523631841 |
| 21 | 388 | 382.8125 | 0.01336984536 |
| 22 | 384 | 354.3125 | 0.07731119792 |
| 23 | 370 | 354.3125 | 0.04239864865 |
| 24 | 398 | 395.875 | 0.00533919598 |
| 25 | 412 | 411.3125 | 0.00166868932 |
| 26 | 372 | 354.3125 | 0.04754704301 |
| 27 | 386 | 382.8125 | 0.008257772021 |

| | | | |
|---|---|---|---|
| 28 | 320 | 312.75 | 0.02265625 |
| 29 | 290 | 286.625 | 0.01163793103 |
| 30 | 314 | 312.75 | 0.00398089172 |
| 31 | 294 | 286.625 | 0.02508503401 |
| 32 | 296 | 286.625 | 0.0316722973 |
| 33 | 292 | 286.625 | 0.01840753425 |
| 34 | 250 | 256.5416667 | 0.02616666667 |
| 35 | 246 | 256.5416667 | 0.04285230352 |
| 36 | 248 | 256.5416667 | 0.0344422043 |
| 37 | 224 | 225.2708333 | 0.005673363095 |
| 38 | 242 | 235.5625 | 0.02660123967 |
| 39 | 234 | 235.5625 | 0.006677350427 |
| 40 | 220 | 215.375 | 0.02102272727 |
| 41 | 204 | 199.9375 | 0.01991421569 |
| | | AFER | 2.97130033% |

Based on the results presented in Table 4, the comparison can be visualized in the following graph.

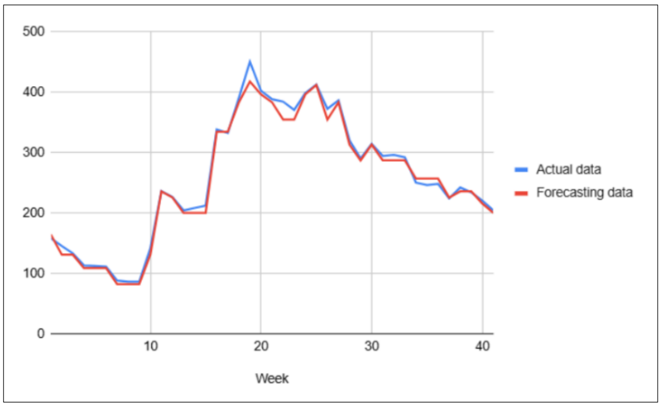


Figure 2. Graph of the forecasting and actual data

The graph above illustrates a comparison between two datasets: the blue line represents the actual data, while the orange line represents the forecasted data. By applying the short cross-association fuzzy logical relationship method and its defuzzification process, the forecasted value for the future is obtained as 226.091 IDR. Furthermore, the accuracy level, based on the Absolute Forecast Error Rate (AFER), results in an error of 2.97%, which is less than 10%. This indicates that the short cross-association fuzzy logical relationship method demonstrates a highly effective criterion for modeling the stock closing price forecast of PT Wijaya Karya (Persero) Tbk Indonesia.

## Conclusion

The application of the multi-factor fuzzy time series (FTS) forecasting method can effectively predict the stock closing prices of construction companies, particularly PT Wijaya Karya (Persero) Tbk. This method is utilized because forecasting a dataset is inherently influenced by various supporting factors. In this case, the data used includes the highest stock price as the influence factor (second factor) in addition to the closing stock price, which serves as the main factor for the forecasted data.

The short cross-association method applied during the defuzzification stage in the analysis helps optimize the determination of forecast values. Specifically, this method is employed to predict the closing stock price of PT Wijaya Karya (Persero) Tbk based on time series data. The forecasting results obtained from this method predict the next week's stock closing price to be 226.091 IDR, with an accuracy level measured using the Average

Forecasting Error Rate (AFER) of 2.97%. Since the AFER value is less than 10%, based on AFER criteria, this forecasting method demonstrates a highly accurate performance.

However, when using the conventional multi-factor fuzzy time series method, the Fuzzy Logical Relationships (FLR) premises become excessively large, particularly in high-order multi-factor fuzzy time series models. In such cases, no available FLRs can be identified, as the number of premises to be matched becomes too extensive, rendering the prediction values indeterminable. Therefore, the Short Cross-Association Fuzzy Logical Relationship (SCAFLR) method is employed to increase the likelihood of identifying available FLRs in forecasting. The presence of short cross-association influences implies that the forecast is affected by influence factors. Hence, when constructing FLRs in forecasting models, it is essential to consider the SCAFLR approach.

## Recommendations

For future research, it is recommended to develop a more optimal short association method by modifying the interval and its fuzzification components. Furthermore, a comparative analysis between the short association method used in this study and other methods could be conducted to evaluate the accuracy level.

## Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

## Conflict of Interest

* The authors have no conflicts of interest in any area.

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