Comparative Analysis of the Fuzzy Time Series Chen and Saxena-Easo Model on the Closing Price of the Composite Stock Price Index

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Comparative Analysis of the Fuzzy Time Series Chen and Saxena-Easo Model on the Closing Price of the Composite Stock Price Index

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Abstract: *The stock price index is one of the indicators in looking at stock price movements. Stock investment is hard to do when the country's economy is down. Therefore, investors are expected to be able to predict the stock price. In this study, the objective was to find out the closing price of the combined stock for the next three periods using the Fuzzy Time Series method of Chen and Saxena-Easo models as well as the error rate of the prediction result through the Mean Absolute Percentage Error (MAPE) error values. The data used is the daily closing price of the combined stock price index January 1, 2018 – October 31, 2023. The results achieved in this study were the forecast of the closure price of a combined share for November 1 - 3, 2023, which is 6,712.59, 6,757.00 and 6,733.96 along with the error value of the MAPE Fuzzi Time Series model Chen of 1.53% and Saxena-Easo of 0.24%.*

Keywords: Fuzzy Time Series Chen Model; Fuzzy Time Series Saxena-Easo Model; Mean Absolute Percentage Error (MAPE); Closing Price of the Composite Stock Price Index

1. INTRODUCTION

Stock is proof of ownership of a company [1]. An overview of stock movements can be seen from various indicators, one of which is the stock price index. There are various types of stock price indices, the most commonly used and first launched type is the composite stock price index [2]. An overview of the movement of all stocks in one or more charts can be obtained using the composite stock price index, a concise statistical analysis [3]. The increase or decrease in the movement of the composite stock price index depends on the economic conditions of a country. A good economic environment is seen when the composite stock price index shows an increasing trend and vice versa. Investors face challenges in deciding whether to invest, as stock prices are not always fixed, so forecasting is required to determine the closing price of the composite stock price index.

This research uses fuzzy time series Chen and Saxena-Easo to forecast the closing price of composite stock price index. One technique that utilizes artificial intelligence and is always evolving is fuzzy time series. Unlike other time series methods, the fuzzy time series approach relies on data prediction without requiring the completion of assumption tests [4]. The classical method is extended with fuzzy time series Chen model [5] by modifying the number of intervals and dividing the number of highest frequencies. The development of Stevenson & Porter's approach is the Saxena-Easo fuzzy time series model [6] which determines the percentage change from the actual data. Saxena-Easo then developed this approach by changing the number of intervals.

Based on research [7], the closing prices of shares in the top five issuers of the Forbes Global 2000 version, namely BBRI, BBCA, BMRI, TLKM, and BBMI are predicted using Chen's fuzzy time series forecasting method. This research analysis resulted in the findings of forecasting accuracy measures using Mean Absolute Percentage Error (MAPE) of 3.2197%, 3.1983%, 2.3894%, 2.2243%, and 2.8066%. Whereas in research [8] gold prices are predicted using the Saxena-Easo fuzzy time series. The predicted data shows that the MAPE accuracy rate is 0.024277%. The Chen and Saxena-Easo fuzzy time series approaches can anticipate well, as evidenced by the MAPE accuracy rate of the two studies being less than 20%. Thus, a comparison of the two models will be conducted in this study to determine the best model in forecasting the closing price of the JCI. In comparing the accuracy of the two models, the Mean Absolute Percentage Error (MAPE) calculation is used.

To predict inflation in Indonesia in February and March 2020, Alfania et al. [9] proposed the use of Fuzzy Time Series Average Based and Saxena-Easo models as research methods and MAPE calculations to compare the prediction errors of the two models. Referring to the calculation of inflation data in Indonesia for the period January 2014 - January 2020, the Fuzzy Time Series Average Based method produces inflation of 2.67 in February and March 2020 with a total interval of 60 and a MAPE value of 0.05448%, while Saxena-Easo produces predictions for the next 2 periods, namely February predictions of 2.5929 and March 2020 of 2.5355 with a total interval of 7 which is then repartitioned to reach 18 intervals and produces a MAPE value of 0.0135%. This shows that the Saxena-Easo fuzzy time series is good for predicting inflation data in February and March 2020.

Fuzzy Time Series Chen's Model was compared with Lee's Model by Febrino et al. [10] to predict the closing price of JCI and find the superior method between the two. The results obtained from this study are that the Lee model fits the actual data better than the Chen model based on the prediction analysis of the weekly closing price of the composite stock price index (JCI) for the period October 2017 - September 2022. It was also found that using the Chen model, the closing price of the JCI for the next period can be predicted to be 6,904. While the prediction result of the next period JCI closing price using Lee's Fuzzy Time Series method is 7,046. In addition, the results of this study show that the JCI closing price forecast made with the Chen fuzzy time series model has a MAPE value of 4.03% and a prediction accuracy of 95.97%, while the JCI closing price forecast made with the Lee fuzzy time series model has a MAPE value of 3.10% and a prediction accuracy of 96.9%. Based on these results, it can be concluded that the Lee model is superior in predicting the closing price of the JCI compared to the Chen fuzzy time series model. Other research is related to case forecasting in other fields, For example, imbalanced flood forecast dataset resampling using smote-tomek link [11], in this paper discusses the challenges of applying machine learning algorithms to highly skewed data and the significance of researching performance evaluation metrics other than accuracy for binary classification.

This is because a skewed dataset may make it difficult to determine the trained model's accuracy and the process of resampling aids in the creation of a balanced dataset, which improves classification performance. while other cases concern time series problems, for example in [12], the study focuses on a one-hour-ahead forecasting model, classified as short-term forecasting, three Neural Network dynamic time series models to identify the best-performing model and then compares the different input sizes and calculates training times to assess accuracy and training duration for practical applications. The relationship between power forecasting accuracy and the number of input variables is considered in training time series models.

This research aims to anticipate closing prices of composite stock price index using the fuzzy time series of Chen and Saxena-Easo as well as identify the best model in predicting the closing price of shares over the next three periods. As a result, this information can be a matter of consideration for investors when making decisions, used to study stock price predictions, and used as a source for scientific writing or new research projects. In connection with the importance of stock price prediction to investor decisions, a desktop application in the form of a Graphical User Interface (GUI) will be created to show the results of the prediction of the closing price of the combined stock price index.

2. MATERIAL AND METHODS

2.1 Data Collection

The data in this research was obtained from the website www.yahoofinance.com [13] in the form of the closing price of the composite stock price index on January 1, 2018 to October 31, 2023 as much as 1451 data. To maintain data integrity and ensure that the forecasting model can work optimally, data preprocessing is carried out by eliminating data that has null values, so that the historical data to be implemented amounts to 1418 data.

2.2 Fuzzy Time Series Chen

The following is the flowchart of the Chen fuzzy time series model is used in this research.

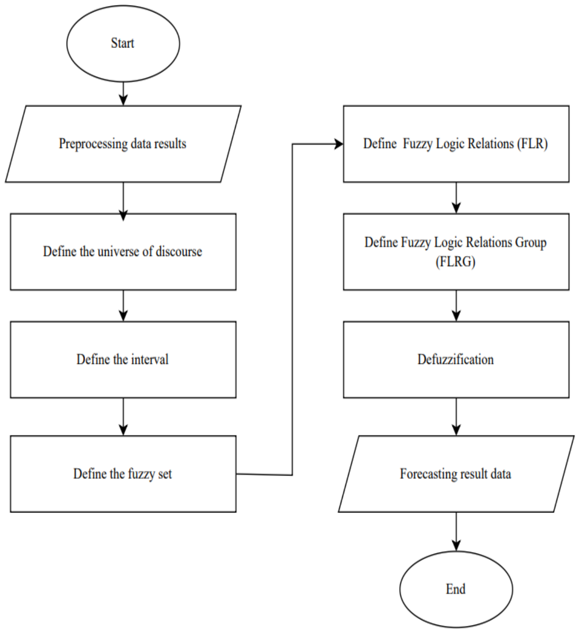

Fig. 1. Flowchart of Fuzzy Time Series Chen

Based on the picture in fig.1 above, the data analysis stages of the Chen model are carried out using the equations as follows:

1. Determine the universe of discourse

$$U = [D_{\min}, D_{\max}] \tag{1}$$

D_{min} is the historical data that has the smallest value, while D_{max} is the largest historical data.

2. Define the interval

At this stage, using Sturges' rule, multiple intervals of equal width can be created from the universe set.

$$K = 1 + 3.3 \log n \tag{2}$$

where K indicates the number of classes created and n indicates the amount of historical data used. The next step is to use the following equation to find the width of the interval class.

$$P = \frac{D_{\min} - D_{\max}}{number\ of\ interval} \tag{3}$$

After obtaining the number of interval classes and length interval length, it will produce u_1 to u_n which are the intervals of the universe set (U)

3. Define the fuzzy sets

This stage involves changing the universe set that has been divided. Furthermore, the fuzzy sets are transformedusing the obtained intervals. For example, the linguistic values of the linguistic variables form the fuzzy sets A_1, A_2,…, A_n.

$$\begin{aligned} A_1 &= 1/u_1 + 0.5/u_2 + \ldots + 0/u_m \\ &\vdots \\ A_k &= 0/u_1 + \ldots + 0.5/u_{m-1} + 0/u_m \end{aligned} \tag{4}$$

where "/" denotes the degree of membership, with a value between 0.5 and 1, and u_m (i=1,2, … m) is an element of the universe set (U).

4. Fuzzification
The membership value of each fuzzy set that ranges from 0 to 1 is determined using historical data.

5. Define Fuzzy Logical Relationship (FLR)
Suppose $F(i) = A_i$ and $F(i+1) = A_j$. The fuzzy logical connection, represented by $A_i \rightarrow A_j$, shows the relationship between two ordered observations, $F(i)$ and $F(i+1)$, so that it becomes $F(i) \rightarrow F(t+1)$, A_i is called the left side and A_j is called the right side.

6. Define Fuzzy Logical Relationship Group (FLRG)
FLRG is the combination of each FLR value that has been obtained. The value must be grouped based on its leftside. For example, $(A_i) : A_i \rightarrow A_{j1}$, $A_i \rightarrow A_{j1}$ and $A_i \rightarrow A_{j2}$. These relations can be combined into $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j2}$, where $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j1}$ are only taken as one, because both relations are considered the same.

7. Defuzzification
Each group generated at the FLRG stage is averaged using the following equation.

$$F(t) = \frac{\sum_i^n m_i}{n} \quad (5)$$

where $F(t)$ is the final forecasting value, m_i is the middle value of u_i, and n is the number of data from the group for which the average is to be calculated.

3.3 Fuzzy Time Series Saxena-Easo Model

The following is the flowchart of the Saxena-Easo fuzzy time series model is used in this research.

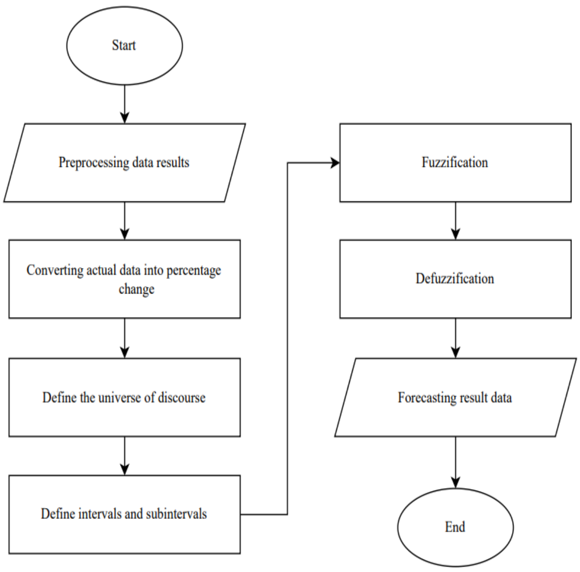

Fig. 2. Flowchart Fuzzy Time Series Saxena-Easo

According to the flowchart in Fig.2, the following analysis of Saxena-Easo model :

1. Converting actual data into percentage change
Data conversion to percentage change is the first step in the Saxena-Easo fuzzy time series. The amount of change in the value of t with t-1 is expressed in percentage change. The equation for calculating the amount of data change is as follows.

$$q = \left(\frac{x_t - x_{t-1}}{x_{t-1}}\right) \times 100\% \quad (6)$$

where x_t is the closing price data on the observed day and x_{t-1} is the closing price data on the previous day.

2. Determine the universe of discourse

$$U = [D_{\min}, D_{\max}] \quad (7)$$

D_{min} and D_{max} are the minimum and maximum values of the percentage change. To find the class interval, use equations (2) and (3).

3. Define intervals and subintervals
Dividing the interval in the previous stage into equal length intervals based on the number of frequencies ofeach interval. One way to divide an interval into smaller intervals is to divide its length by the number of frequencies of the data.

4. Fuzzification
Data prediction results given in the form of percentage changes are called data fuzzification. The following formula can be used to calculate data fuzzification.

$$t_j = \begin{cases} \dfrac{1+0.5}{\dfrac{1}{a_1} + \dfrac{0.5}{a_2}}, if\ j = 1 \\ \dfrac{0.5+1+0.5}{\dfrac{0.5}{a_{j-1}} + \dfrac{1}{a_j} + \dfrac{0.5}{a_{j+1}}}, \\ \text{if } 2 \le j \le n-1 \\ \dfrac{0.5+1}{\dfrac{0.5}{a_{n-1}} + \dfrac{1}{a_n}}, \text{ if } j = n \end{cases} \quad (8)$$

where t_j is the predicted percentage change, the current data in the subinterval is denoted by a_j, the previous and next data are denoted by a_{j-1} and a_{j+1}, and the first and last data in the subinterval are denoted by a_1 and a_n.

5. Defuzzification
The process of making decisions by converting the percentage change results into a single value is called defuzzification. Here is the defuzzification formula:

$$F(t) = \left(\frac{t_j}{100} \times x_{t-1}\right) + x_{t-1} \quad (9)$$

where t_j is the predicted percentage change and x_{t-1} is the previous actual value.

Both models were evaluated by calculating the error value using MAPE through the following formula to get the best model in predicting the closing price of the composite stock price index.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \times 100\% \quad (10)$$

where $\boldsymbol{n}$ is the amount of data, A_i is the actual result value, and F_i is the predicted value. After getting the best fuzzy time series model through the calculation of MAPE, the closing price of the composite stock price index is predicted in the next three periods by taking the prediction results in the last three periods.

3. RESULTS AND DISCUSSION

One of the indicators used to see changes in stock prices is the stock price index. Investing in stocks becomes a challenge when the country's economy is experiencing difficulties. Therefore, stock price predictions are needed by investors. The purpose of this study is to determine the error rate of the prediction results using the Mean Absolute Percentage Error (MAPE) error value and the closing price of the joint stock for three periods using the Chen and Saxena-Easo Fuzzy Time Series model approach. The data used is the daily closing price of the composite stock price index for the period January 1, 2018 to October 31, 2023 as seen the example in Table 1. The results include the prediction of theclosing price of the joint stock for the period of January 1, 2018 to October 31, 2023.

Table 1. Example of data history

Date	Close price
January 2, 2018	6339.24
January 3, 2018	6251.48
January 4, 2018	6292.32
:	:
October 30, 2023	6735.89
October 31, 2023	6752.21

In the Chen model, the step taken after preprocessing is the formation of the universe set. Based on the data collected, the smallest and largest data obtained are 3937.63 and 7318.02. Then the universe set is formed as follows U = [3937.63, 7318.02]. Interval formation is the next step. The number of interval classes and interval width must be determined before an interval can be formed. The number of interval classes obtained is as follows K = 1 +3.3 log 1418 = 11.40 ≈ 11. Then the width of the interval class can be determined with the following results P = 307.31.
After the calculation, eleven interval classes with a width of 307.31 were found. Therefore, based on the number of intervals with the same width, $u_1, u_2, u_3, \ldots\ u_{11}$ and their middle values are made as Table 2 follows.

Table 2. Interval of the universal set

No	Interval	Midpoint ($\boldsymbol{m}$)
1	u_1 = [3937.63; 4244.94]	m_1 = 4019.29
2	u_2 = [4244.94; 4552.25]	m_2 = 4398.59
:	:	:
10	u_{10} = [6703.40; 7010.71]	m_{10} = 6857.05
11	u_{11} = [7010.71; 7318.02]	m_{11} = 7164.36

Identifying the fuzzy set in the universe is the next step. Between 0, 0.5, and 1 are the membership values of the fuzzy set A_i. For each i, there are 11 intervals, where 1 ≤ i ≤ 11. Here's how to write about creating a fuzzy setusing the closing price of the composite stock price index.

$$A_1 = \left\{ \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8} + \frac{0}{u_9} + \frac{0}{u_{10}} + \frac{0}{u_{11}} \right\}$$

$$A_2 = \left\{ \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8} + \frac{0}{u_9} + \frac{0}{u_{10}} + \frac{0}{u_{11}} \right\}$$

$$\vdots$$

$$A_{11} = \left\{ \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8} + \frac{0}{u_9} + \frac{0.5}{u_{10}} + \frac{1}{u_{11}} \right\}$$

As seen from the fuzzy assembly construction, A_{11} has definitions of $u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8$, and u_9 with respective membership degrees of 0 and 0.5, whereas u_{10} has a membership degree of 0.5, and the u_{11} degree of membership of 1. Fuzzification is the next stage that depends on the intervals obtained. The size of the resulting interval can be used to calculate the linguistic value. In Table 3 show a notation of the linguistic numbers resulting from data fuzzification.

Table 3. Fuzzification of the closing price of the composite stock price index

Date	Close price	Fuzzification
January 2, 2018	6339.24	A_8
January 3, 2018	6251.48	A_8
January 4, 2018	6292.32	A_8
:	:	:
October 30, 2023	6735.89	A_{10}
October 31, 2023	6752.21	A_{10}

Next, determine Fuzzy logic relation (FLR) for $1 \leq i \leq 11$ by observing fuzzy A_i daily. Here in table 4 is the FLR result for the closing price of the combined stock price index.

Table 4. Fuzzy logic relation

Date	Fuzzification	FLR
January 2, 2018	A_8	NA
January 3, 2018	A_8	$A_8 \rightarrow A_8$
January 4, 2018	A_8	$A_8 \rightarrow A_8$
:	:	:
October 30, 2023	A_{10}	$A_{10} \rightarrow A_{10}$
October 31, 2023	A_{10}	$A_{10} \rightarrow A_{10}$

Grouping all FLRs with the same left side of $F(t-1)$ will result in FLRG. The next step is to apply Chen's fuzzy time series model to predict the value and perform the fefuzzification process after obtaining FLG. In the table below it is seen that group 1 consists of the Fuzzy relationship gorup A_1 and A_2 so that A_1uses $m_1$as the middlevalue of u_1, as well as with A_2. Then the two middle values are synchronized using the formula (5). Here's the calculations in Table 5 to determine the predictive value of each group.

Table 5. FLRG value

Group	FLRG	F(t)	FLRG Value
1	$A_1 \rightarrow A_1, A_2$	$\frac{m_1+m_2}{2}$	4244.94
2	$A_2 \rightarrow A_1, A_2, A_3$	$\frac{m_1+m_2+m_3}{3}$	4398.59
:	:	:	:
10	$A_{10} \rightarrow A_9, A_{10}, A_{11}$	$\frac{m_9+m_{10}+m_{11}}{3}$	6857.05
11	$A_{11} \rightarrow A_{10}, A_{11}$	$\frac{m_{10}+m_{11}}{2}$	7010.71

Based on the table above, the result of the prediction with FLRG is in Table 6 as follows :

Table 6. Prediction result of Chen model

Date	Close price	Fuzzification	FLRG value	Result prediction
January 2, 2018	6339.24	$A8$	6242.44	NA
January 3, 2018	:51.48	$A8$	6242.44	6242.44
January 4, 2018	6292.32	$A8$	6242.44	6242.44
:	:	:	:	:
October 30, 2023	6735.89	$A10$	6857.05	6857.05
October 31, 2023	6752.21	$A10$	6857.05	6857.05

In the second model, Saxena-Easo, the first step taken after the data passes the preprocessing phase is to convert the data into a percentage of change using the formula (6) so that the result is in Table 7 as follows.

Table 7. Percentage of change

Date	Close price	Percentage change
January 2, 2018	6339.24	NA
January 3, 2018	6251.48	-1.384
January 4, 2018	6292.32	0.653
:	:	:
October 30, 2023	6735.89	-0.339
October 31, 2023	6752.21	0.242

Based on the calculation of the percentage of change, the largest value is 10.191 and the smallest value -6.579. So based on the equation (7) the value of U = [−6.579; 10.191]is obtained. The next step is to form intervals. As with the Chen model, the number of interval classes and the width of intervals must be determined before an interval can be formed. Using the same data results in the same number of interval classes as the Chen model is 11. Then the width of the interval class can be determined with the result as follows P = 1.525. Therefore, based on the number of intervals of the same width, we make $u1$, $u2$, $u3$, … $u11$. The next step is to form a subinterval. Oneway to divide an interval into smaller intervals is by dividing its width by the total amount of data frequencies and the result as seen in table 8 follows :

Table 8. The Interval

No	Interval	Freq	Number of subinterval
1	u_1 = [−6.579; −5.054]	2	2
2	u_2 = [−5.054; −3.530]	8	3
3	u_3 = [−3.530; −2.005]	27	5
4	u_4 = [−2.005; −0.481]	310	7
5	u_5 = [−0.481; 1.044]	912	8
6	u_6 = [1.044; 2.568]	125	6
7	u_7 = [2.568; 4.093]	10	4
8	u_8 = [4.093; 5.617]	1	1
9	u_9 = [5.617; 7.142]	0	0
10	u_{10} = [7.142; 8.666]	0	0
11	u_{11} = [8.666; 10.191]	1	1

According to the above Table 8, there are 8 different frequencies or percentages of data change: 912, 310, 125, 27, 10, 8, 2 and 1. Thus, the interval with the highest first frequency is 912 divided into 8 subintervals, with the second highest frequence is 310 will be divided in 7 equal subintervalls, as well as the others. The resulting fuzzy assembly domain consists of 37 subintervals. Subinterval is then formed by searching for new interval widths in the following way. $P = \frac{10.191-(-6.579)}{37} = 0.453$. So we get the subinterval with its middle value as in Table 9 below

Table 9. Subinterval

No	Interval	Midpoint ($\boldsymbol{aj}$)	Fuzzy Set
1	[-6.579; -6.125]	-6.352	$A1$
2	[-6.125; -5.672]	-5.899	$A2$
:	:	:	:
36	[9.284; 9.738]	9.511	$A36$
37	[9.737; 10.191]	9.964	$A37$

The next step is to do a fuzzification by calculating the prediction of the percentage of change. To calculate the predictions of the percent of change can be done calculating using the formula on the equation (8).

For $j = 1$ then,

$$t_1 = \frac{1+0.5}{\frac{1}{a_1}+\frac{0.5}{a_2}} = \frac{1+0.5}{\frac{1}{-6.252}+\frac{0.5}{-5.899}} = -6.193$$

For $j = 2$ then,

$$t_2 = \frac{0.5+1+0.5}{\frac{0.5}{a_{j-1}}+\frac{1}{a_j}+\frac{0.5}{a_{j+1}}} = \frac{0.5+1+0.5}{\frac{0.5}{a_1}+\frac{1}{a_2}+\frac{0.5}{a_3}}$$

$$= \frac{0.5+1+0.5}{\frac{0.5}{-6.352}+\frac{1}{-5.899}+\frac{0.5}{-5.446}} = -5.881$$

For $2 < j \leq 36$ can be done the same way with $j = 2$

For $j = 37$ then,

$$t_{37} = \frac{0.5+1}{\frac{0.5}{a_{n-1}}+\frac{1}{a_n}} = \frac{0.5+1}{\frac{0.5}{a_{36}}+\frac{1}{a_{37}}} = \frac{0.5+1}{\frac{0.5}{9.511}+\frac{1}{9.964}}$$

$$= 9.808$$

Based on the above calculations, then the prediction of the percentage change is in Table 10 as follows.

Table 10. Prediction results from percentage of change

No	Interval	Midpoint (a_j)	Fuzzy Set	Prediction of percentage change
1	[-6.579; -6.125]	-6.352	$A1$	-6.193
2	[-6.125; -5.672]	-5.899	$A2$	-5.881
:	:	:	:	:
12	[-1.593; -1.140]	-1.367	$A12$	-1.287
:	:	:	:	:
37	[9.737; 10.191]	9.964	$A37$	9.808

From the results of the prediction of the percentage of change is obtained the result of fuzzification and then by using the equation (9), a defuzzification is performed to convert the outcome of the forecast of the percent of change into the closing price of the combined stock price index.

$$F(3\ januari\ 2018) = \left(\frac{-1.287}{100} \times 6339.24\right) + 6339.24 = 6257.65$$

Table 11 shows fuzzification and defuzzification data as the results of the closing price prediction.

Table 11. Fuzzification and prediction results of Saxena - Easo

Date	Close Price	% change	Fuzzification	Prediction result
Jan 2, 2018	6339.24	NA	NA	NA
Jan 3, 2018	6251.48	-1.384	$A12$	6257.65
Jan 4, 2018	6292.32	0.653	$A16$	6249.69
:	:	:	:	:
Oct 30, 2023	6735.89	-0.339	$A14$	6757.00
Oct 31, 2023	6752.21	0.242	$A16$	6733.96

As a comparison of the performance of the fuzzy time series method with other methods, the ARIMA method is used here. The following are the results of the ARIMA analysis. Before modeling, a stationary test was first carried out on variance and mean. The results of the stationary test on variance obtained a p-value of 2.22 x 10-16. Since the p-value is less than 0.05, reject H0. This shows that the data is not stationary with variance. The results of the stationarity test on variance were obtained as lambda of 4.25, then the data was transformed using the power of 4. The results of the stationary test on variance for the composite stock price index transformation data show that the transformation data is stationary to variance because it has a p-value of 0.29677. Furthermore, the stationarity test against the mean. The results of the Augmented Dickey-Fuller test obtained a p-value of 0.4478. Because the p-value is greater than 0.05, it fails to reject H0. This shows that the data is not stationary to the mean and needs to be differentiated. Based on these results, ARIMA(2,1,2) modeling was carried out and the results of the estimated parameters of the ARIMA model were obtained in Table 12.

Table 12. ARIMA model

Variable	Estimate	Z value	p-value
AR 1	0.2868	3.8263	0.00013
AR 2	-0.8836	-10.8156	2.2×10^{-16}
MA 1	-0.3268	-4.7070	2.514×10^{-6}
MA 2	0.8870	10.3530	2.2×10^{-16}

Based on Table 12, all variables have a p-value smaller than 0.05. This indicates that all the variables are significant in the model. Therefore, the ARIMA(2,1,2) model can be used to predict the composite stock price index. However, to evaluate the model, the MAPE value is calculated on the model. The results of the MAPE calculation on the ARIMA model obtained a value of 10.55%. The following are the results of the ARIMA model prediction. One of the weaknesses of the ARIMA model is that it predicts that it will stuck at a certain value for a long period. This results in the prediction of the ARIMA model still having a large MAPE. Therefore it can be concluded that the fuzzy time series method has better model performance if compared to the ARIMA model.

Based on the results of the predictions of both fuzzy time series models Chen and Saxena-Easo comparative graphs can be described as in fig. 3 follows.

Fig. 3. Comparison Graph between Actual Data and Predicted Results of the Chen and Saxena-Easo

This graph shows a considerable difference between actual data movements and the results of the Chen model predictions, while there is an almost identical movement between the actual data and the Saxena-Easo model prediction results. This proves that the Saxena-Easo model predicted results are better than the chen model. However, in order to ensure the best model, MAPE calculations can be performed to see the comparison of the error values of the two models using the formula (10). After calculating the MAPE error value, it is known that the Saxena-Easo model has an error value of 0.24% where the error value is smaller than the Chen model so that it proves that the Saxena-Easo model is the most accurate model in predicting the closing price of the composite stock price index for the period January 1, 2018, to October 31, 2023. Therefore, the Saxena-Easo model is used to predict the closing prices of the IHDG for the next three periods, namely November 1 - 3, 2023 by taking the last three predictions as seen in Table 13 follows:

$$MAPE_{chen} = \frac{1}{1418}\left(\begin{array}{c}\left(\frac{|6242.44-6251.48|}{6242.44}\times 100\%\right)+...+\\ \left(\frac{|6733.96-6752.21|}{6733.96}\times 100\%\right)\end{array}\right) = 1.53\%$$

$$MAPE_{saxena-easo} = \frac{1}{1418}\left(\begin{array}{c}\left(\frac{|6257.65-6251.48|}{6257.65}\times 100\%\right)+...+\\ \left(\frac{|6857.05-6752.21|}{6857.05}\times 100\%\right)\end{array}\right) = 0.24\%$$

Table 13. Close Price Prediction

Date	Close price prediction
November 1, 2023	6712.59
November 2, 2023	6757.00
November 3, 2023	6733.96

The analysis process performed using a designated application showed the same results in fig 4 as follows.

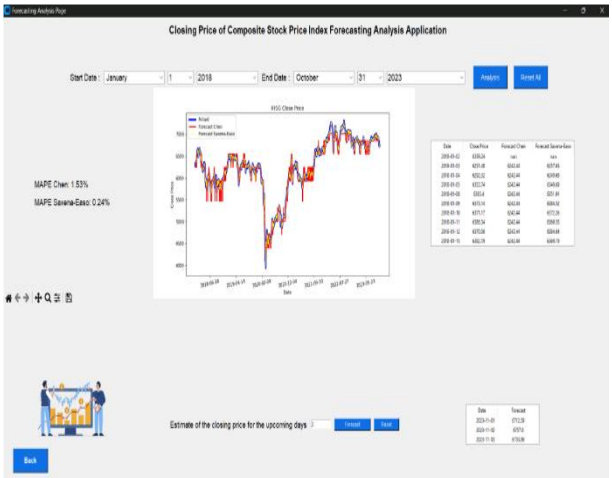

Fig. 4. Analysis Results with the Desktop Application

4. Conclusion

Based on the analysis that has been done, it can be concluded that the fuzzy time series method has better model performance if compared to the ARIMA model, and the best model between the fuzzy time series models Chen and Saxena-Easo is the Saxena-Easo model because it has a smaller MAPE error value compared to Chen is 0.24%. From the model obtained the results of the closing price of the composite stock price index prediction for the next three periods namely 1 - 3 November 2023 at 6712.59, 6757, and 6733.96. Subsequently, the application designed with Python programming successfully fulfilled the research objectives where the application could provide analysis of the closing price of the composite stock price index predictions for the period January 1, 2018 – October 31, 2023, and forecasts for the next three periods.

5. References

[1] B. Tannady, Friendy. "Ilmu Saham," Kompas Gramedia, (2021).

[2] "Indeks," http://www.idx.co.id/id/produk/indeks, accessed:2023.

[3] "Apa Itu IHSG? Ini Pengertian, Fungsi, & Cara Hitungnya," https://www.ocbc.id/id/article/2021/08/09/ihsg-adalah, accessed:2023.

[4] W. Widiyani, Y. Setyawan, and M. T. Jatipaningrum, "Perbandingan Metode Fuzzy Time Series-Chen Dan Weighted Fuzzy Integrated Time Series Untuk Memprediksi Data Indeks Harga Saham Gabungan," *Jurnal Statistika Industri Dan Komputasi*, vol. 7, no.1, pp. 81-87, (2022).

[5] L. C. Ramadhani, D. Anggraeni, A. Kamsyakawuni, and A. F. Hadi, "An algorithm of Saxena-Easo on fuzzy time series forecasting," *In Journal of Physics: Conference Series*, vol. 1008, no.1, (2018).

[6] F. Aditya, D. Devianto, and Maiyastri, "Peramalan Harga Emas Indonesia Menggunakan Metode Fuzzy Time Series Klasik," *Jurnal Matematika UNAND*, vol. 8, no. 2, pp. 45-52, (2019).

[7] S. C. Sihombing, A. Dahlia, "Prediction Of Stock Close Price On The Five Best Issuers Forbes Global 2000 Version Using Chen's Fuzzy Time Series Method," *In International Conference of Business and Social Sciences*, pp. 1163-1171, (2022).

[8] A. Fernando, R. Syafitri, and H, Cipta, "Gold Price Using the Fuzzy Time Series Saxena-Easo Method," *In International Conference on Sciences Development and Technology*, vol.1, no. 1, pp. 69-77, (2021).

[9] A. C. Udin, M. T. Jatipaningrum, "Peramalan Inflasi Di Indonesia Menggunakan Metode Fuzzy Time Series Based Average Dan Fuzzy Time Series Saxena-Easo: Studi kasus: Data Inflasi di Indonesia," *Jurnal Statistika Industri dan Komputasi*, vol. 5, no. 2, pp. 1-10, (2020).

[10] M. R. Febrino, D. Permana, Syafriandi, and N. Amalita, "Comparison of Forecasting Using Fuzzy Time Series Chen Model and Lee Model to Closing Proce of Composite Stock Price Index," *UNP Journal of Statistics and Data Science*, vol. 1, no. 2, pp. 74-81, (2023).

[11] A.H. Zuhairi, F. Yakub, M. Omar, and M. Sharifuddin, "Imbalanced Flood Forecast Dataset Resampling Using SMOTE-Tomek Link," International Exchange and Innovation Conference on Engineering & Sciences. Vol 10, pp.845-850, (2024).

[12] T, Mamee, U. Boonbumrung, Syafriandi, N. Ditnin, and P. Sripadungtham, "Short-Term Photovoltaic Power Forecasting Using a Neural Network Dynamic Time Series, "*International Exchange and Innovation Conference on Engineering & Sciences*, Vol 10, pp.183-189, (2024).

[13] "IDX Composite (^JKSE)," https://finance.yahoo.com , accessed: 2023.