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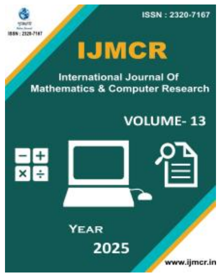

Modeling of Arima and Fuzzy Time Series Saxena Easo in Forecasting the Stock Price of PT. Indofood Sukses Makmur Ltd

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ARTICLE INFO	ABSTRACT
Published Online: **09 October 2025**	Stock is one of the most popular investment instruments due to its ability to provide attractive benefit. One widely recognized company with a strong position both domestically and globally is PT. Indofood Sukses Makmur Ltd. It is also included in the IDX30 index. Investor require forecasting method as a basis for making informed decisions in response to stock price fluctuation. This study aims to model Autoregressive Integrated Moving Average (ARIMA) and Fuzzy Time Series (FTS) Saxena Easo, and to determine the best method based on the lowest RMSE value. The data used is sample data of daily closing stock prices from March 2023 to October 2024. The dataset is divided into 377 training data points and 19 testing data points. For the ARIMA method, the model that satisfy all assumptions and yields the lowest RMSE value is ARIMA (1,1,0), with an RMSE value equal 78.2319. The FTS Saxena Easo uses fuzzy logic produces an RMSE is 3.0619. The result shows that the RMSE value of the FTS Saxena Easo is lower than ARIMA (1,1,0), so FTS Saxena Easo is chosen as the best method. Forecasting using FTS Saxena Easo produces a Mean Absolute Percentage Error (MAPE) equal 0.0063%. Since the MAPE value is less than or equal to 10%, FTS Saxena Easo is considered very good for forecasting the closing price of PT. Indofood Sukses Makmur Ltd.
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KEYWORDS: Stock, Indofood, ARIMA, Fuzzy Time Series Saxena Easo, RMSE, MAPE

I. INTRODUCTION

Investment is a commitment to allocating certain resources in order to obtain future return. Investment instruments may consist of real assets or financial assets [1]. Stock is among the most popular financial assets because it offers the potential for attractive return. In general, stock represents evidence of capital ownership by an individual or entity in a corporation or limited liability company. As at September 2024, the Indonesia Stock Exchange recorded more than six million stock investors with Single Investor Identification (SID), including over 744 thousand new investors [2]. This reflects the growing public interest in stock market activity.

PT. Indofood Sukses Makmur Ltd (stock code: INDF.JK) is recognized as one of the leading companies in Indonesia stock market. Its large market capitalization, strong fundamental, and high liquidity have placed Indofood in the IDX30 index. The company operates its entire production process through four key business segments: consumer branded product (CBP), agribusiness, Bogasari, and distribution [3]. Indofood also holds a strong global market presence, exporting to more than 100 countries [4]. Its strong domestic and international position makes Indofood an attractive option for investor.

Investors must closely monitor stock price fluctuation as part of their investment strategies. Stock price forecasting serves as a decision-support tool in investment activities. Among the commonly applied methods are the Autoregressive Integrated Moving Average (ARIMA) and Fuzzy Time Series (FTS). ARIMA can forecast non-stationary time series data and seasonal patterns, but they require certain statistical assumptions to be satisfied. In contrast, the fuzzy time series approach utilizes fuzzy logic to process imprecise data expressed in linguistic values and they are more flexible as they do not rely on the statistical assumptions required by ARIMA.

The fuzzy time series method has undergone various developments. Saxena et al. [5] applied forecasting using percentage changes as the universe of discourse, similarly to Stevenson and Porter [6]. The method known as Fuzzy Time Series Saxena Easo, it modifies Stevenson and Porter's approach in determining fuzzy intervals. Their study revealed that the Average Forecasting Error Rate (AFER) of the Saxena

Easo method was lower at 0.34% than be compared to Stevenson and Porter's at 0.57%. This indicates that the Saxena Easo method improves forecasting accuracy.

This study aims to construct ARIMA and Fuzzy Time Series Saxena Easo models for the closing stock price of PT. Indofood Sukses Makmur Ltd. The result is expected to identify the best-performing method based on the lowest Root Mean Square Error (RMSE), evaluate model performance using the Mean Absolute Percentage Error (MAPE), and provide useful insights to support investor decision-making.

II. LITERATURE REVIEW

A. Stock Price

A stock price is the value avowed in a certificate of capital ownership, determined by market valuation factors such as supply and demand on the stock exchange [7]. Stock price in the capital market is inherently volatile, as its value may change at any time. For investment considerations, investor can access historical stock price data through online financial platform. These data include several key components, namely opening price (open), highest price (high), closing price (close), lowest price (low), and adjusted closing price (adj close).

B. Forecasting

Forecasting is the process of estimating future value based on historical data [8]. Historical data may take the form of many time series, they defined as a set of observations arranged sequentially over consistent time interval [9]. When historical data are available and meet the required criteria, quantitative forecasting method is generally more efficient than qualitative method [10]. Time series analysis method can be broadly classified into two categories: classical approaches, based on statistical and mathematical concepts such as ARIMA and exponential smoothing; and modern heuristic approaches, based on soft computing algorithm such as fuzzy time series and artificial neural networks [11].

C. ARIMA

ARIMA (Autoregressive Integrated Moving Average) is a statistical method for forecasting time series data, assuming stationarity in both variance and mean. Variance stationarity occurs when fluctuation in data variability is independent of time. Variance stationarity can be tested using the lambda value estimated through Maximum Likelihood Estimation (MLE). Data are considered stationary in variance if the estimated $\lambda = 1$. If the data are not stationary in variance, the Box-Cox transformation may be applied, which is a power transformation with parameter λ for time series data [12].

Time series data must also be stationary in mean, they mean that the average value remains constant over time without upward or downward trend. Stationarity in mean can be examined using the Augmented Dickey-Fuller (ADF) Test. Handling non-stationary data in the mean is carried out by applying differencing [13]. The formula for dth order differencing is expressed as follows:

$$\Delta^d Z_t = (1 - B)^d Z_t$$

where Z_t is the data at time t, and $(1 - B)^d$ is the dth order differential polynomial with B as the backshift operator.

The ARIMA model can be identified through ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. The correlation between Z_t and Z_{t+k} can be measured using the ACF. Meanwhile, the degree of association between Z_t and Z_{t+k}, while ignoring the influence of previous lags up to lag $k - 1$, can be measured using PACF [8].

ARIMA consists of three components, namely autoregressive (AR) of order p, integrated (I) of order d, and moving average (MA) of order q. These components can be mathematically expressed as follows:

Autoregressive (AR(p)):

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t$$

Moving Average (MA(q)):

$$Z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}$$

Autoregressive Integrated Moving Average (ARIMA(p,d,q)):

$$\phi_p(B)(1 - B)^d Z_t = \theta_0 + \theta_q(B) a_t$$

where $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ represents the AR(p) operator; $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ represents the MA(q) operator; $(1 - B)^d Z_t$ denotes the dth order differencing operator; Z_t is the time series data at time t; and a_t is the residual at time t, it be assumed to follow white noise. Data that are already stationary without undergoing the differencing process ($d = 0$) can be modeled using ARIMA (p, 0, q), which is also known as the ARMA (p,q) model. The parameter θ_0 is related to the process mean. Therefore, when the data undergo differencing ($d > 0$), it is assumed that $\theta_0 = 0$ [14].

The ARIMA model can be determined based on the characteristic of the ACF and PACF. The estimation of the appropriate ARIMA model is guided by several rules, as summarized in Table 1 [14].

Table 1. Characteristics of ACF and PACF

Process	ACF	PACF
AR(p)	Tails off as exponential decay or damped sine wave	Cuts off after lag p
MA(q)	Cuts off after lag q	Tails off as exponential decay or damped sine wave

ARMA(p,q)	Tails off after lag ($q-p$)	Tails off after lag ($p-q$)

After obtaining a preliminary ARIMA model, the next step is parameter estimation and testing the significance of the estimated parameters [15]. Parameters ϕ and θ can be estimated using the Maximum Likelihood Estimation (MLE) method. The estimated AR and MA parameters must be tested to determine whether they are significant and they can be used in the model.

Diagnostic checking is conducted to ensure that the ARIMA model satisfies the required assumptions. A forecasting model is considered adequate if the residual exhibit the characteristic of white noise, namely being uncorrelated or independent, having a mean equal to zero, and possessing constant variance [14]. To confirm these conditions, the Ljung-Box Test can be applied to verify the independence of residuals. The Kolmogorov–Smirnov Test can be used to examine the normality of residuals, and the Lagrange Multiplier (LM) Test can be applied to detect possible heteroskedasticity in the time series data. If the ARIMA model fulfills all of these assumptions, it can be considered valid and suitable for forecasting.

D. Fuzzy Time Series Saxena Easo

Fuzzy refers to something vague or uncertain, but a fuzzy system is structured based on fuzzy logic. In contrast to crisp logic, which is precise, fuzzy logic provides a more flexible approach to dealing with uncertainty [16]. According to Kusumadewi and Purnomo [17], fuzzy logic is a component of soft computing that is founded on fuzzy set theory. Within the universe of discourse (U), a fuzzy set can be represented by a membership function with values ranging from 0 to 1. A membership function is a curve that maps each input data point to its degree of membership in the fuzzy set, with values between 0 and 1. The region between 0 and 1 is referred to as fuzzy, uncertain, or indistinct [18].

Fuzzy Time Series (FTS) is capable to forecasting value by transforming historical data into linguistic value. One of the FTS approaches that provides high forecasting accuracy is the FTS Saxena Easo method. The following are the stages of analysis using FTS Saxena Easo.

1. Transform the data into percentage change using the following equation:
$$d_t = \left(\frac{Z_t - Z_{t-1}}{Z_{t-1}}\right) \times 100\% \, ; \; Z_{t-1} \neq 0$$
where d_t denotes the percentage change and Z_t is the actual data at time t.
2. Define the universe of discourse (U) as follows:
$$U = [D_{min} - D_1, D_{max} + D_2]$$
where D_{min} and D_{max} are the minimum and maximum values of the percentage change data, and D_1 and D_2 are random positive numbers.
3. Form several equal-length intervals (u_i) from the universe of discourse (U). The length (L) of each interval can be calculated as follows:
$$L = \frac{Range}{B}$$
where *Range* is the difference between the upper and lower bounds of U, and B is the number of classes. The number of classes is determined using Sturges formula:
$B = 1 + (3.322 \times \log n)$
Where n is the number of observations.
4. Determine the length of each subinterval based on the frequency of data within each interval. To obtain the frequency, every percentage change value (d_t) is mapped into u_i according to the predefined intervals. The length (L) of a subinterval is calculated where $Range$ is the difference between the upper and lower bounds of each interval u_i, and B is the frequency of data within that interval.
5. Construct fuzzy sets based on the subintervals and calculate the midpoint (a_j) of each subinterval using the following equation:
$$a_j = \frac{D_{min}(A_j) + D_{max}(A_j)}{2}$$
where $D_{min}(A_j)$ and $D_{max}(A_j)$ are the minimum and maximum values of each subinterval of the fuzzy set A_j, for $j = 1, 2, \ldots, n$.
6. Fuzzify the data by defining the percentage change values in relation to the fuzzy sets A_j.
7. Defuzzify the data to obtain the predicted percentage change value (t_j) according to the following rule:
$$t_j = \begin{cases} \dfrac{1+0{,}5}{\left(1/a_1\right)+\left(0{,}5/a_2\right)} & , jika\ j = 1 \\ \dfrac{0{,}5+1+0{,}5}{\left(0{,}5/a_{j-1}\right)+\left(1/a_j\right)+\left(0{,}5/a_{j+1}\right)} & , jika\ 2 \leq j \leq (n-1) \\ \dfrac{0{,}5+1}{\left(0{,}5/a_{n-1}\right)+\left(1/a_n\right)} & , jika\ j = n \end{cases}$$
where a_{j-1}, a_j, and a_{j+1} are the midpoints of u_{j-1}, u_j, and u_{j+1}; n is the number of fuzzy sets A_j; and j is the index of the fuzzy subinterval.
8. Calculate the historical forecast values by converting the percentage change data into actual data using the following formula:
$$\hat{Z}_t = \left(\frac{t_j}{100} \times Z_{t-1}\right) + Z_{t-1}$$
where t_j is the predicted percentage change, Z_{t-1} is the actual value at time $t-1$, and $\hat{Z}_t$ is the forecast value at time t.

E. RMSE and MAPE

The primary objective of forecasting method is to generate optimal forecast values [14]. The desired outcome is a forecast with no residual or with residual as small as possible.

A commonly used method to measure forecasting accuracy is the Root Mean Square Error (RMSE), defined as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2}{n}}$$

Another widely used accuracy measure is the Mean Absolute Percentage Error (MAPE), defined as:

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right|}{n} \times 100\%$$

Smaller values of the performance parameters indicate be better forecasting accuracy. The criteria for forecasting performance based on MAPE are as follow [19]:

a. If $MAPE \leq 10\%$, the forecast is considered highly accurate.
b. If $10\% < MAPE \leq 20\%$, the forecast is considered good.
c. If $20\% < MAPE \leq 50\%$, the forecast is considered reasonable.
d. If $MAPE > 50\%$, the forecast is considered inaccurate.

III. RESEARCH METHOD

This study employs quantitative data obtained from Yahoo Finance website. The variable analyzed is the daily closing price of PT. Indofood Sukses Makmur Ltd stocks (stock code: INDF.JK) for the period from March 2023 to October 2024. The dataset is divided into a training set consisting of 377 observations, covering the period from March 1, 2023, to October 4, 2024, for model construction, and a testing set consisting of 19 observations, covering the period from October 7, 2024, to October 31, 2024, for forecast evaluation. The methods applied in this study are ARIMA and Fuzzy Time Series Saxena Easo. They using R Studio and Microsoft Excel software. The research procedure consists of the following steps:

1. Collecting the data.
2. Dividing the dataset into training and testing data.
3. Plotting the time series and conducting exploratory data analysis.
4. Performing analysis and computation using the ARIMA method, including stationarity tests for variance and mean, model identification based on ACF and PACF plots, parameter estimation, parameter significance testing, residual diagnostic checking, and selecting the best ARIMA model based on the smallest RMSE value.
5. Performing analysis and computation using the Fuzzy Time Series Saxena Easo method, including calculating the percentage change, defining the universe of discourse (U), dividing U into several intervals, determining the subinterval length, constructing fuzzy sets, performing fuzzification, performing defuzzification, computing forecast values, and calculating the RMSE value.
6. Selecting the best method based on the smallest RMSE value.
7. Forecasting the testing data using the best method.
8. Evaluating forecasting performance based on the MAPE value of the best method.

IV. RESULT AND DISCUSSION

Exploratory data analysis is useful for identifying data pattern and obtaining preliminary information related to the dataset. The descriptive overview includes the number of observations, minimum and maximum values, mean, standard deviation, and variance. A total of 377 training data points was used for model development, with a minimum stock price was 5875 and a maximum was 7450. The average stock price was 6580.3714, with a standard deviation was 410.0459 and a variance was 168137.6277, reflecting considerable fluctuation and dispersion in the data. Pattern in the time series, such as trends and seasonality, can be observed through the ACF and PACF plots be shown in Figure 1 and 2.

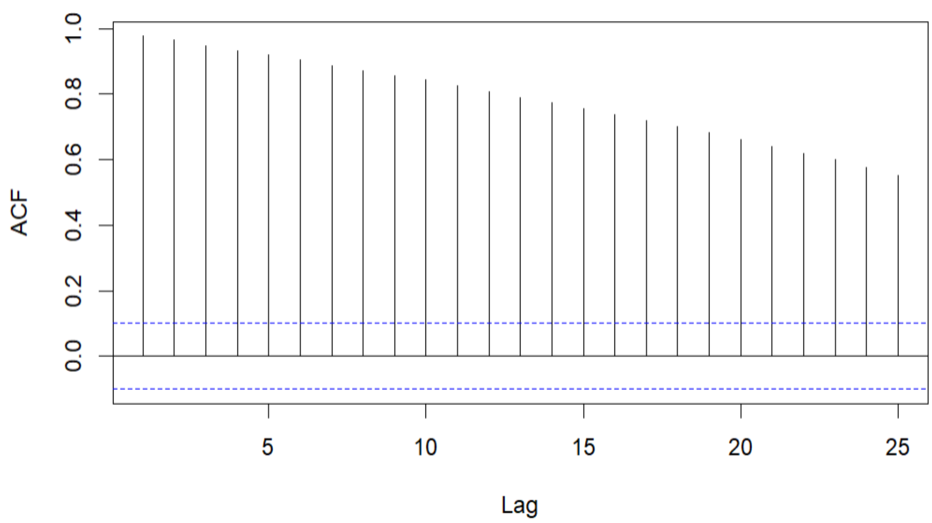

Figure 1. ACF Plot of Training Data

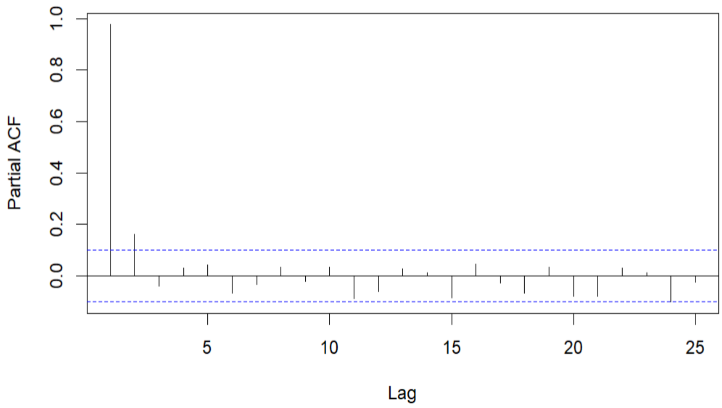

Figure 2. PACF Plot of Training Data

Based on Figure 1, the ACF plot shows a gradual decline, it indicate the presence of a trend in the data. Meanwhile, Figure 2 presents the PACF plot of the training data, it displays a significant spike only at lag 1, suggesting a strong autoregressive effect at the first lag. Although the PACF does not directly indicate the trend, this pattern supports the presence of autoregression associated with the trend. Furthermore, the training data do not exhibit any seasonal pattern, as neither the ACF nor the PACF plots show periodic spikes at specific lags. Therefore, it can be concluded that the training data are characterized by a trend without seasonality. The prerequisite for applying the ARIMA method is that the data must be stationary. Stationarity in variance was examined by checking the Box-Cox lambda value using R Studio. The lambda value obtained was 1.0016 ≈ 1, indicating that the training data can be considered stationary in variance. Stationarity in mean was tested using the ADF test, which resulted in $ADF = -1.5242$ and $p - value = 0.7779$, so H_0 failed to be rejected at the 5% significance level. This result indicates that the data are not stationary in mean and require differencing. After performing the first differencing (d = 1), the ADF test yields ADF $= -7.0708$ and $p - value = 0.01$, so H_0 was rejected, and the data can be considered stationary in mean.

The ARIMA (p,d,q) model can be identified through the following ACF and PACF plots.

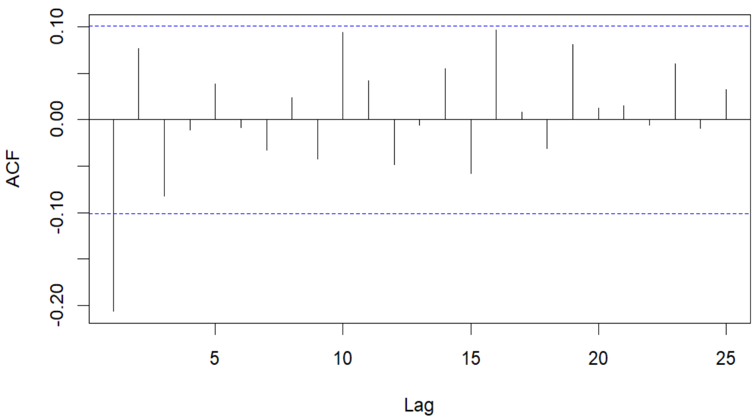

Figure 3. ACF Plot of Training Data After First Differencing

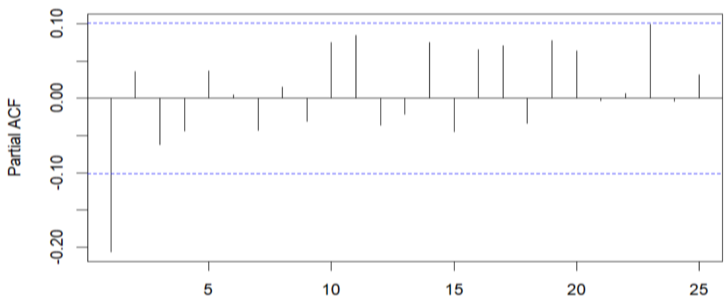

Figure 4. PACF Plot of Training Data After First Differencing

Based on Figures 3 and 4, two plots show a cut off at lag 1, these results show the candidate models are ARIMA (1,1,0), ARIMA (0,1,1), and ARIMA (1,1,1). After parameter estimation and significance testing, they were found that

ARIMA (1,1,0) and ARIMA (0,1,1) have significant parameters, whereas ARIMA (1,1,1) has insignificant parameters.

Diagnostic checks were conducted to verify the adequacy of the models. Residual independence was tested using the Ljung-Box test, which concluded that ARIMA (1,1,0) and ARIMA (0,1,1) have no residual autocorrelation across lags. Residual normality was tested using the Kolmogorov-Smirnov test, it indicates the residual of ARIMA (1,1,0) and ARIMA (0,1,1) follow a normal distribution. Residual homoskedasticity was tested using the Lagrange Multiplier test, it results the residuals of ARIMA (1,1,0) and ARIMA (0,1,1) are not affected by ARCH/GARCH effects. The models that satisfy all residual assumptions are ARIMA (1,1,0) and ARIMA (0,1,1).

The models that satisfy both parameter significance and residual diagnostic checks consist of two candidates. Therefore, the best model is determined based on the lowest RMSE value. ARIMA (1,1,0) has an RMSE was 78.2319, which is smaller than the RMSE of ARIMA (0,1,1). The RMSE of ARIMA (0,1,1) was 78.3666. Thus, ARIMA (1,1,0) is selected as the best ARIMA model with the following mathematical form:

$$\hat{Z}_t = 0.7946 Z_{t-1} + 0.2054 Z_{t-2}$$

The comparison between the training data and the forecasts using ARIMA (1,1,0) is shown in Figure 5.

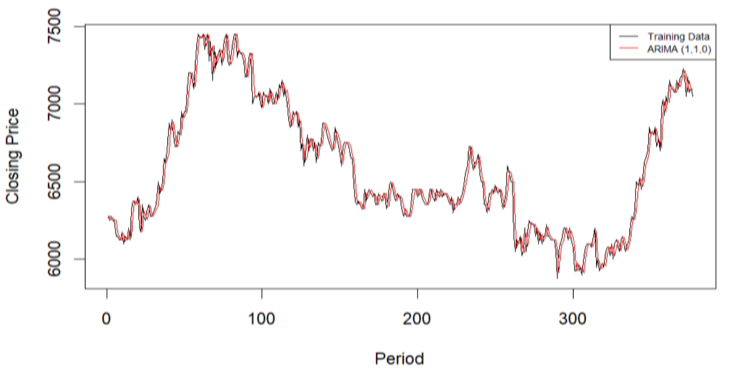

Figure 5. Comparison of Training Data and ARIMA (1,1,0) Forecasts

Fuzzy time series Saxena Easo begins with transforming the actual data into percentage change (d_t).

Table 2. Percentage Change of Training Data

Period (*t*)	Data (Z_t)	Percentage Change (d_t)
1	6275	-
2	6250	-0.3984
3	6275	0.4000
4	6250	-0.3984
⋮	⋮	⋮
377	7050	-0.7042

The definition of the universe of discourse U begins with determining the minimum and maximum values of the data, along with positive random numbers D_1 and D_2. The minimum value of the percentage changes is -5.3846, while the maximum value is 4.1045. The values of D_1 and D_2 used for rounding are 0.0154 and 0.0955, respectively. Therefore, we can make the universe of discourse is

$$U = [-5.4000\ , 4.2000]$$

Based on Sturges method, the universe of discourse U is divided into 10 interval classes (u_i) for $i = 1,2, \ldots ,10$, with each interval having a length of 0.9600. Each percentage change value (d_t) is then mapped to its corresponding u_i, and the frequency of each u_i is calculated. Each interval u_i is further divided into several subintervals (A_j), with the number of subinterval classes corresponding to the frequency of each u_i.

Table 3. Length of Subinterval

u_i	Interval	Frequency	Length of Subinterval
u_1	$[-5.4000, -4.4400]$	1	0.9600
u_2	$[-4.4400, -3.4800]$	2	0.4800
u_3	$[-3.4800, -2.5200]$	5	0.1920
u_4	$[-2.5200, -1.5600]$	18	0.0533
u_5	$[-1.5600, -0.6000]$	80	0.0120
u_6	$[-0.6000, 0.3600]$	114	0.0084
u_7	$[0.3600, 1.3200]$	113	0.0085
u_8	$[1.3200, 2.2800]$	32	0.0300
u_9	$[2.2800, 3.2400]$	9	0.1067
u_{10}	$[3.2400, 4.2000]$	2	0.4800

Based on Table 3, there are 376 frequency counts. It means that the initial 10 intervals (u_i) are divided into 376 subintervals. These subintervals form the fuzzy sets A_j ($j = 1,2,3,\dots,376$). The calculation of subinterval values is carried out by adding the lower bound of each interval and the subinterval length in Table 3. Then the midpoint of each subinterval is denoted as a_j.

Table 4. Midpoint of Subinterval

A_j	Subinterval	Midpoint (a_j)
A_1	$[-5.4000, -4.4400]$	-4.9200
A_2	$[-4.4400, -3.9600]$	-4.2000
A_3	$[-3.9600, -3.4800]$	-3.7200
A_4	$[-3.4800, -3.2880]$	-3.3840
⋮	⋮	⋮
A_{376}	$[3.7200, 4.2000]$	3.9600

The fuzzification of the data is performed by assigning each percentage change value (d_t) to the corresponding fuzzy set (A_j). Then this step is followed by the defuzzification process, in which the linguistic representation is transformed into a numerical form to obtain the predicted value of the percentage change (t_j). As the basis for the defuzzification process, the midpoints (a_j) and the predicted values of the percentage change (t_j) for each fuzzy set A_j are presented in Table 5.

Table 5. Prediction of Percentage Change

A_j	Midpoint (a_j)	Predicted Percentage Change (t_j)
A_1	-4.9200	-4.6541
A_2	-4.2000	-0.5618
A_3	-3.7200	-0.6113
A_4	-3.3840	-0.6406
⋮	⋮	⋮
A_{376}	3.9600	3.7859

Based on the t_j values in Table 5, defuzzification can be carried out as shown in Table 6.

Table 6. Defuzzification Results for Percentage Change

Period (t)	Percentage Change (d_t)	Fuzzification	Defuzzification
1	-	-	-
2	-0.3984	A_{130}	-0.5558
3	0.4000	A_{225}	0.4255
4	-0.3984	A_{130}	-0.5558
⋮	⋮	⋮	⋮
377	-0.7042	A_{98}	-0.8640

The defuzzified data are transformed into the forecasted values ($\hat{Z}_t$) of INDF.JK stock closing prices. Table 7 presents the forecasting results of the training data obtained through the Fuzzy Time Series Saxena Easo method.

Table 7. Forecasting Results of Training Data Using the Fuzzy Time Series Saxena Easo Method

Period (t)	Training Data (Z_t)	FTS Saxena Easo ($\hat{Z}_t$)
1	6275	-
2	6250	6240.1248
3	6275	6276.5914
4	6250	6240.1248
⋮	⋮	⋮
377	7050	7038.6551

The Fuzzy Time Series Saxena Easo method yields an RMSE value namely 3.0619. A comparison between the training data and the forecasted closing prices of PT. Indofood Sukses Makmur Ltd using the Fuzzy Time Series Saxena Easo method is presented in Figure 6.

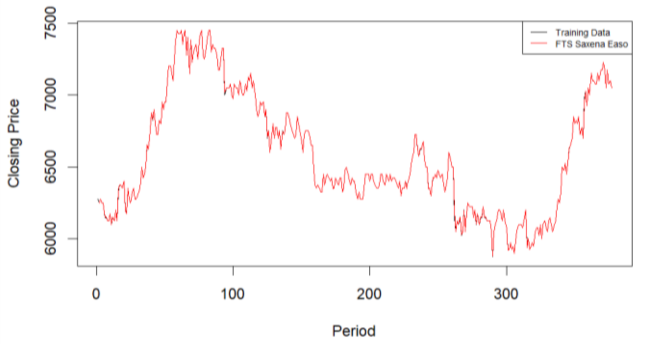

Figure 6. Comparison of Training Data and Fuzzy Time Series Saxena Easo Forecasts

The best method is determined based on the smallest RMSE value. Both the ARIMA model and the Fuzzy Time Series Saxena Easo method yield low error rates. However, the RMSE value of the Fuzzy Time Series Saxena Easo method is smaller than that of ARIMA. This indicates that the Fuzzy Time Series Saxena Easo method is more suitable for forecasting the closing prices of PT. Indofood Sukses Makmur Ltd.

Table 8. RMSE Values of the ARIMA and FTS Saxena Easo Methods

Method	RMSE
ARIMA (1,1,0)	78.2319
FTS Saxena Easo	3.0619

The testing phase was conducted by forecasting 19 data points using the FTS Saxena Easo method. The fuzzification and defuzzification processes utilized the model established from the training data. A comparison between the testing data and the forecasted results from the Fuzzy Time Series Saxena Easo method is presented in Figure 7.

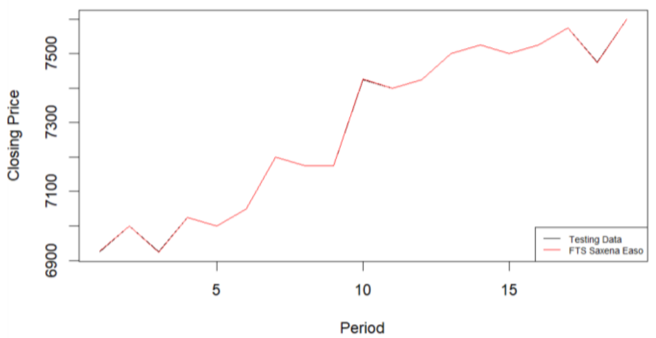

Figure 7. Comparison of Testing Data and Fuzzy Time Series Saxena Easo Forecasts

Figure 7 shows the forecast line of the FTS Saxena Easo method following the trend pattern of the testing data. The result is excellent.

The following shows the forecasting results using the Fuzzy Time Series Saxena Easo method as written in Table 9.

Table 9. Forecasting Results Using the Fuzzy Time Series Saxena Easo Method

Date	FTS Saxena Easo	Testing Data
07 October 2024	6926.9174	6925
08 October 2024	7000.2289	7000
09 October 2024	6924.8247	6925
10 October 2024	7025.7373	7025
11 October 2024	6999.7169	7000
14 October 2024	7049.8761	7050
15 October 2024	7199.0925	7200
16 October 2024	7175.3001	7175
17 October 2024	7175.3237	7175
18 October 2024	7426.5237	7425
21 October 2024	7400.1537	7400
22 October 2024	7425.0744	7425
23 October 2024	7499.9833	7500
24 October 2024	7524.7814	7525
25 October 2024	7499.8190	7500
28 October 2024	7524.7814	7525
29 October 2024	7574.7808	7575
30 October 2024	7474.5596	7475
31 October 2024	7599.4385	7600

Based on Table 9, we can compute the MAPE. The MAPE value is 0.0063%. Since $MAPE \leq 10\%$, the forecasting results are categorized as highly accurate.

V. CONCLUSION

The ARIMA and Fuzzy Time Series Saxena Easo models for forecasting the closing stock price of PT. Indofood Sukses Makmur Ltd show different levels of forecasting accuracy. Based on the training data, the RMSE value is 3.0619 using the Fuzzy Time Series Saxena Easo method, which is smaller than the RMSE value of ARIMA (1,1,0) namely 78.2319. The smaller RMSE value indicates that Fuzzy Time Series Saxena Easo is the better method for forecasting. Meanwhile, based on the MAPE calculation yielded a result was 0.0063%. This indicates the model category with high accuracy, since $MAPE \leq 10\%$. Therefore, the Fuzzy Time Series Saxena Easo method has high capability to predict daily closing stock prices.

REFERENCES

1. E. Tandelilin, *Pasar Modal: Manajemen Portofolio dan Investasi*. Sleman: PT Kanisius, 2017.
2. Bursa Efek Indonesia, "Jumlah Investor Saham di Indonesia Lampaui 6 Juta SID," 2024. https://www.idx.co.id/id/berita/siaran-pers/2224 (accessed Nov. 19, 2024).
3. Indofood, "Remain Strong Despite Prolonged Global Uncertainties: Annual Report 2024," 2024. [Online]. Available: https://www.indofood.com/investor-relation/annual-report.
4. J. D. Sihombing and L. A. Pratomo, "Indofood's Global Strategy: Balancing Innovation, Sustainability, and Market Expansion," *Jurnal Ekonomi Trisakti*, vol. 4, no. 2, pp. 405–414, 2024.
5. P. Saxena, K. Sharma, and S. Easo, "Forecasting Enrollments based on Fuzzy Time Series with Higher Forecast Accuracy Rate," *Int. J. Computer Technology & Applications*, vol. 3, no. 6, pp. 956–961, 2012.
6. M. Stevenson and J. E. Porter, "Fuzzy Time Series Forecasting Using Percentage Change as the Universe of Discourse," *World Academy of Science, Engineering, and Technology*, vol. 55, pp. 154–157, 2009.
7. I. S. Sinaga and K. Munthe, "Pengaruh Struktur Modal, Kepemilikan Institusional, Kebijakan Dividen, dan Pertumbuhan Perusahaan Terhadap Harga Saham pada Perusahaan Manufaktur yang Terdaftar di Bursa Efek Indonesia Periode 2019-2021," *KUKIMA: Kumpulan Karya Ilmiah Manajemen*, vol. 2, no. 2, pp. 208–220, 2023.
8. S. Makridakis, S. C. Wheelwright, and V. E. McGEE, *Forecasting: Methods and Applications*, 2nd ed. Translated by U.S. Andriyanto and A. Basith. Jakarta: Erlangga, 1999.
9. J. D. Cryer and K. Chan, *Time Series Analysis With Applications in R*, 2nd ed. Iowa: Springer Science+Business Media, LLC, 2008.
10. F. Ahmad, "Penentuan Metode Peramalan pada

Produksi Part New Granada Bowl ST di PT. X,” *Jurnal Integrasi Sistem Industri*, vol. 7, no. 1, pp. 31–39, 2020.

11. W. Sulandari, Suhartono, and Y. Yudhanto, *Aplikasi Fuzzy pada Pemodelan Runtun Waktu*. Bandung: Khazanah Intelektual, 2020.
12. G. E. P. Box and D. R. Cox, “An Analysis of Transformations,” *Journal of the Royal Statistical Society*, vol. 26, no. 2, pp. 211–252, 1964.
13. Z. Soejoeti, *Analisis Runtun Waktu*. Jakarta: Karunika, 1987.
14. W. W. S. Wei, *Time Series Analysis Univariate and Multivariate Methods*, 2nd ed. United States: Pearson Education, Inc., 2006.
15. S. Nurman, M. Nusrang, and Sudarmin, “Analysis of Rice Production Forecast in Maros District Using the Box-Jenkins Method with the ARIMA Model,” *ARRUS Journal of Mathematics and Applied Science*, vol. 2, no. 1, pp. 36–48, 2022.
16. N. Fauziah, S. Wahyuningsih, and Y. N. Nasution, “Peramalan Mengunakan Fuzzy Time Series Chen (Studi Kasus: Curah Hujan Kota Samarinda),” *Jurnal Statistika*, vol. 4, no. 2, 2016.
17. S. Kusumadewi and H. Purnomo, *Apliksi Logika Fuzzy untuk Pendukung Keputusan*, 2nd ed. Yogyakarta: Graha Ilmu, 2013.
18. E. S. Puspita and L. Yulianti, “Perancangan Sistem Peramalan Cuaca Berbasis Logika Fuzzy,” *Jurnal Media Infotama*, vol. 12, no. 1, 2016.
19. İ. Uluocak and H. Yavuz, “Model Predictive Control Coupled with Artificial Intelligence for Eddy Current Dynamometers,” *Computer System Science & Engineering*, vol. 44, no. 1, pp. 221–234, 2021.