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Prediction Of Unemployment Rate Using The Fuzzy Time Series Chen Model Method

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ABSTRACT

Unemployment is a significant socio-economic problem in Lhokseumawe City that requires serious attention from policymakers. The unemployment rate fluctuates from year to year, making accurate forecasting an important aspect in formulating effective strategies and policies to reduce unemployment. One method that can be used to analyze and forecast time series data with uncertainty is the Fuzzy Time Series (FTS) method, which applies fuzzy logic concepts to handle vague and imprecise data patterns. In this study, the Fuzzy Time Series method is applied to predict the number of unemployed people in Lhokseumawe City. The data used are historical unemployment data over a period of 10 years, from 2013 to 2022. The research process begins with defining the universe of discourse (U), determining the number and length of interval classes, defining fuzzy sets on U, and fuzzifying the unemployment data. Furthermore, Fuzzy Logical Relationships (FLR) are identified and grouped into Fuzzy Logical Relationship Groups (FLRG). The defuzzification process is then carried out to obtain crisp values, followed by forecasting calculations.The analysis was conducted using the RStudio application. The forecasting results show that the predicted number of unemployed people in 2023 is 10,514.125, which is rounded to 10,514 people. The accuracy of the forecasting model is evaluated using Mean Absolute Percentage Error (MAPE) and Average Forecasting Error Rate (AFER), both of which yield values of 6.70%. Since the MAPE and AFER values are less than 10%, the forecasting results can be categorized as very good and reliable for decision-making purposes.

INTRODUCTION

The prediction of unemployment rates is essential for the government to formulate appropriate economic policies and strategies aimed at reducing unemployment by understanding future unemployment trends. By analyzing these trends, the government can develop effective policies to create new job opportunities. Forecasting can be carried out using various methods, one of which is the Fuzzy Time Series (FTS) method. FTS is a concept used for forecasting problems in which historical data are represented in linguistic values. In other words, past data in FTS are expressed as linguistic data, while the resulting predictions are represented as numerical values (Fauziah et al., 2020).

Fuzzy Time Series is a method used to analyze time series data by applying fuzzy logic. This method enables the processing of historical data and uncertain information to predict future outcomes. By applying the Fuzzy Time Series method to unemployment data, accurate predictions regarding the decrease or increase in unemployment rates can be obtained.

Based on the explanation above, forecasting is necessary to assist the government in developing policies that can minimize the rise of unemployment in future periods. To make such predictions, this study employs the Fuzzy Time Series Chen Model due to its ability to handle data uncertainty as well as its simplicity and ease of implementation. Therefore, this research is titled **"**Prediction of Unemployment Rate Using the Fuzzy Time Series Chen Model Method." The study focuses on predicting unemployment rates using the Fuzzy Time Series Chen Model approach.

LITERATURE REVIEW

Wahyu et al. (2021) investigated the use of the Double Exponential Smoothing method to forecast rice harvest yields in Meurah Mulia District over a five-year period. The study utilized 240 data points collected between 2015 and 2019 from the Agricultural Extension Office. This method calculates harvest data from the past five years using specific parameters to generate forecasts for the following five years. The study used 240 data points from 2015–2019 obtained from the Agricultural Extension Office. The output of the developed application is a trend graph of forecast results, calculated and processed using the Double Exponential Smoothing method implemented on a web and GIS platform. The system can display the estimated rice yields for 2020–2024 in a graphical trend format, making it easier for users to understand whether future yields will increase or decrease, thus aiding in planning rice supply according to demand.

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The developed system produced satisfactory results. For instance, the village of Paya Sutra was forecasted to produce 270.3184 tons of rice in 2020, 270.35136 tons in 2021, 270.38432 tons in 2022, 270.41728 tons in 2023, and 270.45024 tons in 2024, with forecast errors of SSE = 0.002172723%, MSE = 0.001086362%, and MAPE = 0.012189313%.

Wuryanto and Puspita (2021) proposed an average-based fuzzy time series model to predict the development of confirmed positive COVID-19 cases by utilizing the fuzzy time series approach as the forecasting method and the average-based length algorithm to determine the interval length. An effective interval length can influence prediction accuracy. The data used in this research were the confirmed positive COVID-19 case developments from November 2020 to July 2021, obtained from the official COVID-19 task force website. Based on the performance of the predictive application, the Mean Absolute Percentage Error (MAPE) obtained was 10.50 percent. This can serve as a decision support tool for management authorities in providing information and making policies related to preparation, planning, mitigation, and control efforts for the spread of COVID-19.

Ikhsanudin, Santoso, and Wahyudiono (2022) applied the Chen fuzzy time series model to predict the number of active COVID-19 cases in Indonesia and found that daily new cases continued to increase in 2021, indicating that the pandemic had not yet ended. The prediction of active cases for the following day can be used for policymaking and for preparing medical equipment supplies. This study presents the use of the Fuzzy Time Series Chen Model to predict the number of active COVID-19 cases in Indonesia one day ahead, based on data from the previous 30 days. Official government data were used as the actual data for validating predictions. The results showed that within the 30-day range from July 19, 2021, to August 17, 2021, the Fuzzy Time Series Chen Model predicted that on August 18, 2021, there would be 376,339 active cases, with a MAPE error ratio of 3.53%, which falls into the category of very good forecasting accuracy.

METHOD

The following is a flowchart for implementing the fuzzy time series Chen model.

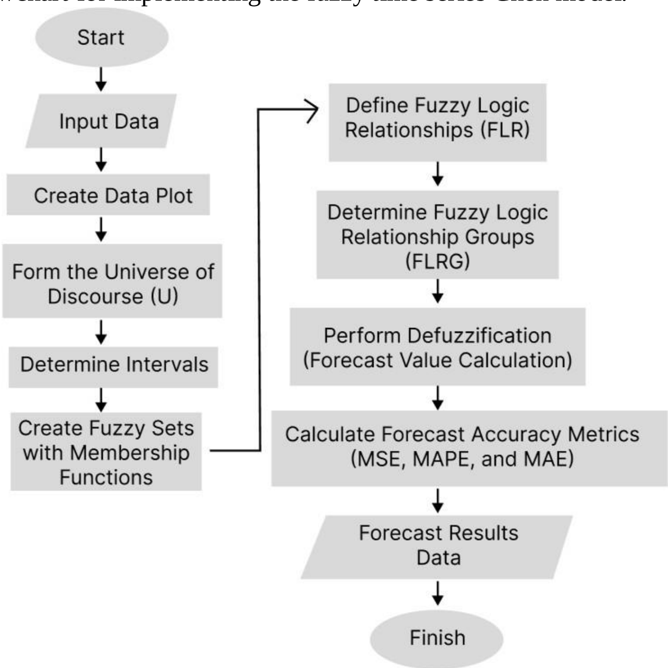

Figure 1. Flowchart Algoritma Fuzzy Time Series Model Chen

The following are the stages carried out in the process of predicting the unemployment rate:

1. Data Input: The first step is to input the time series data used in the study. The data used consist of unemployment data from 2013 to 2022.
2. Universe of Discourse Formation [U]: Next, the universe of discourse is created, which represents the range of all possible values of the dataset.
3. Descriptive Analysis: Perform descriptive analysis on the data within the universe of discourse that has been formed.
4. Interval Formation: Construct intervals that consist of the interval length and width to divide the universe of discourse into several sub-ranges.
5. Fuzzification: Perform fuzzification on the time series data based on the universe of discourse and the intervals that have been created.

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6. Fuzzy Logic Relationship (FLR) and Fuzzy Logic Relationship Group (FLRG) Formation: To obtain the forecasting values, form the FLR and FLRG based on the relationships obtained from the fuzzification results.
7. Defuzzification (Chen's Model): Defuzzification is the final step in fuzzy logic. The goal of this stage is to convert the results from the inference engine, expressed in fuzzy sets, into real numerical values.
8. Error Measurement: Measure the forecasting accuracy using the Mean Absolute Percentage Error (MAPE) method.
9. Analysis and Conclusion: Analyze the results and draw conclusions based on the research findings.
10. Completion: The research process is completed.

This section discusses the results of the analysis of unemployment rate predictions based on unemployment data obtained from the Central Bureau of Statistics (BPS) of Lhokseumawe City. The study is conducted using the Fuzzy Time Series approach. In this research, the focus is on applying the Fuzzy Time Series Chen Model method, which is used to forecast the unemployment rate data in Lhokseumawe City for the upcoming period. Perhitungan Manual Fuzzy Time Series Model Chen.

RESULT

The following is the FTS model using Chen's algorithm:

Fuzzy Time Series Calculations

The unemployment data for Lhokseumawe City shown in Table 1 will be used for manual calculations.

Table 1. Unemployment Rate Data of Lhokseumawe City

Period	Year	Unemployment Rate
1	2013	5.279
2	2014	8.526
3	2015	11.122
4	2016	10.344
5	2017	9.046
6	2018	10.144
7	2019	9.881
8	2020	11.262
9	2021	10.804
10	2022	9.052

The sequential steps of the Fuzzy Time Series (FTS) process are as follows:

1. Define the Universe of Discourse (U) using the difference in the time series data.

$$U = [V_{min} - V_1, V_{max} + V_2] \quad (1)$$

Description:

- V_{min} : The smallest value in the time series data.
- V_{max} : The largest value in the time series data.

Based on the data:

$$V_{min} = 5.279 \text{ and } V_{max} = 11.262 \quad (2)$$

Thus, the range of the data is:

$$11.262 - 5.279 = 5.983 \quad (3)$$

2. Determine the number of classes using Sturges' formula:

$$K = 1 + 3.3 \log n \quad (4)$$

Description:

- K: Number of classes in the distribution table
- n: Number of data points

Substituting the values:

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$$K = 1 + 3.3 \log 10 = 4.3 \text{ (rouded to 4 classes)} \quad (5)$$

3. Calculate the class interval using the formula:

$$\text{Interval} = \frac{\text{Range}}{\text{Number of Clasess}} = \frac{5.983}{4} = 1.496 \quad (5)$$

Hence, each interval has a width of 1.496.
The following is Table 2 showing the calculation results:

Table 2. Calculation Results of Class Intervals

Mins	**5.279**
Max	11.262
Range	5.983
Number of clases	4,3
Class interval	1.496

4. Divide the universe U into several partitions or equal-length segments.

$$U = \{u_i + u_2 + \ldots, un\} \quad (3)$$

$$B = U_{max} - U_{min} \quad (4)$$

$$U_i = [u_{ib}, u_{ia}] \quad (5)$$

$$U_{ia} = u_{ib} + B \quad (6)$$

$$U_{(i+1)b} = u_{ia} \quad (7)$$

Description:

- n : number of partitions
- U_{min} : lower boundary value of the universe U
- U_{max} : upper boundary value of the universe U
- B : length of one partition (interval width)
- U_i : the i-th partition
- U_{ib} : lower boundary of the i-th partition
- U_{ia} : upper boundary of the i-th partition

The following are the calculation results shown in Table 3 Interval Table:

Table 3. Interval

Formed Intervals		
Interval	**Lower Bound**	**Upper Bound**
A1	5.279	6.775
A2	6.775	8.271
A3	8.271	9.766
A4	9.766	11.262

5. Define the fuzzy Sets

$$A_i\, A = (u_1)\, u_1 + \mu A(u_2)\, u_2 + \cdots + \mu_A(u_n)\, u_n \quad (8)$$

Description:
A = fuzzy set A
n = number of partitions μA
(u) = egree of membership of ui in fuzzy set A

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Next, define the linguistic variables, for example: A1, A2, A3, A4. The following are the fuzzy sets that are formed:

A1 ={ 1/u1 + 0,5/u2 + 0/u3 +0/u4 }
A2 ={ 0,5/u1 + 1/u2 + 0,5/u3 +0/u4 }
A3 ={ 0/u1 + 0,5/u2 + 1/u3 +0,5/u4 }
A4 ={ 0/u1 + 0/u2 + 0,5/u3 +1/u4 }

6. Perform the fuzzification process on the difference data found in Table 3. Table 4. shows the results of the fuzzification process.

Table 4. Fuzzification Table

Period	Year	Unemployment Rate	Fuzzification
1	2013	5.279	A1
2	2014	8.526	A3
3	2015	11.122	A4
4	2016	10.344	A4
5	2017	9.046	A3
6	2018	10.144	A4
7	2019	9.881	A4
8	2020	11.262	A4
9	2021	10.804	A4
10	2022	9.052	A3

7. Determine the Fuzzy Logical Relationships (FLR) by linking the fuzzification results in Table 4. one by one from top to bottom.

To determine the Fuzzy Logical Relations (FLR), use the actual data. An FLR is denoted by Ai→Aj where Ai is called current state dan Aj next state For example, in the previous table the first fuzzified value is A1 and the next is A3, where A1 is the current state dan U3 is the next state.

$$\mathrm{A}i \to \mathrm{A}j \qquad (9)$$

Table 5 contains the resulting Fuzzy Logical Relationships formed from the fuzzification.

Tabel 5. Fuzzy Logical Relationships

No	FLRG
1	A1→A3
2	A3→A4
3	A4→A4
4	A4→A3

Table 6. Results of Fuzzification and Fuzzy Logical Relationships

Year	Unemployment Rate	Fuzzification	Current state	Next state
2013	5.279	A1	NA	A1
2014	8.526	A3	A1	A3
2015	11.122	A4	A3	A4
2016	10.344	A4	A4	A4
2017	9.046	A3	A4	A3
2018	10.144	A4	A3	A4
2019	9.881	A4	A4	A4
2020	11.262	A4	A4	A4
2021	10.804	A4	A4	A4
2022	9.052	A3	A4	A3

8. Form the FLRG (Fuzzy Logical Relation Groups) from the FLR obtained previously by grouping identical left-sides together. he FLRG is formed by grouping fuzzy sets that share the same current state into one group. For example, in the FLR formation shown in Table 4.5 where A1 and so on, these can be grouped as (→) to A3 , A3→A4. Then tobe A1→ A3, A3→A4 and A4→ A3,A4. The following is the FLRG formation table:

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$$\left.\begin{array}{l} Ai \rightarrow Aj1 \\ \\ Ai \rightarrow Aj \end{array}\right\} \Rightarrow Ai \rightarrow Aj1, Aj2.... \tag{10}$$

There is Table 7. which presents the results of the Fuzzy Logical Relationship Groups (FLRG) formed based on the previously obtained Fuzzy Logical Relationships (FLR).

From this table, it can be seen that fuzzy logic relationships with the same *current state* are grouped together into one category.

The following shows Table 7. The Results of Fuzzy Logical Relationship Groups (FLRG) Formation**:**

Table 7. *Fuzzy Logical Relationship*

Formed FLRG	
A1	A3
A3	A4
A4	A3,A4

9. Predict the difference between *t* and *t–1* by defuzzifying the fuzzy output. The following are several defuzzification rules:
   a. If the membership value in the unioned FLRG output is zero (0), then the predicted difference is also zero.
   b. If the membership values in the unioned FLRG have exactly one maximum value, the midpoint of the partition corresponding to that single maximum value becomes the predicted difference.
   c. If the membership values in the unioned FLRG contain two or more consecutive maximum values, the predicted difference is the midpoint of those consecutive partitions.
   d. For any other condition besides the three above, perform defuzzification using the centroid method. The centroid method multiplies each membership value in the unioned FLRG with the midpoint of the corresponding partition, sums all results, and then divides that sum by the total of the membership values in the FLRG.

$$v = \frac{\sum S_i M_i}{\sum S_i} \tag{11}$$

Explanation:
V : predicted difference
S_i : the *i*-th membership value in the unioned FLRG
M_i : the midpoint value of the *i*-th section or partition
To obtain the midpoint value of each interval, simply add the upper-bound value and the lower-bound value of the partition and then divide the result by two. Table 4.8 shows the midpoint values for each section or partition.

Table 8. Midpoint Values of Each Partition

Formed Intervals				
Interval	**Lower Bound**	**Upper bound**	**Midpoint Value**	
U1	5.279	6.775	6026,875	A1
U2	6.775	8.271	7522,625	A2
U3	8.271	9.766	9018,375	A3
U4	9.766	11.262	10514,125	A4

10. Suppose the prediction for the year 2014 is being calculated. Refer to the fuzzy set (A) and its FLRG derived from the actual difference in 2013. In Table 4.4, the actual value in 2013 belongs to fuzzy set A1**,** and its FLRG can be seen in Table 4.6, which is **A1** → **A3**. Therefore, the corresponding fuzzy set is:
    a. A3= 9018.375
    b. A4 = 10514.125
    c. A4= (9018,375+10514.125) /2 = 9766,25

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A clearer result can be seen in Table 9 below:

Tabel 9. Predicted values based on the formed FLRG

No	Format Flrg		Predicted value calculation
1	A1	A3	9018,375
2	A3	A4	10514,125
3	A4	A3,A4	9766,25

11. The following is table 10. which shows the results of the predicted unemployment figures in the city of Lhokseumawe:

Determine the defuzzification and calculate the forecasting results and absolute error. The predicted unemployment figures (Table 10) and the absolute errors can be seen in Table 11. Below is Table 10, which shows the predicted unemployment figures for Lhokseumawe city:

Tabel 10. Predicted Unemployment figures for lhokseumawe city

Year	Value	Fuzzyfication	*Current state*	Flg value	Prediction
2013	5.279	A1	NA	9018,375	NA
2014	8.526	A3	A1	10514,125	9018,375
2015	11.122	A4	A3	9766,25	10514,125
2016	10.344	A4	A4	9766,25	9766,25
2017	9.046	A3	A4	10514,125	9766,25
2018	10.144	A4	A3	9766,25	10514,125
2019	9.881	A4	A4	9766,25	9766,25
2020	11.262	A4	A4	9766,25	9766,25
2021	10.804	A4	A4	9766,25	9766,25
2022	9.052	A3	A4	10514,125	9766,25
2023	-	-	-	-	10514,125

Below is Table 11, which shows the absolute error based on the prediction results:

Tabel 11. *Absolute Error* of prediction results

Year	Number	Prediction	*Error*	*Abs error*	*Absolut error*/aktual
2013	5.279	NA	5.279	5.279	1
2014	8.526	9018,38	-492	492,375	0,057749824
2015	11.122	10514,1	608	608	0,054655188
2016	10.344	9766,25	578	578	0,055853635
2017	9.046	9766,25	-720	720	0,07959319
2018	10.144	10514,1	-370	370	0,036474763
2019	9.881	9766,25	115	115	0,011638498
2020	11.262	9766,25	1.496	1496	0,132836086
2021	10.804	9766,25	1.038	1.038	0,096075528
2022	9.052	9766,25	-714	714	0,078877596
		Total *Absolute Error*			0,603754308 / 9
					0,067083812

The result of calculating the absolute error for the predicted unemployment figures from 2013 to 2022 is **0.067083812**. After obtaining the value of the absolute error/actual data, the next step is to calculate the error rate of the prediction results.

12. **Calculation of MAPE (Mean Absolute Percentage Error)**

Error calculation is performed using the MAPE formula. The MAPE equation measures the error level in percentage form. The following is the formula based on reference (2.1):

$$\text{MAPE} = \left(\frac{1}{n} \sum \frac{|x-y|}{x} \right) * 100\%$$

Explanation:
n = number of data points
x = actual data value
y = predicted value

$$\text{MAPE} = \left(\frac{\sum|\text{Data actual} - \text{Prediction Data}}{\text{Amount of Data}} \right) * 100\%$$

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MAPE = 0.067083812×100
MAPE = 6.708347

Based on this, which displays the MAPE values for each year, the average MAPE value is calculated to be 6.70%**.**

13. Calculation of AFER (Average Forecasting Error Rate)

$$\text{MAPE} = \left(\frac{1}{n} \sum_{i=1}^{n} \frac{A_i - F_i}{A_i} \right) * 100\%$$

Information

- A_i = actual data in period iii
- F_i = Fuzzy Time Series prediction data for period iii
- n = Amount of Data
- |·| = absolute value

Based on the above formula, the AFER value is **6.70%**.

This result indicates that the average forecasting error rate of the fuzzy time series prediction model is relatively low, meaning that the predicted values are close to the actual data. An AFER value of 6.71% suggests that the model provides good forecasting accuracy and can be considered reliable for predicting the unemployment rate.
Which shows the AFER error values for each year, the average error value is calculated to be **6.70%**.Plot Actual Data and Prediction Data.
Below is the graph showing the actual data and the predicted data.

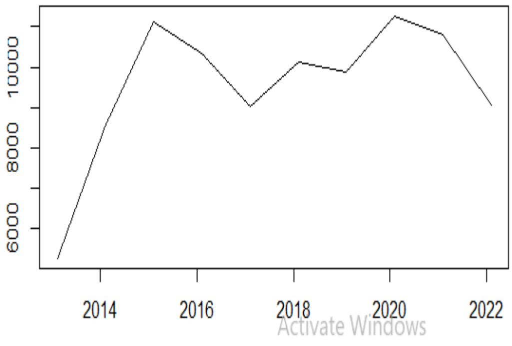

Figure 2. Actual Data

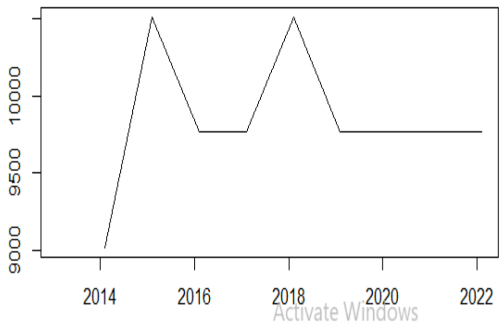

Figure 3. Prediction data

Below is the combined graph of the actual data and the predicted data, as presented in Figure 3.

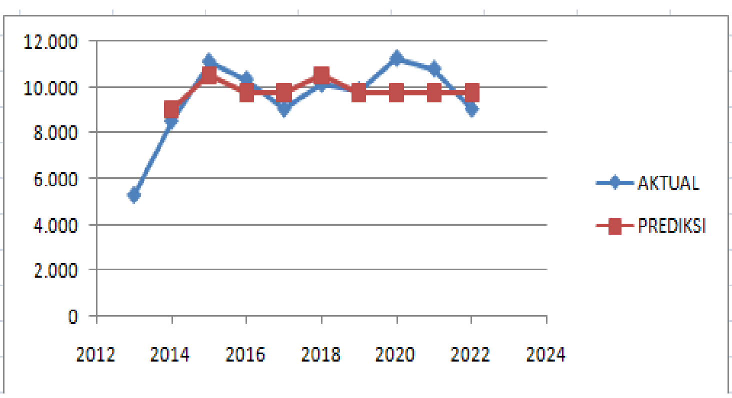

Figure 4. Graph of Actual Data and Predicted Data

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DISCUSSION

The results of this study show that forecasting unemployment rates using the Fuzzy Time Series (FTS) Chen Model provides reliable and meaningful predictions of future unemployment trends. This method is highly suitable for socio-economic data because it can handle uncertainty and transform historical numerical data into linguistic forms, allowing patterns and fluctuations to be interpreted more flexibly.

The forecasting process starting from fuzzification, interval formation, construction of Fuzzy Logical Relationship Groups (FLRG), and finally defuzzification produces numerical predictions that can be compared with actual unemployment data. The model's performance was evaluated using MAPE and AFER, both of which resulted in an average error of approximately 6.70%. This relatively low error rate indicates that the Chen Model provides good predictive accuracy and can reliably represent the actual movements of unemployment data.

These findings demonstrate that the Fuzzy Time Series Chen Model is an effective and straightforward approach for forecasting economic indicators such as unemployment. Its simplicity and ability to manage uncertain or fluctuating data make it particularly useful for real-world applications. With accurate forecasting results, policymakers can better anticipate future changes in unemployment and prepare targeted strategies to address them. This may include creating new job opportunities, improving vocational training programs, or adjusting economic policies to stabilize employment levels.

Overall, this study highlights that the Fuzzy Time Series Chen Model is a practical and valuable method for understanding unemployment trends and supporting government planning efforts aimed at reducing unemployment in future periods.

CONCLUSION

Based on the results and data analysis conducted using the Fuzzy Time Series method, the following conclusions can be drawn:

1. Based on the research carried out using the Fuzzy Time Series method to predict unemployment rates in Lhokseumawe City, accurate results were obtained. The prediction for the year 2023 shows an unemployment rate of 10,514**.** In addition, the Mean Absolute Percentage Error (MAPE) and Absolute Fractional Error (AFER) values produced were 6.70% each.
2. With MAPE and AFER values below 10%, it can be concluded that the predictions generated using the Fuzzy Time Series method are very good and accurate. These results indicate that the method can be used as an effective tool for forecasting future unemployment rates.

The implication of this study is the importance of using unemployment forecasts in policy-making and economic planning.

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