JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. X, No. Y, Month 20XX, pp. XX-YY

Forecasting Electricity Consumption Using the Fuzzy Time Series Chen and Markov Chain Method in the City of Mataram

Nirwanto[1], Syamsul Bahri[2], Lisa Harsyiah[3]
[1,2,3]Departement of Mathematics, Universitas Mataram, Indonesia
g1d019052@student.unram.ac.id[1],

Article History:

Received : D-M-20XX
Revised : D-M-20XX
Accepted : D-M-20XX
Online : D-M-20XX

Keyword:

Forecasting;
Electric Energy;
FTSC;
FTSMC;
MAPE.

ABSTRACT

The consumption of electrical energy continues to experience fluctuations every month, and these fluctuations cannot be accurately predicted. This uncertainty can become a problem if not projected and planned for effectively. Therefore, PT PLN (Persero) needs to be able to provide and distribute electricity supply in an appropriate amount. The aim of this research is to forecast electricity consumption based on historical data from January 2016 to April 2023 using the Fuzzy Time Series Chen (FTSC) method and the Fuzzy Time Series Markov Chain (FTSMC) method. The results of this research show that the forecast for May 2023 using the FTSC and FTSMC methods is 136,878,489 kWh and 143,498,523 kWh, respectively, with MAPE accuracy rates of 11.61739% and 4.85428%, respectively. Therefore, the forecast using the FTSMC method is better than the FTSC method, with a smaller MAPE value.

https://doi.org/10.31764/jtam.vXiY.ZZZ

This is an open access article under the CC–BY-SA license

A. INTRODUCTION

Electricity is one of the most essential needs for human life. Without electricity, various human activities cannot function smoothly. Electricity consumption experiences fluctuations every month, and these fluctuations cannot be accurately predicted. This uncertainty can become a problem if not projected and planned for effectively.

PT PLN (Persero), as the provider and distributor, must be capable of supplying and distributing electricity in the right amount (PLN, 2021). PT PLN (Persero) records that electricity consumption in the West Nusa Tenggara Province increased by 3.02 percent compared to the previous year. Similarly, the growth in electricity consumption in NTB is observed in the various regions of the NTB province. In September 2021, PLN NTB recorded electricity consumption in the city of Mataram reaching 83.94 GWh (PLN NTB, 2021). Changes in electricity consumption cannot be precisely predicted, which is why time series analysis is necessary to forecast electricity consumption.

Time series is a series of observations made at the same time intervals. The purpose of time series analysis is to forecast future values based on past data (Chatfield, 2017). Time series analysis cannot be used when the data is linguistic, so other methods need to be employed, such as the Fuzzy Time Series Chen (FTSC) proposed by Chen (1996) and the Fuzzy Time Series Markov Chain (FTSMC) developed by Tsaur (2012).

Fuzzy Time Series (FTS) is effectively used to forecast data where the trend of the data is known or unknown and when the information is either complete or ambiguous (Tsaur, 2012). According to Jatipaningrum (2016), the FTSMC method provides better forecasting performance with higher accuracy compared to classical FTS methods. FTSC can handle data that is robust (uncertain), has clear or unclear data patterns, and high data fluctuations (Chen, 1996).

The purpose of this research is to forecast electricity consumption in the city of Mataram from January 2016 to April 2023 using the Fuzzy Time Series Chen and Fuzzy Time Series Markov Chain methods, providing insights into the forecasted electricity consumption, which significantly impacts the economy of a country or region, especially the city of Mataram.

B. METHODS

In the section discusses Chen methods and Tsaur method from previous method.

1. Fuzzy Time Series Chen (FTSC) Method (Chen, 1996)
   Chen developing a fuzzy time series based on Song & Chissom (1993) in their research, this method treats time series as linguistic variables with membership values in each time interval. Chen proposed a technique for dividing time series into fuzzy intervals using simple operations that can handle robustness (uncertainty), clear or unclear data patterns, and high fluctuations. The steps for forecasting using FTSC are as follows:
   a) Define universe of discours with random coefficient value K_1 and K_2.
   b) Partition the universe in equal length.
   c) Define fuzzy sets using grades of membership 0, 0.5, 1 for linguistic interval.
   d) Fuzzification.
   e) Build Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG) based fuzzification.
   f) Defuzzification.
   g) Calculate the Moving Average Percentage Eror (MAPE).
2. Fuzzy Time Series Markov Chain (FTSMC) Method (Tsaur, 2012)
   Tsaur developing The Fuzzy Time Series method proposed by Chen involves the addition of a Markov Chain process or a Markov transition probability matrix. The transition probabilities are used as the basis for obtaining forecasting results. The Markov transition matrix is obtained by fuzzifying every sequential pair of historical data and defining them as Fuzzy Logic Relationships (FLR). The determination of the Markov Chain transition matrix is based on the Fuzzy Logic Relationship Group (FLRG) obtained from the grouping of FLR. In this approach, the historical data is first transformed into fuzzy relationships (FLRs), which capture the patterns and relationships between sequential data points. These FLRs are then grouped into FLRG based on their similarity or shared characteristics. The Markov transition matrix is calculated from these FLRG, and it represents the probabilities of transitioning from one FLRG to another. The Markov Chain component adds a probabilistic element to the Fuzzy Time Series method, allowing for the modeling of transitions between different historical data patterns. This combination enhances the forecasting capabilities of the method by taking into account the uncertainty and transitions present in the data. Forecasting using FTSMC are as follows:
   a) Define universe of discours with random coefficient value K_1 and K_2.

b) Partition the universe in eqaul length.
c) Define fuzzy sets using grades of membership 0, 0.5, 1 for linguistic interval.
d) Fuzzification.
e) Build Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG) based fuzzification.
f) Calculate the forcasted outputs $\check{Y}_t$.
g) Adjust the tendency of the forecasting values D_t.
h) Obtain adjusted forecasting result $\check{Y}_{adj}(t)$.
i) Calculate the Moving Average Percentage Eror (MAPE). As shown in Figure 1.

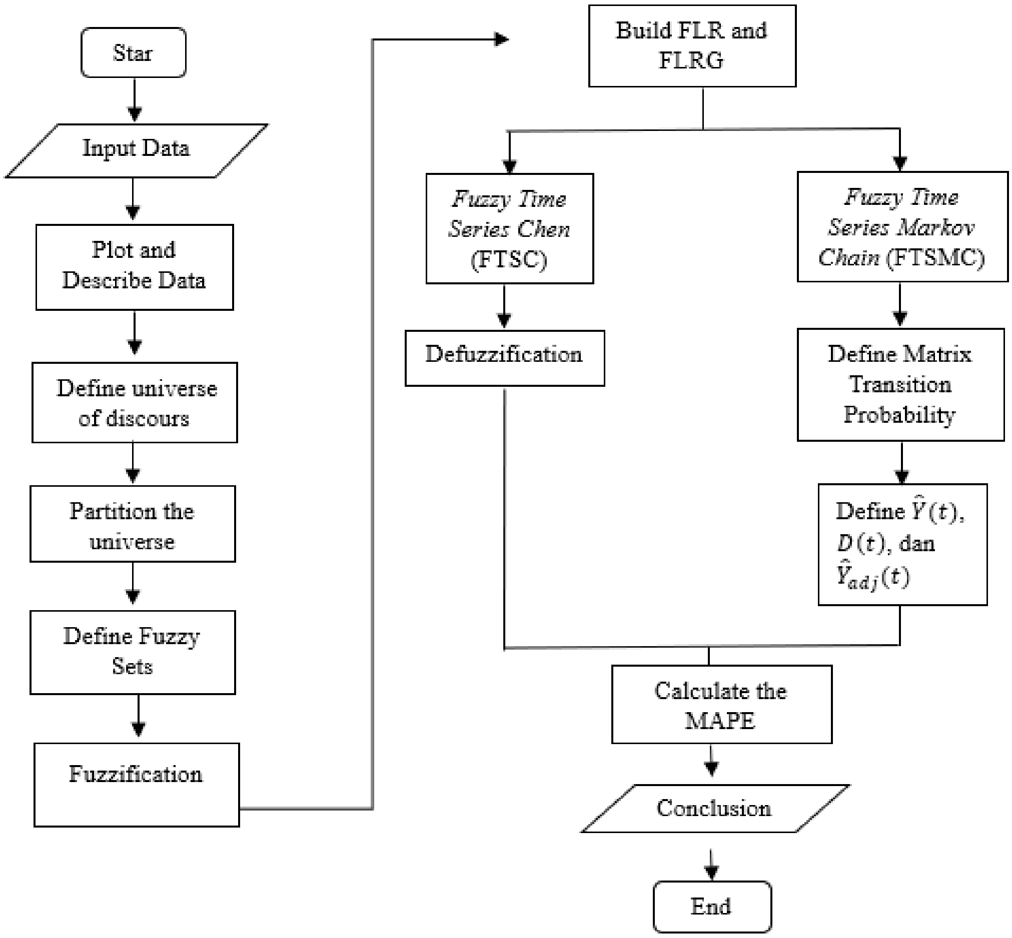

Figure 1. Research Flow

Based on the forecasting results, it is necessary to perform validation using metrics or parameters to measure how accurately the forecast predicts the actual data. One measure of forecasting accuracy that can be used is the Mean Absolute Percentage Error (MAPE). MAPE represents the average absolute error over a certain period, multiplied by 100% to obtain the result as a percentage. It is used when the accuracy of the forecast is highly dependent on the variable being forecasted, as seen in the MAPE equation. MAPE is a relative measure that describes the error in percentage form relative to the actual data (Makridakis, 1995). MAPE can be seen in the following Equation 1:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{1}$$

Where n is amount of data, A_t is actual data, and F_t is forecasting result.

C. RESULT AND DISCUSSION

In this section expalined the result of the analysis is the forecast of electricity consumption in the city of Mataram from January 2016 to April 2023. The forecasting methods used are the FTS Chen model and Markov Chain. Before conducting the forecast, a data description of electricity consumption is performed to observe the data patterns or the general data overview. Subsequently, forecasting is carried out using FTS Chen and Markov Chain. To assess the forecasting accuracy of both methods, Mean Absolute Percentage Error (MAPE) is used. The purpose of using MAPE is to evaluate the accuracy level and the percentage of errors in the forecasting process. The data can be seen in the Table 1.

Table 1. Data Consumptions

No	Month	Consumptions (kWh)
1	Jan-16	93106502.00
2	Feb-16	86094377.00
3	Mar-16	95258907.00
…..	…………	…………………
88	Apr-23	145082649.13

1. Describe Data

Based on the electricity consumption data in the city of Mataram, a general overview can be obtained by conducting a statistical data description. Descriptive data can be examined as follows:

Table 2. Descriptive Statistic

Data Konsumsi	
Vars	1
N	88
Mean	1,173827e+08
Median	1,134679e+08
Standar Deviasi	1,913789e+07
Minimum	8,391821e+07
Maximum	1,765987e+08
Range	9,268048e+07
Skew	4,047332e-01
Kurtosis	-4,867868e-01
Se	2,040106e+06

This Research electriciy consumption data in city of Mataram from January 2016 to April 2023. The data is consisting of 88 data with maximum value is $M_{mx} = 1765987686.70$, maximum value is $M_{min} = 83918211.41$ can be seen in the Table 2.

2. Fuzzy Time Series Chen (FTSC)

Step 1: Define universe of discours (U) with $M_{mx} = 1765987686.70$ and $M_{min} = 83918211.41$, based best simulation choose $K_1 = 0$ and $K_2 = 10$. Thus, $U = [83918211, 176598697]$.

Step 2: Partition the universe to several equal length intervals. U is divided into 7 intervals represented fuzzy sets, universe of discourse (U), the partition can be seen in Table 2 follows:

Table 3. Universe of Discours (U)

Kelas	Interval $(\boldsymbol{u})$	Middle Point $(\boldsymbol{m})$
1	$u_1 = [83.918.211, 97.158.281]$	90.538.246
2	$u_2 = [97.158.281, 110.398.350]$	103.778.315
3	$u_3 = [110.398.350, 123.638.419]$	117.018.385

4	$u_4 = [123.638.419, 136.878.489]$	130.258.454
5	$u_5 = [136.878.489, 150.118.558]$	143.498.523
6	$u_6 = [150.118.558, 163.358.627]$	156.738.593
7	$u_7 = [163.358.627, 176.598.697]$	169.978.662

Step 3: Define fuzzy sets with automatically get unequal partition length using interval ratio with grades of membership 0, 0.5, 1 for linguistic interval, fuzzy sets after we have the universe of discourse and the partition can bee seen below:

$$A_1 = \left\{\frac{1}{u_i}, \frac{0,5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\}$$

$$A_2 = \left\{\frac{0,5}{u_i}, \frac{1}{u_2}, \frac{0,5}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\}$$

$$A_3 = \left\{\frac{0}{u_i}, \frac{0,5}{u_2}, \frac{1}{u_3}, \frac{0,5}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\}$$

$$A_4 = \left\{\frac{0}{u_i}, \frac{0}{u_2}, \frac{0,5}{u_3}, \frac{1}{u_4}, \frac{0,5}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\}$$

$$A_5 = \left\{\frac{0}{u_i}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0,5}{u_4}, \frac{01}{u_5}, \frac{0,5}{u_6}, \frac{0}{u_7}\right\}$$

$$A_6 = \left\{\frac{0}{u_i}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0,5}{u_5}, \frac{1}{u_6}, \frac{0,5}{u_7}\right\}$$

$$A_7 = \left\{\frac{0}{u_i}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0,5}{u_6}, \frac{1}{u_7}\right\}$$

Step 4: fuzzification the historical data after we have fuzzy sets, example fuzzification electrical consumption at December 2020 value is 102039436.30. The grade of membership $\frac{0,5}{u_i}, \frac{1}{u_2}, \frac{0,5}{u_3}$ so the data is fuzzified into inervals u_2, which are represented as A_2 and so forth. The fuzzification obtained based on historical electricity consuption can be seen in Table 4.

Table 4. Fuzzification

No	Month	Consumption Value	Fuzzification
1	Jan-16	93.106.502	A_1
2	Feb-16	86.094.377	A_1
3	Mar-16	95.258.907	A_1
….	…………	……………….…..	…………
88	Apr-23	96.726.478	A_5

Step 5: Build FLR and FLRG based fuzzification historical data electriciy comsuption, described as shown in Table 5.

Table 5. FLR

Bulan	Urutan Data	FLR	No. FLR
Jan-16	…………	………..	………….
Feb-16	1-2	$A_1 \rightarrow A_1$	1
Mar-16	2-3	$A_1 \rightarrow A_1$	2
……….	…………..	………..	……………
Mar-23	86-87	$A_4 \rightarrow A_6$	87
Apr-23	87-88	$A_6 \rightarrow A_5$	88

Define FLRG based on the grouping of FLR that share the same left-hand side A_1 or F_{t-1}, commonly reffered to as the Left Hand Side (LHS), as those formed in Table 5. For exampe, if A_1 is the LHS related to $A_1 \to A_1, A_1 \to A_2$, and $A_1 \to A_3$, then the resulting FLRG would be $A_1 \to A_1. A_2, A_3$. The FLRG can be seen in the Table 6.

Table 6. FLRG

Group	FLRG
A_1	$A_1 \to A_1, A_2, A_3$
A_2	$A_2 \to A_1, A_2, A_3, A_4, A_7$
A_3	$A_3 \to A_2, A_3, A_4, A_6$
A_4	$A_4 \to A_1, A_2, A_3, A_4, A_5, A_6$
A_5	$A_5 \to A_4, A_5$
A_6	$A_6 \to A_5$
A_7	$A_7 \to A_4$

Step 6: Defuzzification is the process of conferting linguistic variable values into numeric variables using FTSC. Example, in the case of A_5 forming the FLRG $A_5 \to A_4, A_5$, you can use the midpoint of A_5, represented by the midpoint value $u_4(m_4)$ and the midpoint of A_5, represented by the midpoint value $u_5(m_5)$, as obtained in Table 6 using equation $Y_t = \frac{m_4+m_5}{2}$ and so forth. The defuzzification values from historical electricity consumption data, as shown in Table 7.

Table 7. Defuzzification

FLRG	Equation	Defuzzification
$A_1 \to A_1, A_2, A_3$	$\frac{m_1 + m_2 + m_3}{3}$	103.778.315
$A_2 \to A_1, A_2, A_3, A_4, A_7$	$\frac{m_1 + m_2 + m_3 + m_4 + m_7}{5}$	120.990.405
$A_3 \to A_2, A_3, A_4, A_6$	$\frac{m_2 + m_3 + m_4 + m_6}{4}$	125.293.428
$A_4 \to A_1, A_2, A_3, A_4, A_5, A_6$	$\frac{m_1 + m_2 + m_3 + m_4 + m_5 + m_6}{6}$	123.638.419
$A_5 \to A_4, A_5$	$\frac{m_4 + m_5}{2}$	136.878.489
$A_6 \to A_5$	m_5	143.498.523
$A_7 \to A_4$	m_4	130.258.454

Based Table 7, forecasting using FTSC to estimate electrcity consumption in the city of Matarm for May 2023 involves obtaining the forcasted value by examining the formed FLR. The formed FLR is then matched with the previously established FLRG. In the forecasting case for May 2023, group A_5 with $A_5 \to A_4, A_5$is used, resulting in a forcasted value of 136,878, 489 kWh in May 2021.

3. Fuzzy Time Series Markov Chain (FTSMC)

The calculation of FTSMC is based on calculations using FTSC, where steps 1 to 5 are performed in the same way. The next step involves using the Markov Chain process with the Tsaur method (2012) as follows:

Based Table 6 it is evident that there is a varying number of Right Hand Side (RHS) for each Left Hand Side (LHS). For example, in the case of LHS A_4, it has the largest number of RHS transitions, totaling 6 transitions, including $A_1, A_2, A_3, A_4, A_5, A_6$. According to Tsaur (2012), the movement from LHS to RHS is used to determine the Markov transition matrix as the basis for determining the forecasted values. The movement from LHS to RHS is illustrated more clearly in Figure 2.

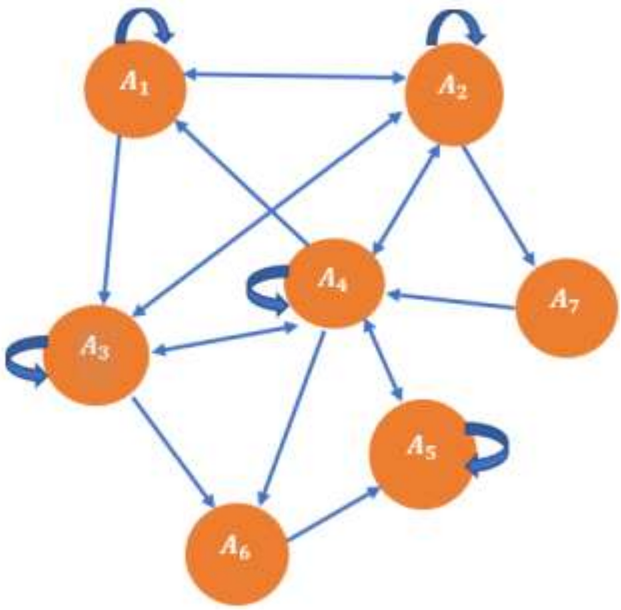

Figure 2. Process Markov Chain Transition

Based on Figure 5.2 above, you can observe the transition process between fuzzy sets. Bidirectional arrows ($\leftrightarrow$) indicate the transition process from one state to another, for example, ($A_4 \leftrightarrow A_5$) and vice versa. On the other hand, unidirectional arrows represent LHS transitioning only to RHS, as examples $A_3 \rightarrow A_6, A_4 \rightarrow A_6, A_6 \rightarrow A_5$. Additionally, states with arrows pointing towards themselves represent transitions to the same state, such as (A_1, A_2, A_3, A_4, and A_5). All fuzzy sets have transitions in the forecasting transition process.

Step 6: Define the transition probability matrix ($\boldsymbol{P}$) is determined based on the number of intervals (i) formed to determine the dimension of the matrix. As a result, a 7×7 dimensional matrix is obtained, with 7 being the number of fuzzy sets formed based on the number of intervals (i). The Markov Chain probability matrix is observed based on the formation of FLRG in step 5. For example, in the second row of the matrix, state A_2 transitions to state A_1 five times, stays in state A_2 itself 15 times, transitions to state A_3 four times, transitions to state $A4$ once, and transitions to state A_7 a total of 26 times. This results in transition probability matrix entries of $\frac{5}{26}, \frac{15}{26}, \frac{4}{26}, \frac{1}{26}$, and $\frac{1}{26}$, respectively. The complete transition probability matrix is as follows:

$$\begin{bmatrix} 0{,}462 & 0{,}462 & 0{,}077 & 0, & 0 & 0 & 0 \\ 0{,}192 & 0{,}577 & 0{,}154 & 0{,}039 & 0 & 0 & 0{,}039 \\ 0 & 0{,}308 & 0{,}308 & 0{,}308 & 0 & 0{,}077 & 0 \\ 0{,}048 & 0{,}048 & 0{,}191 & 0{,}524 & 0{,}143 & 0{,}048 & 0 \\ 0 & 0 & 0 & 0{,}364 & 0{,}636 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

Step 7: Calculate the result of forcasting based based on the Markov Chain transition probability matrix. For example, the calculation of the forecast for March 2023 based on the transition from state $A_4 \rightarrow A_6$ by examining the previous data. The calculation of the forecast is as follows:

$$\begin{aligned} \hat{Y}_t &= m_1 P_{41} + m_2 P_{42} + m_3 P_{43} + m_4 P_{44} + m_5 P_{45} + m_6 P_{46} + m_7 P_{47} \\ &= 90.538.246 \times 0{,}048 + 103.778.315 \times 0{,}048 + 117.018.385 \times \\ &\quad 0{,}191 + 130.258.454 \times 0{,}524 + 143.498.523 \times 0{,}143 \\ &\quad + 156.738.593 \times 0{,}048 + 169.978.662 \times 0 \end{aligned}$$

$= 127.736.536$

Next, calculate the trend adjustment value (D_t) to reduce the magnitude of the forecasting deviation. The trend adjustment value is obtained based on the rule that if the first fuzzy set state transitions to another fuzzy set state, then the adjustment value is calculated as $D_t = \frac{l}{2}$, where l is the length of the interval, and it is multiplied by the number of transitions/jumps made. For example, calculating the forecast adjustment value is as follows:

- In April 2016, it is known that the formed FLR is $A_1 \rightarrow A_1$, with its adjustment value: $D_{Apr-2016} = 0$.
- In January 2021, it is known that that the formed FLR is $A_2 \rightarrow A_7$, with its adjustment value:

$$D_{(Jan-2021)} = \frac{l}{2} \times 5 = \left(\frac{13{,}240{,}069}{2} \times 5\right) = 33{,}100{,}175$$

The adjustment values (D_t) from the forcasted data and the adjusted forecasted data are shown, as shown in Table 8.

Table 8. The Adjusted Forcasted Resluts

No	Bulan	Nilai Konsumsi	$\widehat{Y}_t$	D_t	$\widehat{Y}_{adj}(t)$
1	Jan-16	93.106.502,00			
2	Feb-16	86.094.377,00	98.685.981	0	98.685.981
….	………..	………………...	………..	…………..	……………
86	Feb-23	104.093.322,00	138.683.953	-6.620.035	132.063.918
87	Mar-23	99.639.277,00	127.736.536	19.860.105	140.976.605
88	Apr-23	96.726.478,00	143.498.523	-6.620.035	138.683.953
89	Mei-23	-	138.683.953	6.620.035	143.498.523

Based on Table 8, we can see the adjusted forecasted results ($\check{Y}_{adj}(t)$). The adjusted forecasted results are obtained by adding the initial forecasted result ($\check{Y}_t$) to the adjustment value (D_t). For example, in May 2023, with the formed FLR $A_5 \rightarrow A_6$, the initial forecasted result ($\check{Y}_t$) is 138,683,953 kWh, and the trend adjustment value (D_t) is 6,620,035 kWh. Therefore, the forcasted for May 2023 is 143,498,523 kWh after adjustment.

4. Compare the Forcasted Results

To compare the result of FTSC and FTSMC of electicity consumption from January 2016 to April 2023, as well as the forcasting results are shown Table 7 and Table 8. It is obvious that FTSMC is better than FTSC with smallest forecasting eror according to MAPE. Thus, FTSMC model is the most accurate of the approaches used. Comparison of electricity consumption values in Mataram city with forecasts using the FTSC and FTSMC methods can be observed in Figure 3, which shows the Comparison Pattern of Actual Data with FTSMC and FTSC methods. The orange color represents actual electricity consumption data, the yellow color represents the results of the FTSC method forecast, and the green color represents the results of the FTSMC method forecast. The y-axis represents consumption data, and the x-axis represents the time period, with a total of 88 data points. It is evident that the average of the forecasts with the FTSMC method tends to closely follow the consumption data pattern or the actual data plot. This means that from January 2016 to April 2023, the FTSMC method's forecasted values tend to approximate the actual electricity consumption values. On the other hand, the FTSC method's forecasts tend to exhibit a seasonal pattern. For example, in May 2016, the forecasted values increase, while in September, they tend to decrease. Similar patterns occur in the years 2017, 2018, and 2019. On average, the FTSC method's forecasts do not follow the actual data plot, as they tend to deviate from the consumption data or actual data. Therefore, the results suggest that the FTSMC method performs better than the FTSC method in forecasting electricity consumption in Mataram city. This observation is further supported by the lower MAPE values for the FTSMC method compared to the MAPE values for the FTSC method.

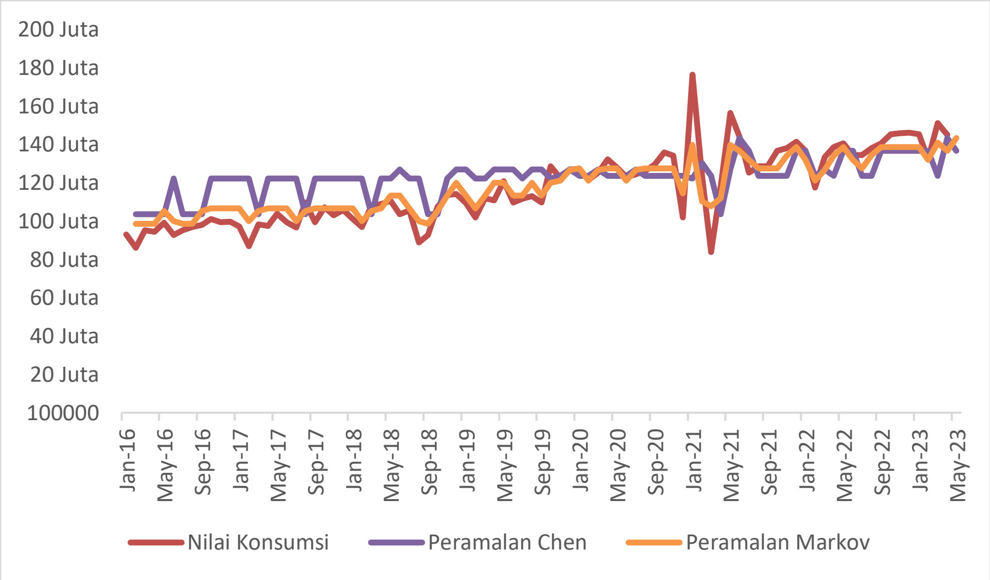

Figure 3. The Comparisone in Electricity consumption Forcasting

Table 9. Comparison of Forcasting Eror

	Metode FTSC	**Metode FTSMC**
Peramalan (kWh)	136.878.489	143.498.523
MAPE (%)	11,61739	4,854528

D. CONCLUSION AND SUGGESTIONS

In this section, the forecasting using the Fuzzy Time Series Chen (FTSC) and Fuzzy Time Series Markov Chain (FTSMC) methods is an effective approach for electricity consumption forecasting in Mataram city. This is based on the forecasting results and the MAPE values obtained. The forecasting results obtained with the FTSC method for May 2023 are 136,878,489 kWh, while the FTSMC method provides a forecast of 143,498,523 kWh. The corresponding MAPE values for FTSC and FTSMC are 11.61739% and 4.85428%, respectively. The MAPE value for FTSC is higher compared to FTSMC. Based on the MAPE scale for forecasting accuracy, FTSC is categorized as "good" because it falls within the 10%-20% range, while FTSMC is categorized as "excellent" because its MAPE value is less than 10%. Therefore, it can be concluded that forecasting using the FTSMC method provides a higher level of forecasting accuracy compared to the FTSC method.

ACKNOWLEDGEMENT

The authors are grateful to Mr. Syamsul Bahri and Mrs. Lisa Harsyiah for supporting this research.

REFERENCES

Alyousifi, Y. Dkk., 2020. Predicting Daily Air Pollution Index Based on Fuzzy Time Series Markov Chain Model*. Journal Symmetry*. 12:2-18.

Arnita, Afnisah, N. dan Marpaung, F., 2020. *A Comparison of The Fuzzy Time Series Methods of Chen, Cheng and Markov Chain in Predicting Rainfall in Medan*. Journal of Physics. 1462: 1-11.

Badan Pusat Statistik. (2020). Statistik Listrik 2020. Jakarta: Badan Pusat Statistik.

Chen, S.M., 1996. *Forecasting enrollments based on fuzzy time series, Fuzzy Sets and Systems*. 81 (3): 311-319.

Chatfield, C. 2017. The Analaysis of Time Series An Introduction Sixth Edition. CHAPMAN & HALL/CRC. New York.

Efendi, R., Ismail, Z., & Deris, M.M. 2015. A new linguistic out-sample approach of fuzzy time series for daily forecasting of Malaysian electricity load demand. *Applied Soft Computing.* 28 (2015). 422 – 430.

Fahriza, R., 2023. Antara News Mataram: Konsumsi Listrik Di NTB Meningkat Dampak Membaiknya Ekonomi (Konsumsi listrik di NTB meningkat dampak membaiknya ekonomi - ANTARA News Mataram - Berita NTB Terkini), di akses jam 11:07 WITA tanggal 11 Januari 2023.

Guney, H and Bakir, M.A. 2015. Modeling Of Capacity Utilization Ratio with Fuzzy Time Series Based on Markov Transition Matrix. *Journal*, 64: 63-75.

Ikhsanudin, A., Dkk., 2022. Metode *Fuzzy Time Series* Model Chen Untuk Memprediksi Jumlah Kasus Aktif COVID-19 di Indonesia. Jurnal Transformasi. 18 (1): 40-53.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: with Applications in R. Springer.

Jatipaningrum, M.T. 2016. Peramalan Data Produk Domestik Bruto Dengan *Fuzzy Time Series markov Chain*. Jurnal Teknologi. 9:31-38.

Klir, G. J., & Yuan, B. (1995). Fuzzy sets and fuzzy logic: theory and applications. Prentice Hall.

Maharani, E., 2019. Pemilihan *Fuzzy Time Series* Markov Chain Berbasis Rata-Rata Dan *Fuzzy Time Series* Markov Chain Dengan Fungsi Keanggotaan Gauss Pada Data Tingkat Inflasi Indonesia. Skripsi, 17.

Makridakis, S. (1993). Accuracy measures: Theoretical and practical concerns. International Journal of Forecasting, 9, 527-529.

Makridakis, S., & Hibon, M. (1995). Evaluating accuracy (or error) measures. INSEAD Working Papers Series 95/18/TM. Fontainebleau, France.

Montano, J.J.M., Pol, A.P., Abad, A.S., and Blasco, B.C. 2013. Using the R-MAPE index as a resistant measure of forecast accuracy. Psicothema, 25:500-506.

Ningsih, F.K. 2016. Peramalan Kurs Rupiah Terhadap Dolar Dengan Metode Berbasis Rata-rata *Fuzzy* Time Series Markov Chain. Skripsi. Institut Pertanian Bogor. Bogor.

Nurkhasanah, L.A., Suparti, dan Sudarno. 2015. Perbandingan Metode Runtun Waktu *Fuzzy*-Chen Dan *Fuzzy*-Markov Chain Untuk Meramalkan Data Inflasi di Indonesia. Jurnal Gaussian. 4(4): 917-926.

PLN. 2014. Rencana Usaha Penyediaan Tenaga Listrik PT PLN (Persero) 2015 – 2024. Jakarta.

PLN. 2021. Perusahaan Listrik Negara (PLN) Persero, Annual Report 2021. Jakarta.

Prihandini, I. A., & Suharto, B. (2018). Analisis Pengaruh Pertumbuhan Ekonomi, Kebijakan Pemerintah, dan Pola Konsumsi Masyarakat Terhadap Konsumsi Listrik di Provinsi Jawa Tengah. Jurnal Ekonomi Pembangunan, 16(2), 98-106.

Rahmawati, Cynthia, E.P., dan Susilowati, K. 2019. Metode *Fuzzy Time Series Cheng* dalam Memperediksi Jumlah Wisatawan Di Provinsi Sumatera Barat. Journal of Education Informatic Technology and Science (JeITS), 1:11-23.

Rosen, W. J., & Klein, M. J. (2019). Supply and Demand in the Electric Power Industry. Handbook of the Economics of the Electric Power Industry, 1-16.

Ross, Sheldon M., 2003, Stochastic Process Second Edition. JOHN WILLEY &SONS.INC. New York.

Song, Q., & Chissom, B. S. (1993). *Fuzzy* time series and its models. *Fuzzy* Sets and Systems, 54(3), 269-277.

Song, Q. and Chissom, B.S. 1993. *Forecasting Enrollments with Fuzzy Time Series* – Part I. *Fuzzy* Sets and Systems, 54: 1-9.

Sutojo, T., Edy, M., dan Vincent, S. 2011. *Kecerdasan Buatan*. ANDI. Yogyakarta.

Tsaur, R.C. 2012. A *Fuzzy* Time Series-Markov Chain Model with An Application to Forecast the Exchange Rate Between the Taiwan and US Dollar. *International Journal of Innovative Computing, Information and Control,* 8:4931-4942.

Wahyuni, Nur, 2015, Average- Based *Fuzzy Time Series Markov Chain* Untuk Meramalkan Kurs Nilai Tukar USD-IDR, Tesis, Program Studi Sistem Informmasi Fakultas Teknologi Informasi Universitas Institut Teknologi Sepuluh November, Surabaya.

Wang, L.X. 1997. *A Course in Fuzzy Systems and Control*. Prentice-Hall International, Inc. United State.

Wei, W.W.S. 2006. *Time Series Analysis Univariate and Multivariate Methods, Second Edition.* Pearson Education. New York.

Zadeh, L.A. 1965. *Fuzzy* sets. Journal Information and Control, 8:338-353.