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COMPARATIVE ANALYSIS OF FUZZY TIME SERIES CHEN AND MARKOV CHAIN METHODS FOR FORECASTING ELECTRICITY CONSUMPTION IN MATARAM CITY

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ABSTRACT

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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 effectively. Therefore, PT PLN (Persero) needs to be able to provide and distribute electricity supply in an appropriate amount. This research aims 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 are 136.878.489 kWh and 143.498.523 kWh, respectively, with MAPE values of 11.61739% and 4.85428%, respectively. Therefore, forecasting in May 2023 using the FTSMC method is better than the FTSC method because the MAPE value is smaller.

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1. INTRODUCTION

PT. PLN (Persero), in its role as the supplier and distributor, needs to possess the capacity to deliver electricity in appropriate quantities [1]. One of the units of PT. PLN (Persero) is PT. PLN (Persero) West Nusa Tenggara Region. PLN NTB has a large number of consumers or customers in the West Nusa Tenggara region and serves the community's electricity needs [2]. PT. PLN (Persero) notes a 3.02 percent rise in electricity usage in West Nusa Tenggara Province compared to the previous year. This trend of increased electricity consumption is also evident across various regions within the province. For instance, in September 2021, PLN NTB documented electricity usage in Mataram City at 83.94 GWh. Given the unpredictability of electricity consumption fluctuations, employing time series analysis becomes imperative for accurate consumption forecasts.

A time series consists of observations collected at regular intervals. Time series analysis aims to predict future values using historical data as a basis. [3]. Often the assumptions of time series analysis cannot be met when forming a model, so other methods need to be employed, such as the Fuzzy Time Series Chen (FTSC) proposed by Chen [4] and the Fuzzy Time Series Markov Chain (FTSMC) developed by Tsaur [5].

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 [5]. According to Jatipaningrum [6], 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 [4].

This study aims to predict future electricity consumption in Mataram City based on historical data spanning from January 2016 to April 2023. This research employs the Fuzzy Time Series Chen and Fuzzy Time Series Markov Chain methods to offer insights into anticipated electricity usage. Such forecasts hold considerable importance for the economy of a country or region, particularly impacting the city of Mataram.

2. RESEARCH METHODS

This section discusses Chen's method [4] and Tsaur's method from the previous method.

2.1 Fuzzy Time Series Chen (FTSC) Method

Chen developed a fuzzy time series based on Song and Chissom [7], the steps for FTSC according to Chen are as follows:

a. Determine the universe of discussion ($\boldsymbol{U}$) for historical data, starting by determining the largest data and the smallest data. Then calculate $\boldsymbol{U}$ with the following formula:

$$\boldsymbol{U = [M_{min} - K_1 \, , M_{max} + K_2]} \tag{1}$$

where $\boldsymbol{M_{min}}$ is the smallest value, $\boldsymbol{M_{max}}$ is the largest value and $\boldsymbol{K_1, K_2}$ are positive random numbers.

b. Partition the universe of speech ($\boldsymbol{U}$) into intervals of equal length. The number of classes ($\boldsymbol{i}$) can be calculated using the Sturges formula:

$$\boldsymbol{i = 1 + 3.322 \log (k)} \tag{2}$$

where $\boldsymbol{k}$ is the number of observation data. The interval length is calculated after determining the number of interval classes using the following formula:

$$\boldsymbol{l = \frac{(M_{max} - M_{min})}{number\ of\ intervals}} \tag{3}$$

Then the partition is formed according to the following equation:

$$\boldsymbol{U = \{u_1, u_2, \dots, u_n\}} \tag{4}$$

where $\boldsymbol{U}$ is the universal set and $\boldsymbol{u_j}$ is the partition of $\boldsymbol{U}$, for $\boldsymbol{j = 1, 2, \dots, n}$.

c. Determine the fuzzy set according to the number of intervals ($\boldsymbol{i}$) through the following equation:

$$A_i = \frac{f_{A_j(u)}}{u_j} \tag{5}$$

d. Define the fuzzy set of the speech universe U and performs fuzzification.

e. Determine the Fuzzy Logic Relationship (FLR) and Fuzzy Logic Relationship Group (FLRG) from the fuzzification results.

f. Determine the forecasting results $\hat{Y}_t$, the forecasting results are determined based on the FLR grouping. Then the value of each current state to the next state is the middle value of the fuzzification results that are defuzzified.

g. Calculate the Mean Absolute Percentage Error (MAPE).

2.2 Fuzzy Time Series Markov Chain (FTSMC) Method

The FTSMC method was developed by Tsaur [5] in his research using the following steps:

a. Determine the universe of discussion (U) for historical data, starting by determining the largest data and the smallest data. Then calculate U using the formula in **Equation (1)**.

b. Partition the universe of speech (U) into intervals of equal length. The number of classes (i) can be calculated using the Sturges formula in **Equation (2)**. Calculate the interval length after determining the number of interval classes using the formula in **Equation (3)**. Then the partition is formed according to **Equation (4)**.

c. Determine the fuzzy set according to the number of intervals (i) in **Equation (5)**.

d. Defines the fuzzy set of the speech universe U and performs fuzzification.

e. Determine the fuzzy logic relationship (FLR) and fuzzy logic relationship group (FLRG) from the fuzzification results.

f. Calculating transition opportunities is done by looking at the number of intervals (i) formed. Assess the transition opportunity based on FLRG, using the following equation:

$$P_{ij} = \frac{R_{ij}}{R_i} \qquad i, j = 1, 2, \dots, n \tag{6}$$

g. Determine the forecasting results $\hat{Y}_t$ based on the transition probability matrix.

h. Calculating the forecasting tendency value D_t is determined by dividing the interval length (l) by 2, then looking at the movement or jump from the current state to the next state.

i. Calculate the adjusted forecasting results $\hat{Y}_{adj}(t)$, the forecasting results are determined by adding or subtracting the forecasting results from the forecasting tendency value D_t.

j. Calculate the Mean Absolute Percentage Error (MAPE).

The explanation is shown in **Figure 1**.

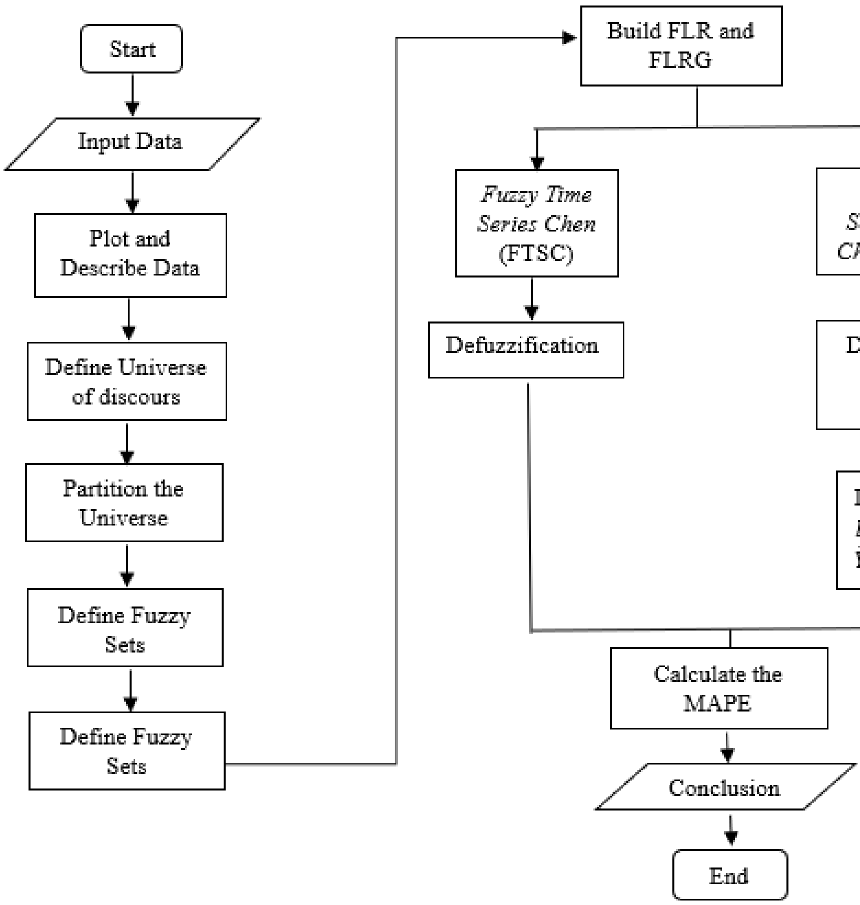

Figure 1. Research Flow

After the forecasting process, it is important to validate the results to measure the accuracy of the forecast compared to the actual data. To do so, one commonly used method is by calculating the Mean Absolute Percentage Error (MAPE). MAPE functions as a relative measure, describing the error in percentage relative to the actual data [8]. The MAPE calculation can be seen in Equation (7) below:

$$\boldsymbol{MAPE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{t}=\mathbf{1}}^{\boldsymbol{n}}\left|\frac{\boldsymbol{A_t} - \boldsymbol{F_t}}{\boldsymbol{A_t}}\right| \times \mathbf{100}\% \tag{7}$$

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

3. RESULTS AND DISCUSSION

In this section, we elucidate the results of the analysis, which entail the forecast of electricity consumption in the city of Mataram spanning from January 2016 to April 2023. The forecasting methodologies employed encompass the FTS Chen model and Markov Chain. Before conducting the forecast, a data description of electricity consumption is conducted to examine data patterns and obtain a general overview. Subsequently, forecasting is executed utilizing the FTS Chen and Markov Chain methods. To evaluate the forecasting accuracy of both approaches, Mean Absolute Percentage Error (MAPE) is employed. The rationale behind utilizing MAPE is to assess the accuracy level and quantify the percentage of errors in the forecasting process. The data of this analysis can be found in the provided dataset in Table 1.

Table 1. Data Consumptions

No	Month	Consumptions (kWh)
1	Jan-16	93,106,502.00
2	Feb-16	86,094,377.00
3	Mar-16	95,258,907.00
⋮	⋮	⋮
88	Apr-23	145,082,649.13

3.1 Data Description

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 Consumptions	
Vars	1
N	88
Mean	1.173827e+08
Median	1.134679e+08
Standard Deviation	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 data is the electricity consumption in the city of Mataram from January 2016 to April 2023. The data consists of 88 data with a maximum value $M_{max} = 1{,}765{,}987{,}686.70$ and minimum value $M_{min} = 83{,}918{,}211.41$ which can be seen in **Table 2**.

3.2 Fuzzy Time Series Chen (FTSC)

Step 1: Define the universe of discourse (U) with $M_{max} = 1{,}76{,}598{,}686.70$ and $M_{min} = 83918211.41$, based best simulation choose $K_1 = 0$ and $K_2 = 10$. Thus, $U = [83{,}918{,}211, 176{,}598{,}697]$.

Step 2: Partition the universe into several equal length intervals. U is divided into 7 intervals represented by fuzzy sets, the universe of discourse (U), the partition can be seen in **Table 3** as follows:

Table 3. Universe of Discours $(\boldsymbol{U})$

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 the linguistic interval. Fuzzy sets after we have the universe of discourse and the partition can be 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, as an example fuzzification electrical consumption in December 2020 value is 102,039,436.30. The grade of membership $\frac{0,5}{u_i}, \frac{1}{u_2}, \frac{0,5}{u_3}$ so the data is fuzzified into intervals u_2, which are represented as A_2 and so forth. The fuzzification obtained based on historical electricity consumption 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 electricity consumption, described as shown in **Table 5**.

Table 5. FLR

Month	Order	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 FLRs that share the same left-hand side A_1 or F_{t-1}, commonly referred to as the Left Hand Side (LHS), as those formed in **Table 5**. For example, if A_1 is the LHS related to $A_1 \rightarrow A_1, A_1 \rightarrow A_2$, and $A_1 \rightarrow A_3$, then the resulting FLRG would be $A_1 \rightarrow A_1 . A_2, A_3$. The FLRG can be seen in **Table 6**.

Table 6. FLRG

Group	FLRG
A_1	$A_1 \rightarrow A_1, A_2, A_3$
A_2	$A_2 \rightarrow A_1, A_2, A_3, A_4, A_7$
A_3	$A_3 \rightarrow A_2, A_3, A_{4,} A_6$
A_4	$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6$
A_5	$A_5 \rightarrow A_4, A_5$
A_6	$A_6 \rightarrow A_5$
A_7	$A_7 \rightarrow A_4$

Step 6: Defuzzification is the process of converting linguistic variable values into numeric variables using FTSC. For example, in the case of A_5 forming the FLRG $A_5 \rightarrow A_4, A_5$, 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
$A_1 \rightarrow A_1, A_2, A_3$	$\frac{m_1 + m_2 + m_3}{3}$	103,778,315
$A_2 \rightarrow A_1, A_2, A_3, A_4, A_7$	$\frac{m_1 + m_2 + m_3 + m_4 + m_7}{5}$	120,990,405
$A_3 \rightarrow A_2, A_3, A_4, A_6$	$\frac{m_2 + m_3 + m_4 + m_6}{4}$	125,293,428
$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6$	$\frac{m_1 + m_2 + m_3 + m_4 + m_5 + m_6}{6}$	123,638,419
$A_5 \rightarrow A_4, A_5$	$\frac{m_4 + m_5}{2}$	136,878,489
$A_6 \rightarrow A_5$	m_5	143,498,523
$A_7 \rightarrow A_4$	m_4	130,258,454

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

3.3 Fuzzy Time Series Markov Chen (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 on **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**.

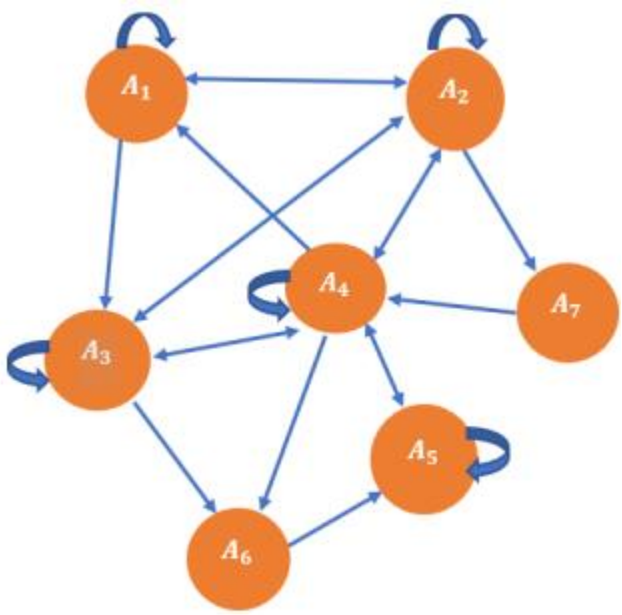

Figure 2. Process Markov Chain Transition

Based on **Figure 2** above, you can observe the transition process between fuzzy sets. Bidirectional arrows (↔) 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: Defining the transition probability matrix (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 the state A_2 itself 15 times, transitions to the 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 forecasting 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:

$$\hat{Y}_t = m_1 P_{41} + m_2 P_{42} + m_3 P_{43} + m_4 P_{44} + m_5 P_{45} + m_6 P_{46} + m_7 P_{47}$$

$$= 90{,}538{,}246 \times 0.048 + 103{,}778{,}315 \times 0.048 + 117{,}018{,}385 \times 0.191 + 130{,}258{,}454 \times 0.524 + 143{,}498{,}523 \times 0.143 + 156{,}738{,}593 \times 0.048 + 169{,}978{,}662 \times 0$$

$$= 127736536$$

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 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 forecasted data and the adjusted forecasted data are shown, as shown in **Table 8**.

Table 8. The Adjusted Forecasted Results

No	Month	Consumption Value	$\hat{Y}_t$	D_t	$\hat{Y}_{adj}(t)$
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 forecast for May 2023 is 143,498,523 kWh after adjustment.

3.4 Comparison of the Forecasted Results

A 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 blue color represents actual electricity consumption data, the purple color represents the results of the FTSC method forecast, and the red color represents the results of the FTSMC method forecast. The y-axis represents consumption data, and the x-axis represents the period, with a total of 88 data points. 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 increased, while in September, they tended 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.

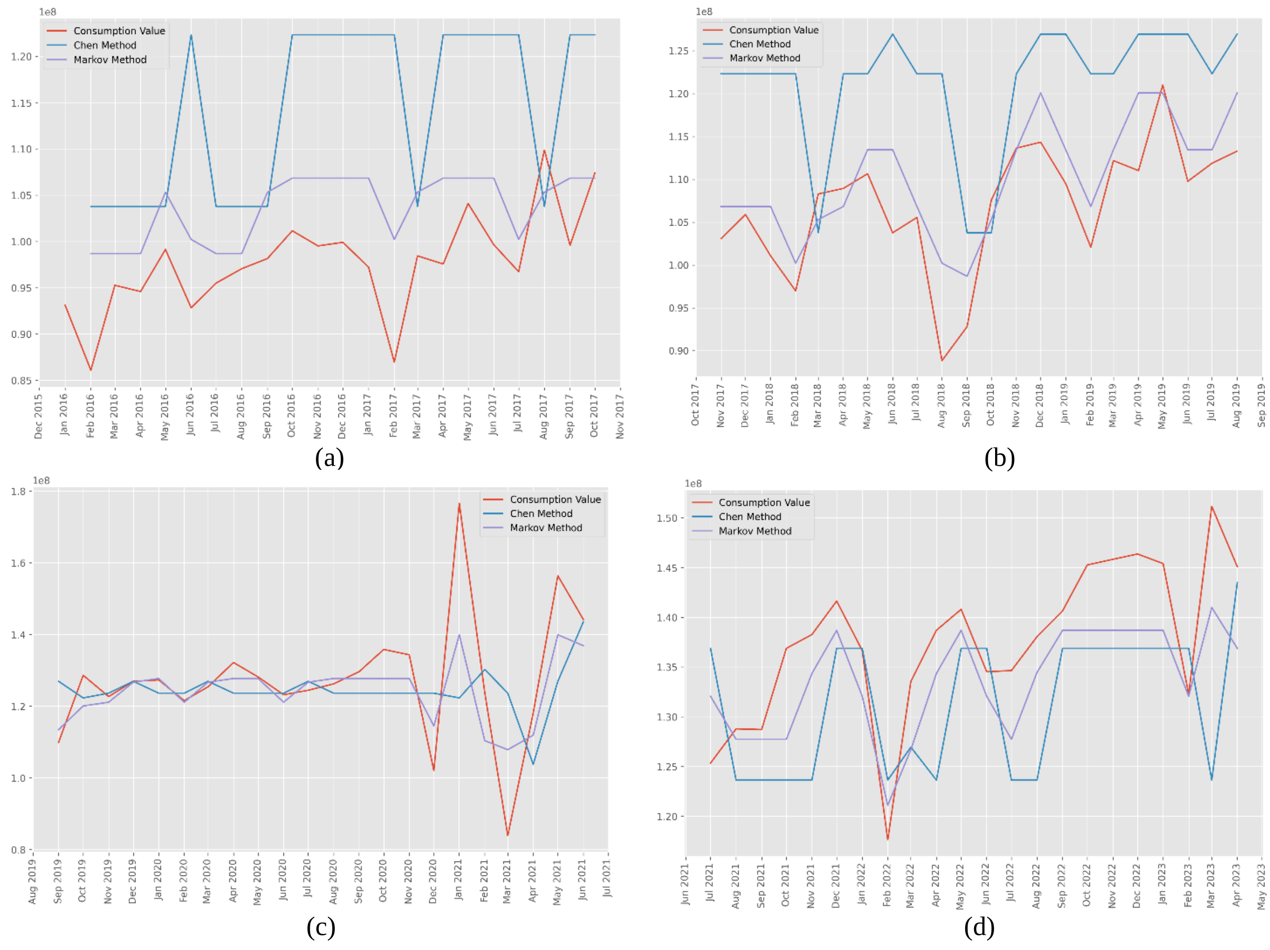

Figure 3. The Comparison (a) Data January 2016 - October 2017, (b) Data November 2017 - August 2019, (c) Data September 2019 - June 2021, (d) Data July 2021 - April 2023

Table 9. Comparison of Forecasting Error

	Metode FTSC	Metode FTSMC
Forecasting (kWh)	136,878,489	143,498,523
MAPE (%)	11.61739	4.854528

Based on Table 9, the MAPE obtained using the FTSC method is 11.61739% and the FTSMC method is 4.85428%. Based on the two MAPE values above, forecasting using the FTSMC method is more accurate than forecasting using the FTSC method. The predicted value of 143,498,523 kWh shows that electricity consumption is increasing and is the highest compared to previous months. Thus, the solution to overcome fluctuations in electricity use in Mataram City is through an energy-saving program. Efforts to optimize electricity use during the May 2023 period so that in the following period we can reduce the risk of electricity shortages or excess demand.

4. CONCLUSIONS

Based on the research analysis carried out, it was concluded that the forecasting results obtained using the FTSC method for May 2023 were 136,878,489 kWh, while the FTSMC method provided a forecast of 143,498,523 kWh. The solution to overcome fluctuations in electricity use in Mataram City is through an energy-saving program. Efforts to optimize electricity use during the May 2023 period so that in the following period we can reduce the risk of electricity shortages or excess demand. 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. On the MAPE forecasting accuracy scale, FTSC is categorized as "good" because it is in the range of 10% - 20%, while FTSMC is categorized as "very good" because the MAPE value is less than 10%. Therefore, forecasting in May 2023 using the FTSMC method is better than the FTSC method because the MAPE value is smaller.

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