ISSN:2302-8149
e-ISSN:2540-9719

Implementation of Fuzzy Time Series Markov Chain Method to Predict Electricity Consumption in Aceh Province

[1]Virza Gavinda, [2]Nurdin*, [3]Fajriana
[1,2,3]Department of Information Technology, Faculty of Engineering, Universitas Malikussaleh
[1,2,3]Jl. Batam, Bukit Indah - Lhokseumawe, Aceh, Indonesia
*e-mail: nurdin@unimal.ac.id

(***received*****:** 28 November 2024, ***revised*****:** 20 February 2025, ***accepted*****:** 21 February 2025)

Abstract

The use of electrical energy is expected to always increase every year. This is due to the increasing needs of the community that must be met. Electricity has become the foundation for welfare and economic progress as well as a growth engine both domestically and globally, to meet the need for electrical energy in the future so that a system is needed that can predict future electrical energy consumption. Various prediction methods have developed along with the problems that arise. These methods include the Fuzzy Time Series Markov Chain method and the Markov Chain Monte Carlo method. This study aims to apply the Fuzzy Time Series Markov Chain (FTSMC) method to predict electricity consumption (KWH) in Aceh Province until 2030 using the electricity consumption dataset from 2018 to 2022. The FTSMC method combines fuzzy time series modeling with Markov chain state transitions, allowing for effective handling of uncertainty in time series data. The results reveal an impressive forecast accuracy, with a Mean Absolute Percentage Error (MAPE) of 3.2483%, demonstrating the model's robustness and suitability for electricity consumption forecasting, with a predicted 314,606,308 kWh in January 2023 and 482,982,495 kWh in December 2030, representing an overall increase of 53.5% over the eight-year period. The FTSMC model effectively stabilizes predictions over time, ultimately converging to a stable value. This stability suggests that FTSMC is well-suited for forecasting in contexts where historical patterns are expected to persist. Further application of this model could benefit other sectors requiring accurate, stable forecasts.

Keywords: fuzzy time series, markov chain, electricity consumption, forecasting, MAPE.

1 Introduction

The development of technology in Indonesia has been very rapid, the technology that we feel today is also not far from the use of electrical energy which is getting bigger every day. In today's modern era electricity is very developed and has become a basic need that must be fulfilled. In fact electricity has become the foundation for economic prosperity and progress as well as an engine of growth, both at the domestic and global levels [1]. Aceh Province is one of the regions in Indonesia that has a significant level of electrical energy consumption. Economic development, population growth and changes in people's behavior can affect electrical energy consumption patterns [2]. The International Energy Agency (IEA) states that energy, especially electricity, plays a very important role in supporting socio-economic development in a country [3]. As the population increases, economic growth, as well as the increase in various activities and the use of life facilities that require electricity, the use of electrical energy will continue to increase [4].

Based on BPS Statistics of Aceh Province, the amount of electrical energy sold in 2017 amounted to 2,409,106,479 KWh increased by 3.40% compared to 2016 of 2,329,926,957 KWh and the number of customers at the end of 2017 amounted to 1,359,132 customers increased by 4.62% from the end of 2016 of 1,296,302 customers. Meanwhile, the amount of electrical energy sold in 2018 amounted to 2,587,712,373 KWh increased by 7.41% compared to 2017 and the number of

 ISSN:2302-8149
e-ISSN:2540-9719

customers at the end of 2018 amounted to 1,426,423 customers increased by 4.95% compared to 2017. According to PT Perusahaan Listrik Negara (Persero) Electricity Supply Business Plan (RUPTL) 2017-2026, Aceh has potential primary energy sources consisting of water (1,655 MW) in 18 locations, geothermal (1,307 MWe) in 19 locations, oil (151 MMSTB), gas (6.39 tscf) and coal (451 million tons). NAD electricity sales are projected to increase from 2,678 GWh (Giga Watt per Hour) in 2017 to 7,223 Gwh in 2026 or an average increase of 11.7% per year. While the realization of electricity growth in 2016 was 2,330 GWh with electricity growth of 8.8% in the last 5 years [5]. Electricity demand in Aceh Province has shown a steady increase due to population growth and industrial expansion. This increase requires accurate forecasting methods to ensure that electricity supply is aligned with consumption, thus supporting sustainable development and economic stability.

Therefore, it is necessary to have an accurate prediction system model related to electrical energy consumption to help strategic planning in electrical energy management. There are several methods used to predict electrical energy consumption in Aceh Province, namely the Fuzzy Time Series - Markov Chain method and the Markov Chain Monte Carlo Method. Markov chain is a mathematical system that models the relationship between an event or process where the next process does not depend on a series of previous events but only depends on the current state [6]. The Markov Chain Monte Carlo method is a simulation method to obtain sample data from a random variable with a sampling technique that uses Markov chain properties [7] [8]. Fuzzy Time Series, Markov Chain and Markov Chain Monte Carlo methods are *soft comp* uting algorithms that occupy an interesting position in the development of computational methods and problem solving at present [9].

The state of the art and novelty of this research is based on an overview of several related previous studies, such as research conducted by [10] prediction of electrical energy demand in Bireuen district using LEAP software. Research [11] predicted the deviation of electricity flow at PLN Area Binjai using the backpropogation method. Other research conducted by [12] also predicted electricity consumption in Aceh province using the Adaptive Neuro Fuzzy Inference System method. Another study [13] predicted electricity demand in Jambi province by doing descriptive econometric analysis on SPSS software and Microsoft Excel. In research conducted by [14] also predicts the electrical energy needs of PLN Parapat Simalungun city using simple regression analysis and other research [15] predicts the electrical energy consumption of PLN UPJ Purbalingga region using LEAP software.

Based on previous research, it can be seen that the research that the researcher proposes is different from other people's previous research, namely the differences in the methods and data used and the resulting research model. Based on our observations this research has not been done, so this*novelty* is the basis for conducting this research and becomes a reference for further research. This research also makes a significant contribution to the development of more accurate and effective methods of predicting electrical energy consumption, as well as assisting decision making related to electrical energy management in Aceh Province.

2 Literature Review

Related or previous research is one of the references for researchers in conducting this research to get an overview or comparison that has been done by previous researchers, so that the differences with this research will be seen. There are several studies that are studied in this literature review, including research conducted by Tsaur entitled "Fuzzy Time Series Model - Markov Chain with Application to Forecast the Exchange Rate of Taiwan Dollar and US Dollar" This research uses the Fuzzy Time Series-Markov Chain method aimed at predicting the value of the Taiwanese currency against the USD from January 2006 to August 2009 with forecasting results that have a very small absolute error value (MAPE) from other methods, namely 1.4042% [16]. Research conducted by Aliek et al., entitled the application of the Fuzzy Time Series-Markov Chain model for weather forecasting on the Gresik-Bawean crossing route. This research is one of the latest studies related to the Fuzzy Time Series-Markov Chain method in weather forecasting. This forecast aims to examine the level of accuracy of the Fuzzy Time Series-Markov Chain method on wind and wave data. The results of the MAPE value forecasting of each data are less than 10%, which means that this study meets the criteria very well [17].

ISSN:2302-8149
e-ISSN:2540-9719

Research conducted by Saputra, entitled Fuzzy Time Series-Markov Chain Model for Forecasting Fish Farming Products. This study uses the Fuzzy Time Series-Markov Chain method on fish farming sales data in November 2018 and aims to predict the price of fish farming, where the selling price of fish fluctuates due to several factors. The results of this study obtained a MAPE value of 1.4% so that the FTS-MC forecasting accuracy level was 98.6% [18]. Research conducted by Sri Bintang et al., entitled Forecasting Indonesian Seaweed Exports: Comparison of Fuzzy Time Series Methods with No Markov Chain. This study predicts Indonesian seaweed export data using 2 forecasting methods, namely Fuzzy Time Series & Fuzzy Time Series - Markov Chain. Seaweed export data was obtained from BPS and the Ministry of Maritime Affairs and Fisheries (KKP) (1989 to 2018). The results obtained MAPE values for FTSMC of 1.1% and FTS of 2.0%, this means that FTSMC is more accurate in predicting Indonesian seaweed export data for the future [19].

Research conducted by Ramadani and Devianto, entitled Bitcoin price forecasting model with fuzzy time series Markov chain and Chen logic method. In the study, predicting bitcoin prices based on data from 2010 to 2020 used a comparison of 3 methods, namely the method with FTS Markov Chain, the FTS Chen Logical Method, and the FTS Segmented Chen Logical method. The forecasting results of the FTS Markov Chain method have the smallest accuracy error (8.80%) based on the Mean Absolute Percentage Error (MAPE) compared to the FTS Segmented Chen Logical Method (40.80%) & FTS Chen Logical Method (470.65%). This means that the FTS Markov Chain method meets very good criteria [20]. Research conducted by Permana and Fitri, entitled Fuzzy Time Series Application - Markov Chain Method in Forecasting Riyal-Rupiah Exchange Rate Data. This study concerns predicting the exchange rate between Riyal and Rupiah. Data was obtained from the official website of Bank Indonesia on August 23, 2018 to February 19, 2019. The method used to predict the exchange rate between Riyal to Rupiah in the next 10 days is the Fuzzy Time Series-Markov Chain method. The results of this study were assessed from the form of accuracy of the prediction error value using the AFER and MEA methods, each value was 0.827% and Rp 32.96. This states that the prediction model obtained has a very small level of error value accuracy [21].

Research conducted by Mubarrok et al., entitled Application of Fuzzy Time Series Markov Chain for Rice Production Forecasting. This study predicts rice production data in Yogyakarta using the FTS Markov Chain method. The data is rice production ranging from 1970 to 2017 obtained from www.pertanian.go.id. The results obtained a small error accuracy value, namely MAPE 4.156% [22]. Alyousifi et al. developed an FTSMC model applied to predict the Air Pollution Index in Malaysia. This model employed a grid partition method to optimize fuzzy intervals, which was proven to improve forecasting accuracy. By evaluating the model using MAPE and RMSE, this study showed that FTSMC achieved higher accuracy than other models in air quality forecasting. This highlights FTSMC's ability to handle highly dynamic and fluctuating data, making it an ideal method for similar applications in electricity consumption, where daily and seasonal changes can significantly impact consumption patterns [23]. Research conducted by Gavinda et al., entitled Predicting Electricity Consumption in Aceh Province Using the Markov Chain Monte Carlo Method. This study predicts electricity consumption using the Markov Chain Monte Carlo method, with the results showing an increase in electricity consumption of 32.4% over the past five years. The prediction model achieves high accuracy with a Mean Absolute Percentage Error (MAPE) of 2.41%, demonstrating its reliability in predicting future electricity needs [24].

Another study by Arinanda, Sutoyo, and Rini compared several variants of Fuzzy Time Series methods (Chen, Cheng, and Markov Chain) in forecasting rainfall in Medan. They found that the Chen method achieved the highest accuracy with the lowest MAPE, demonstrating the effectiveness of fuzzy time series for environmental data with high variability. Although the FTSMC method in this study did not yield the best results, it still showed significant potential for handling weather-related time series data, which share similar fluctuation characteristics with electricity consumption that can be affected by weather patterns [25]. Furthermore, Hariyanto et al. developed an FTSMC model based on frequency density partitioning to forecast stock indices, also employing an average-based interval analysis. This partitioning technique enabled improved prediction accuracy by considering the density distribution of data, as evidenced by low MSE and MAPE values. This accomplishment underscores the significant potential of the modified FTSMC method in generating reliable forecasting results on time series data influenced by multiple factors, such as electricity consumption driven by daily and seasonal demand variations [26].

 ISSN:2302-8149
e-ISSN:2540-9719

Overall, these studies confirm that FTSMC is a robust method for forecasting time series affected by uncertainty and complex variations. FTSMC has shown superiority in capturing historical patterns and considering the probability of transitions between states. Therefore, this method is highly relevant for use in forecasting electricity consumption in Aceh Province, where consumption patterns are influenced by seasonal changes, economic growth, and demand fluctuations.

3 Research method

The research flowchart for this research involve several key steps in Figure 1.

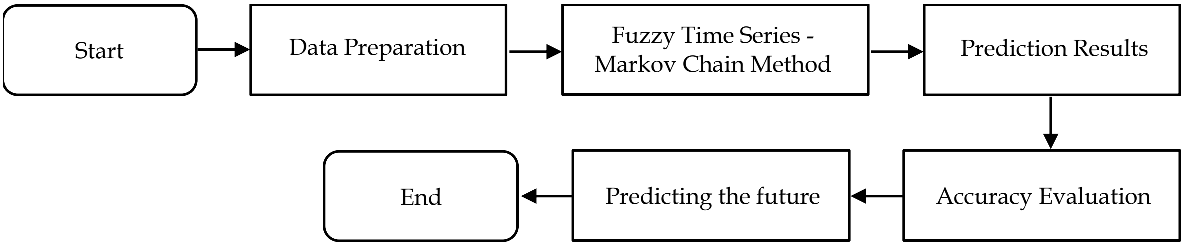

Figure 1. Research flowchart

The process carried out after data collection involves data analysis and processing using the R Studio application. The system scheme of the Fuzzy Time Series - Markov Chain method for predicting electricity consumption in Aceh province in Figure 2.

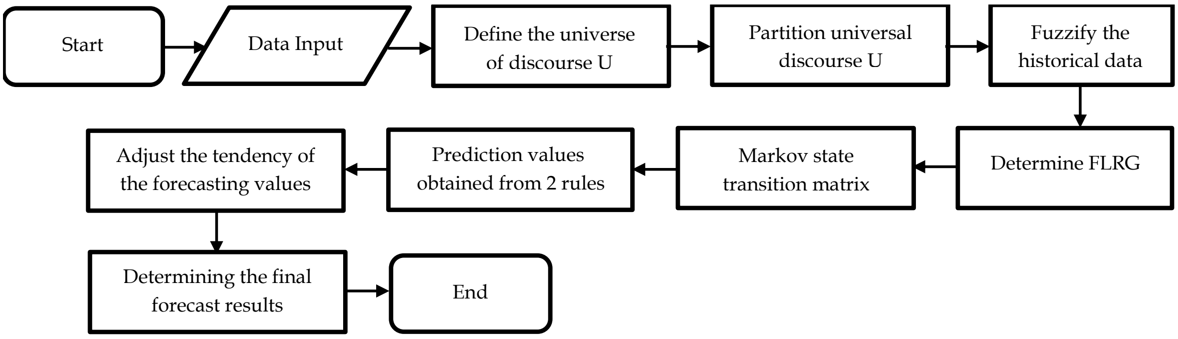

Figure 2. System scheme of the fuzzy time series - markov chain method

3.1 Fuzzy Time Series Markov Chain Method

The steps in the Fuzzy Time Series Markov Chain method generally include the following [27]:

1. Definition of the Universe of Discourse
   D_{min} and D_{max} represent the minimum and maximum data values, respectively. To determine the universe of discourse, the formula is as follows:
   $U = [D_{min} - D_1, D_{max} + D_2]$, where D_1 and D_2 are positif numbers. (1)
2. Interval Division and Fuzzy Set Determination
   $$l = \frac{(D_{min}-D_1)-(D_{max}+D_2)}{n} \quad (2)$$
   Where l = the difference between two consecutive intervals, n = the number of intervals
   Each interval can then be calculated as follows:
   $$u_1 = [D_{min} - D_1, D_{min} - D_1 + l]$$
   $$u_2 = [D_{min} - D_1 + l, D_{min} - D_1 + 2l]$$
   $$\vdots$$
   $$u_n = [D_{min} - D_1(n-1)l, D_{min} - D_1 + nl] \quad (3)$$
   where each u_i represents the i-th interval in the universe of discourse.
3. Data Fuzzification
   Convert historical data values into fuzzy sets by determining each data point's membership degree within the defined fuzzy intervals. Suppose there are 4 fuzzy sets A_i (where $i = 1,2,3,4$), each defined over 4 intervals. These intervals are represented as follows:

ISSN:2302-8149
e-ISSN:2540-9719

$$u_1 = [d_1, d_2],\ u_2 = [d_2, d_3],\ u_3 = [d_3, d_4],\ u_4 = [d_4, d_5] \quad (4)$$

Therefore, the fuzzy sets A_1, A_2, A_3, A_4 can be defined as follows:

$$A_1 = \left\{\frac{1}{u_1}, \frac{0{,}5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}\right\},\ A_2 = \left\{\frac{0{,}5}{u_1}, \frac{1}{u_2}, \frac{0{,}5}{u_3}, \frac{0}{u_4}\right\},\ A_3 = \left\{\frac{0}{u_1}, \frac{0{,}5}{u_2}, \frac{1}{u_3}, \frac{0{,}5}{u_4}\right\},\ A_4 = \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0{,}5}{u_3}, \frac{1}{u_4}\right\} \quad (5)$$

In each fuzzy set A_i the notation $x\ /\ u_y$ represents the membership degree x of the interval u_y within that fuzzy set.

4. Formation of Fuzzy Logical Relationships (FLR)
   Identify logical relationships between fuzzy data by examining data sequence patterns, such as whether one fuzzy set is followed by another at specific times.
5. Formation of Fuzzy Logical Relationship Groups (FLRG)
   Combine FLR results into Fuzzy Logical Relationship Groups (FLRG) for each fuzzy set, helping to structure the relationships between intervals that appear in the data.
6. Markov Transition Matrix
   We can create a Markov transition matrix of dimension $n \times n$, where n is the number of intervals in the fuzzy set. If state A_i transitions to state A_j and passes through another state A_k, where $i, j, k = 1, 2, \ldots, n$, we can obtain the Fuzzy Logical Relationship Group (FLRG). Thus, the transition probability P_{ij} can be written as:

   $$P_{ij} = \frac{M_{ij}}{M_i} \quad (6)$$

   Where P_{ij} represents the probability of transitioning from state A_i to state A_j, M_{ij} is the number of transitions from state A_i to state A_j, M_i is the total number of occurrences of state A_i.
   The transition probability matrix R can be written as follows:

   $$R = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (7)$$

   where each entry P_{ij} represents the probability of transitioning from state A_i to state A_j. The sum of probabilities in each row should equal 1, i.e.,

   $$\sum_{j=1}^{n} P_{ij} = 1 \text{ for each } i = 1,2, \ldots, n. \quad (8)$$

   This matrix R provides a comprehensive view of all possible state transitions and their respective probabilities in the fuzzy time series Markov Chain model.
7. Data Prediction
   If $F(t-1) = A_i$, the process is defined to be in state A_i at time $t-1$; then forecasting of $F(t)$ is conducted using the row vector $[P_{i1}, P_{i2}, \ldots P_{in}]$. The forecasting of $F(t)$ is equal to the weighted average of $m_1, m_2, \ldots, m_n$, the midpoint of $u_1, u_2, \ldots, u_n$. The expected forecasting values are obtained by the following Rules:
   Rule 1: If the fuzzy logical relationship group of A_i is one-to-one (i.e., $A_j \to A_k$, with $P_{ik} = 1$ and $P_{ij} = 0, j \neq k$), then the forecasting of $F(t)$ is m_k, the midpoint of uk, according to the equation $F(t) = m_k P_{ik} = m_k$.
   Rule 2: If the fuzzy logical relationship group of A_i is one-to-many (i.e., $A_j \to A_1, A_2, \ldots, A_n, j = 1,2, \ldots n$, when collected data $Y(t-1)$ at time $t-1$ is in the state A_i, then the forecasting of $F(t)$ is equal as $F(t) = m_1 P_{j1} + m_2 P_{j2} + \cdots + m_{j-1} P_{j(j-1)} + Y(t-1) P_{jj} + \cdots + m_{j+1} P_{j(j+1)} + \cdots + m_n P_{jn}$, where $m_1, m_2, \ldots, m_{j-1}, m_{j+1}, \ldots, m_n$ are the midpoint of $u_1, u_2, \ldots, u_{j-1}, u_{j+1}, \ldots, u_n$, and m_j is substituted for $Y(t-1)$ in order to take more information from the state A_j at time $t-1$.
8. Adjust the tendency of the forecasting values.
   The adjusting rule for the forecasting value is described below.
   Rule 1. If state A_i communicates with A_i, starting in state A_i at time $t-1$ as $F(t-1) = A_i$, and makes an increasing transition into state A_j at time $t, (i < j)$, then the adjusting trend

 ISSN:2302-8149
e-ISSN:2540-9719

value D_t is defined as $D_{t1} = \left(l/_2\right)$.
Rule 2. If state A_i communicates with A_i, starting in state A_i at time $t-1$ as $F(t-1) = A_i$, and makes an increasing transition into state A_j at time t, $(i < j)$, then the adjusting trend value D_t is defined as $D_{t1} = -\left(l/_2\right)$.
Rule 3. If the current state is in state A_i at time $t-1$ as $F(t-1) = A_i$, and makes a jump-forward transition into state A_{i+s} at time t, $(1 \le s \le n-i)$, then the adjusting trend value D_t is defined as $D_{t2} = \left(l/_2\right)s$, $(1 \le s \le n-i)$, where l is the length that the universal discourse U must be partitioned into as n equal intervals.
Rule 4. If the process is defined to be in state A_i at time $t-1$ as $F(t-1) = A_i$, then makes a jump-backward transition into state A_{i+v} at time t, $(1 \le v \le i)$, the adjusting trend value D_t is defined as $D_{t2} = -\left(l/_2\right)v$, $1 \le v \le i)$.

9. Obtain adjusted forecasting result.
When v is the jump step, the general form for forecasting result $F'(t)$ can be obtained as
$$F'(t) = F(t) \pm D_{t1} \pm D_{t2} = F(t) \pm \left(l/_2\right) \pm \left(l/_2\right)v \quad (9)$$
10. Accuracy Evaluation
Calculate prediction accuracy by using metrics like Mean Absolute Percentage Error (MAPE) to assess the model's performance in forecasting data [28].
$$MAPE = \frac{1}{n}\sum_{n}^{t=1}\left|\frac{Y(t)-\hat{Y}(t)}{Y(t)}\right| \times 100\% \quad ; Y(t) \neq 0 \quad (10)$$
where $Y(t)$ is the actual value at time t , $\hat{Y}(t)$ is the forecasted value at time t , n is the total number of observations in Table 1.

Table 1. The significance of MAPE

Prediction Accuracy	MAPE Value
Excellent Accuracy	MAPE < 10%
Good Accuracy	10% ≤ MAPE < 20%
Reasonable Accuracy	20% ≤ MAPE < 50%
Poor Accuracy	MAPE ≥ 50%

4 Results and Discussion

The results and discussion consist of the results of data collection, application of Fuzzy Time Series–Markov Chain Method, prediction results, accuracy evaluation and predicting the future.

4.1 Data Collection Results

Electrical energy consumption data in Aceh Province from January 2018 to December 2022 is presented in Table 2a and Table 2b.

Table 2a. Electricity consumption data (KWH) in aceh province for the period 2018 - 2022 (monthly)

Month/Years	Total KWH	Month/ Years	Total KWH	Month/ Years	Total KWH
Jan 2018	203.589.362	Jan 2019	222.690.699	Jan 2020	239.097.474
Feb	193.315.100	Feb	205.737.083	Feb	224.714.451
Mar	218.138.334	Mar	235.790.615	Mar	244.161.249
Apr	216.667.245	Apr	232.927.295	Apr	262.372.897
May	224.525.573	May	248.827.597	May	252.108.245
Jun	218.130.610	Jun	231.953.629	Jun	252.444.359
Jul	222.739.187	Jul	240.359.071	Jul	252.916.028
Aug	222.282.160	Aug	240.602.261	Aug	263.633.215
Sep	214.382.436	Sep	234.370.371	Sep	248.191.166

ISSN:2302-8149
e-ISSN:2540-9719

Oct	216.932.141	Oct	229.294.156	Oct	253.299.482
Nov	217.823.202	Nov	226.906.042	Nov	247.329.852
Dec	219.187.023	Dec	232.042.802	Dec	197.730.766

Table 2b. Electricity consumption data (KWH) in aceh province for the period 2018 - 2022 (monthly)

Month/Years	Total KWH	Month/ Years	Total KWH
Jan 2021	283.739.141	Jan 2022	252.643.513
Feb	236.223.021	Feb	235.801.520
Mar	209.827.249	Mar	256.855.792
Apr	246.041.129	Apr	272.486.855
May	298.736.020	May	265.483.320
Jun	264.817.443	Jun	272.560.682
Jul	251.673.583	Jul	271.937.571
Aug	257.269.699	Aug	271.828.917
Sep	251.003.973	Sep	271.193.256
Oct	263.317.444	Oct	256.595.952
Nov	254.341.476	Nov	256.979.175
Dec	257.475.964	Dec	269.647.552

4.2 Application of Fuzzy Time Series Markov Chain Method

From Table 2a and Table 2b we can get the universe of discourse $U = [D_{min} - D_1, D_{max} + D_2] = [193.315.100 - 100,\ 298.736.020 + 980] = [193.315.000, 298.737.000]$**.** With a class interval (n) of 7 intervals, and an interval length (l) of 15.060.286, then the universe of discourse U can be divided into several intervals:

$$u_1 = [193.315.000\,, 208.375.286], \qquad u_2 = [208.375.286\,, 223.435.571],$$
$$u_3 = [223.435.571\,, 238.495.857] \qquad u_4 = [238.495.857\,, 253.556.143],$$
$$u_5 = [253.556.143\,, 268.616.429], \qquad u_6 = [268.616.429, 283.676.714],$$
$$u_7 = [283.676.714, 298.737.000]$$

The fuzzy sets $A_1, A_2, \cdots, A_7$ are defined as follows:

$$A_1 = \left\{\frac{1}{u_1}, \frac{0,5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\},\ A_2 = \left\{\frac{0,5}{u_1}, \frac{1}{u_2}, \frac{0,5}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\},\ A_3 = \left\{\frac{0}{u_1}, \frac{0,5}{u_2}, \frac{1}{u_3}, \frac{0,5}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\},$$
$$A_4 = \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0,5}{u_3}, \frac{1}{u_4}, \frac{0,5}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\},\ A_5 = \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0,5}{u_4}, \frac{1}{u_5}, \frac{0,5}{u_6}, \frac{0}{u_7}\right\},\ A_6 = \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0,5}{u_5}, \frac{1}{u_6}, \frac{0,5}{u_7}\right\},$$
$$A_7 = \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0,5}{u_6}, \frac{1}{u_7}\right\}$$

The equivalent fuzzy sets to each month's enrollment are shown in Table 3a and Table 3b. The fuzzy logical relationship group is obtained as shown in Table 4.

Table 3a. Fuzzify the historical data

Month/ Years	Total KWH	Fuzzy Value	Month/ Years	Total KWH	Fuzzy Value	Month/ Years	Total KWH	Fuzzy Value
Jan 2018	203.589.362	A_1	Jan 2019	222.690.699	A_2	Jan 2020	239.097.474	A_4
Feb	193.315.100	A_1	Feb	205.737.083	A_1	Feb	224.714.451	A_3
Mar	218.138.334	A_2	Mar	235.790.615	A_3	Mar	244.161.249	A_4
Apr	216.667.245	A_2	Apr	232.927.295	A_3	Apr	262.372.897	A_5
May	224.525.573	A_3	May	248.827.597	A_4	May	252.108.245	A_4

 ISSN:2302-8149
e-ISSN:2540-9719

Jun	218.130.610	A_2	Jun	231.953.629	A_3	Jun	252.444.359	A_4
Jul	222.739.187	A_2	Jul	240.359.071	A_4	Jul	252.916.028	A_4
Aug	222.282.160	A_2	Aug	240.602.261	A_4	Aug	263.633.215	A_5
Sep	214.382.436	A_2	Sep	234.370.371	A_3	Sep	248.191.166	A_4
Oct	216.932.141	A_2	Oct	229.294.156	A_3	Oct	253.299.482	A_4
Nov	217.823.202	A_2	Nov	226.906.042	A_3	Nov	247.329.852	A_4
Dec	219.187.023	A_2	Dec	232.042.802	A_3	Dec	197.730.766	A_1

Table 3b. Fuzzify the historical data

Month/ Years	Total KWH	Fuzzy Value	Month/ Years	Total KWH	Fuzzy Value
Jan 2021	283.739.141	A_7	Jan 2022	252.643.513	A_4
Feb	236.223.021	A_3	Feb	235.801.520	A_3
Mar	209.827.249	A_2	Mar	256.855.792	A_5
Apr	246.041.129	A_4	Apr	272.486.855	A_6
May	298.736.020	A_7	May	265.483.320	A_5
Jun	264.817.443	A_5	Jun	272.560.682	A_6
Jul	251.673.583	A_4	Jul	271.937.571	A_6
Aug	257.269.699	A_5	Aug	271.828.917	A_6
Sep	251.003.973	A_4	Sep	271.193.256	A_6
Oct	263.317.444	A_5	Oct	256.595.952	A_5
Nov	254.341.476	A_5	Nov	256.979.175	A_6
Dec	257.475.964	A_5	Dec	269.647.552	A_6

Table 4. Fuzzy logical relationship group

Present State	→	Fuzzy Value
A_1	→	A_1, A_2, A_3, A_7
A_2	→	A_1, A_2 (8), A_3, A_4
A_3	→	A_2 (2), A_3 (4), A_4 (4), A_5
A_4	→	A_1, A_3(4), A_4 (5), A_5(4), A_7
A_5	→	A_4 (5), A_5(3), A_6(3)
A_6	→	A_5(2), A_6(3)
A_7	→	A_3, A_5

Using the fuzzy logical relationship group in Table 4, the transition probability matrix R may be obtained.

$$R = \begin{bmatrix} 0,250 & 0,250 & 0,250 & 0,000 & 0,000 & 0,000 & 0,250 \\ 0,091 & 0,727 & 0,091 & 0,091 & 0,000 & 0,000 & 0,000 \\ 0,000 & 0,182 & 0,364 & 0,364 & 0,091 & 0,000 & 0,000 \\ 0,067 & 0,000 & 0,267 & 0,333 & 0,267 & 0,000 & 0,067 \\ 0,000 & 0,000 & 0,000 & 0,455 & 0,273 & 0,273 & 0,000 \\ 0,000 & 0,000 & 0,000 & 0,000 & 0,400 & 0,600 & 0,000 \\ 0,000 & 0,000 & 0,500 & 0,000 & 0,500 & 0,000 & 0,000 \end{bmatrix}$$

4.3 Prediction Results

The prediction calculation using the Fuzzy Time Series Markov Chain is based on the formed Fuzzy Logical Relationship Groups (FLRG). For example, to predict electricity consumption in Aceh in February 2021, the FLRG obtained is $A_7 \rightarrow A_3, A_5$ (based on the FLRG $\hat{Y}(t-1)$. This relationship is one-to-many, so according to equation 2.15, the predicted value is as follows:

$$\hat{Y}(Feb\ 2021) = m_3 P_{7,3} + m_5 P_{7,5} = (230.965.714)(0,5) + (261.086.286)(0,5) = 246.026.000$$

Based on the calculation above, the prediction for February 2021 is influenced by $m_3, m_5, P_{7,3}, P_{7,5}$ as the next states for A_7 are A_3 and A_5. Since A_7 does not transition to itself and $P_{7,7} = 0$, the predicted

ISSN:2302-8149
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electricity consumption for February 2021 is not affected by previous electricity consumption. The calculation of $D(t)$ for February 2021 is based on the FLR $Y(t-1)$ (January 2021), which is $A_7 \rightarrow A_3$. The transition from A_7 to A_3 is a backward step of 4, and since A_7 does not commute with A_7, then:

$$D(t) = -\left(\frac{l}{2}.v\right) = -\left(\frac{15.060.286}{2}.4\right) = -30.120.572$$

The adjusted prediction result $\hat{Y}_{adj}(t)$ for February 2021 is 215.905.428, obtained by summing $\hat{Y}(t)$ and $D(t)$. The following are the prediction results at time t $\hat{Y}(t)$, the prediction trend value $D(t)$, and the adjusted prediction result $\hat{Y}_{adj}(t)$, as presented in Table 5a, Table 5b and Table 5c.

Table 5a. The prediction results of the fuzzy time series markov chain method

Month/Years	$Y(t)$	$\hat{Y}(t)$	$D(t)$	$\hat{Y}_{adj}(t)$
Jan 2018	203.589.362	-	-	-
Feb	193.315.100	235.416.841	-	235.416.841
Mar	218.138.334	232.848.275	15.060.286	247.908.561
Apr	216.667.245	220.267.615	-	220.267.615
May	224.525.573	219.197.736	15.060.286	234.258.022
Jun	218.130.610	234.102.653	-7.530.143	226.572.510
Jul	222.739.187	220.261.997	-	220.261.997
Aug	222.282.160	223.613.677	-	223.613.677
Sep	214.382.436	223.281.295	-	223.281.295
Oct	216.932.141	217.536.063	-	217.536.063
Nov	217.823.202	219.390.387	-	219.390.387
Dec	219.187.023	220.038.429	-	220.038.429
Jan 2019	222.690.699	221.030.295	-	221.030.295
Feb	205.737.083	223.578.413	-7.530.143	216.048.270
Mar	235.790.615	235.953.771	15.060.286	251.014.057
Apr	232.927.295	238.199.073	-	238.199.073
May	248.827.597	237.157.855	15.060.286	252.218.141
Jun	231.953.629	246.962.317	-7.530.143	239.432.174
Jul	240.359.071	236.803.792	15.060.286	251.864.078
Aug	240.602.261	244.139.503	-	244.139.503
Sep	234.370.371	244.220.565	-7.530.143	236.690.422
Oct	229.294.156	237.682.616	-	237.682.616
Nov	226.906.042	235.836.701	-	235.836.701
Dec	232.042.802	234.968.287	-	234.968.287

Table 5b. The prediction results of the fuzzy time series markov chain method

Month/Years	$Y(t)$	$\hat{Y}(t)$	$D(t)$	$\hat{Y}_{adj}(t)$
Jan 2020	239.097.474	236.836.218	15.060.286	251.896.504
Feb	224.714.451	243.718.975	-7.530.143	236.188.832
Mar	244.161.249	234.171.337	15.060.286	249.231.623
Apr	262.372.897	245.406.883	15.060.286	260.467.169
May	252.108.245	258.701.533	-7.530.143	251.171.390
Jun	252.444.359	248.055.855	-	248.055.855
Jul	252.916.028	248.167.892	-	248.167.892
Aug	263.633.215	248.325.113	15.060.286	263.385.399

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Sep	248.191.166	259.045.259	-7.530.143	251.515.116
Oct	253.299.482	246.750.175	-	246.750.175
Nov	247.329.852	248.452.930	-	248.452.930
Dec	197.730.766	246.463.073	-22.590.429	223.872.644
Jan 2021	283.739.141	233.952.192	45.180.858	279.133.050
Feb	236.223.021	246.026.000	-30.120.572	215.905.428
Mar	209.827.249	238.356.313	-7.530.143	230.826.170
Apr	246.041.129	214.223.212	15.060.286	229.283.498
May	298.736.020	246.033.503	22.590.429	268.623.932
Jun	264.817.443	246.026.000	-15.060.286	230.965.714
Jul	251.673.583	259.368.234	-7.530.143	251.838.091
Aug	257.269.699	247.910.969	15.060.286	262.971.255
Sep	251.003.973	257.309.738	-7.530.143	249.779.595
Oct	263.317.444	247.687.768	15.060.286	262.748.054
Nov	254.341.476	258.959.139	-	258.959.139
Dec	257.475.964	256.511.123	-	256.511.123

Table 5c. The prediction results of the fuzzy time series markov chain method

Month/Years	$Y(t)$	$\hat{Y}(t)$	$D(t)$	$\hat{Y}_{adj}(t)$
Jan 2022	252.643.513	257.365.992	-7.530.143	249.835.849
Feb	235.801.520	248.234.276	-7.530.143	240.704.133
Mar	256.855.792	238.203.039	15.060.286	253.263.325
Apr	272.486.855	257.196.853	15.060.286	272.257.139
May	265.483.320	267.926.627	-7.530.143	260.396.484
Jun	272.560.682	259.549.839	15.060.286	274.610.125
Jul	271.937.571	267.970.923	-	267.970.923
Aug	271.828.917	267.597.057	-	267.597.057
Sep	271.193.256	267.531.864	-	267.531.864
Oct	256.595.952	267.150.468	-7.530.143	259.620.325
Nov	256.979.175	257.125.987	-	257.125.987
Dec	269.647.552	257.230.503	15.060.286	272.290.789

4.4 Accuracy Evaluation

The accuracy of the forecasting method can be seen by calculating the MAPE value, the smaller the MAPE value means the smaller the percentage of forecasting error. In the electricity consumption data in Aceh Province for the period January 2018 to December 2022 using the fuzzy time series Markov chain (FTSMC) method, the MAPE value shown in equation 10 is obtained as 3.2483% which means that the average percentage of forecasting error is 3.2483% and refers to table 1 the accuracy of the FTSMC method for this data has excellent accuracy. Figure 4 shows that the forecasting results using the fuzzy time series Markov chain have the same trend as the historical data. The absolute value of the difference between historical data and adjusted forecast values in Table 6a and Table 6b.

Table 6a. The absolute value of the difference between historical data and adjusted forecast values

Month/Years	$\lvert Y(t) - \hat{Y}_{adj}(t)\rvert$	$\left\lvert \frac{Y(t) - \hat{Y}_{adj}(t)}{Y(t)} \right\rvert$	Month/ Years	$\lvert Y(t) - \hat{Y}_{adj}(t)\rvert$	$\left\lvert \frac{Y(t) - \hat{Y}_{adj}(t)}{Y(t)} \right\rvert$
Jan 2018	-	-	Jan 2020	12.799.030,4	0,0535305965

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Feb	42.101.740,5	0,2177881630	Feb	11.474.380,7	0,0510620507
Mar	29.770.227,0	0,1364740734	Mar	5.070.373,9	0,0207664971
Apr	3.600.369,9	0,0166170473	Apr	1.905.728,2	0,0072634339
May	9.732.449,0	0,0433467281	May	936.855,1	0,0037160827
Jun	8.441.900,3	0,0387011262	Jun	4.388.504,0	0,0173840447
Jul	2.477.189,6	0,0111214808	Jul	4.748.136,1	0,0187735675
Aug	1.331.517,2	0,0059902118	Aug	247.815,7	0,0009400018
Sep	8.898.859,2	0,0415092736	Sep	3.323.950,5	0,0133927025
Oct	603.921,9	0,0027839209	Oct	6.549.307,0	0,0258559824
Nov	1.567.184,9	0,0071947564	Nov	1.123.078,0	0,0045408106
Dec	851.405,8	0,0038843805	Dec	26.141.878,2	0,1322094623

Table 6b. The absolute value of the difference between historical data and adjusted forecast values

Month/Years	$\left\|Y(t) - \hat{Y}_{adj}(t)\right\|$	$\left\|\frac{Y(t) - \hat{Y}_{adj}(t)}{Y(t)}\right\|$	Month/ Years	$\left\|Y(t) - \hat{Y}_{adj}(t)\right\|$	$\left\|\frac{Y(t) - \hat{Y}_{adj}(t)}{Y(t)}\right\|$
Jan 2021	4.606.091,5	0,0162335428	Jan 2022	2.807.663,6	0,0111131435
Feb	20.317.593,0	0,0860102157	Feb	4.902.612,9	0,0207912691
Mar	20.998.921,3	0,1000771890	Mar	3.592.467,4	0,0139863203
Apr	16.757.630,9	0,0681090637	Apr	229.716,1	0,0008430356
May	30.112.087,8	0,1007983162	May	5.086.835,7	0,0191606603
Jun	33.851.729,0	0,1278304352	Jun	2.049.442,6	0,0075192158
Jul	164.508,0	0,0006536560	Jul	3.966.647,5	0,0145866108
Aug	5.701.556,1	0,0221617863	Aug	4.231.860,1	0,0155681013
Sep	1.224.378,3	0,0048779238	Sep	3.661.391,5	0,0135010419
Oct	569.390,0	0,0021623710	Oct	3.024.372,9	0,0117865183
Nov	4.617.663,2	0,0181553685	Nov	146.811,7	0,0005712981
Dec	964.840,5	0,0037473033	Dec	2.925.485,0	0,0126075232

Based on table 6, the MAPE value is

$$MAPE = \frac{1}{n}\sum_{n}^{t=1}\left|\frac{Y(t) - \hat{Y}(t)}{Y(t)}\right| \times 100\% = \frac{1}{59} \times 1{,}9165478257 \times 100\% = 3{,}2483\%$$

Results Comparison of forecast data and historical data in Figure 3.

ISSN:2302-8149
e-ISSN:2540-9719

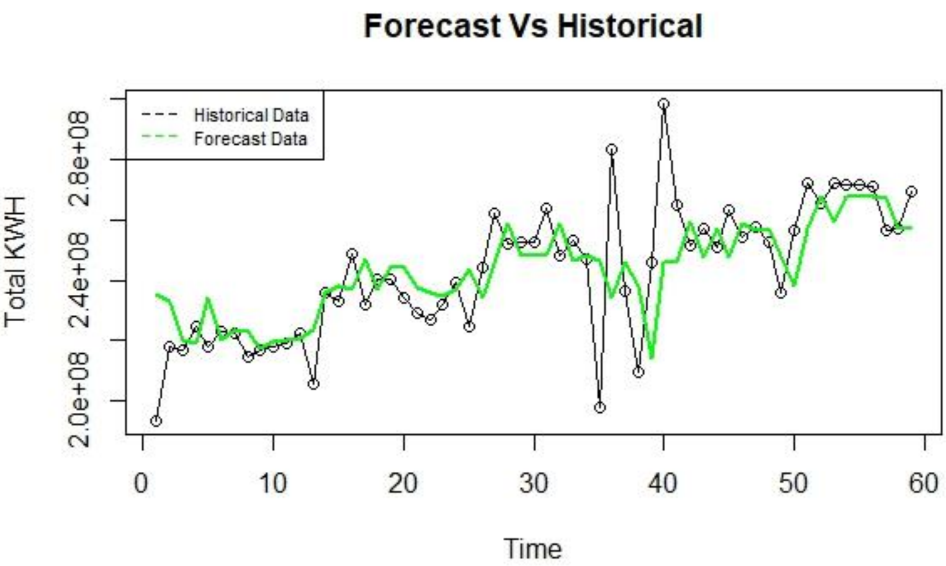

Figure 3. Comparison of forecast data and historical data

4.5 Predicting The Future

After we know the accuracy of the FTSMC method has excellent accuracy, then we will make predictions for the next few months which follow the previous flow and rules. The data that we have is data from January 2018 to December 2022, to predict electricity consumption in Aceh in January 2023, the FLRG obtained is $A_6 \rightarrow A_5, A_6$ (based on the FLRG $\hat{Y}(t-1)$. This relationship is one-to-many, so according to equation 2.15, the predicted value is as follows:

$$\hat{Y}(Jan\ 2023) = m_5 P_{6,5} + Y(\text{Dec } 2022) P_{6,6} = (261.086.286)(0{,}4) + (276.146.572)(0{,}6) = 266.223.045$$

Based on the calculation above, the prediction for December 2022 is influenced by $m_5, Y(\text{Dec } 2022), P_{6,5}, P_{6,6}$ as the next states for A_6 are A_5 and A_6. A_6 transition to itself (communicates). Prediction result $\hat{Y}(t)$ for January 2023 is 266.223.045. The predictions for december 2030 are shown in Table 7a, Table 7b and Table 7c.

Table 7a. The predictions for electricity consumption data (KWH) in aceh province for the period 2023 - 2030 (monthly).

Month/Years	Total KWH	Month/ Years	Total KWH
Jan 2023	266.223.045	Jan 2024	261.097.467
Feb	264.168.342	Feb	261.092.995
Mar	262.935.519	Mar	261.090.311
Apr	262.195.826	Apr	261.088.701
May	261.752.010	May	261.087.735
Jun	261.485.720	Jun	261.087.155
Jul	261.325.946	Jul	261.086.807
Aug	261.230.082	Aug	261.086.599
Sep	261.172.564	Sep	261.086.474
Oct	261.138.052	Oct	261.086.398
Nov	261.117.346	Nov	261.086.353
Dec	261.104.922	Dec	261.086.326

Table 7b. The predictions for electricity consumption data (KWH) in Aceh Province for the period 2023 - 2030 (monthly).

Month/	Total KWH	Month/Y	Total KWH	Month/	Total KWH

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Years		ears		Years	
Jan 2025	261.086.310	Jan 2026	261.086.286	Jan 2027	261.086.286
Feb	261.086.300	Feb	261.086.286	Feb	261.086.286
Mar	261.086.294	Mar	261.086.286	Mar	261.086.286
Apr	261.086.291	Apr	261.086.286	Apr	261.086.286
May	261.086.289	May	261.086.286	May	261.086.286
Jun	261.086.288	Jun	261.086.286	Jun	261.086.286
Jul	261.086.287	Jul	261.086.286	Jul	261.086.286
Aug	261.086.286	Aug	261.086.286	Aug	261.086.286
Sep	261.086.286	Sep	261.086.286	Sep	261.086.286
Oct	261.086.286	Oct	261.086.286	Oct	261.086.286
Nov	261.086.286	Nov	261.086.286	Nov	261.086.286
Dec	261.086.286	Dec	261.086.286	Dec	261.086.286

Table 7c. The predictions for electricity consumption data (KWH) in aceh province for the period 2023 - 2030 (monthly).

Month/ Years	Total KWH	Month/ Years	Total KWH	Month/ Years	Total KWH
Jan 2028	261.086.286	Jan 2029	261.086.286	Jan 2030	261.086.286
Feb	261.086.286	Feb	261.086.286	Feb	261.086.286
Mar	261.086.286	Mar	261.086.286	Mar	261.086.286
Apr	261.086.286	Apr	261.086.286	Apr	261.086.286
May	261.086.286	May	261.086.286	May	261.086.286
Jun	261.086.286	Jun	261.086.286	Jun	261.086.286
Jul	261.086.286	Jul	261.086.286	Jul	261.086.286
Aug	261.086.286	Aug	261.086.286	Aug	261.086.286
Sep	261.086.286	Sep	261.086.286	Sep	261.086.286
Oct	261.086.286	Oct	261.086.286	Oct	261.086.286
Nov	261.086.286	Nov	261.086.286	Nov	261.086.286
Dec	261.086.286	Dec	261.086.286	Dec	261.086.286

Based on Figure 4, we can see that the trend of predicted data for 2023 to 2030 forms a pattern towards stability, which is also shown in Table 7a, Table 7b and Table 7c. The predicted figures start to stabilize and remain the same in the 32nd month on August 2025. Starting from that month, the prediction shows a value of 261,086,286 which remains the same until December 2030.

ISSN:2302-8149
e-ISSN:2540-9719

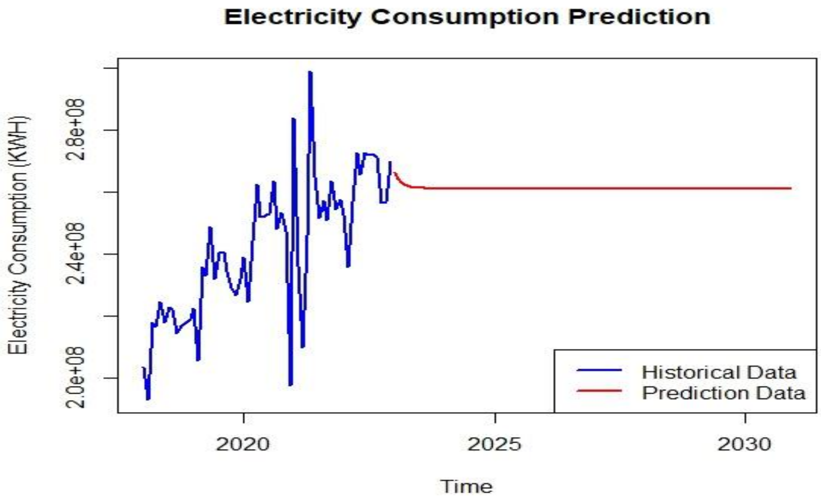

Figure 4. Comparison of forecast data and historical data

5 Conclusion

In this study, a fuzzy time series-Markov Chain (FTSMC) approach was applied to analyze electricity consumption data (KWH) in Aceh Province over the period of 2018–2022. The results show that this model achieves excellent forecasting accuracy, with a Mean Absolute Percentage Error (MAPE) of 3.2483%, highlighting the model's strong predictive performance and potential as a reliable tool for energy consumption forecasting. The monthly predicted values show stability due to several factors inherent to the Fuzzy Time Series-Markov Chain method: **Dominant Transition Matrix for a Single Class**, the model's transition matrix exhibits a high probability of remaining within certain dominant classes. This tendency causes the forecast to converge toward the midpoint of these classes, resulting in a stabilized prediction of approximately 261,086,286. This midpoint represents a balancing point due to the high probability of remaining in the dominant class. **Convergence in the Fuzzy Model**, within the Fuzzy Time Series method, the model naturally gravitates toward a specific value when the historical data lacks significant variability or when most transitions occur within a single dominant class. This characteristic drives the forecast to stabilize around the dominant class's midpoint in the transition matrix. **Effect of Class Midpoints (Fuzzy Intervals)**, the FTSMC model leverages fuzzy intervals and transition probabilities, which means that if dominant classes share a stable midpoint, the forecast values will converge to this midpoint. This phenomenon is evidenced in the stabilized predictions observed in this study.

The long-term forecast stabilizes around 261,086,286, indicating that the model assumes electricity consumption in Aceh Province remains constant over time, with no significant upward or downward trend. This stability suggests that the FTSMC model is particularly suited to contexts where historical patterns are expected to persist without major disruptions. This research confirms the efficacy of the FTSMC approach for stable data series and suggests its potential applicability in other domains where stability and consistency are essential in forecasting. Future research could explore integrating other variables or hybridizing this method with trend-based models to enhance forecasting adaptability to dynamic changes.

Acknowledgments

We acknowledge the support master's thesis research funding received from The the Directorate of Research, Technology, and Community Service. Ministry of Education, Culture, Research and Technology in 2024.

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