

Forecasting building permit submissions with fuzzy time series at DPMPTSP Medan

Buyung Satrio Dasopang¹, Rakhmat Kurniawan²

^{1,2}Departement of Computer Science, Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara, Indonesia

ARTICLE EI NFO	ABSTRACT
Article history: Received Jul 15, 2025 Revised Jul 22, 2025 Accepted Jul 27, 2025 Keywords: Building Permit; Data Uncertainty; Fuzzy Time Series; MAPE; Urban Spatial Planning.	Public service is a vital part of government performance, including how the Investment and One-Stop Integrated Services Agency (DPMPTSP) handles building permit applications (IMB). This study aims to estimate the number of IMB applications in Medan City using a method called Fuzzy Time Series (FTS). The forecast is intended as a preliminary step to support better spatial planning, especially as urban building density continues to rise. The FTS method was chosen for its ability to process time series data containing uncertainty. The forecasting process involves several stages: identifying the dataset, setting interval ranges, performing fuzzification, forming fuzzy logical relationships (FLR), grouping fuzzy logical relationship groups (FLRG), applying defuzzification, and measuring accuracy using Mean Absolute Percentage Error (MAPE). The data used include IMB applications from 2022 to 2023, with predictions made for 12 months in 2024. The results show that the FTS model closely follows historical data patterns, evidenced by a MAPE value of 1.99%, which indicates excellent accuracy as it is well below the 10% threshold. A comparative graph between actual and predicted data further supports this, revealing similar trends. In conclusion, the Fuzzy Time Series method is effective for forecasting IMB application volumes and can serve as a valuable reference for urban planning decisions and future time series-based forecasting research involving uncertainty.

This is an open access article under the [CC BY-NC](#) license.



Corresponding Author:

Buyung Satrio Dasopang,
Computer Science,
Universitas Islam Negeri Sumatera Utara,
Jl. Lap. Golf No.120, Kp. Tengah, Pancur Batu District, Deli Serdang Regency, North Sumatra 20353,
Indonesia
Email: dasopang029@gmail.com

1. INTRODUCTION

Public service has become a critical topic in this country, as it represents a fundamental aspect that must be provided by the government. The Investment and One-Stop Integrated Services Agency (DPMPTSP), in accordance with Presidential Regulation No. 97 of 2014, plays a role in implementing a one-stop integrated service system with the authority to process various types of permits, both licensing and non-licensing. One of the permits that can be processed is the building permit (IMB) (Mustaghfiri & Susiloadi, 2021). A building permit is a primary necessity, and the central government has the authority to regulate the number, layout, and feasibility of a building. As stated in Article 10 Paragraph 2 of Law No. 32 of 2004 concerning Regional Government, regional governments have the authority to implement the broadest possible regional autonomy to regulate and manage governmental affairs, based on the principles of autonomy and co-administration, except for authority in foreign politics, defense, security, justice, monetary and fiscal policy, religion, and other specific matters (Selasakmida et al., 2021).

An article by Gloria Trivena May Ary on the Liputan6 website (2024) explains that the Medan City Government experienced regional tax growth of 16.46%, from IDR 1.6 trillion in 2023 to IDR 2 trillion in 2024. This was reported by the Head of the Regional Financial and Asset Agency (BKAD) of Medan City, Zulkarnanin Lubis, at Medan City Hall. He stated that this increase in tax revenue was significantly influenced by improved performance in the Land and Building Tax (PBB) sector and the tax on the acquisition of land and building rights (BPHTB). Given this, Medan City faces the potential for increased building density, particularly in urban areas, which may lead to significant imbalances in urban spatial planning. Consequently, there is a growing potential for overcrowding in urban areas of Medan. The reported 16.46% increase in regional tax revenue in Medan City—driven by improved performance in the Land and Building Tax (PBB) and the Tax on the Acquisition of Land and Building Rights (BPHTB)—indicates a significant rise in physical development activity. The growth in revenue from the PBB and BPHTB sectors reflects an increase in property transactions and development, which is also marked by a rise in building permit (IMB) applications. With the growing contribution of the PBB and BPHTB sectors to regional tax revenue, forecasting the number of IMB applications using the Fuzzy Time Series (FTS) method becomes increasingly urgent—not only to support well-structured spatial planning, but also to enhance the quality of sustainable regional fiscal planning.

Considering this potential, the Fuzzy Time Series (FTS) method is used to forecast the number of building permit applications. Forecasting is the process of estimating or predicting future events based on historical or current data (Yuliyanto et al., 2023). The objective of forecasting is to serve as a preventive action to minimize the occurrence of unwanted future events. Based on the time horizon, forecasting can be categorized into three types: short-term, medium-term, and long-term (Muhammad Wahdeni Pramana et al., 2021). FTS is a forecasting method that utilizes time series data by applying fuzzy logic principles. Forecasting methods that use fuzzy logic principles are known as Fuzzy Time Series. In order to be effective, FTS must be able to identify patterns in past data to project future data (Arfiana et al., 2022). This study tests how accurately FTS can predict building permit applications by comparing the forecasted data with actual data. Previous studies have demonstrated the effectiveness of FTS. For example, research by Laily et al., (2023), titled “Implementation of Fuzzy Time Series-Markov Chain Method in Rainfall Forecasting for Rice Planting Schedules,” concluded that the FTS-Markov Chain method offers excellent accuracy, with a MAPE value of 4.30% (Laily et al., 2023).

Hafiyya et al., in their study “Implementation of Fuzzy Time Series Method in Forecasting Gold Prices in Indonesia,” reported that the Chen FTS method produced an error value of just 0.60515% for data from January 1 to June 30, 2022—well below the 10% threshold, indicating excellent forecasting ability (Hafiyya et al., 2022). Sarbaini et al., in “Prediction of Belida Rice Prices in Pekanbaru Using Fuzzy Time Series Cheng,” concluded that the method achieved excellent and efficient performance with a MAPE of 3.48% (Sarbaini et al., 2023). Fathoni et al., in “Forecasting LPG Sales at Grocery Stores Using Fuzzy Time Series Method,” reported an average MAPE of only 0.3% (Fathoni & Wijayanto, 2021). Andika et al., in “Comparison of Chen and Lee Models in Fuzzy Time Series Method for Forecasting Farmer Exchange Rates (NTP) in Aceh Province,” reported a forecasting error of 1.50% (Andika et al., 2024).

Unlike previous studies that typically forecast a single value using large historical datasets, this study forecasts monthly data for 12 months in 2024 using data from 2022–2023. The forecast spans from January to December 2024, and the MAPE for each month is calculated. These results are then combined to determine the overall MAPE for the year 2024, thus providing an overall measure of forecasting accuracy using the FTS method (Citra Utami et al., 2023). This study is expected to serve as a reference for policymakers in formulating optimal urban development strategies. It may also serve as a reference demonstrating that the Fuzzy Time Series method is appropriate for forecasting in time series case studies that involve uncertainty or fuzziness (Wantoro et al., 2020).

2. RESEARCH METHOD

The objective of this study is to compare the predicted data with the actual data using historical data and the MAPE formula, thereby producing forecast results. In addition, this research also evaluates the accuracy of the Fuzzy Time Series method in predicting a case study that involves uncertainty (fuzziness) (Ahmad, 2020).

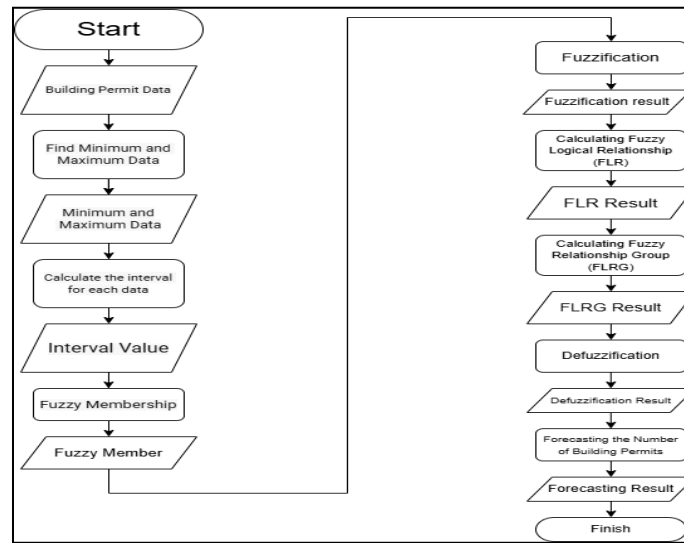


Figure 1. Fuzzy time series flowchart

The next step is determining the length of the interval range by utilizing quantity distribution through the following stages:

- a. Determine the interval using the following formula:

$$R = [d \text{ max} - d \text{ min}] \text{ (Arvie, 2022)}$$

Where R is the range; d max is the maximum data value; and d min the minimum data value.

- b. Determine the number of class intervals using Sturges' Formula:

$$K = 1 + 3.322 \times \log(n)$$

Determine the interval length using the formula: $K = \frac{\text{range data (R)}}{1}$

- c. Determine the median using the equation:

$$mi = \frac{(\text{Upper Bound} + \text{Lower Bounds})}{2} \text{ (Rahmawati et al., 2021)}$$

Fuzzy sets can be formed by considering various quantitative values. The first step is to divide the most frequent value into h equal intervals. Then, the second most frequent value is divided into h-1 equal intervals, the third most frequent into h-2 intervals, and so on, until the frequencies can no longer be divided. Next is the construction of fuzzy sets A_i and the fuzzification process of the observed actual data. For instance, $A_1, A_2, \dots, A_n$ are fuzzy sets with linguistic values, where $(i = 1, 2, \dots, p)$ represents the members of the universe of discourse (U). A number denoted by "f" defines the membership degree ($U(A_i (U_i))$) to A_i ($i = 1, 2, \dots, p$) which can be 0, 0.5, or 1 (Alfajriani et al., 2020). The Fuzzy Logical Relationship (FLR) table is determined based on the actual data. An FLR is symbolized as $A_i \rightarrow A$ where A_i represents the current state and A represents the next state (Agustina, 2024). Determining the weight of FLR relations to form FLRG (Fuzzy Logical Relationship Groups) involves including all existing relationships and assigning weights based on order and frequency of occurrence (Lestari & Yurinanda, 2023). To calculate the defuzzification value for forecasting, the standardized weight matrix (W) is multiplied by the median (mi) of the fuzzy set interval, which can be calculated using Equation $F_i = W_{i1} \cdot (m_1) + W_{i2} \cdot (m_2) + \dots + W_{ip} \cdot (m_p)$ (Ipan, Syaripuddin, 2022). The best forecast is one with the smallest forecasting error. One of the metrics that can be used to measure forecasting error is the Symmetric Mean Absolute Percentage Error (sMAPE). MAPE (Mean Absolute Percentage Error) is one of the evaluation methods used to measure the accuracy level of a forecasting model (Rahmawati, 2021). MAPE is calculated using the following formula:

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

Where:

A_t = actual value at period t

F_t = forecasted value at period t
 n = number of observation periods (Wardah, 2023).

Table 1. MAPE categories

Value	Description
Dibawah 10%	Very good
Beetwen 10% and 20%	Good
Beetwen 20% and 50%	Fair
Above 50%	Poor

3. RESULTS AND DISCUSSIONS

Data Representation

In this study, the data used were obtained from the Investment and One-Stop Integrated Services Office (DPMPTSP) of Medan City and the official website of the Central Bureau of Statistics (BPS) of Medan City. The following is the building permit (IMB) data for the years 2022–2024.

Table 2. Data 2022 - 2024

	2022	2023	2024
January	102	65	55
February	95	55	49
March	89	48	46
April	98	60	54
May	100	59	52
June	92	46	43
July	88	50	44
August	96	58	53
September	101	57	50
October	97	49	42
November	103	58	49
December	106	38	39
Total	1167	703	636

Determining the Universe of Discourse

Determining the universe of discourse is the first and crucial step in applying the Fuzzy Time Series (FTS) method, as the values from historical data will be divided into several fuzzy intervals. In this study, historical data on Building Permit (IMB) applications obtained from the Investment and One-Stop Integrated Services Agency (DPMPTSP) of Medan City were used as the basis for forming the universe of discourse. The initial step involves identifying the minimum and maximum values of the data, followed by padding to create a tolerance range for potential future value changes. For example, if the minimum value is 200 and the maximum is 600, the universe of discourse can be extended to [180, 620].

After that, the universe is divided into several intervals of equal length, known as fuzzy intervals. The number of intervals can be determined by observation or by applying certain methods such as Sturges' Rule. Each interval is assigned a linguistic label such as A1, A2, A3, and so on, which will be used in the fuzzification stage. The more intervals applied, the higher the potential prediction accuracy—however, the complexity of the calculations also increases. The universe of discourse is used to transform the data into fuzzy sets, which serve as the foundation for analysis and forecasting in this method (Zufria et al., 2024). The universe includes a value range that covers all the data in this study, including the smallest and largest data points. In this case, the smallest monthly data value is 38 and the highest is 106. A buffer of 5 was added to expand the range and accommodate possible data variations (Hafiz & Sriani, 2023). Thus, the resulting universe of discourse U is:

$$U = [d_{\min} - 5, d_{\max} + 5]$$

$$U = [38 - 5, 106 + 5]$$

$$U = (33, 111)$$

To determine the number of data interval, Sturges formula is used.

$$K = 1 + 3.322 \cdot \lceil \log \rceil_{10}(n) \quad (8)$$

$$K = 1 + 3.322 \cdot \sqrt[10]{24}$$

$$K = 1 + 3.322 \cdot 1.3802 = 5.58$$

$$K = 6$$

The result of calculating the value of K using Sturges' formula is 5.58. However, since the number of intervals must be a whole number, it is rounded to 6. After determining the number of intervals, the next step is to calculate the length of each interval. The interval length can be determined using the following formula: (Komaria et al., 2023)

$$\text{Interval Length} = \frac{\text{Maximum Value} - \text{Minimum Value}}{\text{Number of Interval (K)}} = \frac{111-33}{6} = \frac{78}{6} = 13$$

Accordingly, a total of 6 intervals were determined, each with an interval width of 13. Following the calculation of the number and length of intervals, the interval range was established as follows:

$$A_1 = [33, 46]$$

$$A_2 = [46, 59]$$

$$A_3 = [59, 72]$$

$$A_4 = [72, 85]$$

$$A_5 = [85, 98]$$

$$A_6 = [98, 111]$$

Fuzzy Set Determination

The following is the classification of monthly data for the years 2022 and 2023 based on the predetermined fuzzy sets.

Table 3. Fuzzy set

No	Fuzzification Result
1	102 > A6
2	95 > A5
3	89 > A5
4	98 > A6
5	100 > A6
6	92 > A5
7	88 > A5
8	96 > A5
9	101 > A6
10	97 > A5
11	103 > A6
12	106 > A6
13	65 > A3
14	55 > A2
15	48 > A2
16	60 > A3
17	59 > A3
18	46 > A2
19	50 > A2
20	58 > A2
21	57 > A2
22	49 > A2
23	58 > A2
24	38 > A1

Constructing Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG)

After the data is transformed into fuzzy format using the previously defined universe of discourse, the next step is to formulate the fuzzy logical relationships, commonly referred to as Fuzzy Logical Relationships (FLR). FLR are constructed by observing the transition of fuzzy values over time. For example, if in the first year the data falls within range A2, and in the second year it falls within A3, an FLR is formed as $A2 \rightarrow A3$. Once all FLR have been established, they are then grouped into Fuzzy Logical Relationship Groups (FLRG). FLRG serve to cluster FLR based on the current fuzzy state. For instance, if several FLR begin with A2, such as $A2 \rightarrow A3$, $A2 \rightarrow A4$, and $A2 \rightarrow A2$, the FLRG will be expressed as $A2 \rightarrow (A3, A4, A2)$. This grouping process is crucial for

identifying forecasting directions based on the recurrence of past conditions. The construction of FLR and FLRG plays a vital role, as they form the foundation for the defuzzification stage. Accuracy in determining FLR and FLRG depends greatly on how the intervals are divided and how fuzzy values are assigned. FLR describe the relationship between two consecutive fuzzy values, typically linking the fuzzy category of one month to that of the next. Meanwhile, FLRG represent the grouping of those relationships, illustrating the transition patterns between months. The following is the classification of FLR and FLRG for the years 2022 and 2023, based on the predetermined fuzzy sets (Sari et al., 2023).

Table 4. FLR result

Fuzzification	FLR
A6	A5
A5	A5
A5	A6
A6	A6
A6	A5
A5	A5
A5	A5
A5	A6
A6	A5
A5	A6
A6	A6
A6	A3
A3	A2
A2	A2
A2	A3
A3	A3
A3	A2
A2	A2
A2	A2
A2	A2
A2	A2
A2	A2
A2	A2
A2	A1

Table 5. FLRG result

Fuzzy set	FLRG							
A2	A2	A3	A2	A2	A2	A2	A2	A1
A3	A2	A3	A2					
A5	A5	A6	A5	A5	A6	A6		
A6	A5	A6	A5	A5	A6	A3		

Transition Frequency Matrix

After the FLRG have been established, the next step is to construct the transition frequency matrix, which illustrates how often transitions occur from one fuzzy state to another based on historical data. This matrix is presented in a tabular format, where the rows represent the current state, and the columns represent the target (next) state. The values within the cells indicate the frequency of transitions between the corresponding states. For example, if state A2 has transitioned to A3 three times, then the value in cell (A2, A3) would be 3. This matrix provides a quantitative insight into the movement patterns between fuzzy states over time and serves as the foundation for calculating transition probabilities in the next step. It essentially shows how many times each fuzzy set transitioned to another fuzzy set within the fuzzified historical dataset. The following is the resulting transition frequency matrix:

Table 6. Transition frequency matrix result

Transition Frequency Matrix					
1	3	0	0	0	0
3	3	0	0	0	0
0	0	0	0	0	0
0	0	0	0	2	0
0	0	0	2	6	1
0	0	0	0	0	0

Transition Probability Matrix

After obtaining the results from the Transition Frequency Matrix, the next step is to calculate the Transition Probability Matrix. This matrix reflects the likelihood of transitions between one fuzzy set and another based on historical data. It is derived by calculating the proportion (probability) of each transition relative to the total number of transitions in the same row of the frequency matrix. For example, to determine the probability of transition from A2 to A3, the frequency of A2 → A3 is divided by the total number of transitions originating from A2. This process is repeated for each row to generate the complete probability matrix. The Transition Probability Matrix plays a crucial role in forecasting, as it identifies the most probable fuzzy state for the next period. The higher the transition probability, the more likely it is that the prediction will favor that state. The following is the resulting Transition Probability Matrix:

Table 7. Transition probability matrix result

Transition Probability Matrix					
0.2500	0.7500	0	0	0	0
0.5000	0.5000	0	0	0	0
0	0	0	0	0	0
0	0	0	0	1.0000	0
0	0	0	0.2222	0.6667	0.1111
0	0	0	0	0	0

Defuzzification

The final stage in the Fuzzy Time Series approach is defuzzification, which involves converting the fuzzy forecast results back into precise numerical values. In this study, the method applied is the average of the midpoints of the fuzzy sets present in the resulting FLRG. For instance, if the forecast result is A2 → (A3, A4), and the midpoints of A3 and A4 are 400 and 450 respectively, then the predicted value is obtained by calculating the average: $(400 + 450)/2 = 425$. This method assumes equal weighting for all possible values within the FLRG. However, in more advanced methods, transition probabilities can be used to assign different weights to each fuzzy set in the defuzzification process, allowing for a more refined prediction. Through the entire process—from defining the universe of discourse to defuzzification—the Fuzzy Time Series method provides a quantitative estimate based on linguistic logic and historical data patterns. This is particularly valuable in predicting the number of building permit applications as part of more effective regional development planning. Defuzzification is the step that transforms fuzzy set-based predictions into clear numerical values, and it is the final step in the forecasting process. The goal of defuzzification is to produce a forecast result in the form of an actual number that can be directly compared with real data. The predicted value is obtained using the following formula:

$$y_t = \sum_{j=1}^k P_{ij} \times \text{Mid}(A_j)$$

After obtaining the predicted values, the next step is to calculate the MAPE (Mean Absolute Percentage Error). MAPE is an evaluation method used to measure the accuracy of prediction results. The MAPE value can only be calculated when both actual and predicted values are available in numerical form. To compute the MAPE value, the following formula is used:

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

In this study, MATLAB was used to obtain the forecasting results and calculate the MAPE value. If the resulting MAPE is less than 10%, it can be concluded that the forecasting ability of the proposed method is highly accurate. The following are the predicted values for each month in the year 2024, along with the MAPE result generated using MATLAB.

Table 8. MATLAB

Bulan	Actual Data	Predicted Data	Error
1	55	56.83	3.33%
2	49	50.10	2.24%
3	46	47.20	2.61%
4	54	53.90	0.19%
5	52	51.80	0.38%
6	43	44.60	3.72%

Bulan	Actual Data	Predicted Data	Error
7	44	45.00	2.27%
8	53	52.70	0.57%
9	50	49.50	1.00%
10	42	43.10	2.62%
11	49	52.20	2.45%
12	39	40.00	2.56%
MAPE = 1.99%			

The forecast calculation for January 2024 is 56.83, which was obtained using the following equation.

$$\text{MAPE} = \left| \frac{55 - 55.83}{55} \right| \times 100 = \left| \frac{-1.83}{55} \right| \times 100 = 0.033227 \times 100 = 3.33\%$$

And the overall MAPE value is obtained from the total summation of all monthly errors throughout the year 2024.

$$\text{MAPE} = \frac{3.33 + 2.24 + 2.61 + 0.19 + 0.38 + 3.72 + 2.27 + 0.57 + 1.00 + 2.62 + 2.45 + 2.56}{12} = 1.99\%$$

Based on the forecasting results for the number of building permit applications in 2024 using the Fuzzy Time Series method, the Mean Absolute Percentage Error (MAPE) obtained is 1.99%. This value indicates that the forecasting model has a very low error rate. According to the classification in Table 1 a MAPE value below 10% falls into the “very good” category. Therefore, it can be concluded that the model used is highly effective in predicting the data.

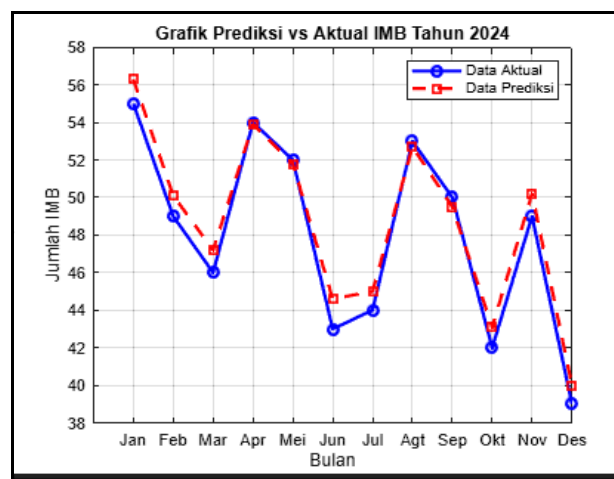


Figure 1. Comparison chart

Figure 2 shows a comparison between the actual data and the predicted number of building permit applications (IMB) for the year 2024 using the Fuzzy Time Series method. The blue line in the graph represents the actual monthly data, while the red line indicates the predicted values. From the graph, it can be observed that the prediction pattern closely follows the trend of the actual data. In almost every month, the predicted values are very close to the actual values, with minimal deviation. This is supported by the quantitative analysis, which produced a MAPE value of 1.99%, indicating a very high level of prediction accuracy. The alignment between the two data lines also demonstrates that the Fuzzy Time Series method is effective in representing data fluctuations, making it a reliable approach for forecasting IMB applications.

4. CONCLUSION

The 2024 prediction of IMB application volume can serve as an initial input in spatial policymaking, although its use remains limited to specific aspects. One actionable policy based on this prediction is the prevention of building density in certain areas, particularly in zones projected to experience a surge in IMB applications. However, for more complex policies such as flood mitigation or traffic congestion management, additional information beyond IMB predictions is required—such as topographic data, infrastructure capacity, mobility patterns, and urban drainage systems.

Therefore, while IMB forecasting is useful as an early indicator of development pressure, more comprehensive spatial policies demand the integration of multi-sectoral data.

Based on the research conducted on forecasting the number of building permit (IMB) applications using the Fuzzy Time Series method, it can be concluded that the Fuzzy Time Series method successfully produced a predictive model that closely follows the historical data patterns, as evidenced by the alignment between the forecasted and actual data for the year 2024. The forecasting process involved several stages, including the construction of the universe of discourse, interval determination, fuzzification, formation of fuzzy logical relationships (FLR), fuzzy logical relationship groups (FLRG), defuzzification, and calculation of MAPE. The obtained Mean Absolute Percentage Error (MAPE) value of 1.99% indicates that the prediction accuracy falls into the "very accurate" category, as it is below the 10% threshold. Despite this success, the study has certain limitations in terms of data, methodology, and technical implementation. Therefore, constructive feedback is highly appreciated.

This method proves to be ideal for predicting time series data that exhibit fluctuating and non-linear patterns, such as building permit application data. For future research, it is recommended to explore higher-order FTS models or to implement adaptive fuzzy time series to capture more dynamic pattern changes. The use of software such as MATLAB greatly aids in systematic fuzzy modeling. It is also suggested to enhance interactive data visualizations to make analysis results easier to interpret. A concrete recommendation is to integrate the predicted IMB application data into the digital licensing system dashboard at DPMPTSP, enabling a zoning map with early warning indicators for areas projected to experience development surges. This visualization would allow policymakers to proactively identify high-risk zones for building density and promptly implement control measures, such as temporary permit restrictions or additional technical evaluations.

REFERENCES

- Agustina, C. (2024). *Penerapan Logika Fuzzy Untuk Peramalan Penjualan Cumi – Cumi Menggunakan Metode Fuzzy Time Series Cheng*. 5(1), 163–172. <https://doi.org/10.30865/klik.v5i1.2105>
- Ahmad, F. (2020). PENENTUAN METODE PERAMALAN PADA PRODUKSI PART NEW GRANADA BOWL ST Di PT.X. *JISI: Jurnal Integrasi Sistem Industri*, 7(1), 31. <https://doi.org/10.24853/jisi.7.1.31-39>
- Alfajriani, A., Wati, M., & Puspitasari, N. (2020). Penerapan Metode Fuzzy Time Series Chen dan Hsu dalam Memprediksi Kunjungan Wisatawan di Museum Mulawarman. *Jurnal Rekayasa Teknologi Informasi (JURTI)*, 4(2), 144. <https://doi.org/10.30872/jurti.v4i2.5802>
- Andika, F., Nurviana, N., & Sari, R. P. (2024). Perbandingan Model Chen dan Lee pada Metode Fuzzy Time Series untuk Peramalan Nilai Tukar Petani (NTP) di Provinsi Aceh. *Jurnal Sains Matematika Dan Statistika*, 10(1), 71. <https://doi.org/10.24014/jsms.v10i1.23463>
- Arfiana, N. M., Alisah, E., & Ismiarti, D. (2022). Penerapan Metode Fuzzy Time Series Chen Orde Tinggi Pada Peramalan Hasil Penjualan (Studi Kasus: KPRI “Serba Guna” Kecamatan Selorejo Kabupaten Blitar). *Jurnal Riset Mahasiswa Matematika*, 1(6), 273–282. <https://doi.org/10.18860/jrmm.v1i6.14561>
- Arvie, D. (2022). Peramalan Import Migas dan Non-migas Menggunakan Metode Fuzzy Time Series Model Cheng. *JATISI (Jurnal Teknik Informatika Dan Sistem Informasi)*, 9(4), 3519–3528. <https://doi.org/10.35957/jatisi.v9i4.2885>
- Citra Utami, H., Agung Cahyadi, T., & Ernawati, R. (2023). Peramalan Harga Batubara Menggunakan Fuzzy Time Series Lee. *Jurnal Sumberdaya Bumi Berkelanjutan*, 2(1), 67–77. <https://ejurnal.itats.ac.id/semitan>
- Fathoni, M. Y., & Wijayanto, S. (2021). Forecasting Penjualan Gas LPG di Toko Sembako Menggunakan Metode Fuzzy Time Series. *Jurnal JUPITER*, 13(2), 87–96. <https://www.academia.edu/download/91366556/489563665.pdf>
- Hafiyaa, N., Virgantari, F., & Widyastiti, M. (2022). Implementasi Metode Fuzzy Time Series Pada Peramalan Harga Emas Di Indonesia. *Interval: Jurnal Ilmiah Matematika*, 2(2), 94–103. <https://doi.org/10.33751/interval.v2i2.6517>
- Hafiz, M. A., & Sriani. (2023). Penerapan Logika Fuzzy Sugeno Untuk Optimasi Stok Biji Kopi Pada Kafe Rooster. *Jurnal Fasikom*, 13(02), 165–172. <https://doi.org/10.37859/jf.v13i02.5460>
- Ipan, Syaripuddin, D. A. N. (2022). Perbandingan Model Chen Dan Model Lee Pada Metode Fuzzy Time Series Untuk Peramalan Produksi Kelapa Sawit Provinsi Kalimantan Timur. *Prosiding Seminar Nasional Matematika, Statistika, Dan Aplikasinya*, 2(1), 28–36. <http://jurnal.fmipa.unmul.ac.id/index.php/SNMSA/article/view/8999%0Ahttps://ejournal.unib.ac.id/index.php/pseudocode/article/view/423>
- Komaria, V., Maidah, N. El, & Furqon, M. A. (2023). Prediksi Harga Cabai Rawit di Provinsi Jawa Timur Menggunakan Metode Fuzzy Time Series Model Lee. *Komputika: Jurnal Sistem Komputer*, 12(2), 37–47. <https://doi.org/10.34010/komputika.v12i2.10644>

- Laily, Y. H., Rakhmawati, F., & Husein, I. (2023). Penerapan Metode Fuzzy Time Series-Markov Chain Dalam Peramalan Curah Hujan Sebagai Jadwal Tanaman Padi. *Jurnal Lebesgue : Jurnal Ilmiah Pendidikan Matematika, Matematika Dan Statistika*, 4(1), 162–174. <https://doi.org/10.46306/lb.v4i1.235>
- Lestari, S., & Yurinanda, S. (2023). Prediksi Pajak Pertambahan Nilai pada Penyediaan Jasa dengan Metode Fuzzy Time Series Model Chen. *Euler : Jurnal Ilmiah Matematika, Sains Dan Teknologi*, 11(2), 267–281. <https://doi.org/10.37905/euler.v11i2.22724>
- Muhammad Wahdeni Pramana, Purnamasari, I., & Prangga, S. (2021). Peramalan Data Ekspor Nonmigas Provinsi Kalimantan Timur Menggunakan Metode Weighted Fuzzy Time Series Lee. *J Statistika: Jurnal Ilmiah Teori Dan Aplikasi Statistika*, 14(1), 1–10. <https://doi.org/10.36456/jstat.vol14.no1.a3747>
- Mustaghfiri, M. H., & Susiloadi, P. (2021). Kualitas Pelayanan Penerbitan Izin Mendirikan Bangunan di Dinas Penanaman Modal dan Pelayanan Terpadu Satu Pintu Kota Surakarta. *Wacana Publik*, 1(1), 99. <https://doi.org/10.20961/wp.v1i1.50893>
- Rahmawati. (2021). Prediction of the Number of Participants BPJS Recipient of Assistance Budget Using the Fuzzy Time Series Cheng Method. *Jurnal Ilmu Matematika Dan Terapan*, 15(2), 373–384.
- Rahmawati, R., Sari, D. E., Rahma, A. N., & Soleh, M. (2021). Prediksi Curah Hujan di PPKS Bukit Sentang Dengan Menggunakan Fuzzy Time Series Ruey Chyn Tsaur. *Jurnal Matematika Integratif*, 17(1), 51. <https://doi.org/10.24198/jmi.v17.n1.32820.51-61>
- Sarbaini, S., Yanti, D., & Nazaruddin. (2023). Prediksi Harga Beras Belida Di Kota Pekanbaru Menggunakan Fuzzy Time Series Cheng. *Jurnal Teknologi Dan Manajemen Industri Terapan*, 2(3), 234–241. <https://doi.org/10.55826/tmit.v2i3.183>
- Sari, F., Mahmud, S. F., & Faisal, R. (2023). Sistem Optimalisasi Pengadaan Alat Kesehatan Menggunakan Metode Fuzzy Time Series. *Jurnal Media Informatika Budidarma*, 7(4), 1766. <https://doi.org/10.30865/mib.v7i4.6405>
- Selasakmida, A. D., Tarno, T., & Wuryandari, T. (2021). Perbandingan Metode Double Exponential Smoothing Holt Dan Fuzzy Time Series Chen Untuk Peramalan Harga Paladium. *Jurnal Gaussian*, 10(3), 325–336. <https://doi.org/10.14710/j.gauss.v10i3.32782>
- Wantoro, A., Syarif, A., Muludi, K., Berawi, K. N., Lampung, U., Indonesia, U. T., & Matching, P. (2020). Penerapan Logika Fuzzy Dan Profile Matching Pada. *Prosiding Seminar Nasional Riset Teknologi Terapan*.
- Wardah, S. (2023). Implementasi Metode Fuzzy Time Series Untuk Meramalkan Jumlah Ekspor Produk Kopi Dari Indonesia. *Industrika : Jurnal Ilmiah Teknik Industri*, 7(2), 127–134. <https://doi.org/10.37090/indstrk.v7i2.1022>
- Yuliyanto, M. R., Wuryandari, T., & Utami, I. T. (2023). Peramalan Pendapatan Bulanan Menggunakan Fuzzy Time Series Chen Orde Tinggi. *Jurnal Gaussian*, 12(1), 61–70. <https://doi.org/10.14710/j.gauss.12.1.61-70>
- Zufria, I., Fadhilah, N., Islam, U., & Sumatera, N. (2024). *PREDIKSI PENJUALAN IKAN DENGAN METODE FUZZY*. 4307(August), 1097–1102.