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A COMPARISON OF FUZZY TIME SERIES CHENG AND CHEN-HSU IN FORECASTING TOTAL AIRPLANE PASSENGERS OF SOEKARNO-HATTA AIRPORT

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ABSTRACT

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In some cases, the demand for flights has increased or decreased unexpectedly. Based on this airport, as a service provider, balance the availability of the service and the needs in the field. To balance all the provided services, the airport needs to predict the total number of passengers that would visit the airport on consecutive days. Thus, a form of time-series forecast is used in this research. We applied fuzzy time series (FTS) to forecast total airplane passengers, where there are several logics in FTS, including FTS Cheng's Logic and FTS Chen-Hsu's Logic. To determine the accuracy of the forecast, use three criteria, namely Root Mean Squared Error (RMSE), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE). In terms of modeling and forecasting data, FTS Chen-Hsu's Logic is better than FTS Cheng's Logic. This is shown in the value of three accuracy criteria of FTS Chen-Hsu's Logic, which are smaller than those of FTS Cheng's Logic. In conclusion, the FTS Chen-Hsu method can be used as a forecasting model for the total number of passenger airplanes at Soekarno-Hatta International Airport.

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1. INTRODUCTION

When traveling, people often use public transportation that is available with a variety of options. Among these public transportation methods, flying with airplanes is one method of transportation that has become a choice for traveling to relatively faraway destinations in a short time [1]. The service place that facilitates the departure or arrival of airplanes namely the airport. In some cases, the demand for flights has increased or decreased unexpectedly [2]. For this reason, the airport, as a service provider, should balance the availability of flight services and the needs in the field.

To determine a value in the future by using time series data, several methods can be used, including ARIMA, Autoregressive, Exponential Smoothing, and Fuzzy Time Series. In some studies, it has proven by using a Fuzzy Time Series (FTS), we can obtain forecast values that are close to the actual values [3], [4], and [5].

The main difference between the conventional time series and FTS is that the values of the former are real numbers while the values of the latter are fuzzy sets [6]. In FTS, there is various logic introduced by many experts that have been used in several research [7], [8], and [9], including the Fuzzy Time Series method with Cheng's[10] and Chen-Hsu's [11] namely FTS Cheng and FTS Chen-Hsu.

In 2008, Cheng proposed a method of FTS to forecast TAIEX [10]. The application of this method has been done by some research[12], [13], and [14]. FTS Cheng is a development of FTS Chen[15]. The difference between FTS Cheng and FTS Chen is in determining the interval and giving weight to each Fuzzy Logical Relationship (FLR). A comparison of these two methods has been done by Cheng and several researchers [16], [17], and [18].

Meanwhile, FTS Chen-Hsu proposed a new method using the first-order and time-variant methods [11]. By using this method, they believed that it could get a higher forecasting accuracy rate for forecasting. Several past researches have proven the method through various applications [19], [20], and [21].

Based on the explanation above, we compare FTS Cheng and FTS Chen-Hsu in forecasting total airplane passengers at Soekarno-Hatta International Airport. The reason we use this airport is that this airport traffic is used as a picture of national aviation traffic conditions since Soekarno-Hatta International Airport is one of the busiest and largest airports in Indonesia. Because these two methods have different steps in adjusting the interval and determining the forecast value, we show which method is better using three criteria: RMSE, MAD, and MAPE. We use the average-based length method [22] to determine the length of interval. Several research had used this method since it has been proven to increase the accuracy of the forecast[23], [24], and [25].

2. RESEARCH METHODS

2.1 Data Collection and Presentation

The data used in this research is the total airplane passengers in Soekarno-Hatta International Airport. The data was taken from January 2006 until June 2022 on the official website of BPS [26]. The plot of the time series is shown in Figure 1.

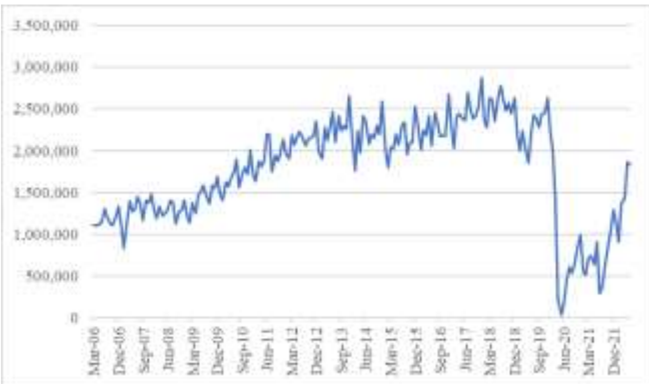

Figure 1. The Plot of Total Airplane Passenger in Soekarno-Hatta International Airport

From the data plot, it is shown that the pattern of time series data forms a trend pattern with a big drop in March 2020 due to decreased demand during COVID-19.

2.2 Algorithm of FTS Cheng

The following are the steps of forecasting using the FTS Cheng method.

1. Define the universe of discourse (U), using **Equation (1)**.

$$U = [X_{min} - D_1, X_{max} + D_2] \tag{1}$$

where D_1 and D_2 are two proper positive numbers.

2. Define the intervals using the average-based length method with the following steps **[22]**:

a. Calculate all $|X_{t-1} - X_t|$ as the first difference and the average of the first difference (m).

b. Take half of the average $\left(\frac{m}{2}\right)$ as the length (p).

c. To determine the base for the length of intervals, use **Table 1**.

Table 1. Base Mapping Table

Range	Base
0.1 – 1.0	0.1
1.0 – 10	1.0
10 – 100	10
100 – 1000	100

Data source: *Effective lengths of intervals to improve forecasting in fuzzy time series*

d. Round the length (p) according to the base from the step before as the length of the interval.

Furthermore, each interval can be defined as follows

$$u_j = (X_{min} - D_1 + p(j-1), X_{min} - D_1 + pj), \tag{2}$$

for $j = 1, 2, \dots, k$ where k is the number of intervals that can be determined by **Equation (3)**,

$$k = \frac{(X_{max} + D_2) - (X_{min} - D_1)}{p}. \tag{3}$$

3. Do adjust the interval if the amount of data in the interval is larger than the average amount of all intervals by dividing the interval into two intervals with the same length.

4. Define the fuzzy set of each data, where the fuzzy set can be written as

$$A_i = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \dots + \frac{\mu_{A_i}(u_j)}{u_j}, \tag{4}$$

where $\mu_{A_i}(u_j)$ is the grade of membership of u_j in fuzzy set A_i**[27]**. To determine each grade of membership, we can use this equation:

$$\mu_{A_i}(u_j) = \begin{cases} 1, & if \quad i = j \\ 0.5, & if \quad i = j-1 \quad or \quad i = j+1, \\ 0, & others. \end{cases} \tag{5}$$

5. Define Fuzzy Logic Relationship (FLR), for example two consecutive fuzzy set $A_i(t-1)$ and $A_j(t)$ can be denoted by $A_i \rightarrow A_j$.

6. Define Fuzzy Logic Relationship Group (FLRG), for example some FLRs written $A_i \rightarrow A_j, A_i \rightarrow A_k$ dan $A_i \rightarrow A_j$ can be written as $A_i \rightarrow 2A_j, A_k$. This number is called weight and will construct a matrix called weight matrix.

$$W = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix} \tag{6}$$

7. Normalized weight matrix ($\boldsymbol{W}^*$) by standardizing each of the elements of the weight matrix by using **Equation (7)**,

$$w_{ij}^* = \frac{w_{ij}}{\sum_{j=1}^{k} w_{ij}} \quad (7)$$

8. Calculate forecast value by multiplying defuzzification matrix $\left(L_{df}\right)$ and normalized weight matrix ($\boldsymbol{W}^*$) using **Equation (8)**,

$$F(t) = L_{df}(t-1) \times W^*(t-1). \quad (8)$$

2.3 Algorithm of FTS Chen-Hsu

The following are the steps of forecasting using FTS Chen-Hsu method.

1. Define the universe of discourse (U), using **Equation (9)**

$$U = [X_{min} - D_1, X_{max} + D_2] \quad (9)$$

where D_1 and D_2 are two proper positive numbers.

2. Define the intervals, using the average-based length method with the following steps **[22]**:

a. Calculate all $|X_{t-1} - X_t|$ as the first difference and the average of the first difference (m).

b. Take half of the average $\left(\frac{m}{2}\right)$ as the length (p).

c. To determine the base for the length of intervals use **Table 1**.

d. Round the length (p) according to the base from the step before as the length of the interval.

Furthermore, each interval can be defined as follows

$$u_j = (X_{min} - D_1 + p(j-1), X_{min} - D_1 + pj) \quad (10)$$

for $j = 1, 2, \dots, k$ where k is the number of intervals that can be determined by **Equation (11)**

$$k = \frac{(X_{max} + D_2) - (X_{min} - D_1)}{p} \quad (11)$$

3. Do adjustment intervals by looking at the amount of all intervals. The interval with the largest amount is divided into four sub-intervals with the same length. Intervals with the second largest amount are divided into three sub-intervals with the same length. Intervals with the third largest amount are divided into two sub-intervals with the same length.

4. Define the fuzzy set of each data, where the fuzzy set can be written as

$$A_{\boldsymbol{i}} = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \dots + \frac{\mu_{A_i}(u_j)}{u_j} \quad (12)$$

where $\mu_{A_i}(u_j)$ is the grade of membership of u_j in fuzzy set A_i**[27]**. To determine each grade of membership, we can use this equation:

$$\mu_{A_i}(u_j) = \begin{cases} 1, & if \quad i = j \\ 0.5, & if \quad i = j-1 \quad or \quad i = j+1 \\ 0, & others \end{cases} \quad (13)$$

5. Define Fuzzy Logic Relationship (FLR), for example two consecutive fuzzy set $A_i(t-1)$ and $A_j(t)$ can be denoted by $A_i \to A_j$.

6. Determine forecast value by calculating $DIFF$ using **Equation (14)**,

$$DIFF = (X_{\boldsymbol{t-2}} - X_{\boldsymbol{t-1}}) - (X_{\boldsymbol{t-3}} - X_{\boldsymbol{t-2}}), \quad (14)$$

And follow the rules:

a. If the observation data doesn't have information of X_{t-3}, then:

i) If $\frac{|X_{t-2}-X_{t-1}|}{2}$ is larger than half of the intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of forecast will be upward, and the forecast value falls at the 0.75-point of this interval.

ii) If $\frac{|X_{t-2}-X_{t-1}|}{2}$ is equal to half of the intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the forecast value falls at the middle value of this interval.

iii) If $\frac{|X_{t-2}-X_{t-1}|}{2}$ is smaller than half of the intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of the forecast will be downward and the forecast value falls at the 0.25-point of this interval.

b. If the $DIFF$ value is positive, then:

i) If $(2DIFF + \mathbf{X_{t-1}})$ or $(\mathbf{X_{t-1}} - 2DIFF)$ falls at intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of the forecast will be upward and the forecast value falls at the 0.75-point of this interval.

ii) If $(DIFF/2 + \mathbf{X_{t-1}})$ or $(\mathbf{X_{t-1}} - DIFF/2)$ falls at intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of the forecast will be downward and the forecast value will fall at the 0.25-point of this interval.

iii) If neither is the case, then the forecasting values will be the middle value of intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$.

c. If the $DIFF$ value is negative, then:

i) If $(DIFF/2 + \mathbf{X_{t-1}})$ or $(\mathbf{X_{t-1}} - DIFF/2)$ falls at intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of the forecast will be downward and the forecast value falls at the 0.25-point of this interval.

ii) If $(2DIFF + \mathbf{X_{t-1}})$ or $(\mathbf{X_{t-1}} - 2DIFF)$ falls at intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$, then the trend of the forecast will be upward and the forecast value falls at the 0.75-point of this interval.

iii) If neither on the case, then the forecasting values will be the middle value of intervals that have a degree of membership equal to 1 at fuzzy set $A(t)$.

2.4 Accuracy Criteria

The forecasting method is used to establish forecasting with a low level of error. The smaller the error value, the better the forecast results or it can be stated that the forecast value is approaching the actual value. For example, the actual value and the forecasting value are symbolized as X_t and F_t, then the criteria accuracy can be written as [28]:

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(X_t - F_t)^2}{n}} \tag{15}$$

Mean Absolute Deviation (MAD)

$$MAD = \frac{1}{n}\sum_{t=1}^{n} |X_t - F_t| \tag{16}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|X_t - F_t|}{X_t} \times 100\% \tag{17}$$

The signification of MAPE is shown in Table 2.

Table 2. The Signification of MAPE

MAPE	Signification
$< 10\%$	Excellent Forecasting Ability
$10 - 20\ \%$	Good Forecasting Ability
$20 - 50\ \%$	Reasonable Forecasting Ability
$> 50\ \%$	Bad Forecasting Ability

From **Table 2**, it can be stated that the smaller the MAPE value obtained, the better the forecasting ability.

3. RESULTS AND DISCUSSION

3.1 Forecasting Using FTS Cheng

1. Define the universe of discourse (U).

$$U = [X_{min} - D_1, X_{max} + D_2] = [36960 - 6960,2875602 + 4398] = [30000,2880000] \tag{18}$$

2. Define the intervals. Using the Average-based Length Method, we obtained the average of the first difference (m) is 186654,70 and half of it is 93327,35. Based on **Table 1**, we get the length of each interval is 90000. By using **Equation (3)**, the universe of discourse (U) is divided into 32 intervals where each interval can be written as follows.

$$u_j = (30000 + 90000(j-1), 30000 + 90000j) \tag{19}$$

for $j = 1, 2, \dots, 32$.

3. Do adjustment interval. From the previous step, it shows that 13 intervals have the amount of data more than the average amount of all intervals (r). Further, each interval is divided into two intervals with the same length. Repeat this step until there is no interval more than the average amount of all intervals (r).
4. Fuzzification. For example, the data of January 2006 (X_1) is in the 16-th interval (u_{16}), so the fuzzy set for X_1 is A_{16}. This method is implemented to all data X_t where $t = 1,2,..n$. Based on this fuzzification process, it can be concluded that the index of the fuzzy set on the data in period t is the interval index on the data in period t, or in other words, if X_t belongs to u_j then the fuzzy set is A_j.
5. Define FLRs. For example, the fuzzification of airplane passenger data for January and February 2006 is A_{16} and A_{10}. These two consecutive fuzzy sets can be formed into an FLR, named $A_{16} \rightarrow A_{10}$, where A_{16} can be named as Left-Hand Side (LHS) and A_{10} can be named as Right-Hand Side (RHS). This method is implemented to all data X_t.
6. Define FLRGs. For example, FLR's that the LHS is A_{13}, which is $A_{13} \rightarrow A_9$, $A_{13} \rightarrow A_{14}$, and $A_{13} \rightarrow A_{17}$ can be combined into an FLRG which can be written as $A_{13} \rightarrow (1)A_9, (1)A_{14}, (1)A_{17}$. This step is applied to all fuzzy sets A_i. The weights obtained from each iteration of the same FLR are combined into a matrix called the weight matrix.
7. Normalized weight matrix. Weight matrix obtained before further normalization, the normalized weight matrix (W^*) can be written as

$$W^* = \begin{pmatrix} 0 & 1 & \cdots & 0 & 0 \\ 0{,}5 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \end{pmatrix} \tag{20}$$

8. Calculate Estimate Value. For example, to determine the estimated value for period of May 2020 (F_{173}), where the fuzzy set of X_{173} is A_2, using **Equation (8)** the estimated value for X_{173} can be written as:

$F(t) = L_{df}(t-1) \times W^*(t-1) = [m_1, m_5] \circ [0.5, 0.5] = [75000, 435000] \circ [0.5, 0.5] = 255000.$

This step is applied to all X_t. For January 2006, the estimated value is NA (Not Available) because calculating the estimated value with FTS Cheng requires information from the previous period.

9. Calculate Forecast Value. To obtain the forecast value of July 2022 until October 2022 by combining the actual data with the estimated value, **Table 3** is obtained.

Table 3. Forecast Value of Total Airplane Passengers Using FTS Cheng

Period	Forecast Value
Jul-22	89487
Aug-22	225033
Sept-22	74054.5
Oct-22	14344

Table 3 shows that the forecast value of total airplane passengers at Soekarno-Hatta Airport using FTS Cheng fluctuates for the next 4 periods.

3.2 Forecasting Using FTS Chen-Hsu

1. Define the universe of discourse (U).

$$U = [X_{min} - D_1, X_{max} + D_2] = [36960 - 6960, 2875602 + 4398] = [30000, 2880000] \quad (21)$$

2. Define the intervals. Using the Average-based Length Method, we obtained the average of the first difference (m) is $186654{,}70$ and half of it is $93327{,}35$. Based on **Table 1**, we get the length of each interval is 90000. By using **Equation (11)**, the universe of discourse (U) is divided into 32 intervals where each interval can be written as follows

$$u_j = (30000 + 90000(j-1), 30000 + 90000j), \quad (22)$$

for $j = 1, 2, \dots, 32$.

3. Do adjustment interval. From previous step, it shows that the first, second, and third intervals with the largest amount of consecutive are u_{25}, u_{24}, and u_{26}. Then u_{25} divides into four subintervals with the same length, u_{24} divides into three subintervals with the same length and u_{26} divides into two subintervals with the same length. The rest intervals remain same.

4. Fuzzification. For all X_t, if the data for period t (X_t) is in the j-th interval (u_j), then the fuzzy set of X_t is A_j.

5. Define FLRs. For example, the fuzzification of airplane passenger data for January and February 2006 is A_{14} and A_{10}. These two consecutive fuzzy sets can be formed into an FLR, named $A_{14} \rightarrow A_{10}$. This method is implemented to all data X_t, thus obtaining two consecutive fuzzy sets for all periods formed into an FLR.

6. Calculate the estimate value. For example, to determine the estimated value of August 2020 (F_{176}), it is known that for data of August 2020 (X_{176}), DIFF is negative and the fuzzy set is A_7. Because the value of $2DIFF + X_{175}$ is located in the u_7, so the estimated value of X_{176} (F_{176}) tends to be upward or is at point of the u_7, which is 637500. This method is implemented to all data X_t. For January & February 2006, the estimated value is not obtained because calculating the estimated value with FTS Chen-Hsu requires information from at least 2 previous periods.

7. Calculate Forecast Value. To obtain the forecast value of July 2022 until October 2022 by combining the actual data with the estimated value, **Table 4** is obtained.

Table 4. Forecast Value of Total Airplane Passengers Using FTS Chen-Hsu

Period	Forecast Value
Jul-22	1785000
Aug-22	1785000
Sept-22	1785000
Oct-22	1785000

Table 4 shows that the forecast value of total airplane passengers at Soekarno-Hatta Airport using the FTS Chen-Hsu is constant for the next 4 periods.

3.3 Forecast Accuracy

After the forecast value is obtained, a plot comparison between the actual value of total airplane passengers and the forecast value using FTS Cheng and Chen-Hsu is shown in **Figure 2**.

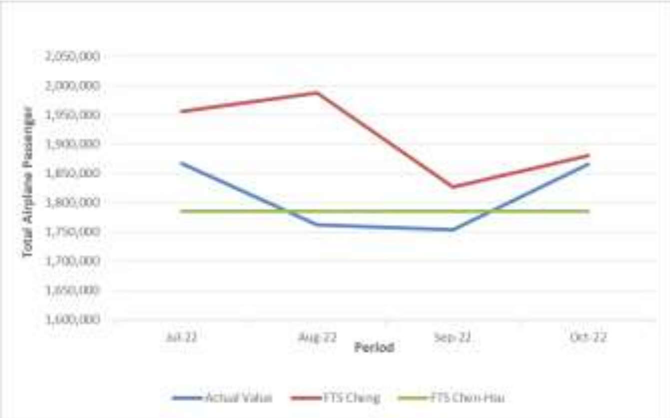

Figure 2. Plot Comparison of Actual Value and Forecast Value

Based on **Figure 2**, the forecast value of FTS Cheng and FTS Chen-Hsu is around the actual value of the total passenger airplanes. To determine which method is the nearest to the actual data, calculate the accuracy of the forecast value using RMSE, MAD, and MAPE.

Table 5. Forecast Accuracy of Total Airplane Passenger

Method	RMSE	MAD	MAPE
FTS Cheng	126.824	67.153	5.64%
FTS Chen-Hsu	60.775	36.199	2.95%

Table 5 shows that the value of three accuracies (RMSE, MAD, and MAPE) of FTS Cheng and Chen-Hsu are smaller than FTS Chen-Hsu. It can also be said that FTS Chen-Hsu has a smaller error than FTS Cheng.

4. CONCLUSIONS

In terms of forecasting the total number of passenger airplanes in Soekarno-Hatta International Airport, FTS Chen-Hsu is better than FTS Cheng. It shows that based on the three accuracies, which are RMSE, MAD, and MAPE, FTS Chen-Hsu has a smaller error than FTS Cheng. These results show that the FTS Chen-Hsu method can be used as a forecasting model for the total number of passenger airplanes in Soekarno-Hatta International Airport with a low level of error, or it can be stated that the forecast value is approaching the actual value.

REFERENCES

[1] "Bepergian dengan Pesawat Disebut Paling Aman, Ini Datanya Halaman all - Kompas.com." Accessed: Oct. 30, 2023. [Online]. Available: https://internasional.kompas.com/read/2019/03/11/20212381/bepergian-dengan-pesawat-disebut-paling-aman-ini-datanya?page=all

[2] "Semester I 2022, Jumlah Penumpang di Bandara Soekarno - Hatta Melonjak jadi 18,15 Juta - Bisnis Tempo.co." Accessed: Oct. 30, 2023. [Online]. Available: https://bisnis.tempo.co/read/1617866/semester-i-2022-jumlah-penumpang-di-bandara-soekarno-hatta-melonjak-jadi-1815-juta

[3] C. D. I. Suryaningrum, N. Yudistira, and K. Rahman, “Perbandingan Metode Fuzzy Time Series Average-Based Interval dan Long Short-Term Memory untuk Peramalan Harga Komoditi Kopi Arabika Sumatera Utara,” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer e-ISSN*, vol. 2548, p. 964X, 2022.
[4] S. Rima. Amatullah, “Perbandingan Metode Dekomposisi dan Metode Fuzzy Time Series Untuk Peramalan Jumlah Penumpang Kereta Stasiun Bogor,” Feb. 2023.
[5] E. Lesmana, N. Anggriani, Sukono, Fatimah, and A. T. Bon, “Comparison of double exponential smoothing holt and fuzzy time series methods in forecasting stock prices (case study: PT bank central Asia Tbk),” in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, 2019.
[6] Q. Song and B. S. Chissom, “Forecasting enrollments with fuzzy time series—Part I,” *Fuzzy Sets Syst*, vol. 54, no. 1, pp. 1–9, 1993.
[7] N. Ritha, T. Matulatan, and R. Hidayat, “Penerapan Fuzzy Time Series Stevenson Porter pada Peramalan Pergerakan Nilai Forex,” *Seminar Nasional Inovasi Teknologi*, no. Query date: 2022-10-05 09:20:54, 2020.
[8] A. Hayatunnufus, I. Purnamasari, and S. Prangga, “Peramalan Menggunakan Fuzzy Time Series Berbasis Algoritma Novel,” *STATISTIKA Journal of Theoretical Statistics and Its Applications*, vol. 21, no. 2, 2022, doi: 10.29313/statistika.v21i2.336.
[9] I. Manfaati Nur, A. Pietoyo, E. Asmaul Basir, M. Semarang, P. Kelautan dan Perikanan Pangandaran, and B. Perikanan Budidaya Laut Ambon, “Implementasi Metode Fuzzy Time Series Singh Pada Peramalan Banggai Cardinalfish di Balai Perikanan Budidaya Laut Ambon,” *Prosiding Seminar Nasional Venue Artikulasi-Riset, Inovasi, Resonansi-Teori, dan Aplikasi Statistika (VARIANSI)*, vol. 2, no. 1, pp. 138–148, Mar. 2021, Accessed: Oct. 30, 2023. [Online]. Available: https://ojs.unm.ac.id/variansistatistika/article/view/19492
[10] C.-H. Cheng, T.-L. Chen, H. J. Teoh, and C.-H. Chiang, “Fuzzy time-series based on adaptive expectation model for TAIEX forecasting,” *Expert Syst Appl*, vol. 34, no. 2, pp. 1126–1132, 2008.
[11] S.-M. Chen and C.-C. Hsu, “A new method to forecast enrollments using fuzzy time series,” *International Journal of Applied Science and Engineering*, vol. 2, no. 3, pp. 234–244, 2004.
[12] T. Tursina, R. Septiriana, and I. Varian, “Prediksi Indeks Harga Konsumen Menggunakan Metode Fuzzy Time Series Cheng,” *Jurnal Locus Penelitian dan Pengabdian*, vol. 2, no. 1, pp. 51–59, 2023.
[13] M. Y. Fathoni, “Implementasi Metode Fuzzy Time Series Cheng untuk prediksi Kosentrasi Gas NO2 Di Udara,” *Jurnal Sistem Informasi Bisnis*, vol. 07, pp. 17–23, 2017.
[14] S. Inayati, Y. Yuliana, and A. Hanafiah, “Prediksi Jumlah Peserta BPJS Penerima Bantuan Iuran (PBI) APBN Menggunakan Metode Fuzzy Time Series Cheng,” *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 15, no. 2, pp. 373–384, 2021.
[15] S.-M. Chen, “Forecasting enrollments based on fuzzy time series,” *Fuzzy Sets Syst*, vol. 81, no. 3, pp. 311–319, 1996.
[16] D. Yustitia, “Perbandingan Metode Fuzzy Time Series Chen dan Fuzzy Time Series Cheng Pada Permintaan Pupuk Pertanian Urea di Kabupaten Blora,” *Repasitori Universitas Muhammadiyah Semarang*, 2019.
[17] Arnita, N. Afnisah, and F. Marpaung, “A Comparison of the Fuzzy Time Series Methods of Chen, Cheng and Markov Chain in Predicting Rainfall in Medan,” in *Journal of Physics: Conference Series*, 2020. doi: 10.1088/1742-6596/1462/1/012044.
[18] G. Change *et al.*, “Perbandingan Metode Fuzzy Chen, Fuzzy Cheng dan Fuzzy Markov Chain Pada Peramalan Harga Pasar Bahan Pokok di Kabupaten Lamongan,” *Paper Knowledge . Toward a Media History of Documents*, vol. 3, no. 2, 2021.
[19] A. Alfajriani, M. Wati, and N. Puspitasari, “Penerapan Metode Fuzzy Time Series Chen dan Hsu dalam Memprediksi Kunjungan Wisatawan di Museum Mulawarman,” *Jurnal Rekayasa Teknologi Informasi (JURTI)*, vol. 4, no. 2, pp. 144–153, 2020.
[20] R. Rahmawati, M. R. R. Putra, and F. Muttakin, “Prediksi Jumlah Pengunjung Perpustakaan Daerah Kabupaten Batang dengan Menggunakan Metode Fuzzy Time Series Chen-Hsu,” *Journal of Mathematics UNP*, vol. 8, no. 1, pp. 110–119, 2023.
[21] Zaenurrohman, S. Hariyanto, and T. Udjiani, “Fuzzy time series Markov Chain and Fuzzy time series Chen & Hsu for forecasting,” in *Journal of Physics: Conference Series*, 2021. doi: 10.1088/1742-6596/1943/1/012128.
[22] K. Huarng, “Effective lengths of intervals to improve forecasting in fuzzy time series,” *Fuzzy Sets Syst*, vol. 123, no. 3, pp. 387–394, 2001.
[23] E. D. Wuryanto and N. V. I. Puspita, “Model Average-Based Fuzzy Time Series untuk Prediksi Perkembangan Kasus Terkonfirmasi Positif COVID-19,” *Jurnal Informatika Upgris*, vol. 7, no. 2, 2021.
[24] S. Solikhin and U. Yudatama, “Fuzzy Time Series dan Algoritme Average Based Length untuk Prediksi Pekerja Migran Indonesia,” *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 6, no. 4, pp. 369–376, 2019.
[25] A. A. Pramesti, W. Sulandari, S. Subanti, and Y. Yudhanto, “Forecasting the Composite Stock Price Index Using Fuzzy Time Series Type 2: Peramalan Indeks Harga Saham Gabungan dengan menggunakan Metode Fuzzy Time Series Tipe 2,” *RADIANT: Journal of Applied, Social, and Education Studies*, vol. 4, no. 2, pp. 118–133, 2023.
[26] “Badan Pusat Statistik.” Accessed: Oct. 30, 2023. [Online]. Available: https://www.bps.go.id/indicator/17/66/1/jumlah-penumpang-pesawat-di-bandara-utama.html
[27] F. Susilo, *Himpunan dan logika kabur serta aplikasinya*. 2006.
[28] D. C. Montgomery, C. L. Jennings, and M. Kulahci, *Introduction to time series analysis and forecasting*. John Wiley & Sons, 2015.