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COMPARISON OF DOUBLE EXPONENTIAL SMOOTHING AND FUZZY TIME SERIES MARKOV CHAIN IN FORECASTING FOREIGN TOURIST ARRIVALS

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ABSTRACT

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Foreign tourist arrivals are one of the factors that make a positive contribution to a country's economy, especially the addition of foreign exchange. This activity is important for the tourism industry and the government to make policies for progress in the tourism sector. This research aims to forecast data on foreign tourist arrivals, especially land routes. This data set, which is a monthly time series covering the period from January 2018 to October 2023, is sourced from the Central Statistics Agency (BPS). The DES technique is a method that quickly adapts to changes in data patterns and can lessen the impacts of random fluctuations, resulting in more stable estimates. Meanwhile, the FTS-MC approach can handle large data variations by utilizing fuzzy sets. Furthermore, combining fuzzy time series with Markov Chains increases forecast accuracy by taking into account state transitions and probability. The research demonstrates that the DES method produces the MAPE value of 0.108530 or 10% which is obtained from the alpha value of 0.9 and beta 0.2. The MAPE 0.108530 means that the ability of the forecasting model is classified as a good category. In the FTS-MC method, the forecast data is close to the actual data. This is indicated by the MAPE value obtained of 0.086850 or 8%, which means that the ability of the forecasting model is very good. Based on the analysis of the two methods, it is concluded that the FTS-MC method is better applied to data on land-based foreign tourist arrivals.

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1. INTRODUCTION

Foreign tourist arrivals are one of the indicators that determine the development of the tourism sector in a country. Increased tourist arrivals will contribute positively to the country's economy. Tourists spend money on accommodation, transportation, food, and various other tourist activities, thus providing a boost to the local economic sector [1]. Besides, the positive impact in the creation of direct and indirect employment. Travel agents, lodging, dining, and various other tourist services require labor to serve tourists in each tourist destination [2], [3]. Furthermore, foreign tourist arrivals have an impact on the exchange rate [4].

Based on data from the Ministry of Tourism and Creative Economy, from 2016 to 2019 foreign tourist arrivals have always increased. There was a decline in 2020 and 2021 which was caused by COVID-19. After the COVID-19 period passed, foreign tourist arrivals increased dramatically again in 2022. Therefore, the tourism industry and government need data information, data analysis, and forecasting of foreign tourist arrivals. This information can be utilized by the tourism industry and the government as a basis for making effective policies in terms of increasing foreign exchange through the tourism sector [5]. One approach is the gastro-diplomacy strategy, which is a branch of diplomacy that engages food as an instrument of diplomacy [6].

Some researchers have analyzed the forecasting of foreign tourist arrivals with several methods. Among them are Tomas Havranek's research applying Google Trends meets mixed-frequency data and other research by applying the Digitization method, exponential smoothing method, and Autoregressive Integrated Moving Average (ARIMA) [7], [8], [9], [10]. In this study, one method is selected that is considered practical but produces forecasts that are close to the actual data, namely the exponential smoothing method. Then finally, this method is compared with the Fuzzy Time Series (FTS) method.

The exponential smoothing method selected based on the research of Hudiyanti et al. applies a comparison of the Double Moving Average (DMA) and Double Exponential Smoothing (DES) methods. The forecasting results explain that the DES method results in better model accuracy than DMA [11]. In the case of forecasting the number of airplane passengers during COVID-19, the DES method also resulted in quite good forecasting [12]. Meanwhile, the Box-Jenkins method, namely the ARIMA model to generate a model that is close to the actual value, the data must be stationary and fulfill the white noise assumption [13], [14]. When time series data experiences seasonal patterns, the Box-Jenkins method is no longer effective, so the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is the solution to this problem [15], [16], [17].

Fuzzy Time Series (FTS) is the application of fuzzy mathematics to time series data, where the data does not need to be stationary and fulfills the white noise assumption [18]. Until now, the FTS method has many developments including the Chen model, Li and Cheng model, Cheng model, Weighted model, and Markov model [19]. These models attempt to perform the forecasting process so that the results obtained are close to the actual data. However, the results show that the Fuzzy Time Series Markov Chain (FTS-MC) model provides quite good accuracy compared to the FTS proposed by Song and Chissom, Singh, Li and Cheng, Cheng et al [20]. In addition, Tsaur's research analyzed the accuracy of predicting the Taiwanese currency exchange rate with the US dollar [21]. The FTS-MC method is a development of the classic FTS method combined with the Markov chain process. The Markov chain process calculates the transition probability matrix used as the basis for forecasting calculations, so FTS-MC can provide better results than other methods.

The novelty of this research is that it uses the FTS-MC method which can overcome high data fluctuations through the use of fuzzy sets. Meanwhile, the Markov chain uses historical data to determine transition probabilities, so it is equipped to effectively utilize past information in future predictions. Furthermore, the DES method can rapidly adjust to trend changes in the data, as it dynamically updates the level and trend components in each period. On the other hand, DES can reduce the effect of random fluctuations that may appear in the data, providing a more stable estimate. Depending on the characteristics of each method, this research aims to identify the best model through a comparison of the two methods based on the best accuracy values, measured by the smallest MAPE for each method. The research results are expected to be a reference for policy-making by the government in the tourism industry sector. In addition, it can be considered for the tourism industry sector, especially in the accommodation, transportation, culinary and other parts.

2. RESEARCH METHODS

The data collection technique used is the documentation technique, where data on foreign tourist arrivals is taken from the Central Statistics Agency (BPS). So, the data is secondary data with a monthly period starting from January 2018 to October 2023. The several ways of data collection conducted by BPS include (1) cooperation with the Directorate General of Immigration, (2) tourist surveys, (3) the use of third parties such as travel agents and other tourism industry associations, and (4) official reporting from local governments or tourism offices in various provinces and cities, which are then compiled and analyzed. The limitation of this research is analyzing the foreign tourist arrivals by land. This research was conducted using Minitab and R-Studio software using DES and FTS-MC methods. The following is an illustration of the stages of the model through a flow chart.

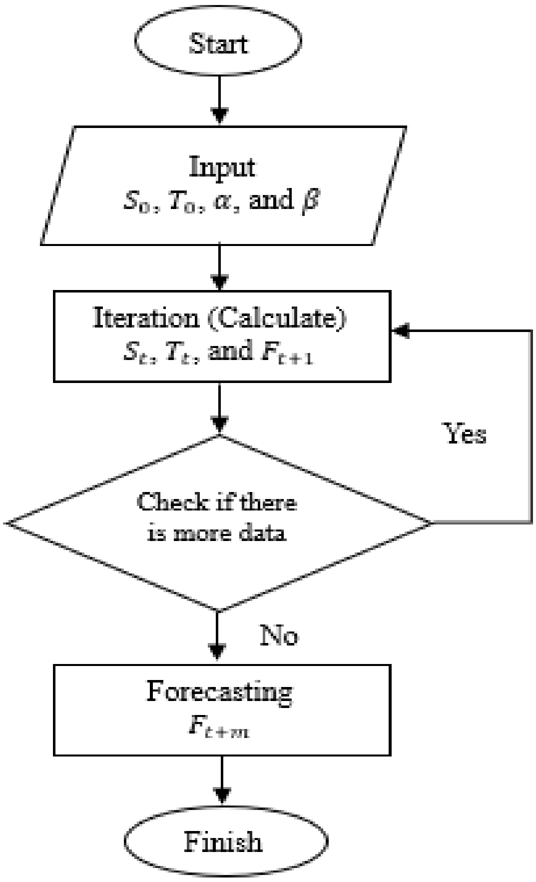

Figure 1. The Flow Chart DES Method

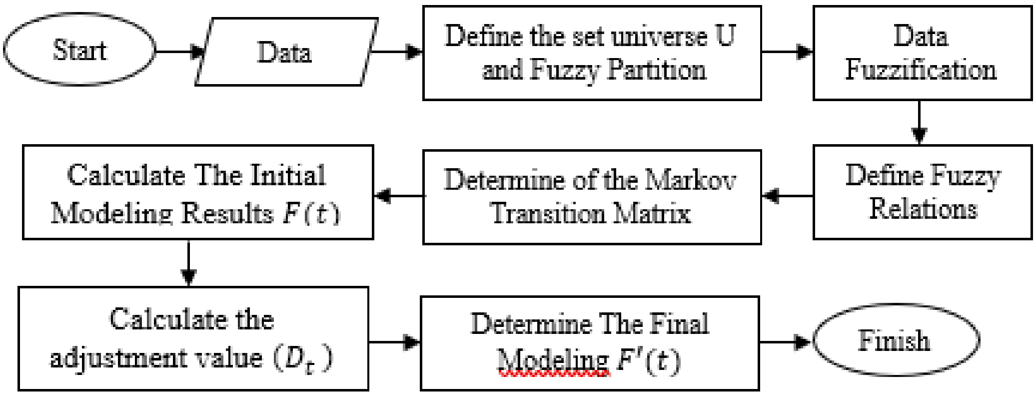

Figure 2. The Flow Chart FTS-MC Method

The explanation of both flowcharts above will be discussed in the following subchapters.

2.1 Double Exponential Smoothing (DES)

The Double Exponential Smoothing (DES) method builds on the Single Exponential Smoothing (SES) method by grouping existing trend data. Thus, the forecasting smoothing in this method is divided into two, namely trend forecasting and data forecasting smoothing. The equations for forecasting trends and data are as follows [12].

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} - T_{t-1}) \quad (1)$$

$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \quad (2)$$

$$F_{t+m} = S_t + T_t m \quad (3)$$

with:

α : Smoothing parameter for the level ($0 < \alpha < 1$).
β : Smoothing parameter for the trend ($0 < \beta < 1$).
X_t : The actual data at the time t.
S_t : Level component at the time t.
T_t : Trend component at the time t.
F_{t+m} : Forecast for m periods ahead of time t.

2.2 Fuzzy Time Series Markov Chain (FTS-MC)

The data that has been collected was analyzed through the following steps [18].

1) Defining the universe set $U = [D_{min} - D_1, D_{max} + D_2]$, by first determining the minimum (D_{min}) and maximum (D_{max}) values of the historical data. Then, the researcher determines the values of D_1 and D_2 freely provided that both values are positive real numbers.

2) Application of Sturges formula to determine the number of intervals in the universe set U and the length of intervals $l = \frac{[(D_{max} + D_2) - (D_{min} - D_1)]}{n}$. Each interval can be determined by $u_n = [B + (n-1)l\,;\ \mathrm{B} + nl]$ where $B = D_{min} - D_1$.

3) Determination of fuzzy sets for the entire universe U with rules:

    a) If the historical data (Y_t) is u_i, then the membership degree of u_i is 1, u_{i+1} is 0.5 and others are 0.

    b) If the historical data (Y_t) is u_i, $1 < i < n$ then the membership degree of u_i is 1, u_{i-1} dan u_{i+1} are 0.5 and others are 0.

    c) If the historical data (Y_t) is u_n, then the membership degree of u_n is 1, u_{n-1} is 0.5 and others are 0.

    So, the fuzzy set for the entire universe U can be expressed as follows:

$$\begin{gathered} A_1 = \frac{1}{u_1}, \frac{0.5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \dots, \frac{0}{u_n}; \\ A_2 = \frac{0.5}{u_1}, \frac{1}{u_2}, \frac{0.5}{u_3}, \frac{0}{u_4}, \dots, \frac{0}{u_n}; \\ A_3 = \frac{0}{u_1}, \frac{0.5}{u_2}, \frac{1}{u_3}, \frac{0.5}{u_4}, \dots, \frac{0}{u_n}; \\ \vdots \\ A_n = \frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \dots, \frac{0.5}{u_{n-1}}, \frac{1}{u_n} \end{gathered} \quad (4)$$

4) Fuzzification of historical data. If the collected historical data belongs to the interval u_i, then the data is fuzzified into A_i.

5) Determine the fuzzy logical relationship (FLR)

Definition 1. [21] Let $F(t-1) = A_i$ and $F(t) = A_j$. The relationship between two consecutive observations, $F(t)$ and $F(t-1)$, referred to as a fuzzy logical relationship (FLR), can be denoted by $A_i \rightarrow A_j$, where A_i is called the lefthand side (LHS) and A_j the right-hand side (RHS) of the FLR.

Definition 2. [21] All fuzzy logical relationships in the training dataset can be further grouped together into different fuzzy logical relationship groups according to the same left-hand sides of the fuzzy logical relationship. For example, there are two fuzzy logical relationships with the same left-hand side (A_i): $A_i \rightarrow A_{j1}$ and $A_i \rightarrow A_{j2}$. These two fuzzy logical relationships can be grouped into a fuzzy logical relationship group.

6) Determination of Markov transition probability matrix with transitional probabilities for states, $P_{ij} = \frac{M_{ij}}{M_i}, i,j = 1,2,3,\ldots,n\,;$ P_{ij} is the transition probability from state to one step, M_i is the amount of data from the state and M_{ij} is the transition time from state to one step. The transition probability matrix R of a state space is written as follows **[20]**.

$$R = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{5}$$

7) Calculate the initial modeling results with the following steps:

   a) If the FLRG of A_i transitions to the empty set $(A_i \rightarrow \phi)$, then the modeling result of F_t is m_i, which is the mean of u_i with the **Equation (6)**,
   $$F(t) = m_i \tag{6}$$
   b) If the FLRG of A_i transitions one to one ($A_i \rightarrow A_k$ with $P_{ij} = 0$ and $P_{ik} = 1, j \neq k$), then the modeling result of $F(t)$ is m_k, which is the mean value of u_k with the **Equation (7)**,
   $$F(t) = m_k P_{ik} = m_k \tag{7}$$
   c) If the FLRG of A_j transitions one to many $(A_j \rightarrow A_1, A_2, \ldots, A_n\ , j = 1,2,\ldots,n)$ and the data set $X(t-1)$ at time $t-1$ is in state A_j, then the modeling result F_t is as follows
   $$F(t) = m_1 P_{j1} + m_2 P_{j2} + \ldots + m_{j-1} P_{j(j-1)} + X(t-1) P_{jj} + m_{j+1} P_{j(j+1)} + \ldots + m_n P_{jn} \tag{8}$$
   where $m_1, m_2, \ldots, m_{j-1}, m_{j+1}, \ldots, m_n$ is the midpoint of $u_1, u_2, \ldots, u_{j-1}, u_{j+1}, \ldots, u_n$ and m_j is substituted into $X(t-1)$ to obtain the information of the state A_j at $t-1$.

8) Calculate the adjustment value (D_t) of the modeling (Adjusted Value) to correct the error caused by the biased Markov Chain matrix with the following rules;

   a) If the state A_i transitions with A_j , starting from state A_i at time $t-1$ as $F(t-1) = A_i$ and there is an upward transition to the state A_j at time t, $(i < j)$ then the adjustment value D_t is $D_{t1} = (l/2)$.

   b) If the state A_i transitions with A_j , starting from state A_i at time $t-1$ as $F(t-1) = A_i$ and there is a downward transition to the state A_j at time t, $(i < j)$ then the adjustment value D_t is $D_{t1} = (l/2)$.

   c) If the state A_i at time $t-1$ as $F(t-1) = A_i$ and there is a jump forward transition to state A_{i+s} at time t, $1 \leq s \leq n-i$, then the adjustment value of D_t is $D_{t2} = (l/2)s$, where s is the number of jump-forward transitions.

   d) If the state A_i at time $t-1$ as $F(t-1) = A_i$ and there is a backward transition jump to the state A_{i-v} at time t, $1 \leq v \leq i$, then the adjustment value of D_t is $D_{t2} = -(l/2)v$, where v is the number of backward transition jumps.

9) Determine the final modeling
$$F'(t) = F(t) \pm D_{t1} \pm D_{t2} \tag{9}$$

The error calculation can be used to see how accurate the modeling data is with the actual data. The smaller the value resulting from the error measure, the better the modeling model used. The measure of modeling accuracy used is the Mean Absolute Percentage Error (MAPE) **[22]**.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - \hat{X}_t|}{X_t} \times 100\% \tag{10}$$

with:
X_t : The actual data at the time t.
$\hat{X}_t$: The forecast data at the time t.
n : Sample size.
MAPE value categories are shown in **Table 1**.

Table 1. MAPE Value Category Table

Range MAPE	Interpretation
< 10%	Highly Accurate
10% – 20%	Accurate
20% – 50%	Reasonable
> 50%	Inaccurate

3. RESULTS AND DISCUSSION

3.1 Double Exponential Smoothing

The Double Exponential Smoothing (DES) method has two parameters, namely alpha and beta parameters. The alpha and beta values used in the model should be between 0 and 1. This test is done by trial and error. Then, determine the initial level S_0 and the initial trend T_0. S_0 is the first actual data and T_0 is the difference between the second and first actual data. Iterate on the time series data, for each period t, calculate the new level S_t using **Equation (1)** and update the trend T_t using **Equation (2)**. The last step is to use **Equation (3)** to predict future values. The following are the candidate models from Double Exponential Smoothing (DES).

Table 2. Comparison of MAPE Values for The Candidate Models from DES

Data	DES Models	
	Parameter	MAPE
The Foreign Tourist Arrival by Land	$\alpha = 0.7$; $\beta = 0.1$	0,11551
	$\alpha = 0.7$; $\beta = 0.2$	0,11078
The Foreign Tourist Arrival by Land	$\alpha = 0.7$; $\beta = 0.3$	0,11352
	$\alpha = 0.8$; $\beta = 0.1$	0,11290
	$\alpha = 0.8$; $\beta = 0.2$	0,10892
	$\alpha = 0.8$; $\beta = 0.3$	0,11059
	$\alpha = 0.9$; $\beta = 0.1$	0,11128
	$\boldsymbol{\alpha = 0.9}$; $\boldsymbol{\beta = 0.2}$	**0,10853**
	$\alpha = 0.9$; $\beta = 0.3$	0,11034

The results in **Table 2** show that the greater the value of the alpha parameter, then the smaller the MAPE value. In contrast to the value of the beta parameter, the smallest value of MAPE is obtained when $\beta = 0.2$. Therefore, based on several combinations of alpha and beta parameters, the smallest value of MAPE is obtained when $\alpha = 0.9$ and $\beta = 0.2$. The comparison of actual and forecast data is presented in **Figure 3**, where the forecasting results do not drift significantly away from the actual data. This indicates that the forecasting results using this model produce good forecasting (accurate) because the MAPE value of 10.853% is below 20%.

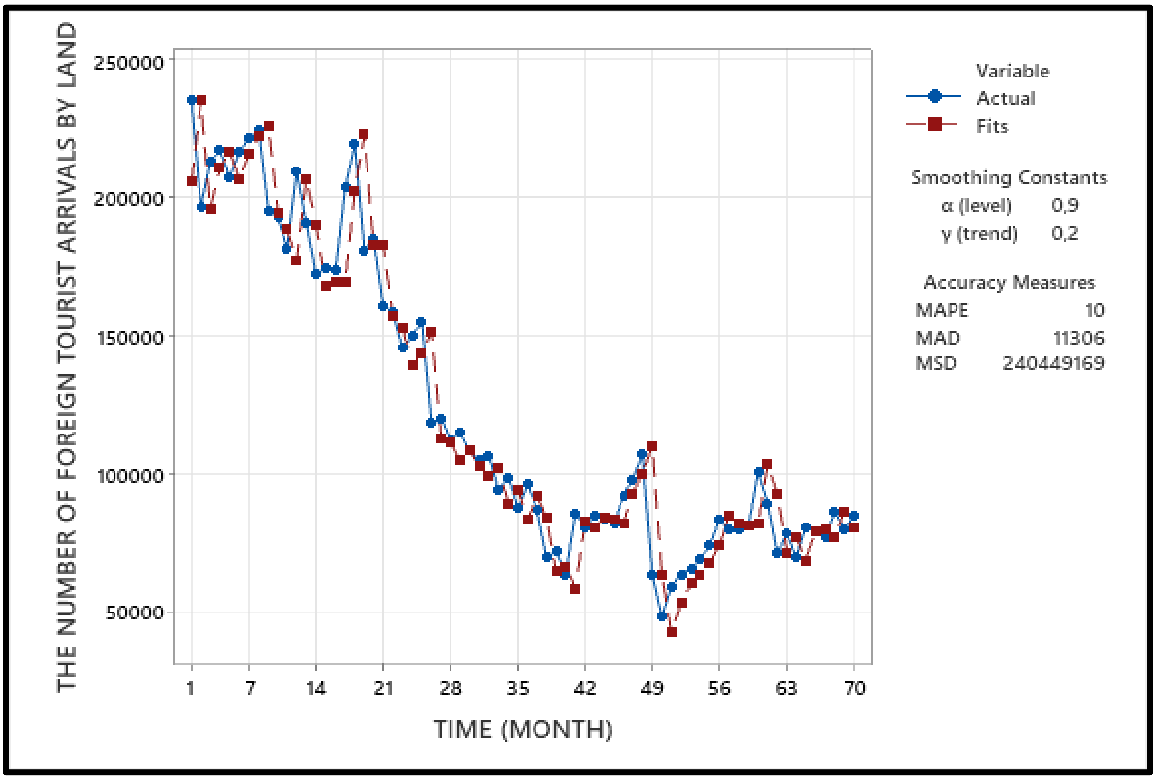

Figure 3. DES Model Using $\alpha = 0.9$ and $\beta = 0.2$

3.2 Fuzzy Time Series Markov Chain

The first step is to determine the minimum value D_{min} and maximum value D_{max}. D_{min} and D_{max} are 48136 and 234618, respectively. The universe set $U = [D_{min} - D_1, D_{max} + D_2] = [48130, 234620]$, where $D_1 = 6$ dan $D_2 = 2$. The universe set U is partitioned into parts with equal intervals (n), using the Sturges formula. Then, determine the length of the interval based on step 2. So that U into seven intervals, u_1, u_2, u_3, u_4, u_5, u_6 dan u_7. Meanwhile,

$u_1 = [48130.00; 74771.43]$, $u_2 = [74771.43; 101412.86]$,
$u_3 = [101412.86; 128054.29]$, $u_4 = [128054.29; 154695.71]$,
$u_5 = [154695.71; 181337.14]$, $u_6 = [181337.14; 207978.57]$,
$u_7 = [207978.57; 234620.00]$.

Define the fuzzy set A_i using the linguistic variable. All the fuzzy sets A_i $(i = 1,2, \dots,7)$ are expressed as follows:

$$A_1 = \frac{1}{u_1} + \frac{0.5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_2 = \frac{0.5}{u_1} + \frac{1}{u_2} + \frac{0.5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_3 = \frac{0}{u_1} + \frac{0.5}{u_2} + \frac{1}{u_3} + \frac{0.5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0.5}{u_3} + \frac{1}{u_4} + \frac{0.5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7}$$
$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0.5}{u_4} + \frac{1}{u_5} + \frac{0.5}{u_6} + \frac{0}{u_7}$$
$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0.5}{u_5} + \frac{1}{u_6} + \frac{0.5}{u_7}$$
$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0.5}{u_6} + \frac{1}{u_7}$$

Then, the fuzzification process is carried out to determine the linguistic intervals of the actual data. Shown in **Table 3**.

Table 3. Fuzzification Process

t	Month	Actual Data	Fuzzy Data
1	Jan 2018	234618	A_7
2	Feb 2018	196019	A_6
3	Mar 2018	212932	A_7
⋮	⋮	⋮	⋮
68	Aug 2023	85993	A_2
69	Sep 2023	79938	A_2
70	Oct 2023	84774	A_2

Linguistic variables have been defined in each table for the actual data. This means that the actual data is in a fuzzy set. The next stage is to determine the relationship between fuzzy sets by constructing fuzzy logic relations (FLR) in accordance with **Definition 1**. The results obtained are shown in **Table 4**.

Table 4. Fuzzy Logic Relations (FLR)

t	Month	FLR
1	Jan 2018 – Feb 2018	$\emptyset \rightarrow A_7$
2	Feb 2018 – Mar 2018	$A_7 \rightarrow A_6$
3	Mar 2018 – Apr 2018	$A_6 \rightarrow A_7$
⋮	⋮	⋮
68	Jul 2023 – Aug 2023	$A_2 \rightarrow A_2$
69	Aug 2023 – Sep 2023	$A_2 \rightarrow A_2$
70	Aug 2023 - Oct 2023	$A_2 \rightarrow A_2$

Based on **Table 4**, the fuzzy set relationship from month to month can be observed. This relationship can be expressed by $A_i \rightarrow A_j$, where A_i is called the left-hand side (LHS), and A_j is called the right-hand side (RHS) of FLR. If A_i appears before A_j multiple times, group them together. Construct the transition probability matrix R (Markov Chain) with calculate transition probabilities P_{ij} from fuzzy set A_i to A_j. The value of P_{ij} is the comparison between number of transitions A_i to A_j and total number of transitions from A_i. The transition probability matrix R obtained is

$$R = \begin{bmatrix} \frac{8}{12} & \frac{4}{12} & \cdots & \cdots & \cdots & 0 \\ \frac{3}{24} & \frac{20}{24} & \frac{1}{24} & \cdots & \cdots & 0 \\ \frac{1}{8} & \frac{1}{8} & \frac{6}{8} & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \frac{1}{8} & \frac{4}{8} & \frac{3}{8} \end{bmatrix}$$

The following is the calculation of the modeled output. For example, the modeling value of $t = 2$ is

$$F(2) = \frac{2}{8} \cdot m_5 + \frac{2}{8} \cdot m_6 + \frac{4}{8} \cdot m_7 = 228299.93$$

The probability matrix R is used to calculate the initial modeling value (F_t). Meanwhile, the adjustment value (D_t) is obtained by following step 8 constructed in **Table 5**.

Table 5. The Results of The Initial Modeling and The Adjustment Values

T	Month	Actual Data	The initial Modeling Value (F_t)	The adjustment vue (D_t)
1	Jan 2018	234618		
2	Feb 2018	196019	206312.73	-13320.71
3	Mar 2018	212932	201658.50	26641,43
⋮	⋮	⋮	⋮	⋮
68	Aug 2023	85993	76284.53	0
69	Sep 2023	79938	84122.83	0
70	Oct 2023	84774	79077.02	0

By using **Equation 9**, the final modeling values are constructed and listed in **Table 6**. The final stage is the comparison of actual and forecast data presented in the graph in **Figure 4**.

Table 6. The Results of The Final Modeling Value

t	Month	Actual Data	Final Modeling Value (F'_t)
1	Jan 2018	234618	
2	Feb 2018	196019	192992.02
3	Mar 2018	212932	228299.93
⋮	⋮	⋮	⋮
68	Aug 2023	85993	76284.53
69	Sep 2023	79938	84122.83
70	Oct 2023	84774	79077.02

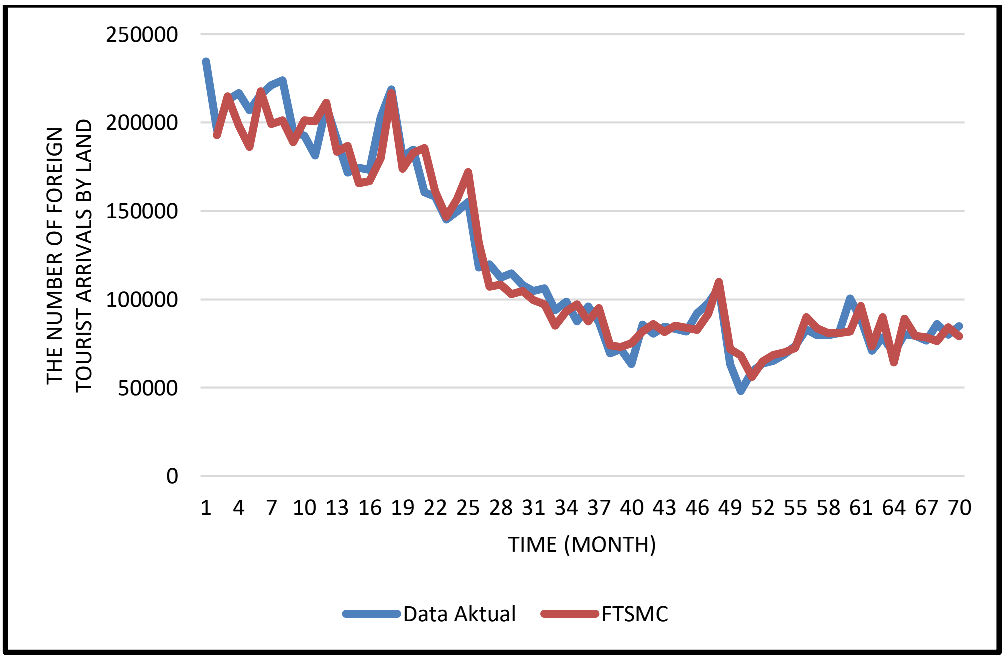

Figure 4. Graph of Actual Data and Forecasting Data

Based on **Figure 4**, it can be seen that the results of the FTS-MC method are almost close to the actual data. It can be concluded that the FTS-MC method can be said to be good at modeling. Furthermore, the MAPE value will be calculated to determine the accuracy of the FTS-MC method and MAPE 0.086850 is obtained.

The accuracy of the forecasting results from FTS-MC compared to DES, is closer to the actual value. This can also be seen from the MAPE value obtained. The MAPE value of the FTS-MC method is smaller than the DES method. The MAPE value obtained with the FTS-MC method 0.086850 is less than 10%, which means the accuracy of the model is very good. Different from the MAPE value obtained by the DES method 0.108530, which ranges from 10% to 20%, meaning that the accuracy of the model is included in the good criteria. Therefore, the FTS-MC method is better at forecasting the results of land-based foreign tourist arrivals.

4. CONCLUSIONS

Based on data analysis of land-based foreign tourist arrivals from January 2018 to October 2023 utilizing the two methodologies, the FTS-MC method outperformed the DES method. This is demonstrated by the MAPE value achieved by FTS-MC, which is lower (0.8%) than the DES method MAPE of 0.10%. As a result, the FTS-MC approach is capable of very accurate predictions. The FTS-MC approach has an advantage in that it combines fuzzy time series with Markov Chains to increase forecasting accuracy by adding state transitions and probability. While the DES approach can swiftly adapt to changes in data patterns and limit the influence of random fluctuations, the FTS-MC method also has these properties. The drawback of this study is that the data used only includes information on the number of land-based foreign tourist arrivals and the year of data collection. Future research can develop both the utilization of data and methodologies.

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