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FORECASTING TOURIST ARRIVALS TO SANGIRAN USING FUZZY WITH CALENDAR VARIATIONS

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ABSTRACT

Fuzzy method has been widely used in time series forecasting. However, the current fuzzy time models have not accommodated the holiday effects so that the forecasting error becomes large at certain moments. Regarding the problem, this study proposes two algorithms, extended of Chen's and seasonal fuzzy time series method (FTS), to consider the holiday effect in forecasting the monthly tourist arrivals to ancient human Sangiran Museum. Both algorithms consider the relationship between Eid holidays as the effect of calendar variations. The forecasting results obtained from the two proposed algorithms are then compared with those obtained from the Chen's and the seasonal FTS. Based on the experimental results, the proposed method can reduce mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) obtained from Chen's method up to 61%, 61%, and 58%, respectively. Moreover, compared to that obtained from the seasonal FTS, the proposed method can reduce the MAE, RMSE, and MAPE values up to 35%, 36%, and 29%, respectively. The method proposed in this paper can be implemented to other time series with seasonal pattern and calendar variation effects.

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INTRODUCTION

Fuzzy logic is useful and has many benefits in its applications in lightening daily human work such as washing machines, air conditioners, vacuum cleaners, antilock braking systems, etc. (Singh et al., 2013). Fuzzy theory and its applications have become a field of interest for many researchers. In medical application, Vlamou and Papadopoulos (2019) have discussed various types of fuzzy systems in early disease diagnosis. Recently, Tayyaba et al. (2020) have developed fuzzy-based devices in a smart home model for navigating blind people. Fuzzy also plays a major role in the field of time series forecasting (see Bas et al., 2021; Egrioglu et al., 2020; Gao & Duru, 2020; Koo et al., 2020).

Fuzzy time series (FTS) was firstly introduced by Song and Chissom (1993b). It was motivated by the ambiguity of human knowledge, which is usually expressed in natural language. FTS model is expressed in terms of the relationship between linguistic variables. FTS has been applied widely after Chen (1996) proposed FTS with a simpler calculation compared to those in Song and Chissom (1993b, 1993a, 1994). Chen (1996) applied FTS to model and forecast a yearly number of enrollments in Alabama University, which had a trend pattern. After that, many researchers developed weighted FTS models, namely Cheng et al. (2008), Lee and Javedani (2011), Lee and Suhartono (2010), and Yu (2005). On the other side, Alpaslan et al. (2012), Cagcag et al. (2013), Liu and Wei (2010), and Sarı (2012) started to combine the FTS with other methods to handle seasonal time series. Liu and Wei (2010) and Sarı (2012) applied moving average ratios to eliminate seasonal patterns before being modeled by FTS. Meanwhile, Alpaslan et al. (2012) and Cagcag et al. (2013) used neural network (NN) in identification the fuzzy relation. Aladag et al. (2012), Lee et al. (2012), and Alpaslan et al. (2012) considered seasonal autoregressive integrated moving average (ARIMA) in determining fuzzy relations. Recently, Sulandari et al. (2020) combined singular spectrum analysis to eliminate more complex seasonal patterns before implemented FTS.

So far, no study has focused on discussing FTS for modeling seasonal time series with the influence of calendar variations. The data with calendar variation effects have periodic and recurring patterns but with varying lengths. This kind of data is usually found in the monthly number of tourist arrivals (Sulandari et al., 2021), hourly electricity load time series (Sulandari et al., 2020), monthly inflow and outflow currency data in Bank Indonesia (Suhartono et al., 2019), inflation and money supply (Sumarminingsih et al., 2018), and monthly sales of clothes (Lee & Hamzah, 2010).

This study proposes a method with two scenarios of FTS algorithms to model and to predict the time series data with calendar variation effect. We implement the two algorithms to the number of visitors to the Sangiran museum. Although there is a large body of literature discussing and recommending ARIMA with dummy variables to deal with the effects of calendar variations (see Anggraeni et al., 2015; Lee & Hamzah, 2010; Ling et al., 2019; Suhartono et al., 2015; Suhartono, 2006), we did not choose to implement this method for two reasons. First, we consider that most time series forecasting contains vagueness, including data on the number of tourist arrivals, as described in Song and Chissom (1993b). Therefore, FTS is needed to accommodate ambiguity in its interpretation. Second, the preliminary study shows that seasonal ARIMA with dummy variables is not appropriate for modeling the data discussed in this paper because it does not meet all the assumptions required in seasonal ARIMA modeling. This is one of the reasons for the limitations of the ARIMA model in its application. On the other hand, FTS is more general. It not only works for modeling the data with linear but also nonlinear relationships. Moreover, it involves the ambiguity of human knowledge.

The proposed method is inspired by the dummy variable added to the ARIMA model in handling the calendar variation effect. We do not combine ARIMA with fuzzy as discussed in Aladag et al. (2012), Lee et al. (2012), and Alpaslan et al. (2012), though in general, the combination of methods offers better results. However, the combinations may require more complicated calculations, which do not necessarily give better results (Makridakis & Hibon, 2000). Therefore, finding a simpler method with high accuracy performance is an interesting challenge to be studied further.

This work proposes a simpler method by expressing the added dummy variable in ARIMA as a new group of fuzzy relationships, namely a group of relationships between holidays. In the implementation, we propose two algorithm scenarios. The idea of the first algorithm is to accommodate the effect of holidays, referring to the Hijri calendar in fuzzy relationship groups that are separate from the groups determined by seasonal patterns as the effect of the Gregorian calendar. Meanwhile, the idea of the second algorithm is almost the same. The difference is that this algorithm also considers the effect of holidays on the Gregorian calendar and defines them into the same groups that describe the effect of holidays on the Hijri calendar. Both of these algorithms are considered capable of increasing the accuracy of forecast results. To determine the effectiveness of the two proposed algorithms, we compared the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error

(MAPE) values of those obtained by Chen's (Chen, 1996) and seasonal FTS methods (Song, 1999). The finding of this study will be the starting point for future research on FTS modeling for data with calendar variation effects.

The organization of this paper is as follows. Section 2 describes the method used in the discussion, namely the proposed method and two other methods as a comparison method, namely Chen's and FTS. The result and discussion are presented in the next section. Section 3 explains the implementation of the two scenarios of algorithms from the proposed method to the data on the number of tourist arrivals at the Sangiran museum. Some examples of determining fuzzy relations and calculating forecast values are given as illustrations. Finally, the conclusion is presented in section 4.

METHOD

Here we provide the algorithm of Chen's FTS (Chen, 1996), Song and Chissom's (1999) seasonal FTS, and our two proposed methods. As stated in Song and Chissom (1993a, 1993b), FTS represented its model by the relationship between the successive fuzzy value. For the convenience of further discussion, let we notate $Y(t)$ and $F(t)$ for $t = 1, 2, \ldots, n$ are time series and FTS defined on $Y(t)$, respectively. Let U be the universe of discourse that can be partitioned into even lengthy and equal length intervals $u_1, u_2, \ldots, u_p$ and a fuzzy set A_i of U is defined by

$$A_i = \frac{f_{A_i}(u_1)}{u_1} + \frac{f_{A_i}(u_2)}{u_2} + \ldots + \frac{f_{A_i}(u_j)}{u_j} + \ldots + \frac{f_{A_i}(u_p)}{u_p} \tag{1}$$

for $i, j = 1, 2, \ldots, p$ and $f_{A_i}(u_j)$ is the grade of membership of u_j in A_i. In this case, $f_{A_i}(u_j) = 1$ for $j = i$, , $f_{A_i}(u_j) = 0.5$ for $j = i - 1$, and $j = i + 1$, and $f_{A_i}(u_j) =$ 0 for others.

The fuzzy model discussed in this study is limited to the first-order FTS and seasonal FTS. The first order FTS is expressed as the relationship between $F(t)$ and $F(t\text{-}1)$, denoted as $F(t\text{-}1) \rightarrow F(t)$. Meanwhile, the first-order seasonal FTS is expressed as the relationship between $F(t)$ and $F(t\text{-}s)$, where s is the seasonal period. It is denoted as $F(t\text{-}s) \rightarrow F(t)$. Let $F(t\text{-}s) = A_i$, $F(t\text{-}1) = A_j$, and $F(t) = A_k$. The FLR then can be written as $A_j \rightarrow A_k$ for the first order FTS and $A_i \rightarrow A_k$ for seasonal FTS. In this case, A_i and A_j are the antecedents or left-hand side of FLR, while A_k is the consequent or right-hand side of FLR.

In this study, we modify the first order seasonal FTS, which involves FLR components that accommodate holiday effects. To determine the effectiveness of the proposed method, we compare it with the existing methods, namely Chen's and the seasonal FTS. The performance of the models is evaluated based on the MAE, RMSE, and MAPE values. The MAE and RMSE are scale-dependent measures commonly used to compare different methods applied to the same set of univariate time series data (Hyndman & Koehler, 2006). In contrast, MAPE is scaled independent and calculated based on percentage error. It has advantage in comparing methods when the values of time series data are large (Hanke et al., 2005). It is popular in measuring the accuracy of the tourism forecasting model (see, Chang & Liao, 2010; Chen, 2011; Chen et al., 2008; Sun et al., 2019; Wong et al., 2007). The MAE, RMSE, and MAPE can be calculated by formula (2), (3), and (4), respectively.

$$\text{MAE} = \text{mean}(|e_t|) \tag{2}$$

$$\text{RMSE} = \sqrt{\text{mean}(e_t^2)} \tag{3}$$

$$\text{MAPE} = \text{mean}(|E_t|) \tag{4}$$

where $e_t = Y(t) - \hat{Y}(t)$ and $E_t = 100e_t/Y(t)$. $Y(t)$ is the actual value at time t and $\hat{Y}(t)$ is the forecast value at time t.

Chen's Fuzzy Time Series

The algorithm of Chen's FTS is presented as follows.

Step 1: Define the universe of discourse, U.

Step 2: Define the fuzzy sets, $A_1, A_2, \ldots, A_p$ on U as in (1) and fuzzify the time series data.

Step 3: Define the fuzzy logical relationship (FLR) that is presented as $A_i \rightarrow A_k$ where A_i is the fuzzy value of observation at time t-1 and A_k is the fuzzy value of observation at time t. We can also rewrite this statement as $F(t\text{-}1) = A_i$, and $F(t) = A_k$, then the FLR is $F(t\text{-}1) \rightarrow F(t)$ or $A_i \rightarrow A_k$. Practically, there are two or more relationships with the same both antecedent and consequent. In this case, we do not take into account the repeated relationships, so those relations are counted only once.

Step 4: Define the FLR groups (FLRG). The FLRs are grouped based on their antecedents. For example, if we have Four FLRs, say, $A_1 \rightarrow A_2$; $A_1 \rightarrow A_3$; A_2

$\rightarrow A_3$, and $A_3 \rightarrow A_4$, we can obtain three FLRGs that are written as $A_1 \rightarrow A_2$, A_3; $A_2 \rightarrow A_3$; $A_3 \rightarrow A_4$.

Step 5: Calculate the forecast output by following these rules:

a. If the current state of the observation, $F(t)$, is A_i and based on the FLRG, we have $A_i \rightarrow A_k$ then $\hat{Y}(t+1) = m_k$ where m_k is the midpoint of u_k.

b. If the current state of the observation, $F(t)$, is A_j and based on the FLRG, we have $A_j \rightarrow A_{k_1}, A_{k_2}, \dots, A_{k_q}$ then $\hat{Y}(t+1)=(m_{k_1} + m_{k_2} + \cdots + m_{k_q})/q$ where $m_{k_1} + m_{k_2} + \cdots + m_{k_q}$ are the midpoint of $u_{k_1}, u_{k_2}, \dots, u_{k_q}$.

c. If the current state of the observation $F(t)$, is A_i and based on the FLRG has no relation with any other fuzzy values, $A_i \rightarrow \#$, then $\hat{Y}(t+1) = m_i$ where m_i is the midpoint of u_i.

Seasonal Fuzzy Time Series

The seasonal fuzzy time series (FTS) discussed in this study follows the rules in Song and Chissom's (1999) and Chen's method. The algorithm is explained in the following steps.

Step 1: Define the universe of discourse as Chen's.

Step 2: Define the fuzzy sets, A_1, A_2, …, A_p on U as in (1).

Step 3: Define the FLR. Different from Chen's, the FLR of seasonal FTS is defined as $F(t-s) \rightarrow F(t)$ where s is the seasonal period. For example, if $F(t-s) = A_i$ and $F(t) = A_j$, then the FLR is $A_i \rightarrow A_j$. As in Chen's, the repeated FLRs are counted only once.

Step 4: Define the FLR groups (FLRG). The FLRs are grouped based on their antecedent. For example, if we have Four FLRs, say, $A_1 \rightarrow A_1$; $A_1 \rightarrow A_1$; $A_2 \rightarrow A_3$, and $A_2 \rightarrow A_4$, we can obtain three FLRGs that are written as $A_1 \rightarrow A_1$; $A_2 \rightarrow A_3, A_4$.

Step 5: Calculate the forecast output by following these rules:

a. If $F(t-s+1)$ is A_i and based on the FLRG, we have $A_i \rightarrow A_k$ then $\hat{Y}(t+1) = m_k$ where m_k is the midpoint of u_k.

b. If $F(t-s+1)$ is A_i and based on the FLRG, we have $A_i \rightarrow A_{k_1}, A_{k_2}, \dots, A_{k_q}$ then $\hat{Y}(t+1)=(m_{k_1} + m_{k_2} + \cdots + m_{k_q})/q$ where $m_{k_1} + m_{k_2} + \cdots + m_{k_q}$ are the midpoint of $u_{k_1}, u_{k_2}, \dots, u_{k_q}$.

c. If $F(t\text{-}s+1)$ is A_i and based on the FLRG has no relation with any other fuzzy values, $A_i \rightarrow \#$, then $\hat{Y}(t+1) = m_i$ where m_i is the midpoint of u_i.

The Proposed Method

In this study, we propose a method with two scenarios of algorithms. The first algorithm considers the effect of holidays on the Christian calendar, while the second algorithm considers the effect of holidays on the Gregorian and Hijri calendars. These two algorithms are described in the following steps.

The 1st scenario of algorithm

The algorithm of the 1st proposed method is explained in the following steps.

Step 1: Define the universe of discourse as Chen's

Step 2: Define the fuzzy sets and fuzzify the time series data.

Step 3: Identify all the observations related to the holiday as affected by calendar variation, i.e. Eid Al-Fitr holiday, and highlight the values. In this case, we consider two groups of data. The first consists of all observations with highlight and the second consists of the non-highlight observations.

a. Define the FLR as in seasonal FTS for all non-highlight observations.

b. Define the FLR for all the highlight observations. The FLR is defined as the relation between the fuzzy value at the month affected by Eid Al-Fitr of the previous year with the fuzzy value at Eid Al-Fitr at the month affected by Eid Al-Fitr holiday of the following year. We notate this FLR by $G(g\text{-}1) \rightarrow G(g)$, where $G(g)$ is the fuzzy value of the month affected by Eid Al-Fitr holiday at year g. The illustrative example is discussed further in the discussion.

Step 4: Define FLRG based on step 3a and 3b. We have two groups of FLRGs, with and without highlight.

Step 5: Calculate the forecast value by following rules. In this case, we need to first check whether the observation in the period we are going to forecast is included in the highlight group or not.

a. If the observation is included in the non-highlight group then the forecast value at time, time $t + 1$ is based on $F(t\text{-}s+1)$ as in seasonal FTS.

b. If the observation is included in the highlight group then the forecast value at time $t + 1$ where $t + 1$ is the month affected by Ied Al-Fitr holiday at year g+1 follow these rules;

1) If $G(g)$ is A_i and based on the FLRG in the highlight group, we have $A_i \rightarrow A_k$ then $\hat{Y}(t+1) = m_k$ where m_k is the midpoint of u_k.

2) If $G(g)$, is A_i and based on the FLRG in the highlight group, we have $A_i \rightarrow A_{k_1}, A_{k_2}, \dots, A_{k_q}$ then $\hat{Y}(t+1)=(m_{k_1} + m_{k_2} + \cdots + m_{k_q})/q$ where $m_{k_1} + m_{k_2} + \cdots + m_{k_q}$ are the midpoint of $u_{k_1}, u_{k_2}, \dots, u_{k_q}$.

3) If $G(g)$, is A_i and based on the FLRG has no relation with any other fuzzy values, $A_i \rightarrow \#$, then $\hat{Y}(t+1) = m_i$ where m_i is the midpoint of u_i.

The 2nd scenario of algorithm

The algorithm of the 1st proposed method is explained in the following steps.

Step 1: Define the universe of discourse as Chen's

Step 2: Define the fuzzy sets and fuzzify the time series data.

Step 3: Identify and highlight all the observations related to the holiday that are influenced by calendar variation, namely the Eid Al-Fitr holiday and all observations in certain months where the number of tourist arrivals tends to be higher than other months. Then we have two groups of fuzzified data, with and without highlight.

a. Define the FLR as in seasonal FTS for all non-highlight observations.

b. Define the FLR for all the highlight observations. In this case, we need to define FLR in the following way.

1) Define the FLR as in the 1st algorithm Step 3b, that is the relation between the fuzzy value at the month affected by Eid Al-Fitr of the previous year with the fuzzy value at ied at the month affected by Eid Al-Fitr holiday of the following year.

2) Determine FLR, $F(t\text{-}s) \rightarrow F(t)$ where s is the seasonal period, based on the fuzzified value in the months affected by holidays according to the Gregorian calendar.

Step 4: Determine the FLRG based on Step 3a and Step 3b. We have two FLRG groups, one with highlights and the other without highlights. The first FLRG cluster is constructed from the FLRs obtained from Step 3a. The next FLRGs group is determined by considering that FLRs represent the relationship between holidays on both the Gregorian and Hijri calendars and collects them into the same group.

Step 5: Calculate the forecast value as in the 1st algorithm. However, first, check whether the observation in the period we are going to forecast is included in the highlight group or not.

a. If the observation is included in the non-highlight groups, then the forecast value at time $t + 1$ is based on $F(t\text{-}s\text{+}1)$ as in seasonal FTS as in the 1st algorithm Step 5a

b. If the observation is included in the highlight groups, it is still necessary to check whether the observation is related to the holidays on the Gregorian or the Hijri calendar.

1) If the observation is related to the holidays on the Gregorian calendar, then the forecast value at time $t + 1$ depends on the fuzzy value at time $t - s + 1$.

2) If the observation is related to the holidays on the Hijri calendar, then the forecast value at time $t + 1$ depends on the fuzzy value at the month that has a holiday effect on Hijri calendar in the previous year. The illustration example can be seen in the discussion.

In this work, we use the IF-THEN function in a Microsoft Excel spreadsheet to obtain forecast values by following the procedures of the seasonal FTS and the proposed methods. In addition, we use Matlab software to determine the forecast values based on the first-order Chen's algorithm. Readers who are interested in the code can contact the corresponding authors.

RESULTS AND DISCUSSION

This section discusses the two proposed methods to forecast the monthly tourist arrivals to Museum Sangiran. The data can be downloaded from www.bps.go.id. We used the monthly tourist arrivals from January 2014 to December 2017 as the training data and observations from January to December 2018 as the testing data. The plot of these time series data is depicted in Figure 1. The behavior of the training data from year to year from January to December can be seen in Figure 2.

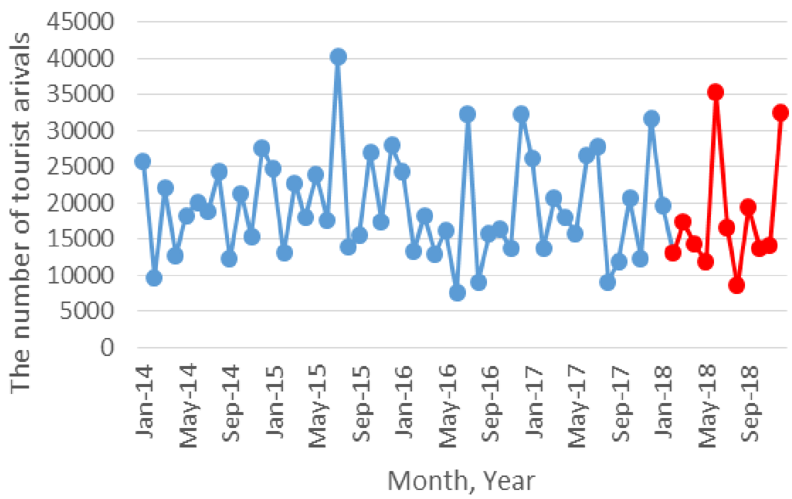

Figure 1. *The number of tourist arrivals to museum Sangiran from January 2014 to December 2018 with training data in blue color and testing data in red color.*

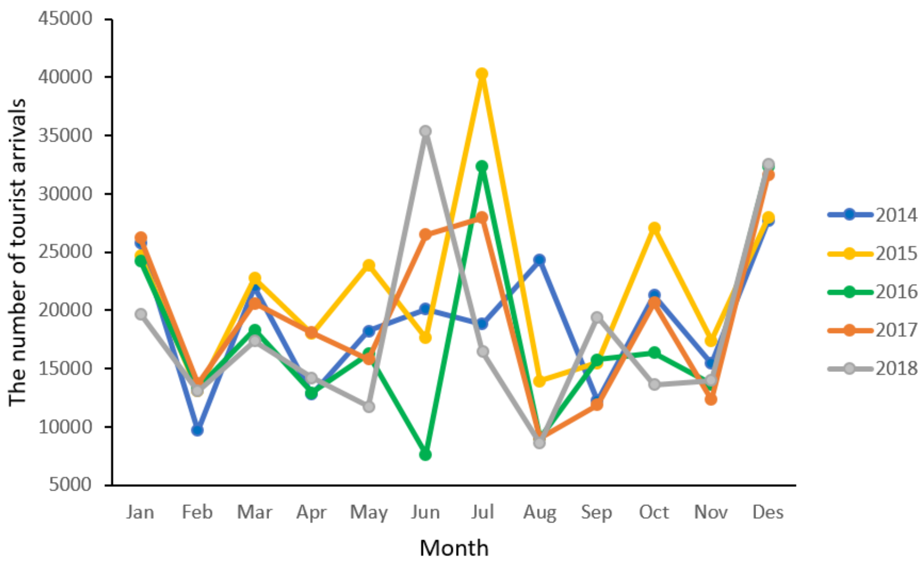

Figure 2. *Time series plot for the number of tourist arrivals from January 2014 to December 2017 (training data) based on behavior from January to December in each different year.*

Based on Figure 2, we can see that the pattern from year to year tends to be the same. However, several spikes were different from certain other months, namely on August 2014, July 2015, July 2016, and July 2017. In addition, we can see that the number of tourist arrivals on January and December tend to be higher than other months.

We define U = [6000, 41000] as the universe of speech for this case. In the experimental study, we divide U by three different interval lengths (denoted by p), i.e., p = 500, 1000, and 2000. Therefore, we have 68, 34, and

17 classes of intervals corresponding to the three interval lengths, respectively.

Since the calculations are almost similar, we discuss only the implementation of the methods with interval length $p = 2000$ and report the overall results. The universe of discourse, U = [7000, 41000] was partitioned into u_1 = [7000, 9000], u_2 = [9000, 11000], …, u_{17} = [39000, 41000]. The fuzzy sets on U are defined as follows:

$$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + \ldots + 0/u_{16} + 0/u_{17}$$

$$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + \ldots + 0/u_{16} + 0/u_{17}$$

$$\vdots$$

$$A_{17} = 0/u_1 + 0/u_2 + 0/u_3 + \ldots + 0.5/u_{16} + 1/u_{17}$$

and the fuzzified tourist arrivals presented in Table 1.

Table 1. *Fuzzified the training data on the number of tourist arrivals to Sangiran Museum*

Month	**Year**							
	2014		***2015***		***2016***		***2017***	
	Actual	**Fuzzified**	**Actual**	**Fuzzified**	**Actual**	**Fuzzified**	**Actual**	**Fuzzified**
Jan	25779	A_{10}	24727	A_9	24264	A_9	26234	A_{10}
Feb	9678	A_2	13080	A_4	13340	A_4	13734	A_4
Mar	22037	A_8	22775	A_8	18325	A_6	20609	A_7
Apr	12813	A_3	17991	A_6	12939	A_3	18108	A_6
May	18249	A_6	23903	A_9	16276	A_5	15837	A_5
Jun	20094	A_7	17644	A_6	7649	A_1	26508	A_{10}
Jul	18846	A_6	40253	A_{17}	32319	A_{13}	27904	A_{11}
Aug	24319	A_9	13924	A_4	9049	A_2	9049	A_2
Sep	12268	A_3	15512	A_5	15770	A_5	11903	A_3
Oct	21314	A_8	27114	A_{11}	16382	A_5	20671	A_7
Nov	15467	A_5	17434	A_6	13654	A_4	12365	A_3
Dec	27694	A_{11}	27953	A_{11}	32409	A_{13}	31629	A_{13}

Note: Green cells represent the influence of holidays referring to the Gregorian calendar in the corresponding month. Blue cells represent holiday effects, referring to the Hijri calendar.

The FLR and FLRGs of tourist arrivals by Chen's, seasonal FTS, and the proposed method can be obtained from Table 1. Chen's defined FLR based on the relationship between the fuzzy values at time t-1 with that at time t. For example, the fuzzified tourist arrival in January 2014 is A_{10}, and February 2014 is A_2, then the FLR is $A_{10} \rightarrow A_2$ (see Table 2). FLRs in green cells in Table 2 are determined based on the relations between the fuzzy values at time $t - s + 1$ and that at time t in green cells in Table 1. As an illustration, the fuzzy value in January 2014 is A_{10}, and the fuzzy value in

January 2015, then FLR, is defined as $A_{10} \rightarrow A_9$. While the FLR $A_9 \rightarrow A_{17}$ in blue cells in Table 2 is determined based on the month affected by the Eid Al-Fitr holiday in 2014, that is August 2014 and month affected by the Eid Al-Fitr holiday in 2015, that is July 2015. We consider the month those affected by the Eid al-Fitr holiday were August 2014 because the Eid Al-Fitr occurred in the last week of July. The same thing happened in July 2017.

Table 2. *FLRs of the tourist arrivals obtained by Chen's, Seasonal FTS, and the proposed method*

	Method			
	Chen's	*Seasonal FTS*	*Proposed method* 1st algorithm	*Proposed method* 2nd algorithm
FLR	$A_{10} \rightarrow A_2$	$A_{10} \rightarrow A_9$	$A_{10} \rightarrow A_9$	$A_2 \rightarrow A_4$
	$A_2 \rightarrow A_8$	$A_2 \rightarrow A_4$	$A_2 \rightarrow A_4$	$A_8 \rightarrow A_8$
	$A_8 \rightarrow A_3$	$A_8 \rightarrow A_8$	$A_8 \rightarrow A_8$	⋮
	$A_3 \rightarrow A_6$	$A_3 \rightarrow A_6$	$A_3 \rightarrow A_6$	$A_5 \rightarrow A_7$
	$A_6 \rightarrow A_7$	$A_6 \rightarrow A_9$	$A_6 \rightarrow A_9$	$A_4 \rightarrow A_3$
	$A_7 \rightarrow A_6$	$A_7 \rightarrow A_6$	$A_7 \rightarrow A_6$	$A_{10} \rightarrow A_9$
	$A_6 \rightarrow A_9$	$A_6 \rightarrow A_{17}$	$A_3 \rightarrow A_5$	$A_{11} \rightarrow A_{11}$
	$A_9 \rightarrow A_3$	$A_9 \rightarrow A_4$	⋮	⋮
	$A_3 \rightarrow A_8$	$A_3 \rightarrow A_5$	$A_4 \rightarrow A_3$	$A_9 \rightarrow A_{10}$
	$A_8 \rightarrow A_5$	$A_8 \rightarrow A_{11}$	$A_{13} \rightarrow A_{13}$	$A_{13} \rightarrow A_{13}$
	⋮	⋮	$A_9 \rightarrow A_{17}$	$A_9 \rightarrow A_{17}$
	$A_7 \rightarrow A_3$	$A_4 \rightarrow A_3$	$A_{17} \rightarrow A_{13}$	$A_{17} \rightarrow A_{13}$
	$A_3 \rightarrow A_{13}$	$A_{13} \rightarrow A_{13}$	$A_{13} \rightarrow A_{11}$	$A_{13} \rightarrow A_{11}$

Note: Green cells represent FLRs defined based on the green cells in Table 1. Blue cells represent FLRs defined based on the blue cells in Table 1.

Further, FLRG in Table 3 is determined based on a collection of FLRs that have the same antecedent. For Chen's and the seasonal FTS method, we can obtain thirteen FLRGs, as seen in Table 3. Meanwhile, for the 1st algorithm, we have two groups of FLRGs, each has twelve and three FLRGs, respectively. We can find antecedent A_9 in the two groups, but they have different FLRGs. In the first group (no highlight), $A_9 \rightarrow A_9$, A_{10}, A_5, while in the second group (orange highlight cells, $A_9 \rightarrow A_{17}$. This shows the difference in the effect of holidays on the number of visitors compared to those periodic seasonal referring to the Gregorian calendar.

Different behavior is shown by the results of grouping FLRG using the 2nd algorithm. In this case, we also consider the effect of holidays on the Gregorian calendar in addition to regular seasonal patterns. The blue and green cells in Table 2 are used in defining FLRG in the orange cells in Table 3.

Table 3. *FLRGs of the tourist arrivals obtained by Chen's, Seasonal FTS, and the proposed method*

	Method			
	Chen's	*Seasonal FTS*	*Proposed method*	
			1st algorithm	2nd algorithm
	$A_1 \rightarrow A_{13}$	$A_1 \rightarrow A_{10}$	$A_1 \rightarrow A_{10}$	$A_1 \rightarrow A_{10}$
	$A_2 \rightarrow A_8, A_5, A_3$	$A_2 \rightarrow A_4, A_2$	$A_2 \rightarrow A_4, A_2$	$A_2 \rightarrow A_4, A_2$
	$A_3 \rightarrow A_6, A_8, A_5, A_7, A_{13}$	$A_3 \rightarrow A_6, A_5$	$A_3 \rightarrow A_6, A_5$	$A_3 \rightarrow A_6, A_5$
	$A_4 \rightarrow A_8, A_5, A_6, A_{13}, A_7$	$A_4 \rightarrow A_4, A_2, A_3$	$A_4 \rightarrow A_4, A_2, A_3$	$A_4 \rightarrow A_4, A_2, A_3$
	$A_5 \rightarrow A_{11}, A_1, A_5, A_4, A_{10}$	$A_5 \rightarrow A_5, A_3, A_7, A_6$	$A_5 \rightarrow A_5, A_3, A_7, A_6$	$A_5 \rightarrow A_5, A_3, A_7, A_6$
	$A_6 \rightarrow A_7, A_9, A_{17}, A_{11}, A_3, A_5$	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_{17}, A_4$	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_4$	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_4$
	$A_7 \rightarrow A_6, A_3$	$A_7 \rightarrow A_6$	$A_7 \rightarrow A_6$	$A_7 \rightarrow A_6$
FLRG	$A_8 \rightarrow A_3, A_5, A_6$	$A_8 \rightarrow A_8, A_6, A_{11}$	$A_8 \rightarrow A_8, A_6, A_{11}$	$A_8 \rightarrow A_8, A_6, A_{11}$
	$A_9 \rightarrow A_3, A_4, A_6, A_4$	$A_9 \rightarrow A_9, A_{10}, A_5, A_4$	$A_9 \rightarrow A_9, A_{10}, A_5$	$A_9 \rightarrow A_5$
	$A_{10} \rightarrow A_2, A_4, A_{11}$	$A_{10} \rightarrow A_9$	$A_{10} \rightarrow A_9$	$A_{11} \rightarrow A_5$
	$A_{11} \rightarrow A_9, A_6, A_9, A_2$	$A_{11} \rightarrow A_5, A_{11}, A_{13}$	$A_{11} \rightarrow A_5, A_{11}, A_{13}$	$A_{10} \rightarrow A_9$
	$A_{13} \rightarrow A_2, A_{10}, A_7$	$A_{13} \rightarrow A_{11}, A_{13}$	$A_{13} \rightarrow A_{13}$	$A_9 \rightarrow A_9, A_{10}, A_{17}$
	$A_{17} \rightarrow A_4$	$A_{17} \rightarrow A_{13}$	$A_9 \rightarrow A_{17}$	$A_{11} \rightarrow A_{11}, A_{13}, A_{15}$
			$A_{17} \rightarrow A_{13}$	$A_{13} \rightarrow A_{13}, A_{11}$
			$A_{13} \rightarrow A_{11}$	$A_{17} \rightarrow A_{13}$

Note: Orange cells represent the FLRGs determined from the green and blue cells in Table 2.

Based on Table 1 and Table 3, we can calculate the number of tourist arrival forecast values, both for insample and outsample data. We only show the forecast process for July 2015, May 2016, January 2018, June 2018, December 2018 by Chen's, seasonal FTS, the 1st and the 2nd proposed methods. Other forecast values can be obtained by the same procedure.

Chen's method

In Chen's method, the forecast value for time t+1 is calculated based on the fuzzy value at time t. Thus, predictions for July 2015, May 2016, January 2017, June 2018, and December 2018 are calculated based on the fuzzy value of the previous month, namely June 2015, April 2016, December 2016, May 2018, and November 2018, respectively (see Table 4). Furthermore, the forecasting value refers to the FLRG and the rules that have been explained before. For example, If the fuzzy value in June 2015 is A_6, then based on Table 3, A_6 has a relationship with A_7, A_9, A_{17}, A_{11}, and A_3. Then, the forecast value can be calculated by

$$\hat{Y}(\text{Jul } 2015) = (20000 + 24000 + 40000 + 28000 + 12000 + 16000)/6 = 23333.33.$$

Since we predict the number of tourist arrivals with discrete values, we round 23333.33 up to 23334. Predictive values for February 2015 and beyond can be calculated in the same way.

Table 4. *Forecast values obtained by Chen's method*

The number of tourists		Predicted based on		FLRG	Forecast value
Month, year	*Actual*	*Month, year*	*Fuzzy value*		
Jul, 2015	40253	Jun, 2015	A_6	$A_6 \rightarrow A_7, A_9, A_{17}, A_{11}, A_3, A_5$	23334[a]
May, 2016	16276	Apr, 2016	A_3	$A_3 \rightarrow A_6$, A8, A_5, A_7, A_{13}	21600
Jan, 2017	26234	Dec, 2016	A_{13}	$A_{13} \rightarrow A_2, A_{10}, A_7$	18667[a]
Jun, 2018	35375	May, 2018	A_3	$A_3 \rightarrow A_6, A_8$	21600
Dec, 2018	32516	Nov, 2018	A_4	$A_4 \rightarrow A_8, A_5, A_6, A_{13}, A_7$	21600

Note: [a]The result is rounded up since the observed data is the number of tourist arrivals in the form of discrete values.

Seasonal FTS

In this case, we can determine the predictive value in a similar way to that in Chen's method. However, it is noted that the predicted value here does not depend on the fuzzy value of the previous month but the value of the same month in the previous year. For example, we wanted to predict the number of tourist arrivals in July 2015. The prediction value is determined based on the fuzzy value in July 2014, which is A_6. Based on Table 3, A_6 is related to A_7, A_3, A_9, A_1, A_{17}, and A_4. Thus the forecast value is $\hat{Y}(\text{Jul } 2015) = (20000 + 12000 + 24000 + 8000 + 40000 + 14000)/6 = 19666.67$, and can be round up to 19667. The forecast values for May 2016, January 2017, June 2018, and December 2018 can be obtained in a similar way. The results are presented in Table 5.

Table 5. *Forecast values obtained by seasonal FTS*

The number of tourists		Predicted based on		FLRG	Forecast value
Month, year	*Actual*	*Month, year*	*Fuzzy value*		
Jul, 2015	40253	Jul, 2014	A_6	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_{17}, A_4$	19667[b]
May, 2016	16276	May, 2015	A_9	$A_9 \rightarrow A_9, A_{10}, A_5, A_4$	20000
Jan, 2017	26234	Jan, 2016	A_9	$A_9 \rightarrow A_9, A_{10}, A_5, A_4$	20000
Jun, 2018	35375	Jun, 2017	A_{10}	$A_{10} \rightarrow A_9$	24000
Dec, 2018	32516	Dec, 2017	A_{13}	$A_{13} \rightarrow A_{11}, A_{13}$	30000

Note: [b]The result is rounded up since the observed data is the number of tourist arrivals in the form of discrete values.

The proposed method

a. by 1st algorithm

The 1st proposed algorithm adds a component of the FLRG group, formed from fuzzy values that reflect the influence of the Eid al-Fitr holiday, which refers to the Hijri calendar. So, there are two groups of FLRGs, and for simplicity, we present them into two blocks, without highlight and with highlight (orange cells), as shown in Table 3, column 3.

In this case, we have to check whether the months we observe have holidays related to Eid or not because there are differences in the rules for predicting the number of tourists in the months influenced by Eid al-Fitr holidays and those that do not. For example, to predict the number of tourists in May 2016, January 2017, and December 2018, we must see the value in May 2015, January 2016, and December 2018, respectively. As for predicting the number of tourists in July 2015 and June 2018, we consider the value in August 2014 and July 2017, respectively. So, we do not necessarily see the same month in the previous year, depending on the months that are also influenced by the Eid al-Fitr holiday. The blue cells in Table 6 show the months associated with the Eid holiday. Therefore, we must look at the FLRGs in the orange cells group in Table 3 to obtain the forecast values. From Table 6, we can see two FLRGs with the same antecedent but different consequences, $A_9 \rightarrow A_{17}$ and $A_9 \rightarrow A_9, A_{10}, A_5$. This relates to the FLRG, where the months we are observing belong, whether included in the white or blue cells. Furthermore, we can perform calculations in the same way.

Table 6. *Forecast values obtained by the 1st proposed algorithm*

The number of tourists		Predicted based on		FLRG	Forecast value
Month, year	*Actual*	*Month, year*	*Fuzzy value*		
Jul, 2015	40253	Aug, 2014	A_9	$A_9 \rightarrow A_{17}$	40000
May, 2016	16276	May, 2015	A_9	$A_9 \rightarrow A_9, A_{10}, A_5$	22000
Jan, 2017	26234	Jan, 2016	A_9	$A_9 \rightarrow A_9, A_{10}, A_5$	22000
Jun, 2018	35375	Jul, 2017	A_{11}	$A_{11} \rightarrow \#^c$	28000
Dec, 2018	32516	Dec, 2017	A_{13}	$A_{13} \rightarrow A_{13}$	32000

Note: [c] It has no relation with any other fuzzy values.

b. by 2nd algorithm

In this case, we must pay attention to the months in which there are holidays related to the Gregorian and Hijri calendars. For simplicity, we have presented three color categories of months in Table 1, white, blue, and green. These categories are considered to determine the forecast values. Thus, we first need to consider where the month we are observing is categorized. Furthermore, FLRG can be easily determined by considering the color. As illustrations, July 2015 and June 2018 are included in the blue category. It means that the number of visits is influenced by the Eid holiday. Therefore, the forecast value is based on the months in the previous year, which are also influenced by the Eid al-Fitr, namely August 2014 and July 2017, respectively. While May 2016 is included in the white category, the forecast value is based on the same month in the previous year. Jan 2017 and Dec 2018 were also predicted by the fuzzy value of the same month in the previous year. The important thing is the determination of FLRG, from which group we should refer, to obtain the forecast value. For example, in July 2015, May 2016, and January 2017, the three forecast values were affected by A_9 (see Table 7). However, because July 2015 and January 2017 were included in the highlighted category, the FLRG used as the basis for prediction was in the orange cells, namely the group affected by holidays. While May 2016 is in white cells, so we consider the white cells for the FLRG. The results can be seen in Table 7.

Table 7. *Forecast values obtained by the 2nd proposed algorithm*

The number of tourists		Predicted based on		FLRG	Forecast value
Month, year	*Actual*	*Month, year*	*Fuzzy value*		
Jul, 2015	40253	Aug, 2014	A_9	$A_9 \rightarrow A_9, A_{10}, A_{17}$	30000
May, 2016	16276	May, 2015	A_9	$A_9 \rightarrow A_5$	16000
Jan, 2017	26234	Jan, 2016	A_9	$A_9 \rightarrow A_9, A_{10}, A_{17}$	30000
Jun, 2018	35375	Jul, 2017	A_{11}	$A_{11} \rightarrow A_{11}, A_{13}, A_{15}$	32000
Dec, 2018	32516	Dec, 2017	A_{13}	$A_{13} \rightarrow A_{13}$	30000

Table 8. *Comparisons of MAE, RMSE, MAPE values obtained by Chen's, seasonal, and the two proposed algorithms for the training and testing data on the number of tourist arrivals to Sangiran Museum*

Method	*p*	Training			Testing		
		MAE	*RMSE*	*MAPE*	*MAE*	*RMSE*	*MAPE*
Chen's	500	3304.61	4577.82	19.69	8026.25	9720.64	46.36
	1000	4282.08	5353.05	24.44	8444.75	10215.19	48.57
	2000	5204.61	6580.69	30.49	8481.33	10037.29	52.25
Seasonal FTS	500	**1203.97**	**1952.14**	**7.38**	5205.08	6457.87	30.44
	1000	2788.64	3872.85	15.65	5142.67	6484.66	31.35
	2000	4169.92	5845.23	24.88	5178.50	6131.02	30.60
The proposed method							
1st algorithm	500	2041.08	4566.12	10.22	4007.25	5002.55	23.43
	1000	2091.78	3188.20	13.64	4545.42	5429.06	27.50
	2000	2817.89	3852.82	17.95	3512.08	4321.56	22.17
2nd algorithm	500	1916.58	3516.35	13.13	4746.75	5766.15	28.54
	1000	2110.08	3053.97	12.80	3642.67	4521.42	22.73
	2000	2806.11	3860.10	16.74	**3345.42**	**3949.41**	**21.74**

Note: Bold values represent the smallest value in each column.

The overall results are summarized in Table 8 by comparing the performance of Chen's method, seasonal FTS, and the proposed method in terms of MAE, RMSE, and MAPE. Table 8 shows that the proposed method can reduce the MAE, RMSE, and MAPE values from the Chen's, both on training and testing data. Meanwhile, the FTS seasonal method gives better results than the proposed method, only on training data with an interval length of 500. Thus, we can conclude that the FTS seasonal method and the proposed method are more suitable for data on the number of visitors to the Sangiran museum than Chen's method.

A visual presentation for comparison of forecast values with actual values can be seen in Figure 3. Based on Figure 3, the forecasting values obtained by the two algorithms in the proposed method tend to be closer than the values predicted by Chen's and seasonal FTS. The proposed method's ability to predict more accurately the number of visits in the months affected by holidays can significantly reduce the MAE, RMSE, and MAPE produced by the Chen method, i.e., up to 61%, 61%, 58%, respectively. Moreover, compared to that obtained from the FTS seasonal method, the proposed method can reduce the MAE, RMSE, and MAPE values up to 35%, 36%, and 29%, respectively.

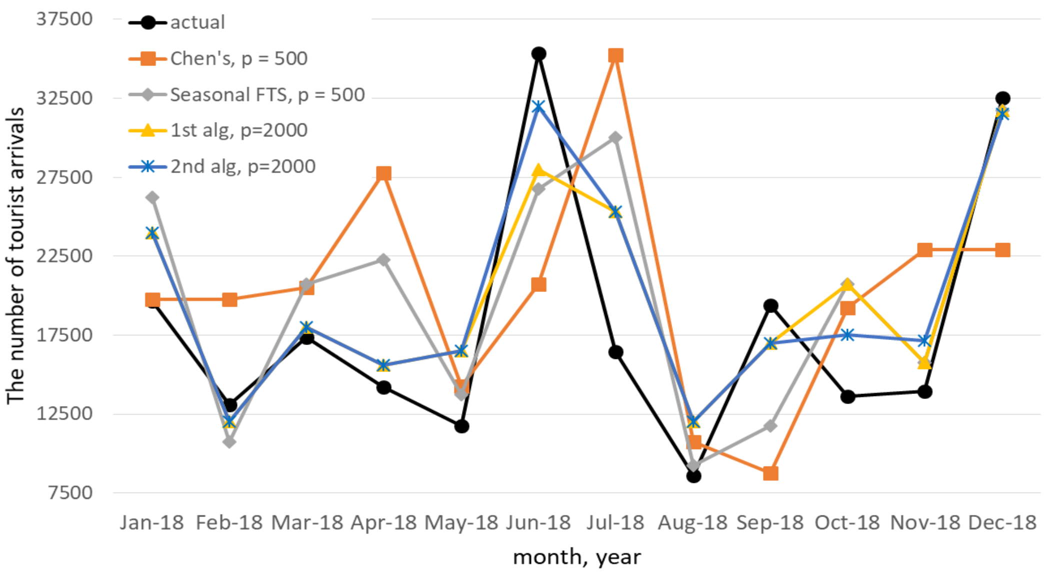

Figure 3. *Comparisons between the actual values of testing data with the forecast values obtained by Chen's. seasonal FTS, the 1st and the 2nd proposed algorithms*

Furthermore, we can predict tourist numbers for one next year similarly. Prediction of the number of tourists in January - December 2019 can be obtained based on the fuzzy values of the corresponding months in 2018 and the FLRGs presented in Table 3. We need to check each category of month we will observe because this relates to which FLRGs group we use as the basis for forecasting. As previously explained, to predict the number of visitors in certain months affected by holidays according to the Gregorian or Hijri calendar, we consider the FLRGs group in the highlighted cells in Table 3. For other months, we refer to the non-highlighted cells. The results can be seen in Table 9.

Table 9. *Forecast values of tourist numbers in 2019 obtained by the 1st and 2nd proposed algorithms with p = 2000*

The number of tourist in	**Predicted based on**		**1st algorithm**		**2nd algorithm**	
	Month, year	***Fuzzy value***	***FLRG***	***Forecast***	***FLRG***	***Forecast***
Jan, 2019	Jan, 2018	A_7	$A_7 \rightarrow$ #[d]	20000	$A_7 \rightarrow$ #[d]	20000
Feb, 2019	Feb, 2018	A_4	$A_4 \rightarrow A_4, A_2, A_3$	12000	$A_4 \rightarrow A_4, A_2, A_3$	12000
Mar, 2019	Mar, 2018	A_6	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_4$	15600	$A_6 \rightarrow A_7, A_3, A_9, A_1, A_4$	15600
Apr, 2019	Apr, 2018	A_4	$A_4 \rightarrow A_4, A_2, A_3$	12000	$A_4 \rightarrow A_4, A_2, A_3$	12000
May, 2019	May, 2018	A_3	$A_3 \rightarrow A_6, A_5$	17000	$A_3 \rightarrow A_6, A_5$	17000
June, 2019	June, 2018	A_{15}	$A_{15} \rightarrow$ #[d]	36000	$A_{15} \rightarrow$ #[d]	36000
Jul, 2019	Jul, 2018	A_5	$A_5 \rightarrow A_5, A_3, A_7, A_6$	16500	$A_5 \rightarrow A_5, A_3, A_7, A_6$	16500
Aug, 2019	Aug, 2018	A_1	$A_1 \rightarrow A_{10}$	26000	$A_1 \rightarrow A_{10}$	26000
Sep, 2019	Sep, 2018	A_7	$A_7 \rightarrow A_6$	18000	$A_7 \rightarrow A_6$	18000
Oct, 2019	Oct, 2018	A_4	$A_4 \rightarrow A_4, A_2, A_3$	12000	$A_4 \rightarrow A_4, A_2, A_3$	12000
Nov, 2019	Nov, 2018	A_4	$A_4 \rightarrow A_4, A_2, A_3$	12000	$A_4 \rightarrow A_4, A_2, A_3$	12000
Dec, 2019	Dec, 2018	A_{13}	$A_{13} \rightarrow A_{11}$	28000	$A_{13} \rightarrow A_{13}, A_{11}$	30000

Note: [d] It has no relation with any other fuzzy values.

Since recent observations may significantly influence future values, we recommend updating the FLRGs when those data are available to consider the most recent information.

CONCLUSION

This paper presents a new method for forecasting the number of tourist visits to the Sangiran Museum. In the proposed method, we present two algorithmic scenarios. The first algorithm considers the effect of holidays referring to the Hijri calendar and the second algorithm considers the effect of holidays referring to the Gregorian calendar, in addition to the Hijr. Based on the experimental results, the proposed method produces smaller MAE, RMSE, and MAPE compared with Chen's and seasonal FTS. It means that the two algorithms in the proposed method can improve the accuracy of forecasting the historical number of tourist arrivals to the Sangiran Museum. The proposed method will be the starting point for developing FTS to model and forecast time series with seasonal patterns and calendar variation effects. In addition, clustering can be considered for further studies to group the effect of holidays to improve forecasting accuracy performance.

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