Journal of Statistics and Its Application, Likelihood Vol 1 No 1, June 2025

Comparison of Chen and Stevenson–Porter Fuzzy Time Series Methods in Forecasting Room Occupancy Rates of Star-Rated Hotels in Bengkulu Province

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Abstract

Considering the importance of room occupancy rate data to determine the condition of the hotel sector in the future, the most up-to-date data is needed. However, indicators for room occupancy rates for the current month issued by BPS are released in the following month, so there are obstacles in being able to estimate the condition of the hotel sector. There are several methods that can be used to forecast time series data, such as Exponential Smoothing, ARIMA, Moving Average and Fuzzy Time Series. However, in this research, the method that will be used is the Fuzzy Time Series model Chen and Stevenson-Porter. Using Fuzzy Time Series Chen method, the MAPE value was 21.82%, so it can be said that the forecasting ability is quite good. Meanwhile, using the Fuzzy Time Series Stevenson-Porter method, a MAPE value of 11.41% was obtained, so it can be said that the forecasting ability is good. So the better method to use is the Fuzzy Time Series Stevenson-Porter because it produces the smallest MAPE value.

Keywords: *Room Occupancy Rate, Fuzzy Time Series Chen, Fuzzy Time Series Stevenson-Porter*

Introduction

The time series method is a statistical analysis approach used to analyze data collected sequentially over regular time intervals. Time series data typically consist of measurements or observations recorded at specific intervals, such as daily, monthly, or annually. Time series analysis aims to understand patterns, trends, and possible cyclical movements within the data. Time series methods are widely applied in various fields, including economics, finance, social sciences, environmental sciences, and others. Several methods can be used to forecast time series data, such as Exponential Smoothing, ARIMA, Moving Average, Fuzzy Time Series, and others.

Fuzzy Time Series is an approach in time series analysis that integrates fuzzy logic concepts to handle uncertainty and vagueness in time series data. The basic concept of fuzzy logic involves variables that have partial values or degrees of membership in a particular set. By applying fuzzy logic to time series data, uncertainty that may arise in modeling and forecasting can be addressed. In this study, the methods used are the Chen and Stevenson–Porter Fuzzy Time Series models for comparison. The Chen Fuzzy Time Series is one of the Fuzzy Time Series methods developed by Professor Ying-Ping Chen from National Chiao Tung University in Taiwan. The main features of this model include fuzzification, rule base, inference engine, defuzzification, improvement in fuzzy rules, and data representation. Meanwhile, the Stevenson–Porter Fuzzy Time Series is a newer model developed by Meredith Stevenson and John E. Porter in 2009. This model was first used to forecast enrollment data at the University of Alabama.

Several studies have discussed Fuzzy Time Series, including the use of the Chen Fuzzy Time Series model to predict the number of active COVID-19 cases in Indonesia. The study produced

https://doi.org/10.54065/likelihood.559

Likelihood, 1(1), June 2025
ISSN: 3089-9729

predictions showing that from July 19, 2021, to August 17, 2021, COVID-19 cases in Indonesia reached 376,339 cases with a MAPE error ratio of 3.53%, categorized as very good forecasting performance. Furthermore, a study entitled "Application of Stevenson–Porter Fuzzy Time Series in Forecasting Forex Value Movements" obtained prediction results with an MSE value of 0.00142, which also falls into the very good forecasting category.

The tourism sector is one of the sectors expected by the government to increase national and regional revenue. This is because tourism can have a broad impact not only on the tourism sector itself but also on other sectors such as transportation, trade, creative industries, accommodation, and others. The government's expectations are reasonable considering that Indonesia is known as a country with highly diverse tourism potential, including natural tourism, cultural tourism, historical tourism, agro-tourism, and others, with tourist attractions spread throughout the archipelago. The tourism potential in Bengkulu Province is quite significant, including natural beauty, cultural diversity and uniqueness, and historical tourism destinations. All of these potentials serve as important capital in developing the tourism sector in Bengkulu Province. One of the activities that plays a crucial role in tourism development is the accommodation or hotel service industry. The development of accommodation or hotel services is essential because tourists visiting a destination require places to stay. Therefore, the hotel industry is an important element of tourism, as it can serve as an indicator of a region's success in promoting and attracting visitors. In addition, the development of accommodation or hotel services contributes to increased regional revenue and expanded employment opportunities.

Room Occupancy Rate (ROR) is one of the indicators used to measure tourism development. If the number of guests staying at a hotel is high, it will affect the hotel's Room Occupancy Rate (ROR), leading to higher revenue for the hotel. Therefore, hotels must implement effective management strategies (such as promotion levels, facilities, and service quality) to attract and satisfy customers or tourists. It is important to examine the ROR of a region, especially in the post-COVID-19 period, to assess the extent of tourism sector recovery. In general, since the occurrence of COVID-19 in 2019 until 2023, the development of room occupancy rates in star-rated hotels in Bengkulu Province has tended to increase. The hotel occupancy rate has gradually recovered after declining due to the COVID-19 pandemic. However, the figures have not yet returned to pre-pandemic levels. As shown in Figure 1, the ROR data for Bengkulu Province remain highly fluctuating and generally below 60%.

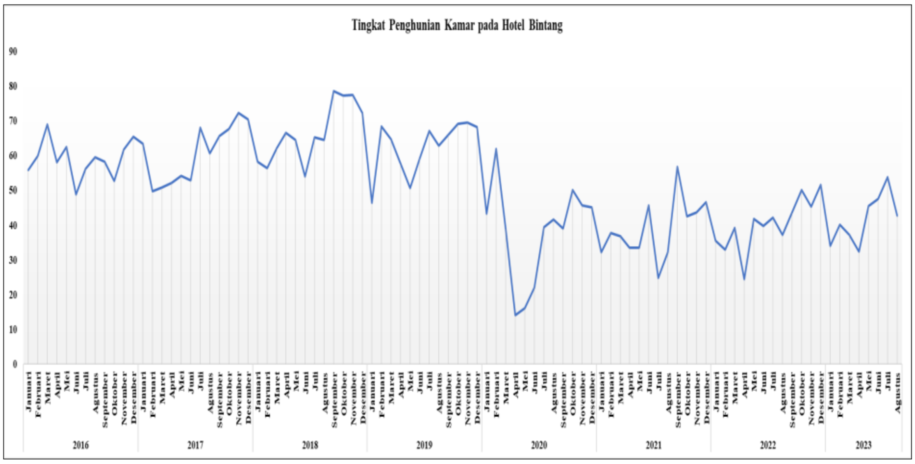

Figure 1 Room Occupancy Rate of Star-Rated Hotels in Bengkulu Province

Considering the importance of Room Occupancy Rate (ROR) data in assessing the condition of the hotel sector, up-to-date data are needed in the future. However, the Room Occupancy Rate (ROR) indicator for the current month published by Statistics Indonesia (BPS) is released in the following month, creating an obstacle in estimating the current condition of the hotel sector. This issue can be addressed by applying a forecasting method that can provide an overview of the most recent conditions. The researcher applies forecasting methods to obtain predictions of the current and future month's ROR so that the present condition of the hotel sector can be identified, since ROR is one of the key indicators generated by the hotel industry. Based on the above explanation, the researcher is interested in conducting a more in-depth study entitled. Comparison of the Application of Chen and Stevenson–Porter Fuzzy Time Series Methods for Forecasting Room Occupancy Rates in Star-Rated Hotels (Case Study: Room Occupancy Rates of Star-Rated Hotels in Bengkulu Province for the Period January 2016 to August 2023).

Method

An important role in time series analysis is played by processes, or some of their components, that do not change over time. If we wish to make predictions, we must assume that something remains constant over time. In extrapolating a deterministic function, it is common practice to assume that the function itself or one of its derivatives is constant. The assumption of a constant first derivative underlies linear extrapolation as a forecasting tool. Our objective, however, is to predict a series that is usually not deterministic but contains a random component. If the random component is stationary, then powerful techniques can be developed to forecast future values [2].

The main objective of time series analysis is to study and understand how the characteristics under investigation evolve over time so that the underlying probabilistic mechanism generating the time series can be determined with reliable accuracy. Once this is achieved, one can attempt to predict the future behavior of those characteristics. The primary goal in analyzing time series is to understand, interpret, and evaluate changes in a phenomenon in order to better anticipate its future course. A good understanding of the mechanism that generates the series can also help us control the phenomena involved in the generating mechanism and thereby influence the future behavior of the process [1].

Forecasting

Forecasting is a process of organizing information about past sequential events in order to estimate or predict future occurrences [4]. Forecasting is generally carried out to predict events that are highly likely to occur, such as rainfall, production demand, and others.

Fuzzy Time Series Chen

According to Chen (1996) [3], the forecasting steps using the Chen Fuzzy Time Series method are as follows::

1. Determine the universe of discourse of the actual data, defined as:

$$U = [D_{min} - B_1, D_{max} + B_2] \tag{1}$$

Where:
D_{min} : minimum data value
D_{max} : maximum data value
B_1 : first arbitrary positive number
B_2 : second arbitrary positive number

2. Partition the universe of discourse U into several equal-length intervals. The number of intervals is determined by the researcher. Suppose U is divided into k k intervals, then the interval length is defined as:

$$l = \frac{[(D_{max}+B_2)-(D_{min}-B_1)]}{k} \tag{2}$$

3. Define fuzzy sets on U and perform fuzzification on the observed historical data. Let A_1, A_2, …, A_p be fuzzy sets with linguistic values of a linguistic variable. The fuzzy sets A_1, A_2, …, A_p on the universe of discourse U are defined as:

$$A_i = \frac{\mu_{A_1}(u_1)}{u_1} + \frac{\mu_{A_2}(u_2)}{u_2} + \frac{\mu_{A_3}(u_3)}{u_3} + \cdots + \frac{\mu_{A_n}(u_n)}{u_n} \quad (3)$$

Each fuzzy set A_i has a membership function μ_{A_1}, such that $\mu_{A_1} : U \rightarrow [0,1]$. if u_i is a member of A_i then μ_{A_1} (u_i) represents the degree of membership of u_i in A_i. A triangular membership function is used to determine the degree of membership.

4. Perform fuzzification, which is the process of mapping input data into fuzzy sets by constructing membership functions. For historical data, the fuzzification process is as follows:

   a. Determine the numerical values of the formed fuzzy sets. These numerical values are used to construct the membership functions. The difference between consecutive numerical values is constant and defined as:

   $$d = \frac{[(D_{max}+B_2)-(D_{min}-B_1)]}{p-1} \quad (4)$$

   The numerical values are then determined as follows:

   $$\begin{aligned} \pi_{A1} &= D_{min} - B_1 \\ \pi_{A2} &= \pi_{A1} + d \\ \pi_{A3} &= \pi_{A2} + d \\ &\vdots \\ \pi_{Ap-1} &= \pi_{Ap-2} + d \\ \pi_{Ap} &= D_{max} - B_2 \end{aligned} \quad (5)$$

   Where
   d : difference between numerical values
   p : number of fuzzy sets
   π_{Ap} : numerical value of fuzzy set A_p

   b. Then, construct the fuzzy membership functions based on the obtained numerical values.

   c. Classify the historical data into fuzzy sets. If the maximum membership degree of a data point in a given period belongs to fuzzy set A_p, then the data point is assigned to fuzzy set A_p.

5. Determine the fuzzy logical relationships (FLR) based on the historical data.

6. Classify the fuzzy logical relationships obtained from Step 4 into groups and combine identical relationships so that there is no repetition of the same relationship.

7. Calculate the forecast value in the Chen Fuzzy Time Series method. There are several forecasting rules that must be considered, including:

   Rule 1: If the fuzzified value at time - t and there is no fuzzy logical relationship (i.e., $A_i \rightarrow \emptyset$, and the maximum membership value of A_i lies in interval u_i with midpoint m_i then the forecast result is: $F_{t+1} = m_i$.

   Rule 2: If the fuzzified value at time - t is A_i and there is only one FLR in the FLRG, such as $A_i \rightarrow A_j$ where the maximum membership of A_i lies in interval u_j with midpoint m_j, then the forecast result is: F_{t+1} is m_j.

   Role 3: If the fuzzified value at time - t is A_j and A_j has several FLRs in its FLRG, such as $A_I \rightarrow A_{j1}, A_{j2}, \ldots, A_{jk}$ where the maximum membership values of A_i, $A_{j1}, A_{j2}, \ldots, A_{jk}$ lie in intervals $u_{j1}, u_{j2}, \ldots, u_{jk}$ with midpoints $m_{j1}, m_{j2}, \ldots, m_{jk}$ then the forecast result is:

   $$F_{t+1} = \frac{m_{j1}, m_{j2}, \ldots, m_{jk}}{k} \quad (6)$$

ISSN: 3089-9729

2.3 Fuzzy Time Series Stevenson-Porter

The Fuzzy Time Series using Percentage Change, also known as the Stevenson–Porter Fuzzy Time Series model, is a newer development of the Fuzzy Time Series method introduced by Meredith Stevenson and John E. Porter in 2009. At that time, the method was applied to forecast enrollment data at the University of Alabama [5].

This method is an extension of earlier Fuzzy Time Series approaches, such as the Frequency Density–Based Partitioning method introduced by Jilani, which constructs frequency density partitions and applies a fuzzy matrix approach for forecasting (Jilani, Burney & Ardil, 2007). It also builds upon the work of Song and Chissom, who developed the Fuzzy Relationship Group (FRG) approach and applied it to the same enrollment dataset from the University of Alabama for the period 1971–1992 (Chen 1996, 2004). In contrast, Stevenson and Porter adopted an approach that utilizes the percentage change of the data as the universe of discourse in forecasting the time series [5].

The steps for obtaining forecast values using the Stevenson–Porter Fuzzy Time Series method are as follows:

1. The forecasting data consist of time series data
$$X_t = \{X_1, X_2, \dots, X_n\} \tag{7}$$
2. Calculate the percentage change of the data from year to year using the equation
$$d_t = \left(\frac{X_t - X_{t-1}}{X_{t-1}}\right) \times 100\% \tag{8}$$
Where:
X_t is the actual data at time -t, X_{t-1} is the actual data at time-$t-1$, n is the total number of observations, and $t = 2, 3, \dots, n$.
3. Determine the class interval length using Sturges' method as follows:
   a. Determine the range (R):
   $$R = Maximum \text{ data} - \text{Minimum data} \tag{9}$$
   b. Determine the number of class intervals (B):
   $$B = 1 + 3.3\log(n) \tag{10}$$
   c. Determine the class interval length (L):
   $$L = \frac{R}{B} \tag{11}$$
4. Determine the universe of discourse U based on Step (c), with $U = [LL, UL]$, Where LL is the lower bound whose value is slightly smaller than the smallest (minimum) percentage change, and UL is the upper bound whose value is slightly greater than the largest (maximum) percentage change.
5. Divide the universe of discourse into several equal intervals. Then, group d_t into the appropriate intervals and calculate the frequency of d_t in each interval.
6. Partition the intervals based on the frequency of d_t in each interval. In the Stevenson–Porter model, the interval with the highest frequency is partitioned into 4 sub-intervals, the interval with the second highest frequency is partitioned into 3 sub-intervals, and the interval with the third highest frequency is partitioned into 2 sub-intervals.
7. Suppose there are $u_1, u_2, \dots, u_n$ intervals; then there will be k fuzzy sets, with each sub-interval obtained through the partitioning in Step (e) serving as the domain of the fuzzy sets.
8. Define the fuzzy sets A_j for $j = 1,2, \dots, n$ based on the formed sub-intervals using a triangular membership function. Then, calculate the midpoint of each obtained sub-interval.

ISSN: 3089-9729

9. Defuzzify the percentage change data using the triangular membership function as follows:

$$t_j = \begin{cases} \dfrac{1+0.5}{\frac{1}{a_1}+\frac{0.5}{a_2}}, & j = 1 \\ \dfrac{1+0.5+1}{\frac{0.5}{a_{j-1}}+\frac{1}{a_j}+\frac{0.5}{a_{j+1}}}, & 2 \le j \le n-1 \\ \dfrac{0.5+1}{\frac{0.5}{a_{n-1}}+\frac{1}{a_n}}, & j = n \end{cases} \tag{12}$$

Where:
$t = 2, 3, \dots, n$
$j = 1, 2, \dots, n$
a_{j-1}, a_j, a_{j+1} are the midpoints of the sub-intervals u_{j-1}, u_j, u_{j+1}.

10. Determine the forecasted data value based on the forecasting result $t_j \rightarrow F(t)$, Where $F(t)$ is the forecasted data value obtained from the percentage change forecast using the formula:

$$F(t) = \left(\frac{t_j}{100} \times X_{t-1}\right) + X_{t-1} \tag{13}$$

Where X_{t+1} is the actual data at time $t + 1$.

Results and Discussion

Based on the descriptive statistical analysis above, it can be observed that from 92 data points of room occupancy rates in star-rated hotels from January 2016 to August 2023 in Bengkulu Province, the mean value is 51.17. This means that the average room occupancy rate of star-rated hotels in Bengkulu Province during that period was 51.17%. The highest room occupancy rate occurred in September 2018 at 78.42%, while the lowest occurred in April 2020 at 13.98%. The low occupancy rate in star-rated hotels at that time was due to the presence of the COVID-19 virus, which restricted people from traveling long distances and staying in hotels.

Table 1. Descriptive Statistical Analysis

Descriptive Statistical Analysis	
Mean	51.17
Standard Error	1.489
Median	51.72
Standard Deviation	14.284
Variance	204.039
Kurtosis	-0.426
Skewness	-0.305
Range	64.44
Minimum	13.98
Maximum	78.42
Sum	4707.55
Count	92

Fuzzy Time Series Chen

1. Determine the Universal Set (U) FTS *Chen*

$$\begin{aligned} U &= [D_{min} - D_1, D_{max} + D_2] \\ &= [13.98 - 1{,}64, 78.42 + 3{,}68] = [12.34, 79.80] \end{aligned}$$

2. Establishment of Chen's FTS Interval

$$Number\ of\ interval = 1 + 3{,}322 \log 10(n)$$

$$= 1 + 3{,}322 \log 10(92) = 7.52 \approx 8$$

$$Interval\ length = \frac{D_{max} - D_{min}}{Number\ of\ interval}$$

$$= \frac{78.42 - 13.98}{8} = 8.06$$

After obtaining 8 class intervals and an interval length of 8.06, the intervals u_1 to u_8 are formed as partitions of the universe of discourse (U) with their respective midpoints shown in the following table:

Table 2 Chen's FTS Interval Length

Interval	Median
$u_1 = [13.98; 22.04]$	$m_1 = 18.01$
$u_2 = [22.04; 30.09]$	$m_2 = 26.06$
$u_3 = [30.09; 38.15]$	$m_3 = 34.12$
$u_4 = [38.15; 46.20]$	$m_4 = 42.17$
$u_5 = [46.20; 54.26]$	$m_5 = 50.23$
$u_6 = [54.26; 62.31]$	$m_6 = 58.28$
$u_7 = [62.31; 70.37]$	$m_7 = 66.34$
$u_8 = [70.37; 78.42]$	$m_8 = 74.39$

3. Formation of Fuzzy Sets (Fuzzification) of FTS Chen

Table 3 Chen's FTS Fuzzification

Month	Room Occupancy Rate in Star Hotels	*Fuzzification*
Januari-16	55.68	A_6
Februari-16	59.68	A_6
Maret-16	68.69	A_7
⋮	⋮	⋮
Juni-23	47.35	A_5
Juli-23	53.65	A_5
Agustus-23	42.62	A_4

In this study, fuzzification is carried out by defining the data into linguistic values according to the appropriate intervals. For example, the room occupancy rate of star-rated hotels in January 2016 was 55.68. This value falls into the linguistic membership degree of A_6, with the interval $[54.26; 62.31]$. The same procedure is applied to the fuzzification results of the other data points.

4. Determine Fuzzy Logic Relations (FLR) FTS Chen

FLR is written $A_i \rightarrow A_j$, A_i is the set of the left side or previous observations, namely $F_{(t-1)}$ and A_j is the set of the right side or current observations, namely $F_{(t)}$ in time series data.

Tabel 4 *Fuzzy Logic Relations* (FLR) FTS *Chen*

Month	Room Occupancy Rate in Star Hotels	Fuzzification	FLR
Januari-16	55.68	A_6	NA
Februari-16	59.68	A_6	$A_6 \rightarrow A_6$
Maret-16	68.69	A_7	$A_6 \rightarrow A_7$
⋮	⋮	⋮	⋮
Juni-23	47.35	A_5	$A_4 \rightarrow A_5$
Juli-23	53.65	A_5	$A_5 \rightarrow A_5$
Agustus-23	42.62	A_4	$A_5 \rightarrow A_4$

In this study, the formation of FLR uses first order, so the FLR for January 2016 has no value. This is because the formation of FLR is based on the previous fuzzification result, namely the data $F_{(t-1)}$. Based on the table above, it can be seen that January 2016 has a fuzzification result of A_6 and Februari 2016 also has a fuzzification result of A_6, Therefore, it can be written in the notation $A_6 \rightarrow A_6$. The same procedure applies to the FLR results for the other data points.

5. Determine FTS Chen's Fuzzy Logic Relations Group (FLRG).

The FLR results that were previously obtained by grouping each FLR that has the same left side or $F_{(t-1)}$ are then combined into the appropriate group.

Table 5 Fuzzy Logic Relations Group (FLRG) FTS Chen

Group	Fuzzy Logic Relations
1	$A_1 \rightarrow A_1, A_4$
2	$A_2 \rightarrow A_3, A_4$
3	$A_3 \rightarrow A_3, A_4, A_6$
4	$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6, A_7$
5	$A_5 \rightarrow A_3, A_4, A_5, A_6, A_7$
6	$A_6 \rightarrow A_4, A_5, A_6, A_7$
7	$A_7 \rightarrow A_4, A_5, A_6, A_7, A_8$
8	$A_8 \rightarrow A_4, A_7, A_8$

6. Defuzzifikasi FTS Chen

There are two stages in the defuzzification process: first, determining the midpoint of each interval; and second, calculating the forecast values based on the three defuzzification rules.

Tabel 6 Defuzzifikasi FTS Chen

Group	FLRG	$F(t)$ Calculation	Forecast Value
1	$A_1 \rightarrow A_1, A_4$	$\frac{m_1 + m_4}{2}$	30.09
2	$A_2 \rightarrow A_3, A_4$	$\frac{m_3 + m_4}{2}$	38.15
3	$A_3 \rightarrow A_3, A_4, A_6$	$\frac{m_3 + m_4 + m_6}{3}$	44.86
4	$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6, A_7$	$\frac{m_1 + m_2 + m_3 + m_4 + m_5 + m_6 + m_7}{7}$	42.17
5	$A_5 \rightarrow A_3, A_4, A_5, A_6, A_7$	$\frac{m_3 + m_4 + m_5 + m_6 + m_7}{5}$	50.23
6	$A_6 \rightarrow A_4, A_5, A_6, A_7$	$\frac{m_4 + m_5 + m_6 + m_7}{4}$	54.26
7	$A_7 \rightarrow A_4, A_5, A_6, A_7, A_8$	$\frac{m_5 + m_6 + m_7}{5}$	58.28
8	$A_8 \rightarrow A_4, A_7, A_8$	$\frac{m_4 + m_7 + m_8}{3}$	60.97

7. Forecasting Results of the Chen FTS Method

The forecast values obtained from the defuzzification process are then directly applied to the entire room occupancy rate data of star-rated hotels based on the previous data fuzzification. The forecasting results for the overall data are as follows:

Table 7 Chen's FTS Forecasting Results

Monthly	Room Occupancy Rate in Star Hotels	Forecast Results
January -16	55.68	NA
February -16	59.68	54.26

Monthly	Room Occupancy Rate in Star Hotels	Forecast Results
March -16	68.69	54.26
⋮	⋮	⋮
June-23	47.35	44.86
July-23	53.65	42.17
August -23	42.62	50.23
		50.23

Based on the forecasting results above, the room occupancy rate in star hotels for September 2023 is 50.23 percent.

8. Calculating the Accuracy of Chen's FTS Forecasting

Table 8 Calculation of Chen's FTS Forecasting Accuracy

Model	MAPE	MSE	MAE
Chen	21.81665	121.09753	8.83473

Based on the forecasting accuracy calculation above, the MAPE value obtained is 21.82%. Since the resulting MAPE value is greater than 20% and less than 50%, it can be concluded that the forecasting performance is fairly good.

4.1 *Fuzzy Time Series Stevenson-Porter*

1. Stevenson-Porter FTS Percentage Change

The percentage change of data at time-t is calculated based on the data from the previous time $(t-1)$. This means that for the percentage change in January 2016 (d_1) since the data for the previous month (December 2015) is unknown, the percentage change for January 2016 cannot be determined. Next, for $t=2$ namely the data for February 2016 (X_2) the percentage change (d_2) can be calculated based on the January 2016 data (X_1) as follows:

$$d_2 = \left(\frac{X_2 - X_1}{X_1}\right) \times 100\% = \left(\frac{59.68 - 55.68}{55.68}\right) \times 100\% = 7.183908\%$$

Likewise with other months. So the results of calculating the percentage change in data are presented in Table 9.

Time (t)	Periode	Star Hotel Room Occupancy Rate	
		Actual	d_t
1	16-Jan	55.68	NA
2	16-Feb	59.68	7.183908
3	16-Mar	68.69	15.09719
⋮	⋮	⋮	⋮
90	23-Jun	47.35	4.571555
91	23-Jul	53.65	13.30517
92	23-Aug	42.62	-20.5592

Based on the percentage change in the room occupancy rate of star-rated hotels, the minimum percentage change occurred in April 2020 at −63.8853%, while the maximum percentage change occurred in July 2020 at 79.42518%. These minimum and maximum values of the percentage change data are subsequently used to determine the class interval length and to define the universe of discourse (U).

2. Stevenson-Porter FTS Class Interval Length

- Determine the range (R) with the equation

$$R = Maximum \text{ data } - \text{Minimum data}$$
$$R = 79.42518 - (-63.8853)$$
$$R = 143.310$$

- Determine the number of interval classes (B) with the equation

$$B = 1 + 3.3\log(n)$$
$$B = 1 + 3.3\log(92) = 8$$

- Determine the length of the class interval (L) with the equation

$$L = \frac{R}{B} = \frac{143.310}{8} = 17.91 \approx 18$$

3. FTS Stevenson-Porter Universal Set

After obtaining the universe of discourse for the Room Occupancy Rate data of star-rated hotels $U = [-63.8853]$ With $L = 17.91 \approx 18.$ the next step is to determine the class intervals of the universe of discourse through the partitioning process of the universe.

4. Partition the Set of the Universe FTS Stevenson-Porter

The universe of discourse (U) obtained in the previous step will be partitioned into several class intervals with equal interval lengths for the Room Occupancy Rate data of star-rated hotels:

- $u_1 = [-64, -46]$
- $u_2 = [-46, -28]$
- $u_3 = [-28, -10]$
- $u_4 = [-10,8]$
- $u_5 = [8,26]$
- $u_6 = [26,44]$
- $u_7 = [44,62]$
- $u_8 = [62,80]$

5. Formation of the Stevenson-Porter FTS Fuzzification Set

Table 10 Stevenson-Porter FTS Fuzzification Set

Period	Room Occupancy Rate in Star Hotels (d_t)	*Fuzzification*
16-Feb	7.184	A_4
16-Mar	15.097	A_5
16-Apr	-15.635	A_3
⋮	⋮	⋮
23-Jun	4.572	A_4
23-Jul	13.305	A_5
23-Aug	-20.559	A_3

In this study, fuzzification is carried out by defining the data into linguistic values according to the appropriate intervals. For example, the percentage change in the room occupancy rate of star-rated hotels in February 2016 was 7.184. This value falls into the linguistic membership degree of A_4, with the interval $[-10,8]$ The same procedure applies to the fuzzification results of the other data points

6. Determine Fuzzy Logic Relations (FLR) FTS Stevenson-Porter

FLR is written $A_i \rightarrow A_j$, A_i is the set of the left side or previous observations, namely $F_{(t-1)}$ and A_j is the set of the right side or current observations, namely $F_{(t)}$ in time series data.

Tabel 11 *Fuzzy Logic Relations* (FLR) FTS *Stevenson-Porter*

Period	Room Occupancy Rate in Star Hotels (d_t)	*Fuzzification*	FLR
16-Feb	7.184	A_4	$A_4 \rightarrow A_5$
16-Mar	15.097	A_5	$A_5 \rightarrow A_3$
16-Apr	-15.635	A_3	$A_3 \rightarrow A_4$
⋮	⋮	⋮	⋮
23-Jun	4.572	A_4	$A_4 \rightarrow A_5$
23-Jul	13.305	A_5	$A_5 \rightarrow A_3$
23-Aug	-20.559	A_3	$A_3 \rightarrow A_0$

Based on the table above, it can be seen that February 2016 had Fuzzification results A_4 and March 2016 had Fuzzification results A_5, so it can be written with the notation $A_4 \rightarrow A_5$. Likewise for the FLR results from other data.

7. Determine the Fuzzy Logic Relations Group (FLRG) FTS Stevenson-Porter

Fuzzy Logic Relations Group (FLRG) is obtained based on the FLR results that have been obtained previously by grouping each FLR that has the same left side or $F_{(t-1)}$ and then combining them into the appropriate group.

Tabel 12 Fuzzy Logic Relations Group (FLRG) FTS Stevenson-Porter

Group	Fuzzy Logic Relations
1	$A_1 \rightarrow A_5$
2	$A_2 \rightarrow A_1, A_5, A_6, A_7, A_8$
3	$A_3 \rightarrow A_3, A_4, A_5, A_6$
4	$A_4 \rightarrow A_2, A_3, A_4, A_5, A_6$
5	$A_5 \rightarrow A_3, A_4, A_5, A_6$
6	$A_6 \rightarrow A_2, A_3, A_4, A_8$
7	$A_7 \rightarrow A_4$
8	$A_8 \rightarrow A_3, A_4$

8. Stevenson-Porter FTS Interval Frequency Rating

Table 13 Stevenson-Porter FTS Interval Frequency Ratings

U	*LL*	*LU*	*Freq*	*Stevenson-Porter*	
				Rank	*L*
u_1	-64	-46	1	1	18.00
u_2	-46	-28	7	4	4.50
u_3	-28	-10	12	6	3.00
u_4	-10	8	42	8	2.25
u_5	8	26	17	7	2.57
u_6	26	44	7	5	3.60
u_7	44	62	1	2	9.00
u_8	62	80	3	3	6.00
			90	36	

Based on the table above, it can be seen that the Stevenson-Porter model has a ranking of the number of frequency intervals. The Stevenson-Porter model partitions the interval with the first largest frequency, namely 42 with L=2.25 into 8 sub-intervals, the second largest frequency interval, namely 17 with L=2.57, will be partitioned into 7 sub-intervals, and so on.

9. Sub-Interval FTS Stevenson-Porter

To divide the intervals into sub-intervals, the interval length can be divided according to the frequency of the data as shown in the table. After obtaining the sub-intervals, calculate the midpoint of each sub-interval using the formula $(LL + LU)/2$. Then, define the fuzzy sets A_j for $j = 1,2, \dots, n$ based on each formed sub-interval. The Stevenson–Porter model produces 28 fuzzy sets.

Table 14 Stevenson-Porter FTS Sub-Intervals

Star Hotel Room Occupancy Rate Data				*Fuzzy*
Sub	*LL*	*LU*	*Mid*	
2.25	-64	-61.75	-94.875	A_1
2.25	-61.75	-59.5	-91.5	A_2
⋮	⋮	⋮	⋮	⋮
9	52.99	61.99	83.985	A_{35}
18	61.99	79.99	101.985	A_{36}

10. Defuzzify Percentage Change With Triangular Membership Functions

Table 15 Defuzzification of Stevenson-Porter FTS Percentage Change

Star Hotel Room Occupancy Rate Data		*Fuzzy*
$Mid\,(a_j)$	t_j	
-94.875	-93.723	A_1
-91.5	-91.438	A_2
⋮	⋮	⋮
83.985	83.671	A_{35}
101.985	95.185	A_{36}

11. Stevenson-Porter FTS Forecast Value

If all percentage change values (t_j) have been obtained, the next step is to forecast the data value at time-t denoted as $(F(t))$ using the percentage change value (t_j) for $t = 2$ namely the data for December 2017 (X_2) the forecast value $F(2)$ can be calculated as follows:

$$
\begin{aligned}
F(t) &= \left(\frac{t_j}{100} \times X_{t-1}\right) + X_{t-1} \\
&= \left(\frac{t_2}{100} \times X_{2-1}\right) + X_{2-1} \\
&= \left(\frac{-88.060}{100} \times 55{,}68\right) + 55{,}68 = -48.976
\end{aligned}
$$

Table 16 Stevenson-Porter forecasting value

(t)	Star Hotel Room Occupancy Rate		*Error*
	Actual	*Stevenson-Porter*	
1	55.68	NA	
2	59.68	58.97	0.7061
⋮	⋮	⋮	⋮
91	53.65	54.07	0.4217
92	42.62	42.77	0.1508

Based on the forecasting results above, the room occupancy rate of star-rated hotels for September 2023 is 42.77 percent. This forecasted value was obtained using the Stevenson–Porter Fuzzy Time Series method.

12. Accuracy of FTS Stevenson-Porter Forecasting

Table 17 Calculation of Stevenson-Porter FTS Forecasting Accuracy

Model	MAPE	MSE	MAE
Stevenson-Porter	11.41	103.9806	4.209101

Based on the calculation results above, the Mean Absolute Percentage Error (MAPE) value obtained is 11.41%. Since the resulting MAPE value is greater than 10% and less than 20%, it can be concluded that the forecasting performance is good.

Conclusion

This study demonstrates that the Stevenson–Porter Fuzzy Time Series method provides superior forecasting performance compared with the Chen Fuzzy Time Series method in modelling the room occupancy rate of star-rated hotels in Bengkulu Province. Based on the empirical results, the Chen model produced a forecast of 50.23% for September 2023, with a MAPE of 21.82%, whereas the Stevenson–Porter model generated a forecast of 42.77% with a lower MAPE of 11.41%. These findings indicate that the Stevenson–Porter approach yields substantially higher predictive accuracy for the dataset under investigation. The better performance of this method may be attributed to its use of percentage change as the universe of discourse, which enables it to better accommodate fluctuations and dynamic movements in hotel occupancy data. In practical terms, this suggests that the Stevenson–Porter method is more reliable for short-term forecasting and may offer greater value for supporting tourism-related planning and decision-making, particularly in contexts characterized by uncertain and volatile demand patterns. Nevertheless, the conclusions of this study should be interpreted within the scope of the available data, which are limited to one province and one tourism indicator. Future research should therefore extend the analysis by incorporating longer observation periods, alternative error measures, and comparisons with other statistical and intelligent forecasting models to assess the robustness and broader applicability of the findings.

Acknowledgment

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