Fuzzy Time Series for Forecasting Railway Passengers in Indonesia

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Abstract. Some fuzzy time series models have their own advantages and disadvantages. In addition, these models sometimes are complex and claimed to have better forecasting result than each other. The suitable model for forecasting depends on a wide variety of considerations. The models proposed by Chen (1996) applied simplified arithmetic operations and claimed more efficiency than before. The model proposed by Chen was introduced in 1996 and still exists in several previous studies. This research aims to forecast the number of railway passengers in Indonesia using the fuzzy time series. In addition, this research also evaluates the forecasting results based on mean absolute error (MAE) and mean absolute percentage error (MAPE). The results showed the forecasting results in this research has accuracy for 86.6%.

1. Introduction
Public transportation is one of the favors to support mobility across cities, provinces, and islands in Indonesia. The railway is one of the most preferred public transportation in Indonesia which is currently managed and operated by the Indonesian Railway Company (PT. Kereta Api Indonesia). According to the data in [1] shows the railway passengers in Indonesia has increased every year from 2006 to 2019. The highest passengers occurred in July 2019 which has reached 39035 passengers. The increase of passengers is correlated with the quality of services provided by the Company. Based on a survey in 2018, Indonesian Railway Company gained the highest Customer Satisfaction Index (CSI) score of 4.08 followed by aircraft with a score of 4.05, shuttle by 3.54, and bus with CSI score of 3.52 [2]. Indonesian Railway Company offers various class services such as sleeper class, priority class, executive class, business class, and economy class to support passenger’s mobility.

However, in April 2020 the railway passengers have significantly decreased to 5898 due to COVID-19 Pandemic. The number of passengers in May 2020 decreased by 5484 and became the lowest in the last decade. Therefore, in terms of business it is important to analyze the movement of historical data to determine what to do in the future. In this case, it is possible to determine the departure schedule by considering the supply and demand to operate Railway at a certain time by using forecasting method. There are various forecasting methods that can be used such as CNN Backpropagation, Regression, Moving Average, Fuzzy Time Series, etc.

This research aims to forecast the dataset of railway passengers by using fuzzy time series proposed by Chen (1996) [3]. Fuzzy time series is one of the forecasting methods which firstly introduced by Song & Chissom in 1993 [4]. There is various development of fuzzy time series models that are used to forecast a set of historical data. However, some of these models have their own advantages and disadvantages. In addition, these models sometimes are complex and claimed to have better forecasting
results than each other. The suitable models in forecasting depends on a wide variety of considerations [5]. Chen found in the proposed model by Song & Chissom used complicated procedures [3]. Therefore, Chen applied simplified arithmetic operations and claimed more efficiency than before. The model proposed by Chen was introduced in 1996 with many developments afterward. This model still exists in several previous studies in [6]–[8]. Based on the comparison forecasting model results in [6] showed that the model proposed by Chen has better results than the model proposed in [9]. In addition, this research also evaluates the forecasting results based on the mean absolute error (MAE) and mean absolute percentage error (MAPE) which commonly used to evaluate forecasting results based on related studies [10], [11].

2. Literature Review

2.1. Fuzzy Time Series
Song & Chissom was introduced fuzzy time series by using the concept of fuzzy sets in [12] as the basis for calculations where the value of historical data are represented by fuzzy sets [4]. Fuzzy sets theory proposed by [12] has good achievement both in theory and practice that allow to make decisions, plans, smart systems, artificial intelligence, etc. Song & Chissom explained their basic forecasting procedure are used the historical data patterns and form it to the next data (forecasting value). Fuzzy time series has 4 characteristics: (1) fuzzy time series is a dynamic process; (2) fuzzy sets as the object; (3) the universe of discourse (U) for the fuzzy sets are subsets of R; and (4) fuzzy time series doesn’t require conventional time series method [4]. Let the universe of discourse (U), U = {u₁, u₂, ..., un}, then a fuzzy set A of U are determined as follow:

\[ A = f_A (u_1)/u_1 + f_A (u_2)/u_2 + \ldots + f_A (u_n)/u_n \]  

where \( f_A \) is the membership function of A, then \( f_A : U \rightarrow [0, 1] \). Membership function is a curve that defines the mapping of input/output points into their membership between 0 and 1. Song & Chissom applied the model of \( A_i = A_{i-1} \circ R \) to forecast the enrollment of students in University of Alabama, where \( A_{i-1} \) is the enrollment of the year \( i - 1 \) terms of a fuzzy set, and the systematic procedures proposed by Song & Chissom show as follows:

- Step 1: Defining the U (universe of discourse) for the fuzzy sets are subsets of R
- Step 2: Collecting the historical linguistic values
- Step 3: Defining the fuzzy sets (fuzzification)
- Step 4: Set up the fuzzy logic relationship (FLR)
- Step 5: Summarizing the FLR
- Step 6: Applying the value of the data to the model and determine the output for the forecasted value
- Step 7: Defuzzification

Chen found in [4] required a large number of calculations to obtain the fuzzy relationship. Chen proposed a new model by using simpler arithmetic operations rather than the complicated max-min composition operations presented in [4]. There are two definitions of fuzzy time series that proposed in [3]. The first definition, let \( Y(t) (t = \ldots, 0, 1, 2, \ldots) \) is a subset of \( R \) (real numbers) be the universe of discourse (U) on fuzzy sets \( f_i(t) (i = 1, 2, \ldots) \). The input sometimes referred from the universe of discourse (U). Then \( F(t) \) is called a fuzzy time series on \( Y(t) \) (t = \( \ldots, 0, 1, 2, \ldots \)). \( F(t) \) represented as linguistic variable, and \( (i = 1, 2, \ldots) \) as possible linguistic value of \( F(t) \), where \( f_i(t) (i = 1, 2, \ldots) \) regarded as fuzzy sets. The values of \( F(t) \) sometimes can be different at certain times due to the fact that the universe of discourse can be different at certain times. When \( F(t) \) only caused by \( F(t - 1) \) then this relationship represented as \( F(t - 1) \rightarrow F(t) \), where \( F(t - 1) \) can be viewed as past time. The second definition, let \( F(t) \) is a fuzzy time series and if \( F(t - 1) \) and \( F(t) \) has unlimited elements, then \( F(t) \) is called a time-variant fuzzy time series. Otherwise, if \( F(t - 1) \) and \( F(t) \) has limited elements it called a time-invariant fuzzy time series.
2.2. Measuring the Forecasting Results

2.2.1. Mean Absolute Error (MAE). MAE is one of the common methods to evaluate model performance because it’s summing the total of absolute error and dividing it by the total of records \( n \) [13]. MAE would be good if the result is closer to 0 and it depends on the size of data. MAE can be obtained by using the following equation:

\[
MAE = \frac{\sum_{i=1}^{n} |A_t - F_t|}{n}
\]  

(2)

2.2.2. Mean Absolute Percentage Error (MAPE). MAPE is one of options for measuring the error of forecasting results. MAPE is easy to understand because it represents the error in percentage [14]. Lewis’s (1982) interpreted MAPE if the value under 10\% regarded as “highly accurate”; 11\% - 20\% regarded as “a good forecast”; 21\% - 50\% is “acceptable”; and >51\% is an “inaccurate forecast” [15]. MAPE can be obtained through this equation:

\[
MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|
\]  

(3)

3. Methods

This research applied the proposed models in [3] to avoid the max-min composition operations, because it would be complicated when the fuzzy relation \( R \) is very big as used in [4].

3.1. Determining the Universe of Discourse

The operations started by determining the maximum of data as \( D_{\text{max}} \) and the minimum of the data as \( D_{\text{min}} \). The universe of discourse \( (U) \) can be obtained by using the following equation:

\[
U = [D_{\text{min}} - D_1; D_{\text{max}} + D_2]
\]  

(4)

where the \( D_1 \) and \( D_2 \) are independent positive numbers. Furthermore, the operation of the forecasting process is as follows:

3.2. Forming Intervals

The forming of intervals is to divide the set of the \( U \) that has been obtained previously into several intervals with the same distance. In determining the intervals of \( U \), the number and length of intervals should be determined first by using the following equation:

\[
\text{Intervals} = 1 + 3.3 \times \log_{10}(n)
\]  

(5)

where \( n \) is the amount of the dataset. The length of intervals can be obtained by using this equation:

\[
\text{Length of Intervals} = \frac{D_{\text{max}} - D_{\text{min}}}{\text{Intervals}}
\]  

(6)

3.3. Fuzzification and Forming Fuzzy Logic Relationship (FLR)

Fuzzification is a process to convert the input from crisp to fuzzy value (linguistic variable) which presented as fuzzy sets with a respective membership function. The fuzzification is carried out based on the determined intervals, from the initial data then grouped according to the number of formed intervals. FLR indicates the association between the fuzzy time series and the composing operator. FLR is a fuzzy logic that has a relationship with a series of data members that have been assigned from the historical data to the forecasted data.
3.4. Fuzzy Logic Relationship Group (FLRG)

FLRG is formed by dividing all the derived FLRs into several groups based on the current states of the enrollments of FLR.

3.5. Defuzzification and Forecasting

The Defuzzification process is used to determine the forecasting value based on the results of FLRG by using 3 rules as follows:

Rules 1: If there is only one logical relation of fuzzy in a series of fuzzy logic relationship, for example $A_1 \rightarrow A_j$, then the forecasting value defined as $F(t) = A_j$.

Rules 2: If there is more than one relationship in a series of fuzzy logic relationship, for example $A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jn}$, then the forecasting value should be the average of the midpoint from $A_{j1}, A_{j2}, \ldots, A_{jn}$ or defined as $F(t) = A_{j1}, A_{j2}, \ldots, A_{jn}$.

Rules 3: If there is no relation on $A_i$ there is nothing like ($A_i \rightarrow \#$), then the forecasting value defined as $F(t) = A_i$.

4. Results

4.1. Determining the Universe of Discourse

The training data in this research are monthly train passenger from January 2006 to July 2021 that available in [1]. The minimum and maximum data (5484 and 39035) are used to determine the $U$ by using equation (4). The values of $D_1 = 4$, and $D_2 = 5$ are obtained arbitrarily to get the appropriate results of the $D_{\text{min}}$ and $D_{\text{max}}$. Therefore, the universe of discourse in this research defined as $U = [5480; 39040]$.

Table 1. Railway Passengers in Indonesia January 2006 – July 2021

| January | February | March | April | May | June | July | August | September | October | November | December |
|---------|----------|-------|-------|-----|------|------|--------|-----------|---------|----------|----------|
| 2006    | 11828    | 11931 | 13314 | 12909 | 13575 | 13203 | 14433  | 13255    | 13436   | 14290    | 13631    | 13614    |
| 2007    | 13960    | 10969 | 13409 | 14415 | 15232 | 15104 | 16454  | 15419    | 15033   | 15866    | 14391    | 15084    |
| 2008    | 15027    | 14378 | 16071 | 15711 | 16363 | 17010 | 17887  | 17108    | 15879   | 17337    | 15973    | 15332    |
| 2009    | 14494    | 13869 | 17112 | 16775 | 17824 | 18143 | 18385  | 17527    | 17281   | 17281    | 16778    | 17581    |
| 2010    | 17424    | 15207 | 16992 | 16832 | 16988 | 17259 | 17680  | 16477    | 17301   | 16908    | 16469    | 17733    |
| 2011    | 16891    | 14890 | 16978 | 16441 | 17522 | 17265 | 18132  | 14846    | 16921   | 16461    | 16179    | 16811    |
| 2012    | 16283    | 15490 | 17090 | 16746 | 17771 | 18062 | 18309  | 17056    | 16368   | 17127    | 15773    | 16104    |
| 2013    | 14900    | 14594 | 15826 | 16000 | 16113 | 17301 | 20245  | 19423    | 19738   | 20534    | 19919    | 21417    |
| 2014    | 21092    | 19998 | 22036 | 21908 | 22988 | 23440 | 22500  | 23199    | 23593   | 24933    | 24356    | 26275    |
| 2015    | 24676    | 22790 | 27267 | 26565 | 27910 | 27562 | 27612  | 27796    | 27549   | 28718    | 27669    | 29831    |
| 2016    | 28358    | 26510 | 28617 | 28435 | 30703 | 29159 | 28831  | 29588    | 29516   | 30263    | 29690    | 32150    |
| 2017    | 30949    | 27342 | 32170 | 31502 | 33745 | 30723 | 34310  | 33791    | 32498   | 35070    | 34361    | 36807    |
| 2018    | 34717    | 31278 | 35875 | 35754 | 35482 | 33030 | 36800  | 35190    | 34504   | 36236    | 35298    | 37965    |
| 2019    | 35122    | 31899 | 35751 | 35809 | 35102 | 35090 | 39035  | 35189    | 35221   | 36448    | 35877    | 37463    |
| 2020    | 34730    | 32383 | 32425 | 58980 | 5484 | 9290   | 12238  | 12774    | 11429   | 11937    | 13722    | 13515    |
| 2021    | 11901    | 11479 | 14284 | 14864 | 14857 | 14556 | 5747   | -        | -       | -        | -        | -        |

4.2. Forming the Interval

Forming the interval data started by determining the number of intervals by using equation (5) and the length of interval by using equation (6). The determined number of intervals are 8 with the length of the interval is 4195. The result of the formed interval are shown in Table 2.

Table 2. Formed Interval Data

| Interval | Bottom | Median | Top |
|----------|--------|--------|-----|
| A0       | 5484   | 7582   | 9679|
| A1       | 9679   | 11777  | 13874|
| A2       | 13874  | 15972  | 18069|
| A3       | 18069  | 20167  | 22264|
| A4       | 22264  | 24362  | 26459|
| A5       | 26459  | 28557  | 30654|
| A6       | 30654  | 32752  | 34849|
| A7       | 34849  | 36947  | 39044|
4.3. Fuzzification and Forming the Fuzzy Logic Relationship (FLR)

The fuzzification process was carried out referred on the intervals that have been determined from the initial data, then grouped according to Table 2. The formed Fuzzification and their relationships are shown in Table 3.

| No. | Data  | Fuzzification | FLR     |
|-----|-------|---------------|---------|
| 1   | 11828 | A1            | -       |
| 2   | 11931 | A1            | A1 → A1|
| 3   | 13314 | A1            | A1 → A1|
| 4   | 12909 | A1            | A1 → A1|
| 5   | 13575 | A1            | A1 → A1|
| 6   | 13203 | A1            | A1 → A1|
| ... | ...   | ...           | ...     |
| 180 | 13515 | A1            | A1 → A1|
| 181 | 11901 | A1            | A1 → A1|
| 182 | 11479 | A1            | A1 → A1|
| 183 | 14284 | A2            | A1 → A2|
| 184 | 14864 | A2            | A2 → A2|
| 185 | 14857 | A2            | A2 → A2|
| 186 | 14556 | A2            | A2 → A2|
| 187 | 5747  | A0            | A2 → A0|

Table 3 shows the first data is 11828 which is fuzzified as A1 and the last data is 5747 which is fuzzified as A0 which is in accordance with the formed intervals in Table 2. The FLR are formed based on previous fuzzification, for example in the first data fuzzified as A1, and then for the second data was also fuzzified as A1. Therefore, the first formed FLR is A1 → A1 as well as next.

4.4. Fuzzy Logic Relationship Group (FLRG)

Table 2 contains 8 intervals from A0 to A7 with the distance of interval by 4195. In addition, Table 3 presents the fuzzification results and established relationship between each data. All established relationship then grouped as in Table 4.

| Group | Fuzzification | FLRG   |
|-------|---------------|--------|
| 1     | A0 →         | A0, A1 |
| 2     | A1           | A1, A2 |
| 3     | A2           | A0, A1, A2, A3 |
| 4     | A3           | A2, A3, A4 |
| 5     | A4           | A0, A3, A4, A5 |
| 6     | A5           | A5, A6 |
| 7     | A6           | A4, A5, A6, A7 |
| 8     | A7           | A6, A7 |

Table 4. The Fuzzy Logic Relationship Group (FLRG)

4.5. Defuzzification and Forecasting

The next step is the defuzzification and determine the forecasting value based on the rules that presented in section 3.5. The defuzzification and forecasting results are shown in Table 5. The forecasting value are obtained from the average of median (midpoint) from the grouped FLR. For example, the A0 → A0, A1 where the midpoint of A0 is 7582, and the midpoint of A1 is 11777 (See Table 2). Therefore, the forecasting results obtained from the group of A0 is 9679.
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4.6. Forecasting Results

In summary, the forecasting results collectively are shown in Table 6.

### Table 6. Forecasting Results

| No. | Date       | Data  | Fuzzification | FLRG               | Forecasting Results |
|-----|------------|-------|---------------|--------------------|---------------------|
| 1   | January 2006| 11828 | A1            | A1 → A1, A2        | -                   |
| 2   | February 2006| 11931 | A1            | A1 → A1, A2        | 13874               |
| 3   | March 2006  | 13314 | A1            | A1 → A1, A2        | 13874               |
| 4   | April 2006  | 12909 | A1            | A1 → A1, A2        | 13874               |
| 5   | May 2006    | 13575 | A1            | A1 → A1, A2        | 13874               |
| 6   | June 2006   | 13203 | A1            | A1 → A1, A2        | 13874               |
| 180 | December 2020| 13515 | A1            | A1 → A1, A2        | 13874               |
| 181 | January 2020| 11901 | A1            | A1 → A1, A2        | 13874               |
| 182 | February 2020| 11479 | A1            | A1 → A1, A2        | 13874               |
| 183 | March 2021  | 14284 | A2            | A2 → A0, A1, A2, A3| 13874               |
| 184 | April 2021  | 14864 | A2            | A2 → A0, A1, A2, A3| 13874               |
| 185 | May 2021    | 14857 | A2            | A2 → A0, A1, A2, A3| 13874               |
| 186 | June 2021   | 14556 | A2            | A2 → A0, A1, A2, A3| 13874               |
| 187 | July 2021   | 5747  | A0            | A0 → A0, A1        | 13874               |
| 188*| August 2021 | -     | -             | -                  | 9679                |

*Forecasted result

While this research was conducted, the available data in Table 1 started from January 2006 to July 2021. Based on the calculations, the railway passengers in August of 2021 approximately will be around 9679 passengers because of the previous relationship was A0 which means A0 → A0, A1 has forecasting value for 9679. Overall forecasting results are presented in Figure 1. The solid line represents the actual data, while the dotted line represents the forecasting results.
Figure 1. Overall Forecasting Results

4.7. Forecasting Evaluation
Forecasting evaluation is an important stage to find the performance of forecasting method. It would be ‘good’ if the forecasting results are similar or close with the actual data, and/or has low of errors value. The MAE and MAPE were applied to evaluate the forecasting results based on the error value obtained in this research.

Table 7. Forecasting Evaluation

| No. | Date           | Data | Forecasting Results | Absolute Error | Absolute Percentage Error |
|-----|----------------|------|---------------------|----------------|--------------------------|
| 1   | January 2006   | 11828| -                   | -              | -                        |
| 2   | February 2006  | 11931| 13874               | 1943           | 0.163                    |
| 3   | March 2006     | 13314| 13874               | 560            | 0.042                    |
| 4   | April 2006     | 12909| 13874               | 965            | 0.075                    |
| 5   | May 2006       | 13575| 13874               | 299            | 0.022                    |
| 6   | June 2006      | 13203| 13874               | 671            | 0.051                    |
| 180 | December 2020  | 13515| 13874               | 152            | 0.011                    |
| 181 | January 2020   | 11901| 13874               | 359            | 0.027                    |
| 182 | February 2020  | 11479| 13874               | 1973           | 0.166                    |
| 183 | March 2021     | 14284| 13874               | 2395           | 0.209                    |
| 184 | April 2021     | 14864| 13874               | 410            | 0.029                    |
| 185 | May 2021       | 14857| 13874               | 990            | 0.067                    |
| 186 | June 2021      | 14556| 13874               | 983            | 0.066                    |
| 187 | July 2021      | 5747 | 13874               | 682            | 0.047                    |
|     | Total          |      |                     | 433957         | 25                       |

Table 7 shows that the total absolute error in this research is 433957, and the total absolute percentage error is 25. Therefore, the MAE and MAPE obtained in this research are 2333 and 0.134 (13.4%) respectively.
5. Conclusion
The results showed that the forecasting model in this research has mean absolute error (MAE) for 2333 and mean absolute percentage error (MAPE) for 13.4% which means has a good forecast based on Lewis’s (1982) interpretation. Therefore, the overall forecasting accuracy is 86.6%. In addition, based on forecasting calculation the railway passengers in August of 2021 will be around 9679 passengers.

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