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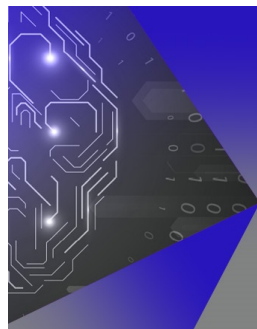
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The Accuracy of the Time-Invariant Fuzzy Method in Forecasting the Number of Ship Passengers at the Port of Makassar

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Abstract. This study aims to examine the accuracy of the time-invariant fuzzy method in forecasting the number of ship passengers at the port of Makassar. Forecasting helps a company establish the number of passengers to come, anticipate their increase, and provide policies for addressing the problem. The Time-Invariant Fuzzy, whose relationship does not depend on time t , was used by utilizing fuzzy sets as historical data. In general, this method has two essential aspects, including the use of historical or actual data and relations. The data used was obtained from the number of ship passengers at Makassar Port from January 2012 to December 2020. The results showed that the Mean Average Percentage Error (MAPE) value in the training and the testing data is 7.9% and 6.8%, respectively. This means that the method is very accurate in predicting ship passengers at Makassar Port.

INTRODUCTION

Transportation is vital and strategic in supporting and encouraging all aspects of life. For instance, it plays a critical role in implanting the mobility of people and goods, and as a part of the economic system, it enhances national and regional development [1]. In Indonesia, South Sulawesi Province is a reasonably large archipelago. Since transportation is an essential means for residents to carry out their activities, its equipment increases alongside the population. The ship is a means of sea transportation that residents use to support their activities in business and tourism [2]. Soekarno Hatta Makassar Port is located in the city of Makassar in the South Sulawesi province with the First-Class title. Because of its geographical location and history, it is the busiest port in eastern Indonesia. There are several ports in Makassar, where some are specifically for passengers, while others are for fishers. This study focuses only on the passenger port, the only place to lean on passenger ships with passengers from various regions. The ships that dock in this include the Tilong Kabila, etc. The port is located in the northern part of the city of Makassar, right at the end of the Ir Sutami toll and Nusantara Roads and crowds every day with passengers crossing between islands in Indonesia, Surabaya, Maluku, and Nusa Tenggara. Large ships from abroad have stopped here several times. The cruise ship almost covers most of the length of the port as it leans [3]. Since Makassar Port has an international status,

it is not surprising that ship passengers increase. Therefore, companies need to do forecasting. They can anticipate the increase and provide a mature policy to deal with the problem [4].

Forecasting activities are conducted to estimate future events using a particular scientific approach. Using the commonly used classical time series forecasting method, predicting data with historical value in the form of actual values will be easy to solve [5]. However, it cannot apply in linguistic value data, which involves words or sentences in an actual or artificial language. Predicting such will be very difficult if classical forecasting methods are used as the solution. An idea emerged that inspired a forecasting case with linguistic data. This problem can be solved since the time series fuzzy method fulfills the shortcomings of the classical time series method function [6]. Time series denotes data in observed values measured over a certain period based on time with uniform intervals. Several methods are used to forecast linguistic time series data. The reasoning system with this method captures past data patterns and uses them to project the future. This method is advantageous because the calculation process does not require complicated systems such as genetic algorithms and neural networks, making it easy to develop. Furthermore, it can solve the problem of historical forecasting data in linguistic values [7].

Time-invariant fuzzy is a forecasting method whose relation does not depend on time t while using fuzzy sets as historical data. It has two essential aspects, the difference between historical or actual data and the relations used to determine forecasting values [8]. After a review, several studies are found to be related. Using the title "Forecasting Using Time-invariant fuzzy Time Series (Case Study: Consumer Price Index of East Kalimantan Province)." the study on Time Series Fuzzy with this method has been conducted [9]. They have also been conducted with the title "Implementation Time-invariant fuzzy Time Series method for predicting the number of departures of domestic shipping passengers at Tanjung Priok Port." and by Malim Muhammad in 2016 with the title "Distribution and Forecasting of New Students of Mathematics Education Universitas Muhammadiyah Purwakerto with Time-invariant fuzzy Time Method, Series" [10]. Since it can minimize errors by multiplying the fuzzy set, using it is very effective. The academician uses it to predict the number of passengers at Soekarno-Hatta Makassar Port.

The data used is the ship passengers at Soekarno-Hatta Makassar Port in 2012 – 2020. The author limits the problem to the Time-invariant fuzzy method with many orders as the number of interval classes. They are seven and four in training and testing data, respectively. Linguistic variables are in words or sentences and not numbers. Words or sentences are used instead of numbers because the linguistic role is less specific, but the information remains informative. Linguistic variables define fuzzy sets in words or sentences. As a data forecasting method, fuzzy time series uses the fuzzy set concept for its calculations. Forecasting systems capture patterns from historical data and use them to project the future. The process does not require a learning system from a complex one, like in genetic algorithms and neural networks. making its use and development easy [11].

Fuzzy Matrix Operation

Maximum of a Matrix

Two fuzzy matrices of the same size are suitable for addition. The max operation is defined as follows [12]:

Definition: Fuzzy Matrix Summation

Suppose $\tilde{A} = [a_{ij}]_{m \times n}$ and $\tilde{B} = [b_{ij}]_{m \times n}$ are two fuzzy matrices, the sum is denoted $\tilde{A} + \tilde{B}$ defined as:

$$\tilde{A} + \tilde{B} = \max\{\tilde{A}, \tilde{B}\} \quad (1)$$

$$[a_{ij} + b_{ij}]_{m \times n} = [\max(a_{ij}, b_{ij})]_{m \times n}; 1 \leq i \leq m, 1 \leq j \leq n \quad (2)$$

Definition: Fuzzy Matrix Subtraction

Suppose $\tilde{A} = [a_{ij}]_{m \times n}$ and $\tilde{B} = [b_{ij}]_{m \times n}$ are two fuzzy matrices, the sum is denoted $\tilde{A} + \tilde{B}$ defined as:

$$\tilde{A} - \tilde{B} = \max\{\tilde{A}, \tilde{B}\} = \tilde{A} + \tilde{B} \quad (3)$$

Minimum of a matrix with a scalar

Definition: Multiplying Fuzzy Matrix by Scalar

Suppose $\tilde{A} = [a_{ij}]_{m \times n}$ is a fuzzy matrix and $k \in F$, where $F = [0,1]$ is a fuzzy unit interval, the scalar multiplication of \tilde{A} with k is denoted by $k\tilde{A}$ or $\tilde{A}k$ is expressed with:

$$k\tilde{A} = \tilde{A}k = [ka_{ij}]_{m \times n} = [\min(k, a_{ij})]_{m \times n}; a_{ij} \in [0,1], 1 \leq i \leq m, 1 \leq j \leq n \quad (4)$$

So $k\tilde{A}$ or $\tilde{A}k$ is a matrix consisting of each entry of \tilde{A} It is multiplied by k .

Maximum-minimum of Matrix

To find the product $\tilde{A}\tilde{B}$ of the two fuzzy matrices \tilde{A} and \tilde{B} according to the product, the size of the columns \tilde{A} = the size of the rows \tilde{B} . The max-min operation on fuzzy matrix multiplication is defined as follows:

For example, $\tilde{A} = [a_{ij}]_{m \times n}$ and $\tilde{B} = [b_{jk}]_{n \times p}$ are two fuzzy matrices. Multiplication $\tilde{A}\tilde{B}$ is defined, then $\tilde{B}\tilde{A}$ is defined as a fuzzy matrix $[c_{ij}]_{m \times p}$, where $c_{ik} = \sum_{j=1}^n a_{ij}b_{jk} = \max \{ \min(a_{ij}, b_{jk}); 1 \leq k \leq p \}$ for $j = 1, 2, \dots, n$.

Measurement of the Accuracy of Forecasting Results - Mean Absolute Percentage Error (MAPE)

Error calculation determines the accuracy of the obtained model. Establishing it makes it possible to determine how the forecasting data from the model and the actual ones are accurate. The Mean Absolute Percentage Error (MAPE) is one of the forecasting methods used. MAPE is the average overall percentage error (difference) between the actual and forecasted data. The MAPE formula is as follows [13]:

$$MAPE = \frac{\sum_{t=1}^n \frac{|x_t - F_t|}{x_t}}{n} \times 100\% \quad (5)$$

MAPE accuracy criteria are as follows: forecasting accuracy is excellent when the MAPE value is < 10%. forecasting accuracy is good when the MAPE value is 10% - 20%, forecasting accuracy is sufficient when the MAPE value is 20% - 50% and forecasting accuracy is not accurate when the MAPE value is > 50%.

METHODS

The study used secondary data obtained from bps.go.id, from January 2012 to December 2020 with the following variables:

- Forecasting accuracy is excellent when the MAPE value is < 10%.
- U = Universal Set
- r_t = Data Variation Value
- F_t = Forecasting Result Value
- x_t = Actual Data Value

The time-invariant fuzzy time series method is as follows:

- Define the universe of discourse (the set of universes U) from the variation of historical data.
- Partition U into equal-length intervals.
- Determine the fuzzy set for the entire universe set (U)

$$A_i = \frac{\mu_{A_i}(u_1)}{u_1} + \frac{\mu_{A_i}(u_2)}{u_2} + \frac{\mu_{A_i}(u_3)}{u_3} + \dots + \frac{\mu_{A_i}(u_n)}{u_n} \quad (6)$$

μ_{A_i} is a membership function of the fuzzy set A_i , such that $\mu_{A_i} : U \rightarrow [0,1]$. If u_i is the membership of A_i then $\mu_{A_i}(u_i)$ is the degree of membership of u_i to A_i .

- Fuzzification of historical forecasting data.
- Determining Fuzzy Logic Relationship (FLR) and Fuzzy Logic Relationship Group (FLRG)
- Determine R_i (combined fuzzy relation in FLRG)

- Determine the forecast output
- Calculates the registration forecast.

RESULT AND DISCUSSION

Training Data

The initial step is to divide the training data to form the best model and the testing data for evaluation. Finding the historical data value (r_t) difference by calculating the difference between x_t and x_{t-1} Calculated from period two is the first step in the Time-invariant fuzzy method. The difference in historical data (r_t) from January 2012 to December 2019 is presented in Table 1:

TABLE 1. Results of the Difference in Historical Data

No.	Month and Year	Total Passenger(x_t)	Variation (r_t)
1	Jan 2012	602051	
2	Feb 2012	531448	-70598
3	Mar 2012	597510	66049
4	Apr 2012	573679	-23820
	⋮	⋮	⋮
95	Nov 2019	1101819	-106639
96	Dec 2019	1087681	-14160

After obtaining the value of (r_t), and sorting it from the smallest to the largest, the value of $r_{min} = -203682$ and the value of $r_{max} = 293600$. Using the values of r_{min} and r_{max} , the universe set is determined, where $d_1 = 8$ and $d_2 = 10$, and that the universal set is obtained as follows:

$$U = [r_{min} - d_1, r_{max} + d_2] = [-203679 - 8, 293611 - 10] = [-203691, 293609]$$

The number of interval classes is then determined

$$K = 1 + 3.22 \log n = 1 + 3.22 \log 96 = 7.41 \text{ is rounded to } 7$$

Determine the range value with the following results:

$$\begin{aligned} \text{Range} &= (r_{max} + d_2) - (r_{min} - d_1) \\ \text{Range} &= 293609 - (-203690) \\ \text{Range} &= 497311 \end{aligned}$$

Then determine the length of the interval as follows:

$$p = \frac{\text{Range}}{K} = \frac{497312}{7} = 71039.77$$

After obtaining the number of intervals which is 7, and the interval length as 71042.285741. the next stage is the fuzzification by finding the lower and the upper limits and median value of 7 fuzzy sets (u_i). U is then partitioned into seven intervals of equal length $u_i, i = \overline{1,8}$. namely:

TABLE 2. Ship Passenger Data Fuzzy Interval

u_i	Lower Limit	Upper Limit	Median
u_1	-203689	-132647.21	-168168.61
u_2	-132647.22	-61604.19	-97125.69
u_3	-61604.31	9438.66	-26082.90
u_4	9438.60	80481.43	44961
u_5	80481.50	151524.31	116002.90
u_6	151524.30	222567.20	187045.69
u_7	222567.09	293609	258088.61

For each data set, determine the fuzzy set for the entire universe set (U) after obtaining the lower and the upper limits and median value of each fuzzy set.

TABLE 3. Linguistic Value and Fuzzification.

A_i	Linguistic Value
A_1	Very Decreasing
A_2	More Decreasing
A_3	Decrease
A_4	Permanent
A_5	Increase
A_6	More increasing
A_7	Very increasing

The next step is to determine FLR and FLRG Fuzzification after having the fuzzy set according to the specified interval.

TABLE 4. Determination of Fuzzification and FLR.

Month / Year	Total Passenger	Variation	Fuzzification	FLR
Jan 2012	602051	-	-	-
Feb 2012	531449	-70588	A_2	-
Mar 2012	597519	66061	A_4	$A_2 \rightarrow A_4$
Apr 2012	573677	-23821	A_3	$A_4 \rightarrow A_3$
⋮	⋮	⋮	⋮	⋮
Nov 2019	1101835	-106639	A_2	$A_4 \rightarrow A_2$
Dec 2019	1087666	-14161	A_3	$A_2 \rightarrow A_3$

After determining Fuzzification from FLR to FLRG, where all FLRs with the same Current state (A_i) are combined into one group. FLRG becomes a combination of fuzzy relations into fuzzy relation groups in case of the same left side. Table 5 presents FLRG results.

TABLE 5. Determination of FLAG

No.	Current State	Next State	FLRG
1	A_1	A_3, A_4, A_5, A_6	$A_1 \rightarrow A_3, A_4, A_5, A_6$
2	A_2	$A_1, A_2, A_3, A_4, A_5, A_6$	$A_2 \rightarrow A_1, A_2, A_3, A_4, A_5, A_6$
3	A_3	A_2, A_3, A_4, A_5, A_7	$A_3 \rightarrow A_2, A_3, A_4, A_5, A_7$
4	A_4	A_1, A_2, A_3, A_4, A_5	$A_4 \rightarrow A_1, A_2, A_3, A_4, A_5$
5	A_5	A_1, A_2, A_3, A_4, A_5	$A_5 \rightarrow A_1, A_2, A_3, A_4, A_5$
6	A_6	A_2	$A_6 \rightarrow A_2$
7	A_7	A_1	$A_7 \rightarrow A_1$

The next step is to determine the Fuzzy (R) relation based on the formed FLRG after the FLRG is obtained according to Table 5, namely:

$$\begin{aligned}
 R_1 &= A_1^T \times A_3 \cup A_1^T \times A_4 \cup A_1^T \times A_5 \cup A_1^T \times A_6 \\
 R_2 &= A_2^T \times A_1 \cup A_2^T \times A_2 \cup A_2^T \times A_3 \cup A_2^T \times A_4 \cup A_2^T \times A_5 \cup A_2^T \times A_6 \\
 R_3 &= A_3^T \times A_2 \cup A_3^T \times A_3 \cup A_3^T \times A_4 \cup A_3^T \times A_5 \cup A_3^T \times A_7 \\
 R_4 &= A_4^T \times A_1 \cup A_4^T \times A_2 \cup A_4^T \times A_3 \cup A_4^T \times A_4 \cup A_4^T \times A_5 \\
 R_5 &= A_5^T \times A_1 \cup A_5^T \times A_2 \cup A_5^T \times A_3 \cup A_5^T \times A_4 \cup A_5^T \times A_5 \\
 R_6 &= A_6^T \times A_2 \\
 R_7 &= A_7^T \times A_1
 \end{aligned}$$

The forecasting output is determined using the max-min composition operator to obtain the following results:

$$\begin{aligned}
 A_1 \circ R_1 &= [0 \quad 0.5 \quad 1 \quad 1 \quad 1 \quad 0.5 \quad 1] \\
 A_2 \circ R_2 &= [1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0.5] \\
 A_3 \circ R_3 &= [0.5 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0.5 \quad 1] \\
 A_4 \circ R_4 &= [1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0.5 \quad 0] \\
 A_5 \circ R_5 &= [1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 0.5 \quad 0] \\
 A_6 \circ R_6 &= [0.5 \quad 1 \quad 0.5 \quad 0 \quad 0 \quad 0 \quad 0] \\
 A_7 \circ R_7 &= [1 \quad 0.5 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]
 \end{aligned}$$

The seven output values are then used to predict the number of passengers. The forecasting outputs for each and t periods are determined by looking at the fuzzification in the previous period ($t - 1$). The defuzzification process follows to obtain the forecast output value (Y). Table 6 shows the complete defuzzification results.

TABLE 6. Forecasting Output for each period

No.	Month/Year	Forecasting Output
1.	Jan 2012	$A_2 \circ R_2$
2.	Feb 2012	$A_4 \circ R_4$
3.	Mar 2012	$A_3 \circ R_3$
4.	Apr 2012	$A_4 \circ R_4$
	⋮	⋮
93	Nov 2019	$A_4 \circ R_4$
94	Dec 2019	$A_2 \circ R_2$

TABLE 7. Forecasting Output Value Results

No	Output of Forecasting	Y
1	$A_1 \circ R_1$	8753.20
2	$A_2 \circ R_2$	28565.11
3	$A_3 \circ R_3$	50879.10
4	$A_4 \circ R_4$	-6706.70
5	$A_5 \circ R_5$	-6706.71
6	$A_6 \circ R_6$	-97121.71
7	$A_7 \circ R_7$	-144481.59

The output value of the forecast can be used to obtain the forecasting value for the number of passengers. Table 8 shows the results.

TABLE 8. Forecasting the number of passengers on the training data

No.	Month/Year	Total Passenger	Fuzzification	Output	F_t
1	Jan-12	622051	-	-	-
2	Feb-12	532053	A_2	-	-
3	Mar-11	598102	A_4	$A_2 \circ R_2$	550019.49
4	Apr-11	563677	A_3	$A_4 \circ R_4$	580799.47
⋮	⋮	⋮	⋮	⋮	⋮
94	Oct-18	1207422	A_4	$A_3 \circ R_3$	1322612.23
95	Nov-18	1101789	A_2	$A_4 \circ R_4$	1201758.48
96	Dec-18	1087721	A_3	$A_2 \circ R_2$	1230391.51

TABLE 9. Error value of training data forecasting results

Month/Year	Total Passenger (x_t)	Forecasting Value (F_t)	$(x_t - F_t)$	$ x_t - F_t $	$\frac{ x_t - F_t }{x_t}$
Jan-12	622051	-	-	-	-
Feb-12	532053	-	-	-	-
Mar-12	598102	550019.49	37486.49	37486.49	0.05
Apr-12	563677	580799.47	-17111.51	17111.50	0.04
May-12	⋮	⋮	-23192.30	23192.31	0.03
⋮	1207422	1322612.23	⋮	⋮	⋮
Nov-20	1101789	1201758.48	-99932.51	99932.51	0.08
Dec-20	1087721	1230391.51	-42718.61	42718.51	0.04

After forecasting using a time-invariant time series, calculating the magnitude of the error with the Mean Percentage Absolute Error (MAPE) is as follows.

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

$$MAPE = 0.073 \times 100\% \rightarrow MAPE = 7.3 \%$$

Data Testing

Forecasting using data testing and processing with training data is the same. The forecasting results from January 2020 to December 2020 are as follows.

TABLE 10. Results of Forecasting the Number of Passengers on testing data for January 2020 to December 2020

No.	Month / Year	Total Passenger	Fuzzification	Output	F_t
1	Jan-20	926338	-	-	-
2	Feb-20	777611	A_1	-	-
3	Mar-20	914563	A_4	$A_1 \circ R_1$	790298.96
4	Apr-20	800506	A_1	$A_4 \circ R_4$	860878.04
5	May-20	813352	A_2	$A_1 \circ R_1$	813195.96
6	Jun-20	931001	A_4	$A_2 \circ R_2$	779809.52
7	Jul-20	927251	A_3	$A_4 \circ R_4$	917402.04
8	Aug-20	934691	A_2	$A_3 \circ R_3$	986752.50

No.	Month / Year	Total Passenger	Fuzzification	Output	F_t
9	Sep-20	940172	A_2	$A_2 \circ R_2$	960144.52
10	Oct-20	953411	A_3	$A_2 \circ R_2$	949631.52
11	Nov-20	963077	A_3	$A_3 \circ R_3$	972911.50
12	Dec-20	962997	A_2	$A_3 \circ R_3$	982597.50

TABLE 11. The results of data forecasting about the number of ship passengers

Month / Year	Forecasting Value (F_t)	$(x_t - F_t)$	$ x_t - F_t $	$\frac{ x_t - F_t }{x_t}$
Jan-21	-	-	-	-
Feb-21	-	-	-	-
Mar-21	790298.96	74263.03	74263.51	0.09
Apr-21	860878.04	-70371.05	70371.06	0.07
May-21	813195.96	-59842.88	59842.88	0.09
Jun-21	779809.52	141276.51	141276.51	0.15
Jul-21	917402.04	59847.88	59847.89	0.06
Aug-21	986752.50	-53064.6	53064.6	0.07
Sep-21	960144.52	-36969.61	36969.61	0.09
Oct-21	949631.52	13777.50	13777.51	0.02
Nov-21	972911.50	183.6	183.4	0.10
Dec-21	982597.50	-9610.6	9610.6	0.00
TOTAL	9113612	59489.95	519206.98	0.81

Mean Percentage Absolute Error (MAPE)

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

$$MAPE = 0.081 \times 100\%$$

$$MAPE = 8.1\%$$

CONCLUSION

Forming a time-invariant fuzzy model requires several steps, including obtaining a universal set (U) and partitioning it into equal interval lengths. The fuzzy set is obtained based on the number of interval classes, followed by the fuzzification of historical forecasting data. The Fuzzy Logic Relationship (FLR) and Fuzzy Logic Relationship Group (FLRG) are then obtained, and the forecast data is obtained using the max-min operator. The output value used to predict the number of passengers can be seen.

Applying this model to forecast the number of ship passengers using four fuzzy sets has an error value of 8.1% in the MAPE calculation. The forecast is accurate since the obtained value is less than 10%. The forecasting data results for Testing the Number of Sea Ship Passengers from January 2021 to December 2021 are 9113612 passengers, while the Mean Percentage Absolute Error (MAPE) is 8.1 %. In general, the forecasting accuracy is perfect when the MAPE value is < 10%.

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