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ABSTRACT

In the subject of railway operation, predicting railway passenger volume has always been a hot topic. Accurately forecasting railway passenger volume is the foundation for railway transportation companies to optimize transit efficiency and revenue. The goal of this research is to use a combination of the fuzzy time series approach based on the rate of change algorithm and the Holt double exponential smoothing method to forecast the number of train passengers. In contrast to prior investigations, we focus primarily on determining the next time period in this research. The fuzzy time series is employed as the forecast basis, the rate of change is used to build the set of universes, and the Holt's Double Exponential Smoothing method is utilized to forecast the following period in this case study. The number of railway passengers predicted for January 2020 is 34799, with a tiny Average Forecasting Error Rate of 0.5791 percent and a Mean Square Error of 58890.6961. It can also help rail firms identify future passenger needs, which can be used to decide whether to expand train cars or run new trains, as well as how to distribute tickets.

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1. INTRODUCTION

Rail transit is a very viable option for meeting public transportation needs. The demand for a more efficient transportation system is growing. Transportation services are a fast-growing industry in a developing country like Indonesia. The planning and management of genuine railway business resources determine the quality of transportation services. Better serve the community and deal with rising transportation costs.

Predicting passenger volume is very important in the field of rail transportation [1]. The key to increasing the operating efficiency and economic income of rail transport companies is the accurate and timely projection of the volume of rail passengers [1]. Accurate transportation volume predictions are critical for formulating strategies for future rail transportation growth, investment, and facility efficiency [2], as well as for local economic development, resource allocation, and cost reduction [3]. It also forms the basis for rail transport companies to determine whether to operate new trains [4], as well as how to allocate tickets [5] and taking ticket prices into consideration [6]. Prediction of the volume of train passengers on a large scale, not only includes predictions of passengers in one area but also passengers in all regions.

The requirement for public transportation services may be controlled sensibly by offering effective ground transportation services, therefore accurate forecasting is critical for every railway firm organization. Surprisingly, the number of train passengers at a station has been discovered to be a proxy for gauging a railway company's resource usage. It is obvious that accurate forecasting of the volume of railway passengers at the stations is critical to the efficient planning and distribution of railway company resources. Evaluating and forecasting the number of train passengers is a difficult and time-consuming task. According to past study, the results of fuzzy time series predictions are generally not obtained directly for the next time period.

Furthermore, the forecasting process and its results must be intelligible not only by rail transportation service company administrators, but also by individuals who make decisions based on the results. However, the current forecasting practice persists, in many ways, completely theoretical and statistically based approaches, notwithstanding the research that has been done to cope with complex time series data. To anticipate train passenger volume, It is vital to use soft computing-based algorithms that are scientifically sound and dependable. This soft computational approach should be able to deal with time series data that is complicated and create approximation values with a small error margin.

Soft computing approaches have been employed to solve prediction difficulties in recent years. In the application section, we describe a novel software system that was created using the presented theory. This covers linguistic study of time series and their trends.

As a result of its ability to solve the forecasting issue in uncertain situations where historical data is incomplete or vague, fuzzy time series are now widely used in a variety of fields, including enrollment forecasting, stock index forecasting, temperature forecasting, and so on, with better forecasting results.

Forecasting is the technique of projecting future performance based on previously collected data. In everyday life, forecasting plays a crucial role. The traditional time squence approach is a prominent forecasting method. The classical time series method, despite its widespread use, has a flaw that the forecasted results are real numbers, what has been described cannot be understood. To circumvent this flaw, the fuzzy time series approach [7] is used. The fuzzy time series approach converts real-number anticipated values into linguistic values.

The goal of this research is to forecast the number of railway passengers using a combination of the Fuzzy Time Series (FTS) and percentage change methods, which are prediction methods based on the percentage change of a datum over a period of time [8] and the classic Double Exponential Smoothing Holt (DES Holt) method. The FTS is employed as the forecasting basis, Percentage of Change is used to build the set of universes, and the DES Holt method is used to forecast the following period in this case study. Thus it can be said that the proposed method has unique characteristic that is, it is a hybrid, in the sense that FTS modeling is combined simultaneously with statistical modeling (DES Holt).

In terms of prediction, numerous researchers recommend using the FTS approach. Song and Chissom [7] were the forerunners of the FTS concept, using it to model academic enrollment data at the University of Alabama [7], [9-21], predict temperature [22, 23], forecast the stock market index [24-35].

Other researchers have developed many improvements to the FTS prediction method, which addressed the following issues [16]: determining the effective interval length [15], [35-41], fuzzy logic relationship [42], and defuzzification methodology [21]. The use of fuzzy metric techniques in predictions [8], [43], [44], as well as the percentage change as the universe of speech [8], [44].

2. RESEARCH METHOD

a. Fuzzy Time Series: A Basic Concept

The first FTS definitions were presented in 1993 [45]. The following are the concepts of FTS. Let U denote the discourse universe, where $U = \{u_1, u_2, \dots u_n\}$. A_i of U is a fuzzy set defined by

$$A_i = fA_i(u_1)/u_1 + fA_i(u_2)/u_2 + \cdots A_i(u_n)/u_n, \quad (1)$$

where f_A is the fuzzy set A_i is membership function; $f_{Ai}: U \to [0,1]$. u_k is a component of the A_i fuzzy set and $f_{Ai}(u_k)$ is the degree to which u_k belongs to A_i, $f_{Ai}(u_k) \in [0,1]$ and $1 < k < n$.

Definition 1. $Y(t)$ $(t = \cdots, 0, 1, 2, \dots)$, is a subset of R. Let $Y(t)$ denote the discourse universe as defined by the fuzzy set $f_i(t)$. If $F(y)$ is made up of $f_1(t)$, $f_2(t)$, and so on, $F(t)$ is a FTS on $Y(u)$ $(t = \dots, 0, 1, 2, \dots)$.

Definition 2. If a fuzzy relationship $R(t-1,t)$ exists such that $F(t) = F(t-1) \times R(t-1,t)$ where $\times$ represents an operator, then $F(t)$ is said to be induced by $F(t-1)$.

Let $F(t) = A_i$ and $F(t-1) = A_j$. The relationship between $F(t)$ and $F(t-1)$ (referred to as a fuzzy logical relationship, FLR) can be denoted by $A_i \to A_j$; where A_i is called the left-hand side (LHS) and A_j the right-hand side (RHS) of the FLR.

Definition 3. Given two FLR on the LHS with the same fuzzy sets, $A_i \to A_{j1}$, $A_i \to A_{j2}$. Both FLR can be combined into FLRG (fuzzy logical relationship groups) $A_i \to A_{j1}, A_{j2}$.

b. The Algorithm's Key Concepts

1) Procedure for event discretization

In FTS theory, the discretization process reduces the complexity of the discourse world. This approach is typically used as a first step in preparing the universe of speech for numerical evaluation by tying events from different time periods together. Differences in time series data have been employed as the universe of discourse in several forecasting systems [46]. Time series data differences can improve forecasting accuracy. However, estimates of growing and decreasing rates of time series data cannot be made solely on the basis of disparities. As a result, the universe of discourse in our method is defined as the percentage of change (PoC) from time t to time $t+1$.

As $PoC(t+1) = (X(t+1) - X(t))\,X(t)$, where $X(t+1)$ is the value at time $t+1$ index and $X(t)$ is the actual value at time t index, the event discretization function can be defined in such a way that its value at time t index correlates with the occurrence of the event at a specific time in the future. PoC is the percentage change in value from time t to time $t+1$.

Table 1. Calculation Example for PoC

Year	Month	Time Series Data	PoC
2012	1	10223	
2012	2	9515	-6.93%
2012	3	10787	13.37%
2012	4	9926	-7.98%

Example: The PoC of period 2012/2 is calculated as (9515-10223)\10223, which equals -6.93 percent, as shown in Table 1. The PoC for the following year/month is calculated in the same way.

2) Procedure for dividing frequency density

- Calculate the number of PoCs that fall in each interval.
- Determine the ranking based on the number of frequencies.
- Divide the interval by the biggest ranking minus one to find the interval.
- Repeat for the next two intervals with the highest frequency.

Table 2. shows sample data at intervals along the number of PoC.

Table 2. PoC Frequency with Interval

Interval	Number of PoC	Ranking
{-15,-10}	1	3
{-10,-5}	4	1
{-5,0}	1	3
{0,5}	3	2

In Table II, the interval {-15,-10} has the highest PoC frequency. It is subdivided into three parts: {-10, -8.33}, {-8.33, -6.67}, and {-6.67, -5}. Furthermore, the interval {-10, -5} is the interval with the next highest frequency of data. It will be separated into two sections: {-10, -7.5} and {-7.5, -5}. After that, leave the intervals {-5, 0} and {0, 5} unaltered.

3) Define fuzzy set based on triangular membership function

Based on the interval produced using the triangular membership function, defining fuzzy set $A_j = 1, 2, 3, 4, \dots, n$ Then, to calculate the anticipated value of the percentage change, find the mean value at the interval obtained. Then, using Equation 2, estimate the percentage change data using the triangle membership function.

$$t_j = \begin{cases} \dfrac{1+0.5}{\frac{1}{a_1}+\frac{0.5}{a_2}} & ,if\ j = 1, \\ \dfrac{0.5+1+0.5}{\frac{0.5}{a_{j-1}}+\frac{1}{a_j}+\frac{0.5}{a_{j+1}}} & ,if\ 2 \le j \le n-2, \\ \dfrac{0.5+1}{\frac{0.5}{a_{n-1}}+\frac{1}{a_n}} & ,if\ j = n. \end{cases} \qquad (2)$$

Where a_{j-1}, a_j, a_{j+1} are the mean of the fuzzy intervals of $x_j - 1$, x_j, $x_j + 1$ respectively. t_j generates prediction of the percentage change in the number of train passengers from month to month.

4) Determining the data value based on the forecasting results $t_j \rightarrow F(t)$.

Where:
x_{t-1}= actual data to $t-1$

5) Determine the prediction for the next time period $t+1$
The combination of methods in research using the DES Holt approach. The DES is a popular technique for predicting the trend of time series data using simple linear equations in business and economics [47]. Introduction A class of forecasting algorithms is described by the exponential smoothing (ES) method [48]. In corporate forecasting, ES is the most used family of forecasting models [49]. The double exponential smoothing (DES) is a trend time series extension of the exponential smoothing (ES) [50].
Calculate the prediction for the next time period $t+1$. Show equation

$$S'_t = \alpha X_t + (1-\alpha)(S'_{t-1} + t_{t-1}) \quad (3)$$

$$t_t = \beta(S'_t - S'_{t-1}) + (1-\beta)t_{t-1} \quad (4)$$

$$F_{t+m} = S'_t + t_{tm} \quad (5)$$

$$S'_1 = X_1 \quad (6)$$

$$t_1 = \frac{(x_2-x_1)+(x_4-x_3)}{2} \quad (7)$$

where:
X_t = Actual data at time t
S'_t = Single smoothing value
t_t = Smoothing trend
α, β = Smoothing parameter between $0-1$
F_{t+m} = Forecast value
m = Future period

6) Steps in the algorithm
Historical data and graphs of the number of train passengers from January 2006 to December 2019 obtained from the Statistics Central Agency (BPS) are shown in Figure 1.

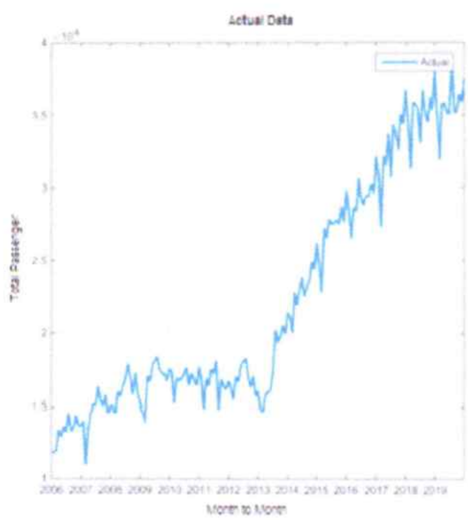

Figure 1. Graph of the Actual Train Passengers Data

In order to solve the prediction issue in this case of the number of train passengers using the FTS and percentage change methods, the steps that follow are carried out:
Step 1: Determining historical data of the actual number of train passengers in the form of time series data $X = x_1, x_2, x_3, x_4, x_5, \ldots, x_n$, then $X = [11828, 11931, 13314, 12909, 13575, \ldots, 37463]$.
Step 2: Determining the set of U universe by:
a. Calculating the real data's percentage change on the number of train passengers using Equation 8.

$$d_t = \left(\frac{X_i - X_{i-1}}{X_{i-1}}\right) * 100 \quad (8)$$

The results of the percentage change for each month-to-month period are shown in Table 3.

Table 3. Percentage of Change

Month Year	%Change	Month Year	%Change	Month Year	%Change	Month Year	%Change
Jan-Feb06	0.8708	Jul-Aug09	-4.6668	Jan-Feb13	-2.0537	Jul-Aug16	2.6256
Feb-Mar06	11.5917	Aug-Sep09	-1.4035	Feb-Mar13	8.4418	Aug-Sep16	-0.2433
Mar-Apr06	-3.0419	Sep-Oct09	0.0000	Mar-Apr13	1.0995	Sep-Oct16	2.5308
Apr-May06	5.1592	Oct-Nov09	-2.9107	Apr-May13	0.7063	Oct-Nov16	-1.8934
May-Jun06	-2.7403	Nov-Dec09	4.7860	May-Jun13	7.3729	Nov-Dec16	8.2856
Jun-Jul06	9.3161	Dec09-Jan10	-0.8930	Jun-Jul13	17.0164	Dec16-Jan17	-3.7356
Jul-Aug06	-8.1619	Jan-Feb10	-12.7238	Jul-Aug13	-4.0603	Jan-Feb17	-11.6547
Aug-Sep06	1.3655	Feb-Mar10	11.7380	Aug-Sep13	1.6218	Feb-Mar17	17.6578
Sep-Oct06	6.3561	Mar-Apr10	-0.9416	Sep-Oct13	4.0328	Mar-Apr17	-2.0765
Oct-Nov06	-4.6116	Apr-May10	0.9268	Oct-Nov13	-2.9950	Apr-May17	7.1202
Nov-Dec06	-0.1247	May-Jun10	1.5952	Nov-Dec13	7.5205	May-Jun17	-8.9554
Dec06-Jan07	2.5415	Jun-Jul10	2.4393	Dec13-Jan14	-1.5175	Jun-Jul17	11.6753
Jan-Feb07	-21.4255	Jul-Aug10	-6.8043	Jan-Feb14	-5.1868	Jul-Aug17	-1.5127
Feb-Mar07	22.2445	Aug-Sep10	5.0009	Feb-Mar14	14.1914	Aug-Sep17	-3.8265
Mar-Apr07	7.5024	Sep-Oct10	-2.2715	Mar-Apr14	-4.0638	Sep-Oct17	7.9143
Apr-May07	5.6677	Oct-Nov10	-2.5964	Apr-May14	4.9297	Oct-Nov17	-2.0217
May-Jun07	-0.8403	Nov-Dec10	7.6750	May-Jun14	3.7063	Nov-Dec17	7.1185
Jun-Jul07	8.9380	Dec10-Jan11	-4.7482	Jun-Jul14	-5.6208	Dec17-Jan18	-5.6783
Jul-Aug07	-6.2903	Jan-Feb11	-11.8465	Jul-Aug14	3.1067	Jan-Feb18	-9.9058
Aug-Sep07	-2.5034	Feb-Mar11	14.0228	Aug-Sep14	1.6983	Feb-Mar18	14.6972
Sep-Oct07	5.5411	Mar-Apr11	-3.1629	Sep-Oct14	5.6373	Mar-Apr18	-0.3373
Oct-Nov07	-9.2966	Apr-May11	6.5750	Oct-Nov14	-2.2750	Apr-May18	-0.7608
Nov-Dec07	4.8155	May-Jun11	-1.4667	Nov-Dec14	7.8790	May-Jun18	-6.9105
Dec07-Jan08	-0.3779	Jun-Jul11	5.0217	Dec14-Jan15	-6.0856	Jun-Jul18	11.4139
Jan-Feb08	-4.3189	Jul-Aug11	-18.1227	Jan-Feb15	-7.6431	Jul-Aug18	-4.3750
Feb-Mar08	11.7749	Aug-Sep11	13.9768	Feb-Mar15	19.6446	Aug-Sep18	-1.9494
Mar-Apr08	-2.2401	Sep-Oct11	-2.7185	Mar-Apr15	-2.5745	Sep-Oct18	5.0197
Apr-May08	4.1500	Oct-Nov11	-1.7131	Apr-May15	5.0631	Oct-Nov18	-2.5886
May-Jun08	3.9540	Nov-Dec11	3.9063	May-Jun15	-1.2469	Nov-Dec18	7.5557
Jun-Jul08	5.1558	Dec11-Jan12	-3.1408	Jun-Jul15	0.1814	Dec18-Jan19	-7.4885
Jul-Aug08	-4.3551	Jan-Feb12	-4.8701	Jul-Aug15	0.6664	Jan-Feb19	-9.1766
Aug-Sep08	-7.1838	Feb-Mar12	10.3292	Aug-Sep15	-0.8886	Feb-Mar19	12.0756
Sep-Oct08	9.1819	Mar-Apr12	-2.0129	Sep-Oct15	4.2433	Mar-Apr19	0.1622
Oct-Nov08	-7.8676	Apr-May12	6.1209	Oct-Nov15	-3.6528	Apr-May19	-1.9744
Nov-Dec08	-4.0130	May-Jun12	1.6375	Nov-Dec15	7.8138	May-Jun19	-0.0342
Dec08-Jan09	-5.4657	Jun-Jul12	1.3675	Dec15-Jan16	-4.9378	Jun-Jul19	11.2425
Jan-Feb09	-4.3121	Jul-Aug12	-6.8436	Jan-Feb16	-6.5167	Jul-Aug19	-9.8527
Feb-Mar09	23.5273	Aug-Sep12	-4.0338	Feb-Mar16	7.9479	Aug-Sep19	0.0909
Mar-Apr09	-2.0838	Sep-Oct12	4.0371	Mar-Apr16	-0.0300	Sep-Oct19	3.4837
Apr-May09	6.2534	Oct-Nov12	-7.9056	Apr-May16	7.9761	Oct-Nov19	-1.5666
May-Jun09	1.7897	Nov-Dec12	2.0985	May-Jun16	-5.0288	Nov-Dec19	4.4207
Jun-Jul09	1.3338	Dec12-Jan13	-7.4764	Jun-Jul16	-1.1249	-	-

b. Determining LL and UL from the results of the percentage change in Table 3, then the obtained value of LL is -21.4255 and UL 23.5273. Thus U can be determined using Equation 9.

$$U = [LL - D_1\ , UL + D_2] \quad (9)$$

The values of D_1 and D_2 are positive integers to assist in defining the set of U universe, so that the set of universes is defined $U = [-22.0000, 26.5395]$.

c. Forming an interval class by calculating the number of intervals using formula 10.

$$B = 1 + 3.3 * \log(n) \quad (10)$$

n = number of percentage change of data.

$$B = 1 + 3.3 * \log(167) = 8.3350 \approx 9$$

d. Calculating the length of the interval class using formula 11.

$$P = \frac{UL - LL}{B} \quad (11)$$

$$P = \frac{23.5273 - (-21.4255)}{8.3350} = 5.3393$$

Step 3: Based on the result of forming the interval class on the set of universe, then the frequency of the percentage change of data included in each of these intervals was calculated and ranked based on the frequency, as shown in Table 4.

Table 4. Frequency and Ranking

Initial Interval Class	Frequency	Ranking
[-22.0000 , -16.6067]	2	1
[-16.6067 , -11.2134]	3	3
[-11.2134 , -5.8202]	18	6
[-5.8202 , -0.4269]	57	9
[-0.4269 , 4.9664]	40	8
[4.9664 , 10.3597]	31	7
[10.3597 , 15.7530]	11	5
[15.7530 , 21.1462]	3	4
[21.1462 , 26.5395]	2	2

Step 4: Determining each fuzzy set x_i based on the divided interval and fuzzification of the historical data of the number of train passengers, where the fuzzy set x_i shows linguistic value from month to month of the percentage change of data represented by the fuzzy set. Dividing the length of the interval based on the ranking of the data with the largest to the smallest frequency, for example $n =$ the largest frequency rating the length of the interval is 5.3933, the ranking that is at the greatest frequency is 9, then for the first interval it is divided into $n - 1 = 9 - 1 = 8$ intervals with the same interval length, namely $5.3933 / 8 = 0.6742$. The second interval is divided into $n - 2 = 9 - 2 = 7$ intervals with the same interval length, namely $5.3933/7 = 0.7705$. The third interval is divided into $n - 3 = 9 - 3 = 6$ intervals with the same interval length, namely $5.3933/6 = 0.8989$ and so on until the ninth last interval. The total number of intervals obtained becomes 37 interval classes. Then determining the mean value of each interval class as shown in Table 5.

Table 5. Frequency Distribution, Fuzzy Set, and Mean Value

Fuzzy	Intervals	Mean
A1	[-22.0000 , -21.3258]	-21.6629
A2	[-21.3258 , -20.6517]	-20.9888
A3	[-20.6517 , -19.9775]	-20.3146
A4	[-19.9775 , -19.3034]	-19.6404
A5	[-19.3034 , -18.6292]	-18.9663
A6	[-18.6292 , -17.9550]	-18.2921
A7	[-17.9550 , -17.2809]	-17.6180
A8	[-17.2809 , -16.6067]	-16.9438
A9	[-16.6067 , -15.8363]	-16.2215
A10	[-15.8363 , -15.0658]	-15.4510
A11	[-15.0658 , -14.2953]	-14.6805
A12	[-14.2953 , -13.5248]	-13.9101
A13	[-13.5248 , -12.7544]	-13.1396
A14	[-12.7544 , -11.9839]	-12.3691
A15	[-11.9839 , -11.2134]	-11.5987
A16	[-11.2134 , -10.3146]	-10.7640
A17	[-10.3146 , -9.4157]	-9.8651
A18	[-9.4157 , -8.5168]	-8.9662
A19	[-8.5168 , -7.6179]	-8.0674
A20	[-7.6179 , -6.7190]	-7.1685
A21	[-6.7190 , -5.8202]	-6.2696
A22	[-5.8202 , -4.7415]	-5.2808
A23	[-4.7415 , -3.6628]	-4.2022
A24	[-3.6628 , -2.5842]	-3.1235
A25	[-2.5842 , -1.5055]	-2.0449
A26	[-1.5055 , -0.4269]	-0.9662
A27	[-0.4269 , 0.9214]	0.2473
A28	[0.9214 , 2.2698]	1.5956
A29	[2.2698 , 3.6181]	2.9439
A30	[3.6181 , 4.9664]	4.2922
A31	[4.9664 , 6.7642]	5.8653
A32	[6.7642 , 8.5619]	7.6630
A33	[8.5619 , 10.3597]	9.4608
A34	[10.3597 , 13.0563]	11.7080
A35	[13.0563 , 15.7530]	14.4046
A36	[15.7530 , 21.1462]	18.4496

A37	[21.1462 , 26.5395]	23.8429

Step 5: Defuzzifying the fuzzy data shown in Table 6.

Step 6: Determining the value of the data based on the results of forecasting $t_j \rightarrow F(t)$ where $F(t)$ is the forecasting value of the data percentage change. The formula 12 is used to determine $F(t)$. The results of $F(t)$ are shown in Table 4.

$$F(t) = \left(\frac{t_j}{100} * x_{t-1}\right) + x_{t-1} \quad (12)$$

Where:

x_{t-1}= actual data to $t - 1$

Whereas for $t + 1$ forecasting used the classic Double Exponential Smoothing Holt (DES Holt) forecasting method with $\alpha = 0.1$ and $\gamma = 0.1$, the value of data smoothing in December 2019 was 34510.2 while the trend smoothing value was 320.12 using formula 3, 4 , 5 , 6, and 7. So that the forecast value for January 2020 is:

$F(Jan\ 2020) = st + bt\ (m) = 34510.2 + (320.12) \cdot (1) = 34830.3$ then the forecast results for January 2020 is:

$$F(Jan\ 2020) = \left(\frac{-7.1117}{100} * 34830.3\right) + 34830.3 = 32353.3$$

Step 7: Calculating the average forecasting error rate (AFER) and mean square error (MSE) [44] between real data and predicted results, namely the formulas 13 and 14 shown in Table 6 and Figure 2.

$$AFER = \frac{\left(\frac{|A_i - F_i|}{A_i}\right)}{n} * 100\% \quad (13)$$

$$MSE = (\Sigma(A_i - F_i)^2)/n \quad (14)$$

Where:

i = 1 .... n

Table 6. Prediction Results

Month Year	Passangers $(A)_i$	% Change(d_t)	Fuzzy Sets	Prediction %(t_j)	Forecast $(F_i)t$	$A_i - F_i$	AFER	MSE
Jan06	11828	-	-	-	-	-	-	-
Feb06	11931	0.8708	A27	0.5209	11890	41	0.3469	1712.9622
Mar06	13314	11.5917	A34	11.5625	13311	3	0.0261	12.0974
Apr06	12909	-3.0419	A24	-2.9255	12924	-15	0.1201	240.2168
May06	13575	5.1592	A31	5.6781	13642	-67	0.4935	4487.1147
Jun06	13203	-2.7403	A24	-2.9255	13178	25	0.1904	631.8499
Jul06	14433	9.3161	A33	9.3610	14439	-6	0.0411	35.1985
Aug06	13255	-8.1619	A19	-8.0170	13276	-21	0.1577	437.0771
Sep06	13436	1.3655	A28	0.7096	13349	87	0.6471	7559.0018
Oct06	14290	6.3561	A31	5.6781	14199	91	0.6374	8297.4763
Nov06	13631	-4.6116	A23	-4.0590	13710	-79	0.5793	6236.0872
Dec06	13614	-0.1247	A27	0.5209	13702	-88	0.6464	7744.6827
Jan07	13960	2.5415	A29	2.5990	13968	-8	0.0561	61.2754
Feb07	10969	-21.4255	A1	-21.4334	10968	1	0.0101	1.2158
Mar07	13409	22.2445	A37	21.7259	13352	57	0.4242	3236.0203
Apr07	14415	7.5024	A32	7.4462	14407	8	0.0523	56.8372
May07	15232	5.6677	A31	5.6781	15233	-1	0.0098	2.2443
Jun07	15104	-0.8403	A26	2.6936	15642	-538	3.5639	289755.2112
Jul07	16454	8.9380	A33	9.3610	16518	-64	0.3883	4081.3494
Aug07	15419	-6.2903	A21	-6.1741	15438	-19	0.1240	365.3292
Sep07	15033	-2.5034	A25	-1.7144	15155	-122	0.8093	14800.3439
Oct07	15866	5.5411	A31	5.6781	15887	-21	0.1298	423.8976
Nov07	14391	-9.2966	A18	-8.9210	14451	-60	0.4141	3551.4615
Dec07	15084	4.8155	A30	4.0978	14981	103	0.6847	10667.9156
Jan08	15027	-0.3779	A27	0.5209	15163	-136	0.9022	18379.9179
Feb08	14378	-4.3189	A23	-4.0590	14417	-39	0.2716	1525.2204
Mar08	16071	11.7749	A34	11.5625	16040	31	0.1901	932.9207
Apr08	15711	-2.2401	A25	-1.7144	15795	-84	0.5377	7136.6636

May08	16363	4.1500	A30	4.0978	16355	8	0.0501	67.1522
Jun08	17010	3.9540	A30	4.0978	17034	-24	0.1383	553.3322
Jul08	17887	5.1558	A31	5.6781	17976	-89	0.4967	7893.4003
Aug08	17108	-4.3551	A23	-4.0590	17161	-53	0.3096	2805.4681
Sep08	15879	-7.1838	A20	-7.1117	15891	-12	0.0777	152.0370
Oct08	17337	9.1819	A33	9.3610	17365	-28	0.1640	808.4463
Nov08	15973	-7.8676	A19	-8.0170	15947	26	0.1622	671.1877
Dec08	15332	-4.0130	A23	-4.0590	15325	7	0.0479	53.9354
Jan09	14494	-5.4657	A22	-5.1533	14542	-48	0.3305	2294.0310
Feb09	13869	-4.3121	A23	-4.0590	13906	-37	0.2645	1346.0490
Mar09	17132	23.5273	A37	21.7259	16882	250	1.4583	62417.4917
Apr09	16775	-2.0838	A25	-1.7144	16838	-63	0.3773	4005.4965
May09	17824	6.2534	A31	5.6781	17728	96	0.5414	9312.0039
Jun09	18143	1.7897	A28	0.7096	17950	193	1.0611	37064.2954
Jul09	18385	1.3338	A28	0.7096	18272	113	0.6160	12827.2097
Aug09	17527	-4.6668	A23	-4.0590	17639	-112	0.6376	12488.6995
Sep09	17281	-1.4035	A26	2.6936	17999	-718	4.1555	515678.0541
Oct09	17281	0.0000	A27	0.5209	17371	-90	0.5209	8103.0115
Nov09	16778	-2.9107	A24	-2.9255	16775	3	0.0152	6.5314
Dec09	17581	4.7860	A30	4.0978	17466	115	0.6568	13333.5786
Jan10	17424	-0.8930	A26	2.6936	18055	-631	3.6189	397608.2038
Feb10	15207	-12.7238	A14	-12.3451	15273	-66	0.4339	4354.6505
Mar10	16992	11.7380	A34	11.5625	16965	27	0.1571	712.3895
Apr10	16832	-0.9416	A26	2.6936	17450	-618	3.6698	381548.9809
May10	16988	0.9268	A28	0.7096	16951	37	0.2152	1336.6430
Jun10	17259	1.5952	A28	0.7096	17109	150	0.8717	22636.1509
Jul10	17680	2.4393	A29	2.5990	17708	-28	0.1559	759.6313
Aug10	16477	-6.8043	A20	-7.1117	16423	54	0.3298	2953.7660
Sep10	17301	5.0009	A31	5.6781	17413	-112	0.6449	12450.2162
Oct10	16908	-2.2715	A25	-1.7144	17004	-96	0.5701	9291.3513
Nov10	16469	-2.5964	A24	-2.9255	16413	56	0.3379	3096.2035
Dec10	17733	7.6750	A32	7.4462	17695	38	0.2125	1420.1835
Jan11	16891	-4.7482	A22	-5.1533	16819	72	0.4253	5160.2225
Feb11	14890	-11.8465	A15	-11.5546	14939	-49	0.3312	2431.7240
Mar11	16978	14.0228	A35	14.3648	17029	-51	0.2999	2592.7160
Apr11	16441	-3.1629	A24	-2.9255	16481	-40	0.2452	1624.7840
May11	17522	6.5750	A31	5.6781	17375	147	0.8416	21745.5071
Jun11	17265	-1.4667	A26	2.6936	17994	-729	4.2223	531401.0399
Jul11	18132	5.0217	A31	5.6781	18245	-113	0.6250	12842.3210
Aug11	14846	-18.1227	A6	-18.2797	14818	28	0.1918	810.8372
Sep11	16921	13.9768	A35	14.3648	16979	-58	0.3404	3317.5536
Oct11	16461	-2.7185	A24	-2.9255	16426	35	0.2128	1226.6704
Nov11	16179	-1.7131	A25	-1.7144	16179	0	0.0013	0.0430
Dec11	16811	3.9063	A30	4.0978	16842	-31	0.1843	959.9501
Jan12	16283	-3.1408	A24	-2.9255	16319	-36	0.2223	1310.0198
Feb12	15490	-4.8701	A22	-5.1533	15444	46	0.2977	2126.3017
Mar12	17090	10.3292	A33	9.3610	16940	150	0.8776	22494.3304
Apr12	16746	-2.0129	A25	-1.7144	16797	-51	0.3046	2601.9222
May12	17771	6.1209	A31	5.6781	17697	74	0.4172	5497.5365
Jun12	18062	1.6375	A28	0.7096	17897	165	0.9129	27191.0153
Jul12	18309	1.3675	A28	0.7096	18190	119	0.6490	14121.0556
Aug12	17056	-6.8436	A20	-7.1117	17007	49	0.2878	2408.9596
Sep12	16368	-4.0338	A23	-4.0590	16364	4	0.0263	18.5162
Oct12	17127	4.6371	A30	4.0978	17039	88	0.5154	7791.9629
Nov12	15773	-7.9056	A19	-8.0170	15754	19	0.1209	363.7255
Dec12	16104	2.0985	A28	0.7096	15885	219	1.3604	47993.7645
Jan13	14900	-7.4764	A20	-7.1117	14959	-59	0.3942	3449.4281
Feb13	14594	-2.0537	A25	-1.7144	14645	-51	0.3464	2555.7474
Mar13	15826	8.4418	A32	7.4462	15681	145	0.9181	21112.5468
Apr13	16000	1.0995	A28	0.7096	15938	62	0.3856	3806.7301
May13	16113	0.7063	A27	0.5209	16083	30	0.1841	879.4783
Jun13	17301	7.3729	A32	7.4462	17313	-12	0.0682	139.3865
Jul13	20245	17.0164	A36	18.2011	20450	-205	1.0125	42013.6483
Aug13	19423	-4.0603	A23	-4.0590	19423	0	0.0013	0.0653
Sep13	19738	1.6218	A28	0.7096	19561	177	0.8976	31390.7652
Oct13	20534	4.0328	A30	4.0978	20547	-13	0.0625	164.4489
Nov13	19919	-2.9950	A24	-2.9255	19933	-14	0.0717	203.8564
Dec13	21417	7.5205	A32	7.4462	21402	15	0.0691	218.7862
Jan14	21092	-1.5175	A25	-1.7144	21050	42	0.1999	1778.5660
Feb14	19998	-5.1868	A22	-5.1533	20005	-7	0.0353	49.9278
Mar14	22836	14.1914	A35	14.3648	22871	-35	0.1518	1202.1964
Apr14	21908	-4.0638	A23	-4.0590	21900	-1	0.0050	1.1810
May14	22988	4.9297	A30	4.0978	22806	182	0.7928	33216.5118
Jun14	23840	3.7063	A30	4.0978	23930	-90	0.3775	8100.4075

Jul14	22500	-5.6208	A22	-5.1533	22611	-111	0.4953	12421.8336
Aug14	23199	3.1067	A29	2.5990	23085	114	0.4924	13047.3506
Sep14	23593	1.6983	A28	0.7096	23364	229	0.9722	52615.1367
Oct14	24923	5.6373	A31	5.6781	24933	-10	0.0387	92.8165
Nov14	24356	-2.2750	A25	-1.7144	24496	-140	0.5737	19521.7030
Dec14	26275	7.8790	A32	7.4462	26170	105	0.4012	11109.9037
Jan15	24676	-6.0856	A21	-6.1741	24653	23	0.0942	540.3196
Feb15	22790	-7.6431	A19	-8.0170	22698	92	0.4049	8514.6609
Mar15	27267	19.6446	A36	18.2011	26938	329	1.2065	108220.8069
Apr15	26565	-2.5745	A25	-1.7144	26800	-235	0.8829	55006.4561
May15	27910	5.0631	A31	5.6781	28073	-163	0.5854	26695.3984
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Sep15	27549	-0.8886	A26	2.6936	28545	-996	3.6143	991444.4899
Oct15	28718	4.2433	A30	4.0978	28678	40	0.1396	1607.7757
Nov15	27669	-3.6528	A24	-2.9255	27878	-209	0.7548	43620.3734
Dec15	29831	7.8138	A32	7.4462	29729	102	0.3410	10345.1117
Jan16	28358	-4.9378	A22	-5.1533	28294	64	0.2267	4132.0371
Feb16	26510	-6.5167	A21	-6.1741	26607	-97	0.3665	9437.8742
Mar16	28617	7.9479	A32	7.4462	28484	133	0.4648	17692.2932
Apr16	28435	-0.6360	A26	2.6936	29388	-953	3.3509	907880.2676
May16	30703	7.9761	A32	7.4462	30552	151	0.4907	22702.3620
Jun16	29159	-5.0288	A22	-5.1533	29121	38	0.1311	1460.5925
Jul16	28831	-1.1249	A26	2.6936	29944	-1113	3.8619	1239719.2924
Aug16	29588	2.6256	A29	2.5990	29580	8	0.0260	59.0179
Sep16	29516	-0.2433	A27	0.5209	29742	-226	0.7661	51132.0145
Oct16	30263	2.5308	A29	2.5990	30283	-20	0.0665	404.8482
Nov16	29690	-1.8934	A25	-1.7144	29744	-54	0.1825	2934.5111
Dec16	32150	8.2856	A32	7.4462	31901	249	0.7752	62112.2134
Jan17	30949	-3.7356	A23	-4.0590	30845	104	0.3359	10809.4490
Feb17	27342	-11.6547	A15	-11.5546	27373	-31	0.1133	958.9456
Mar17	32170	17.6578	A36	18.2011	32319	-149	0.4617	22065.5463
Apr17	31502	-2.0765	A25	-1.7144	31618	-116	0.3697	13567.0127
May17	33745	7.1202	A32	7.4462	33848	-103	0.3043	10547.6852
Jun17	30723	-8.9554	A18	-8.9210	30735	-12	0.0378	134.7584
Jul17	34310	11.6753	A34	11.5625	34275	35	0.1010	1200.8391
Aug17	33791	-1.5127	A25	-1.7144	33722	69	0.2048	4790.1127
Sep17	32498	-3.8265	A23	-4.0590	32419	79	0.2418	6174.2962
Oct17	35070	7.0143	A32	7.4462	34918	152	0.4338	23144.7308
Nov17	34361	-2.0217	A25	-1.7144	34469	-108	0.3136	11612.2004
Dec17	36807	7.1185	A32	7.4462	36920	-113	0.3059	12676.2338
Jan18	34717	-5.6783	A22	-5.1533	34910	-193	0.5566	37335.8500
Feb18	31278	-9.9058	A17	-9.8240	31306	-28	0.0908	806.6691
Mar18	35875	14.6972	A35	14.3648	35771	104	0.2898	10811.3945
Apr18	35754	-0.3373	A27	0.5209	36062	-308	0.8611	94785.7072
May18	35482	-0.7608	A26	2.6936	36717	-1235	3.4808	1525397.2725
Jun18	33030	-6.9105	A20	-7.1117	32959	71	0.2161	5094.1614
Jul18	36800	11.4139	A34	11.5625	36849	-49	0.1334	2410.1963
Aug18	35190	-4.3750	A23	-4.0590	35306	-116	0.3305	13522.8989
Sep18	34504	-1.9494	A25	-1.7144	34587	-83	0.2307	6839.7267
Oct18	36236	5.0197	A31	5.6781	36463	-227	0.6269	51606.9468
Nov18	35298	-2.5886	A24	-2.9255	35176	122	0.3459	14904.5470
Dec18	37965	7.5557	A32	7.4462	37926	39	0.1018	1493.0746
Jan19	35122	-7.4885	A20	-7.1117	35265	-143	0.4073	20461.3270
Feb19	31899	-9.1766	A18	-8.9210	31989	-90	0.2814	8058.0030
Mar19	35751	12.0756	A34	11.5625	35587	164	0.4578	26790.5286
Apr19	35809	0.1622	A27	0.5209	35937	-128	0.3581	16442.1530
May19	35102	-1.9744	A25	-1.7144	35195	-93	0.2652	8665.8419
Jun19	35090	-0.0342	A27	0.5209	35285	-195	0.5553	37965.0876
Jul19	39035	11.2425	A34	11.5625	39147	-112	0.2876	12607.0791
Aug19	35189	-9.8527	A17	-9.8240	35200	-11	0.0318	125.4758
Sep19	35221	0.0909	A27	0.5209	35372	-151	0.4296	22891.5390
Oct19	36448	3.4837	A29	2.5990	36136	312	0.8549	97098.4301
Nov19	35877	-1.5666	A25	-1.7144	35823	54	0.1501	2901.3857
Dec19	37463	4.4207	A30	4.0978	37347	116	0.3092	13417.1203
Jan20	34830	-7.0274	A20	-7.1117	34799	32	0.0906	996.5815
							0.5791	58890.6961

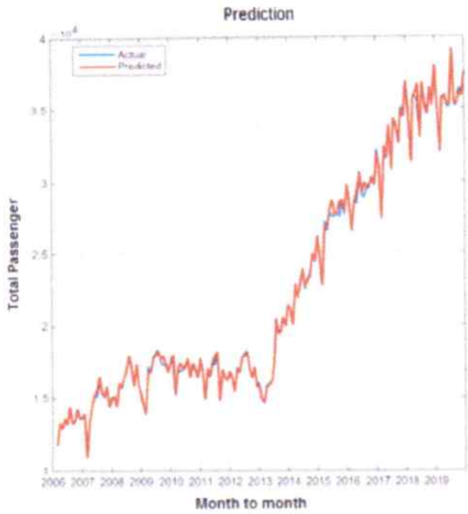

Figure 2. Prediction Result Graph

3. CONCLUSION

In this study, the modeling of the number of train passengers from month to month uses the Percentage Change as the set of universe. It can be observed from Table 6 that the application of the FTS and Percentage Change methods to handle the prediction of the number of train passengers produces small AFER and MSE which shows high degree of accuracy, namely AFER=0.5791% and MSE=58890.6961 which shows the level of accuracy of the FTS PC forecasting method with the DES Holt combination is very high. In future research, the researchers will employ the FTS and Percentage Change methods to handle the prediction of the number of train passengers by constructing a web-based application and/or using additional methods to anticipate the data based on different intervals to gain improved accuracy.

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