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Prediction of passenger train using fuzzy time series and percentage change methods

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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 forecasting 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 38199, with a tiny average forecasting error rate of 0.89 percent and a mean square error of 131325. 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: if 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

2.1. 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:

$$A_i = fA_i\,(u_1)/u_1 + fA_i\,(u_2)/u_2 + \cdots A_i\,(u_n)/u_n, \tag{1}$$

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) $A_i \to A_{j1}, A_{j2}$.

2.2. The algorithm's key concepts

2.2.1. 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 $t + 1$. 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.

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%

2.2.2. Procedure for dividing frequency density

We changed the approach for dividing the frequency density [8], [9], [43], [44] in this session to:

- 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.
- In the same manner, repeat for the next interval.

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

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

2.2.3. Define fuzzy set based on triangular membership function

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

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

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.

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

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

2.2.5. Determine the prediction for the next time period $t+1$

The combination of methods 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]. The calculate prediction for the next time period $t+1$ as shown in (3)-(7):

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

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

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

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

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

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

2.2.6. 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. 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 are carried out in 7 steps.

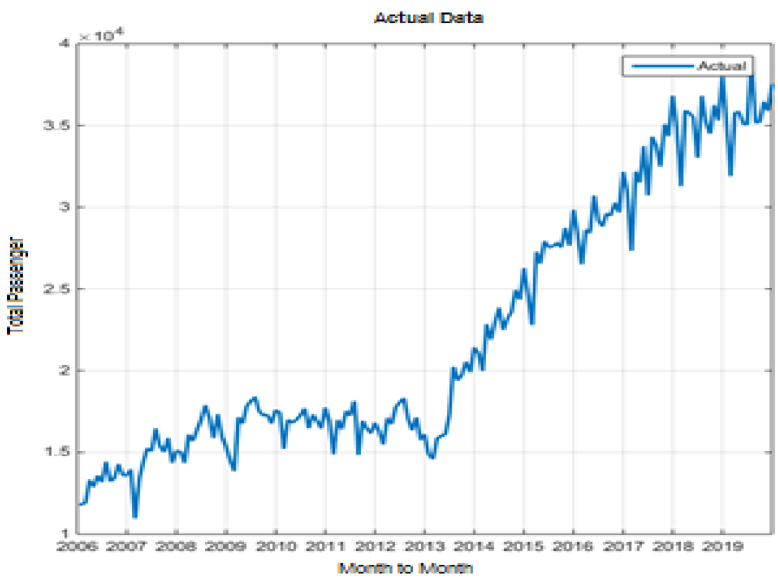

Figure 1. Graph of the actual train passengers data

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 (8).

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

b. Determining LL and UL from the results of the percentage change, then the obtained value of LL is -21.4255 and UL 23.5273. Thus U can be determined using (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 $U = [-23.00, 25.00]$.
c. Forming an interval class by calculating the number of intervals using (10).

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

n=number of percentage change of data.
$B = 1 + 3.3 * \log(167)$ = 8.3350≈8
d. Calculating the length of the interval class using formula 11.

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

$$P = \frac{25.00-(-23.00)}{8} = 6.00$$

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 3.

Table 3. Frequency and ranking

Initial Interval Class	Frequency	Ranking
[-23.00 , -17.00]	2	1
[-17.00 , -11.00]	3	2
[-11.00 , -5.00]	23	5
[-5.00 , 1.00]	65	8
[1.00 , 7.00]	40	7
[7.00 , 13.00]	25	6
[13.00 , 19.00]	6	4
[19.00 , 25.00]	3	3

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 the 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 6.00, the ranking that is at the greatest frequency is 8, then for the first interval it is divided into $n - 1 = 8 - 1 = 7$ intervals with the same interval length, namely $6.00/7 = 0.8571$. The second interval is divided into $n - 2 = 8 - 2 = 6$ intervals with the same interval length, namely $6.00/6 = 1.00$. The third interval is divided into $n - 3 = 8 - 3 = 5$ intervals with the same interval length, namely $6.00/5 = 1.20$ and so on until the ninth last interval. The total number of intervals obtained becomes 29 interval classes. Then determining the mean value of each interval class as shown in Table 4.
Step 5: defuzzifying the fuzzy data shown in Table 5 (in Appendix).
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 (12) is used to determine $F(t)$. The results of $F(t)$ are shown in Table 5.

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

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 $\alpha = 0.38$ and $\gamma = 0.01$, the value of data smoothing in December 2019 was 36766 while the trend smoothing value was 145 using formula 3, 4, 5, 6, and 7. So that the forecast value for January 2020 is:

$F(Jan\ 2020) = st + bt\ (m) = 36766 + 145 * (1) = 36911$ then the forecast results for January 2020 is: $F(Jan\ 2020) = \left(\frac{1.9643}{100} * 37463\right) + 37463 = 38199.$

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 5 and Figure 2.

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

$$\mathrm{MSE} = (\sum(\mathrm{A_i} - \mathrm{F_i})^2)/\mathrm{n} \tag{14}$$

where: i=1 ..., n

Table 4. Frequency distribution, fuzzy set, and mean value

Fuzzy	Intervals	Mean
A1	[-23.0000 , -22.1429]	-22.5714
A2	[-22.1429 , -21.2857]	-21.7143
A3	[-21.2857 , -20.4286]	-20.8571
A4	[-20.4286 , -19.5714]	-20.0000
A5	[-19.5714 , -18.7143]	-19.1429
A6	[-18.7143 , -17.8571]	-18.2857
A7	[-17.8571 , -17.0000]	-17.4286
A8	[-17.0000 , -16.0000]	-16.5000
A9	[-16.0000 , -15.0000]	-15.5000
A10	[-15.0000 , -14.0000]	-14.5000
A11	[-14.0000 , -13.0000]	-13.5000
A12	[-13.0000 , -12.0000]	-12.5000
A13	[-12.0000 , -11.0000]	-11.5000
A14	[-11.0000 , -9.8000]	-10.4000
A15	[-9.8000 , -8.6000]	-9.2000
A16	[-8.6000 , -7.4000]	-8.0000
A17	[-7.4000 , -6.2000]	-6.8000
A18	[-6.2000 , -5.0000]	-5.6000
A19	[-5.0000 , -3.5000]	-4.2500
A20	[-3.5000 , -2.0000]	-2.7500
A21	[-2.0000 , -0.5000]	-1.2500
A22	[-0.5000 , 1.0000]	0.2500
A23	[1.0000 , 3.0000]	2.0000
A24	[3.0000 , 5.0000]	4.0000
A25	[5.0000 , 7.0000]	6.0000
A26	[7.0000 , 10.0000]	8.5000
A27	[10.0000 , 13.0000]	11.5000
A28	[13.0000 , 19.0000]	16.0000
A29	[19.0000 , 25.0000]	22.0000

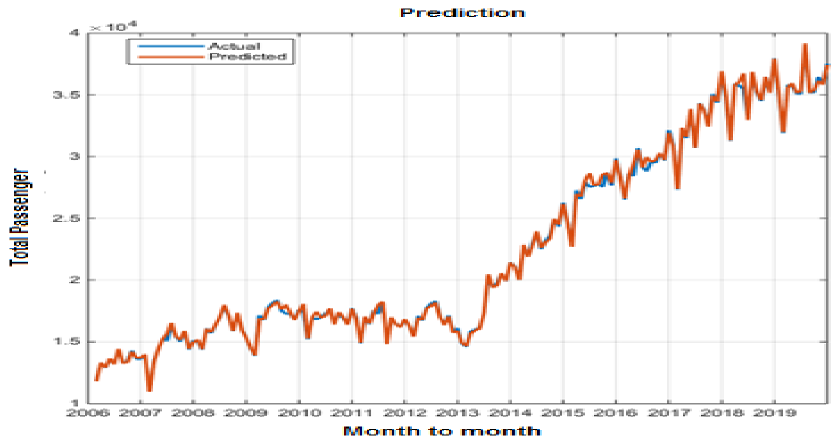

Figure 2. Prediction result graph

3. CONCLUSION

The use of FTS and PC techniques, as well as a combination of DES Holt, has proven to be useful in predicting the number of railway passengers over the next time period. This may be seen in the prediction results for January 2020, which are 38199, with AFER=0.89 percent and MSE=131325. It can be utilized as decision assistance for railway management based on the aforesaid predicted results. Based on the aforementioned forecast results, railway management can use it as decision support to develop policies for the future period in terms of planning, resources, setting departure schedules, deciding ticket prices, adding train carriages, and adding tickets. Researchers will adapt these methods in the future to handle predictions in the same case study by constructing web-based applications and/or employing additional methods to anticipate data based on different intervals in order to improve accuracy.

APPENDIX

Table 5. 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	A22	0.5195	11889	42	0.3483	1726.8835
Mar06	13314	11.5917	A27	11.2975	13279	35	0.2636	1231.5108
Apr06	12909	-3.0419	A20	-2.2694	13012	-103	0.7967	10578.0034
May06	13575	5.1592	A25	5.7063	13646	-71	0.5203	4987.9602
Jun06	13203	-2.7403	A20	-2.2694	13267	-64	0.4842	4086.5635
Jul06	14433	9.3161	A26	8.1813	14283	150	1.0380	22445.2185
Aug06	13255	-8.1619	A16	-7.9090	13291	-36	0.2753	1332.0249
Sep06	13436	1.3655	A23	0.7619	13356	80	0.5955	6401.5189
Oct06	14290	6.3561	A25	5.7063	14203	87	0.6109	7621.6982
Nov06	13631	-4.6116	A19	-3.9495	13726	-95	0.6942	8953.3543
Dec06	13614	-0.1247	A22	0.5195	13702	-88	0.6450	7710.6760
Jan07	13960	2.5415	A23	0.7619	13718	242	1.7355	58696.8138
Feb07	10969	-21.4255	A2	-21.6974	10931	38	0.3460	1440.7369
Mar07	13409	22.2445	A29	26.0741	13829	-420	3.1327	176454.3844
Apr07	14415	7.5024	A26	8.1813	14506	-91	0.6315	8287.6048
May07	15232	5.6677	A25	5.7063	15238	-6	0.0365	30.9390
Jun07	15104	-0.8403	A21	1.9643	15531	-427	2.8284	182499.8772
Jul07	16454	8.9380	A26	8.1813	16340	114	0.6946	13062.1934
Aug07	15419	-6.2903	A17	-6.6924	15353	66	0.4292	4379.0085
Sep07	15033	-2.5034	A20	-2.2694	15069	-36	0.2400	1301.6315
Oct07	15866	5.5411	A25	5.7063	15891	-25	0.1565	616.3887
Nov07	14391	-9.2966	A15	-9.1211	14419	-28	0.1935	775.6801
Dec07	15084	4.8155	A24	3.4286	14884	200	1.3232	39837.9035
Jan08	15027	-0.3779	A22	0.5195	15162	-135	0.9008	18321.9273
Feb08	14378	-4.3189	A19	-3.9495	14434	-56	0.3861	3081.8759
Mar08	16071	11.7749	A27	11.2975	16002	69	0.4271	4711.8030
Apr08	15711	-2.2401	A20	-2.2694	15706	5	0.0300	22.2641
May08	16363	4.1500	A24	3.4286	16250	113	0.6926	12845.3232
Jun08	17010	3.9540	A24	3.4286	16924	86	0.5055	7393.0638
Jul08	17887	5.1558	A25	5.7063	17981	-94	0.5235	8768.5637
Aug08	17108	-4.3551	A19	-3.9495	17181	-73	0.4241	5264.9666
Sep08	15879	-7.1838	A17	-6.6924	15963	-84	0.5294	7065.6406
Oct08	17337	9.1819	A26	8.1813	17178	159	0.9164	25244.2986
Nov08	15973	-7.8676	A16	-7.9090	15966	7	0.0449	51.5504
Dec08	15332	-4.0130	A19	-3.9495	15342	-10	0.0662	103.0784
Jan09	14494	-5.4657	A18	-5.4091	14503	-9	0.0599	75.3133
Feb09	13869	-4.3121	A19	-3.9495	13922	-53	0.3790	2763.1074
Mar09	17132	23.5273	A29	26.0741	17485	-353	2.0617	124759.2597
Apr09	16775	-2.0838	A20	-2.2694	16743	32	0.1896	1011.0514
May09	17824	6.2534	A25	5.7063	17732	92	0.5149	8421.5827
Jun09	18143	1.7897	A23	0.7619	17960	183	1.0097	33561.5265
Jul09	18385	1.3338	A23	0.7619	18281	104	0.5644	10767.7098
Aug09	17527	-4.6668	A19	-3.9495	17659	-132	0.7525	17395.4414
Sep09	17281	-1.4035	A21	1.9643	17871	-590	3.4158	348430.9591
Oct09	17281	0.0000	A22	0.5195	17371	-90	0.5195	8058.9243
Nov09	16778	-2.9107	A20	-2.2694	16889	-111	0.6605	12281.4115
Dec09	17581	4.7860	A24	3.4286	17353	228	1.2955	51872.0474
Jan10	17424	-0.8930	A21	1.9643	17926	-502	2.8830	252346.6025
Feb10	15207	-12.7238	A12	-12.4599	15253	-46	0.3024	2114.8064
Mar10	16992	11.7380	A27	11.2975	16925	67	0.3942	4487.1421
Apr10	16832	-0.9416	A21	1.9643	17326	-494	2.9335	243810.2716

Table 5. Prediction results *(continue)*

Month Year	Passangers $(A)_i$	% Change(d_t)	Fuzzy Sets	Prediction %(t_j)	Forecast $(F_i)t$	$A_i - F_i$	AFER	MSE
May10	16988	0.9268	A22	0.5195	16919	69	0.4036	4700.6050
Jun10	17259	1.5952	A23	0.7619	17117	142	0.8203	20041.3793
Jul10	17680	2.4393	A23	0.7619	17390	290	1.6375	83811.8805
Aug10	16477	-6.8043	A17	-6.6924	16497	-20	0.1200	391.1142
Sep10	17301	5.0009	A25	5.7063	17417	-116	0.6718	13508.4976
Oct10	16908	-2.2715	A20	-2.2694	16908	0	0.0022	0.1352
Nov10	16469	-2.5964	A20	-2.2694	16524	-55	0.3357	3056.5934
Dec10	17733	7.6750	A26	8.1813	17816	-83	0.4702	6953.1214
Jan11	16891	-4.7482	A19	-3.9495	17033	-142	0.8386	20062.5293
Feb11	14890	-11.8465	A13	-11.4264	14961	-71	0.4766	5036.2833
Mar11	16978	14.0228	A28	15.5394	17204	-226	1.3300	50989.8016
Apr11	16441	-3.1629	A20	-2.2694	16593	-152	0.9227	23012.2445
May11	17522	6.5750	A25	5.7063	17379	143	0.8151	20399.8957
Jun11	17265	-1.4667	A21	1.9643	17866	-601	3.4821	361420.0291
Jul11	18132	5.0217	A25	5.7063	18250	-118	0.6518	13969.2683
Aug11	14846	-18.1227	A6	-18.2656	14820	26	0.1746	671.7734
Sep11	16921	13.9768	A28	15.5394	17153	-232	1.3709	53810.9629
Oct11	16461	-2.7185	A20	-2.2694	16537	-76	0.4616	5774.6992
Nov11	16179	-1.7131	A21	1.9643	16784	-605	3.7415	366437.8697
Dec11	16811	3.9063	A24	3.4286	16734	77	0.4598	5973.9756
Jan12	16283	-3.1408	A20	-2.2694	16429	-146	0.8996	21458.6767
Feb12	15490	-4.8701	A19	-3.9495	15640	-150	0.9678	22472.8367
Mar12	17090	10.3292	A27	11.2975	17240	-150	0.8776	22495.7546
Apr12	16746	-2.0129	A20	-2.2694	16702	44	0.2618	1922.2856
May12	17771	6.1209	A25	5.7063	17702	69	0.3907	4819.6927
Jun12	18062	1.6375	A23	0.7619	17906	156	0.8615	24211.9396
Jul12	18309	1.3675	A23	0.7619	18200	109	0.5974	11965.0167
Aug12	17056	-6.8436	A17	-6.6924	17084	-28	0.1623	766.2466
Sep12	16368	-4.0338	A19	-3.9495	16382	-14	0.0879	206.7873
Oct12	17127	4.6371	A24	3.4286	16929	198	1.1550	39129.3890
Nov12	15773	-7.9056	A16	-7.9090	15772	1	0.0036	0.3260
Dec12	16104	2.0985	A23	0.7619	15893	211	1.3091	44447.0644
Jan13	14900	-7.4764	A16	-7.9090	14830	70	0.4675	4852.8136
Feb13	14594	-2.0537	A20	-2.2694	14562	32	0.2203	1033.2097
Mar13	15826	8.4418	A26	8.1813	15788	38	0.2402	1445.1252
Apr13	16000	1.0995	A23	0.7619	15947	53	0.3339	2853.7941
May13	16113	0.7063	A22	0.5195	16083	30	0.1855	892.9961
Jun13	17301	7.3729	A26	8.1813	17431	-130	0.7529	16967.6149
Jul13	20245	17.0164	A28	15.5394	19989	256	1.2622	65299.1872
Aug13	19423	-4.0603	A19	-3.9495	19445	-22	0.1155	503.1867
Sep13	19738	1.6218	A23	0.7619	19571	167	0.8462	27894.0743
Oct13	20534	4.0328	A24	3.4286	20415	119	0.5808	14225.0123
Nov13	19919	-2.9950	A20	-2.2694	20068	-149	0.7480	22200.1946
Dec13	21417	7.5205	A26	8.1813	21549	-132	0.6147	17329.5404
Jan14	21092	-1.5175	A21	1.9643	21838	-746	3.5354	556055.2653
Feb14	19998	-5.1868	A18	-5.4091	19951	47	0.2344	2198.2279
Mar14	22836	14.1914	A28	15.5394	23106	-270	1.1804	72662.1693
Apr14	21908	-4.0638	A19	-3.9495	21934	-26	0.1191	681.2786
May14	22988	4.9297	A24	3.4286	22659	329	1.4306	108154.5990
Jun14	23840	3.7063	A24	3.4286	23776	64	0.2678	4075.5582
Jul14	22500	-5.6208	A18	-5.4091	22550	-50	0.2243	2547.5181
Aug14	23199	3.1067	A24	3.4286	23271	-72	0.3122	5245.8840
Sep14	23593	1.6983	A23	0.7619	23376	217	0.9208	47195.6764
Oct14	24923	5.6373	A25	5.7063	24939	-16	0.0653	265.2320
Nov14	24356	-2.2750	A20	-2.2694	24357	-1	0.0057	1.9389
Dec14	26275	7.8790	A26	8.1813	26349	-74	0.2803	5424.0133
Jan15	24676	-6.0856	A18	-5.4091	24854	-178	0.7204	31599.1873
Feb15	22790	-7.6431	A16	-7.9090	22724	66	0.2879	4305.9719
Mar15	27267	19.6446	A29	26.0741	28732	-1465	5.3738	2147047.0990
Apr15	26565	-2.5745	A20	-2.2694	26648	-83	0.3132	6921.7822
May15	27910	5.0631	A25	5.7063	28081	-171	0.6122	29198.9495
Jun15	27562	-1.2469	A21	1.9643	28458	-896	3.2517	803232.1968
Jul15	27612	0.1814	A22	0.5195	27705	-93	0.3375	8682.3919
Aug15	27796	0.6664	A22	0.5195	27755	41	0.1459	1645.1871
Sep15	27549	-0.8886	A21	1.9643	28342	-793	2.8785	628837.7974
Oct15	28718	4.2433	A24	3.4286	28494	224	0.7816	50383.6272
Nov15	27669	-3.6528	A19	-3.9495	27584	85	0.3079	7260.0493
Dec15	29831	7.8138	A26	8.1813	29933	-102	0.3409	10342.0347
Jan16	28358	-4.9378	A19	-3.9495	28653	-295	1.0397	86928.6133
Feb16	26510	-6.5167	A17	-6.6924	26460	50	0.1880	2484.2384

Table 5. Prediction results *(continue)*

Month Year	Passangers $(A)_i$	% Change(d_t)	Fuzzy Sets	Prediction %(t_j)	Forecast $(F_i)t$	$A_i - F_i$	AFER	MSE
Mar16	28617	7.9479	A26	8.1813	28679	-62	0.2162	3828.3955
Apr16	28435	-0.6360	A21	1.9643	29179	-744	2.6169	553714.1646
May16	30703	7.9761	A26	8.1813	30761	-58	0.1901	3406.4595
Jun16	29159	-5.0288	A18	-5.4091	29042	117	0.4004	13631.2403
Jul16	28831	-1.1249	A21	1.9643	29732	-901	3.1243	811379.6655
Aug16	29588	2.6256	A23	0.7619	29051	537	1,8161	288729.0843
Sep16	29516	-0.2433	A22	0.5195	29742	-226	0.7647	50942.3129
Oct16	30263	2.5308	A23	0.7619	29741	522	1.7253	272605.2430
Nov16	29690	-1.8934	A21	1.9643	30857	-1167	3.9321	1362943.8739
Dec16	32150	8.2856	A26	8.1813	32119	31	0.0963	958.4760
Jan17	30949	-3.7356	A19	-3.9495	30880	69	0.2221	4726.7536
Feb17	27342	-11.6547	A13	-11.4264	27413	-71	0.2584	4990.4990
Mar17	32170	17.6578	A28	15.5394	31591	579	1.8005	335508.4622
Apr17	31502	-2.0765	A20	-2.2694	31440	62	0.1970	3852.9846
May17	33745	7.1202	A26	8.1813	34079	-334	0.9906	111747.5790
Jun17	30723	-8.9554	A15	-9.1211	30667	56	0.1820	3125.3770
Jul17	34310	11.6753	A27	11.2975	34194	116	0.3383	13470.6038
Aug17	33791	-1.5127	A21	1.9643	34984	-1193	3.5304	1423121.4153
Sep17	32498	-3.8265	A19	-3.9495	32456	42	0.1279	1727.4022
Oct17	35070	7.9143	A26	8.1813	35157	-87	0.2474	7529.5272
Nov17	34361	-2.0217	A20	-2.2694	34274	87	0.2529	7549.1064
Dec17	36807	7.1185	A26	8.1813	37172	-365	0.9922	133364.6624
Jan18	34717	-5.6783	A18	-5.4091	34816	-99	0.2854	9816.1021
Feb18	31278	-9.9058	A14	-10.3103	31138	140	0.4490	19719.7005
Mar18	35875	14.6972	A28	15.5394	36138	-263	0.7342	69378.4500
Apr18	35754	-0.3373	A22	0.5195	36061	-307	0.8597	94472.5109
May18	35482	-0.7608	A21	1.9643	36456	-974	2.7459	949281.5670
Jun18	33030	-6.9105	A17	-6.6924	33107	-77	0.2343	5988.9705
Jul18	36800	11.4139	A27	11.2975	36762	38	0.1044	1476.7991
Aug18	35190	-4.3750	A19	-3.9495	35347	-157	0.4450	24523.1591
Sep18	34504	-1.9494	A21	1.9643	35881	-1377	3.9915	1896768.6523
Oct18	36236	5.0197	A25	5.7063	36473	-237	0.6538	56121.4592
Nov18	35298	-2.5886	A20	-2.2694	35414	-116	0.3276	13375.6092
Dec18	37965	7.5557	A26	8.1813	38186	-221	0.5817	48774.9222
Jan19	35122	-7.4885	A16	-7.9090	34962	160	0.4545	25486.2888
Feb19	31899	-9.1766	A15	-9.1211	31918	-19	0.0611	380.1640
Mar19	35751	12.0756	A27	11.2975	35503	248	0.6943	61605.2729
Apr19	35809	0.1622	A22	0.5195	35937	-128	0.3567	16312.3096
May19	35102	-1.9744	A21	1.9643	36512	-1410	4.0180	1989203.2630
Jun19	35090	-0.0342	A22	0.5195	35284	-194	0.5539	37771.2309
Jul19	39035	11.2425	A27	11.2975	39054	-19	0.0494	372.4810
Aug19	35189	-9.8527	A14	-10.3103	35010	179	0.5076	31907.1068
Sep19	35221	0.0909	A22	0.5195	35372	-151	0.4282	22740.6910
Oct19	36448	3.4837	A24	3.4286	36429	19	0.0533	377.2532
Nov19	35877	-1.5666	A21	1.9643	37164	-1287	3.5871	1656222.1856
Dec19	37463	4.4207	A24	3.4286	37107	356	0.9501	126687.2913
Jan20	36911	-1.4735	A21	1.9643	38199	-1288	3.4892	1658636.0900
							0.8948	131324.6120

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