Received: 15 January 2022 | Revised: 8 March 2022 | Accepted: 16 March 2022 | Published online: 25 March 2022

Journal of Computational and Cognitive Engineering
2023, Vol. 2(2) 143–149
DOI: 10.47852/bonviewJCCE2202159

BON VIEW PUBLISHING

RESEARCH ARTICLE

A Study of Time Series Forecasting Enrollments Using Fuzzy Interval Partitioning Method

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Abstract: A time series is a sequence of elements with numerical data in sequential order and having regular intervals. Time series are used in statistics, enrollments, signal processing, econometrics, mathematical finance, and weather forecasting. It helps us to forecast and predict the time series data in different domains. There are many methods to forecast the enrollments in literature which have large applications and are presented in the field of statistics and econometrics. One of the robust methods, we used in our research, is moving average. It helps to forecast and predict the data whenever the fuzziness occurs in time series data, which is not appropriate in crisp time series forecasting. To get rid of this problem, the fuzzy interval partitioning method proved to be more appropriate to generate accurate results. This research will focus to overcome the failure of the crisp method and to show the use of a fuzzy interval partitioning method. The fuzzy interval partitioning method is different from another interval partition schemes because it specifies the linguistic values rather than numerical values. It is also used to deal with uncertain conditions. So, fuzzy interval partitioning improves data utilization and also calculates the higher predicted accuracy rate. Besides this research, we use a quantitative method and a fuzzy moving average with the interval partitioning method. Then we compare the efficiency of moving average model and moving average with fuzzy interval partitioning method for forecasting the enrollments.

Keywords: time series, forecasting, uncertainty, fuzzy interval partitioning, moving average

1. Introduction

The term "time series" is a set of observations that agreed to any activity at different time. The time period may be hourly, daily, weekly, monthly, or yearly. A time series is a sequence of elements with numerical data in sequential order and having regular intervals. Time series is applied in signal processing, econometrics, mathematical finance, weather forecasting, communications engineering, and largely in any field of applied sciences and engineering which involved temporal measurements (Gujarati, 2009). Zadeh (1965) defined a method, a formalism aims to manage more efficiently to provide the parameter of human reason. He introduced the concept of fuzzy set theory. Kirby (1966) studied three diverse time series models, namely exponential smoothing, regression, and moving average using 7-year data from a sewing machine manufacturing goods group in the study. This research concluded that forecasting of medium range duration such as less than for six months, the methods of exponential smoothing and moving averages are appropriate, whereas, for longer duration such as for one year the regression model is most suitable. Song and Chissom (1993) introduced the idea of fuzzy time series based on fuzzy set theory. To forecast enrollments, it was applied on the time series data regarding enrollments of University of Alabama.

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After that, various fuzzy forecasting techniques presented with an objective to find superior forecasting results. Yolcu et al. (2009) proposed the new length of intervals and determined the ratio for the intervals; the authors used a constrained optimization method for determining the intervals. Aggarwal et al. (2017) used fuzzy logic interval partitioning method. They applied different length of intervals in enrollment data and determined the best length of interval to find the superior forecasting results.

However, the different researcher chose used randomly length of intervals partitioning technique. However, the different researcher chose a different length of the interval to obtain better forecasting accuracy. Somehow, the length of the interval affects the performance of different forecasts. Abhishekh and Gautam (2019) used fuzzy time series with 3-year moving average method on two datasets, that is, enrollments and crop production, and found best forecasting result. Chen (1996) presented a new method based on fuzzy time series for forecasting enrollments. He used a historical enrollment observation regarding University of Alabama. The proposed technique generated forecast with higher accuracy using simple arithmetic operation which proved to be a more efficient and robust methodology. Additionally, it was concluded that this proposed method is essay to implement and less time consuming instead of max-min complication operations which is large and time-consuming. Huarng (2001) built up a domain-specific model.

He followed Chen's model (Chen & Pham, 2000) for development of new forecasting method to forecast the time series data.

Chen and Hsu (2004) proposed a method based on the enrollments of fuzzy forecasting. The accuracy rate of other systems was much lower before to introduce this technique. The technique suggested in this study was time variant with first-order fuzzy relationship groups, with taking membership values 0 to 1 to fuzzify the historical enrollments in order to transform linguistic values into crisp values. Yu (2005) recommended the new weighted technique in fuzzy time series modeling to forecast the stock prices of Taiwan Stock Index. In investigation process, weighted models and local regression models were compared, which were diverse in their application.

Li and Cheng (2007) described about fuzzy time series modeling which deals with imprecise, vague, and incomplete datasets. Stevenson and Porter (1972) developed model using the revolutionary work of Zadeh's fuzzy set theory which is functional to many areas. Jilani et al. (2007) proposed a new method for forecasting based on fuzzy time series which is based on frequency density-based partitioning of the historical enrollment data. The proposed method belongs to the kth order and time-variant methods. Saxena et al. (2012), Cai et al. (2013), and Qiu et al. (2015) developed new fuzzy time series models using different mathematical and statistical tools with concepts of generalized fuzzy logical relationship groups. Furthermore, Sophia Mustafa (2016) proposed the strategy identified with fuzzy time series for forecasting stock exchange market. In this research, fuzzy autoregressive integrated moving average model is proposed by utilizing the fuzzy least square technique to manage the fuzzy parameters and developed the new scientific calculation. This forecasting is contrasted, and consequence of autoregressive integrated moving average model is estimated by various criteria. It is a suitable model to be utilized in forecasting the linguistic quantities. Furthermore, recently, Iqbal et al. (2018, 2020) and Iqbal and Zhang (2020) developed robust fuzzy time series models to generate forecasts with higher accuracy.

The main objective of this works is

i. To overcome the uncertainty of time series forecasting enrollment by introducing the fuzzy interval partitioning method.
ii. An application of forecasting the university enrollments has been explored using the moving average with fuzzy interval partitioning (MAFIP) method.
iii. The comparison and numerical interpretation have been performed on the basis of previous findings.

In this paper, we presented a method on MAFIP. The proposed method provides a simple computational algorithm and gives better forecasting accuracy results. In this study, 5-year moving average method is implemented on dataset. In Section 2, we modified the Abhishekh (Gujarati, 2009) replacing the 3-year to 5-year moving average and applied fuzzy interval partitioning techniques. In Section 3, we compared the proposed forecasting model with existing method, and remarks are provided in Section 4.

2. A New Method for Time Series Forecasting Method

In this segment, we modified the Abhishekh method for modeling the enrollments of the University of Alabama based on the MAFIP method for forecasting. We used the enrollment data to define the universe of discourse. Using the Moving average method, the p-period is defined as of the p-consecutives values of the given series, by dropping the very first value and including the sum of first value and after the proceeding total and so on, moving on one after another calculating successive average values. This process will continue till the last p-consecutive values have been added. Generally, moving average is used for forecasting based on most recent observation and takes the average over the period. Mathematically it is presented as:

$$f_{t+1} = \frac{nearest\ p\ values}{n} \tag{1}$$

$$f_{t+1} = \frac{Z_t + Z_{t-1} + Z_{t-2} + \ldots Z_{t-p+1}}{n} \tag{2}$$

where $f_{t+1} = t + 1$ period of forecast and Z_t = actual value with t period of time.

2.1. Step 1:

We calculate the result of 5-year moving average from the actual dataset given as in Table 1.

2.2. Step 2:

To determine the universe of discourse, the maximum and minimum values are taken from the dataset. The universe of discourse is denoted by

$$R = D_{min} - D_1,\ D_{max} + D_2 \tag{3}$$

where D_{max} and D_{min} are the maximum and minimum values, respectively, and D_1 and D_2 are proper number of integers which provides us a suitable universal of discourse U.

$$D_{max} = 18932.2,\ D_{min} = 14128.2,\ D_1 = 28.2,\ D_2 = 67.8, \tag{4}$$

$$U = [14128.2 - 28.2,\ 18932.2 + 67.8] \tag{5}$$

Table 1
5-year moving average calculations for enrollment data set

Year	Number of students	5 year moving average
1971	13055	–
1972	13563	–
1973	13867	14128.2
1974	14696	14579.4
1975	15460	14987.4
1976	15311	15386.2
1977	15603	15808.4
1978	15861	16100.2
1979	16807	16315.6
1980	16919	16281.6
1981	16383	16208.8
1982	15433	15876.4
1983	15497	15525.2
1984	15145	15444.4
1985	15163	15729.6
1986	15984	16260.2
1987	16895	17025.2
1988	18150	17858.2
1989	18970	18528.8
1990	19328	18932.2
1991	19337	–
1992	18876	–

$$U = [14100,\ 19000] \tag{6}$$

Further, we used the seven-equal length of interval for partitioning process, which is given as

$$Difference = \frac{19000 - 14100}{7} \tag{7}$$

$$Difference = 700 \tag{8}$$

2.3. Step 3:

In this step, frequency density-based distribution of the data on the basis of interval partitioning is made (Jilani et al., 2007). The findings are given in Table 2 and Table 3.

2.4. Step 4:

Fuzzy interval partitioning is a continuous-time fuzzy modeling technique (Chen & Hsu, 2004)

$$I_n^{\alpha} = [(\mathrm{n}-1)\alpha \quad (\mathrm{n})\alpha) \quad n = \pm 0, \pm 1, \pm 2 \pm \ldots\ldots \tag{9}$$

where α > 0, α is chosen randomly and fixed any integer number and

$$R = (-\infty, \infty) \tag{10}$$

$$R = \bigcup_{n=-\infty}^{\infty} I_n^{\alpha} \tag{11}$$

where R is the fuzzy interval partitioning. Fuzzy interval partitioning is used with linguistic term and membership function. In step 4, the universe of discourse is further divide into sub-intervals S1, S2, S3, Sn, etc. in the form of linguistic variables.

Table 2
Frequency density-based distribution

Interval	Frequency density
[14100, 14800]	2
[14800, 15500]	3
[15500, 16200]	5
[16200, 16900]	5
[16900, 17600]	1
[17600, 18300]	1
[18300, 19000]	2

Table 3
Fuzzy interval partitioning using frequency density function

Linguistic variable	Intervals
S1	[14100, 14450]
S2	[14450, 14800
S3	[14800, 15033.33]
S4	[15033.33, 15266.66]
S5	[15266.66, 15500]
S6	[15500, 15640]
S7	[15640, 15780]
S8	[15780, 15920]
S9	[15920, 16060]
S10	[16060, 16200]
S11	[16200, 16340]
S12	[16340, 16480]
S13	[16480, 16620]
S14	[16620, 16760]
S15	[16760, 16900]
S16	[16900, 17600]
S17	[17600, 18300]
S18	[18300, 18650]
S19	[18650, 19000]

2.5. Step 5:

Membership functions for fuzzy sets can be defined in any number of ways as long as they follow the rules of the definition of a fuzzy set. The shape of the membership function used defines the fuzzy set and so the decision on which type to use is dependent on the purpose. The membership function choice is the subjective feature of fuzzy logic; it allows the preferred values to be interpreted suitably.

In this study, triangular fuzzy membership function is applied which consists of three parameters. These parameters of triangular function described the shape of membership function which specified the three-corner point of x coordinates. Triangular fuzzy membership function is described using the following formula:

$$T(x; a, b, c) = \begin{cases} 0, & x \le 0 \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-a}{c-b}, & c \le x \le b \\ 0, & c \le x \end{cases} \tag{12}$$

In the above equation, a represents the left point parameter, b represents the center point parameter, and c represents the right point parameter. E_1, E_2, …., E_{19} are defined as triangular fuzzy sets that are similar to fuzzy interval partitioning method as shown : E_1 = (14100, 14450, 14800); E_2 = (1445014800, 14800); E_3 = (14800, 15033.33, 15033.33); E_4 = (15033.33, 15266.66, 15500); E_5 = (15266.6, 15500, 15780); E_6 = (15500, 15640, 15780); E_7 = (15640, 15780, 15920); E_8 = (15780, 15920, 16060); E_9 = (15920, 16060, 16200); E_{10} = (16060, 16200, 16340); E_{11} = (16200, 16340, 16486); E_{12} = (16340, 16486, 16620); E_{13} = (16484, 16620, 16760); E_{14} = (16620, 16760, 16900); E_{15} = (16760, 16900, 17600); E_{16} = (16900, 17600, 18300); E_{17} = (17600, 18300, 18650); E_{18} = (18300, 18650, 19000); and E_{19} = (18650, 19000, 19000)

Fuzzy enrollments are obtained through triangular fuzzy sets. Fuzzy enrollments are given in Table 4.

2.6. Step 6:

Establishing the fuzzy logical relationship: We established the fuzzy logical relationships from the fuzzified data, shown in Table 5. Relationships of fuzzy logic are designed from above fuzzified datasets. According to the rule of fuzzification, if the time series observation F(t-1) is fuzzified as E_1 in year 1973 and F(t) as E_2 in year 1974, then E_1 is mapping into E_2. In the same manner, sets of fuzzy E_2 in year 1974 are interrelated with E_3 in year 1975, sets of fuzzy E_3 in year 1975 are interrelated with E_5 in year 1976, sets of fuzzy E_5 in year 1976 are interrelated with E_8 in year 1977, set of fuzzy E_8 in year 1977 is interrelated with E_{10} in year 1978, set of fuzzy E_{10} in year 1978 is interrelated with E_{11} in year 1979, set of fuzzy E_{11} in year 1979 is interrelated with E_{11} in year 1980, etc. So, in this way, for all years fuzzy relationships are established.

Table 4
Fuzzified enrollments

Year	5-year moving average	Fuzzified enrollments
1971	–	–
1972	–	–
1973	14128.2	E_1
1974	14579.4	E_2
1975	14987.4	E_3
1976	15386.2	E_5
1977	15808.4	E_8
1978	16100.2	E_{10}
1979	16315.6	E_{11}
1980	16281.6	E_{11}
1981	16208.8	E_{11}
1982	15876.4	E_8
1983	15525.2	E_6
1984	15444.4	E_5
1985	15729.6	E_7
1986	16260.2	E_{11}
1987	17025.2	E_{16}
1988	17858.2	E_{17}
1989	18528.8	E_{18}
1990	18932.2	E_{19}
1991	–	–
1992	–	–

Table 5
Fuzzy logical relationships

Years relationships	Fuzzy relationships
1973 → 1974	$\mathrm{E}_1 \to E_2$
1974 → 1975	$\mathrm{E}_2 \to E_3$
1975 → 1976	$\mathrm{E}_3 \to E_5$
1976 → 1977	$\mathrm{E}_5 \to E_8$
1977 → 1978	$\mathrm{E}_8 \to E_{11}$
1978 → 1979	$E_{11} \to E_{11}$
1979 → 1980	$E_{11} \to E_{11}$
1980 → 1981	$E_{11} \to E_{11}$
1981 → 1982	$E_{11} \to E_8$
1982 → 1983	$E_8 \to E_6$
1983 → 1984	$E_6 \to E_5$
1984 → 1985	$E_5 \to E_7$
1985 → 1986	$E_7 \to E_{11}$
1986 → 1987	$E_{11} \to E_{16}$
1987 → 1988	$E_{16} \to \mathrm{E}_{17}$
1988 → 1989	$E_{17} \to \mathrm{E}_{18}$
1989 → 1990	$E_{18} \to E_{19}$

Using the above table, fuzzy relationship group (FLRGs) are formed in Table 6. In group 1, relationship of fuzzy E1 related to E2 is mapping in the same way, the fuzzy relationship of E_2 *is mapping on* E_3, E_3 is mapping on E_5 in group 3, E_5 is mapping on E_8 and E_7 in group 4, E_8 is mapping on E_{10} and E_6 in group 5, E_{10} is mapping on E_{11} in group 6, E_{11} is mapping on E_{11}, E_{11}, E_8, *and* E_{16} in group 7, E_6 is mapping on E_5 in group 8, E_7 is mapping on E_{11} in group 9, E_{16} is mapping on E_{17} in group 10, E_{17} is mapping on E_{18} in group 11, and E_{18} is mapping on E_{19} in group 12. Relationship of fuzzy group is shown in Table 6.

Table 6
Fuzzy logical relationship groups

Fuzzy relationship groups	Fuzzy groups
Group 1	$E_1 \to E_2$
Group 2	$E_2 \to E_3$
Group 3	$E_3 \to E_5$
Group 4	$E_5 \to E_8, E_7$
Group 5	$E_8 \to E_{10}, E_6$
Group 6	$E_{10} \to E_{11}$
Group 7	$E_{11} \to E_{11}, E_{11}, E_8, E_{16}$
Group 8	$E_6 \to E_5$
Group 9	$E_7 \to E_{11}$
Group 10	$\mathrm{E}_{16} \to E_{17}$
Group 11	$E_{17} \to E_{18}$
Group 12	$E_{18} \to E_{19}$

Table 7
Forecasted results

Year	Number of students	Forecasted values
1971	13055	–
1972	13563	–
1973	13867	–
1974	14696	–
1975	15460	14625
1976	15311	14916.66
1977	15603	15383.33
1978	15861	15780
1979	16807	15850
1980	16919	16130
1981	16383	16456.67
1982	15433	16456.67
1983	15497	16456.67
1984	15145	15850
1985	15163	15570
1986	15984	15780
1987	16895	16270
1988	18150	16456.67
1989	18970	17950
1990	19328	18475
1991	19337	18825
1992	18876	18825

2.7. Step 7:

Now we defuzzified the forecasted values obtained by applying operators on all the observations. The defuzzified values are obtained by the arithmetic average of midpoints of specified forecasted values. These defuzzified values are termed as forecasted values presented in Table 7.

2.8. Step 8:

In this step, determined the accuracy measures by using different measurement criteria such as Mean Absolute Percentage Error (MAPE) shows the value 1.481, Mean Absolute Error (MAE) is 297.74, Mean Forecast Error (MFE) is 24.46, Mean Square Error (MSE) is 45687.6111, Theil U-Statistics is 0.0000013370 and Roots mean square error (RMSE) is 213.75. In Figure 1, the comparison graph shows that the fuzzy forecasted and actual value of enrollments are very close to each other.

3. A Comparison of Different Forecasting Method

The forecasting results of the proposed method and existing fuzzy time series methods are presented in Table 8 and also graphically illustrated in Figure 1 from year 1971 to 1992. In comparison with different researchers, the proposed forecasting method shows the linearly increase from year 1971 to 1992 which indicates that each year enrollment will progress in the same pattern.

It is important to know that, which method is performing best and gives significant results among different forecasting methods and proposed fuzzy method. In this paper, comparison between different researcher method and proposed MAFIP method is evaluated using different estimation criteria. Results in terms of mean square error (MSE), root mean square error (RMSE), and average forecasting error (AFE) for proposed MAFIP and different fuzzy forecasting methods are given in Table 9.

The accuracy measures are evaluated as: MSE of Song and Chissom (1993) is 423020.16, Gangwar and Kumar (2015) is 243601.47, Wang et al. (2016) is 123130.81, Bisht and Kumar (2016) is 183723.67, Abhishekh and Gautam (2019) is 56863.1716, and proposed MAFIP is 45689.062; RMSE of Song and Chissom (1993) is 650.4, Gangwar and Kumar (2015) is 493.56,Wang et al. (2016)

Figure 1
Comparison with existing fuzzy time series methods

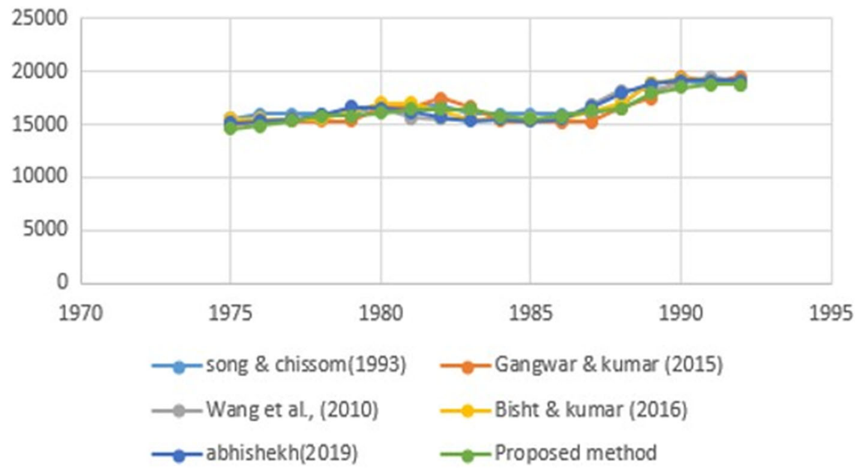

Table 8
A comparison of the forecasting results of different forecasting methods

Year	Enrollments	Song and Chissom (1993)	Gangwar and Kumar (2015)	Wang et al. (2016)	Bisht and Kumar (2016)	Abhishekh and Gautam (2019)	Proposed method
1971	13055	–	–	–	–	–	–
1972	13563	14,000	–	13500	13595.67	–	–
1973	13867	14,000	13693	14155	13814.75	13950	–
1974	14696	14,000	13693	14155	14929.79	14550	–
1975	15460	15,500	14867	15539	15541.27	15150	14625
1976	15311	16,000	15287	15539	15540.62	15350	14916.66
1977	15603	16,000	15376	15502	15540.62	15550	15383.33
1978	15861	16,000	15376	15502	15540.62	15950	15780
1979	16807	16,000	15376	16667	16254.50	16650	15850
1980	16919	16833	16523	16667	17040.41	16550	16130
1981	16383	16833	16606	15669	17040.41	16150	16456.67
1982	15433	16833	17519	15564	16254.50	15750	16456.67
1983	15497	16,000	16606	15564	15540.62	15350	16456.67
1984	15145	16,000	15376	15564	15540.62	15550	15850
1985	15163	16,000	15376	15523	15541.27	15350	15570
1986	15984	16,000	15287	15523	15541.27	15550	15780
1987	16895	16,000	15287	16799	16254.50	16650	16270
1988	18150	16813	16523	18268	17040.41	17950	16456.67
1989	18970	19000	17519	18268	18902.30	18750	17950
1990	19328	19000	19500	18780	19357.30	19150	18475
1991	19337	19000	19000	19575	19168.56	19150	18825
1992	18876	–	19500	18825	19168.56	19150	18825

Table 9
Accuracy measures comparison

Evaluation criteria	Song and Chissom (1993)	Gangwar and Kumar (2015)	Wang et al. (2016)	Bisht and Kumar (2016)	Abhishekh and Gautam (2019)	Proposed method
MSE	423020.16	243601.47	123130.81	183723.677	56863.17	45689.062
RMSE	650.4	493.56	350.9	428.63	428.63	213.75
MFE	3.22	2.36	1.72	1.94	1.29	1.22

is 350.9, Bisht and Kumar (2016) is 428.63, Abhishekh and Gautam (2019) is 238.46, and proposed MAFIP is 213.75; and AFE of Song and Chissom (1993) is 3.22, Gangwar and Kumar (2015) is 2.33, Wang et al. (2016) is 1.72, Bisht and Kumar (2016) is 1.94, Abhishekh and Gautam (2019) is 1.29, and proposed MAFIP is 1.22. These findings in terms of accuracy measures reveal that the values of MSE, RMSE, and AFE for proposed method are less than all the other existing methods, which signify the robustness of the proposed method with higher accuracy.

4. Conclusion and Result

There are various classical forecasting methods that are used to distribute the accurate information, but in a lot of circumstances the rigorous and accurate quantities cannot be achieved. In order to get the significant consequences, the uncertainty inherited in time series data of different domains can be covered by introducing fuzzy ideas. This research is based on the basic idea of the moving average method and fuzzy moving average method with fuzzy interval partitioning. In the proposed work, fuzzy interval partitioning technique and moving average (MA) methods are used, which lead this computations to forecast the enrollment data in order to express to the efficiency of the proposed MAFIP method comparison with conventional moving average (MA) model. The pragmatic result of the MSE, mean forecasting error, RMSE, and fuzzy moving average method with interval partitioning (FMAIP) method as shown in Table 9 is smaller as compared to the proposed method. It indicates that proposed FMAIP forecasting method generates better forecasting results and performs well than other methods.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

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How to Cite: Hanif, R., Mustafa, S., Iqbal, S., & Piracha, S. (2023). A Study of Time Series Forecasting Enrollments Using Fuzzy Interval Partitioning Method. *Journal of Computational and Cognitive Engineering* 2(2), 143–149, https://doi.org/10.47852/bonviewJCCE2202159