In Search of Suitable Fuzzy Membership Function in Prediction of Time Series Data

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Abstract

Many researchers have used fuzzy logic system to predict the time series data. In fuzzy system, the crisp data are converting into fuzzy data based on membership function. The futuristic data is predicted using previous data and fuzzy relation. But, in fuzzy system, there are many existing and derived membership functions which are used to fuzzify data. In this paper, an effort has been made to predict the time series data based on different fuzzy membership functions like Gaussian, Triangular, S-function, trapezoidal, Gbell, Dsigmoidal, Psigmoidal and Pi-shaped. A comparison has been made among the predicted data using different membership functions. One membership function has been selected based on minimum error in prediction of data. This process has been repeated on fifteen time series data sets. Finally, one membership function has been selected which has given minimum error in maximum cases.

Keywords - *Time Series Data, System, Crisp Data, Fuzzy Data and Fuzzy Membership Function.*

1. Introduction

The perception of the real world is pervaded by concepts which do not have sharply defined boundaries – for example, *many, tall, much larger, young,* etc. They are true only to some degree and false to some degree as well. These concepts (facts) can be called *fuzzy* or *gray* (*vague*) concepts – a human brain works with them, while computers may not do it. In the years to come fuzzy computers will employ both *fuzzy hardware* and *fuzzy software*. They will be much closer in structure to the human brain than the present-day computers. The entire real world is complex; it is found that the complexity arises from uncertainty in the form of ambiguity. According to Dr. Lotfi Zadeh, Principle of Compatability, the complexity, and the imprecision are correlated. Fuzzy Logic provides a simple way to definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information.

Song Q and Chissom [3] explained the definition of fuzzy time series and discussed the models using Fuzzy Relational equations. Song and Chisson [1] used a time invariant fuzzy time series model. Sullivien J and Woodall W. H. [2] made a comparative study of Fuzzy Forecasting and Markov Model and suggested that Markov Model would give better prospects. They illustrated the methodology by forecasting the enrollment at the University of Alabama from 20 years of data. Bintley H [4] applied fuzzy logic and approximate reasoning to a practical case of forecasting Sugeno M. and Tanaka K. [11] have proposed successive identification method of a fuzzy model. The structure and initial parameters were determined to identify a model called 'initial model', which has been identified by the off-line fuzzy modeling method using some pairs of input-output data. Zuoyong L, Zhenpei C and Jitao L [12] proposed a method of classification of weather forecasts by applying fuzzy grade statistics. The rainfall in a certain region could be forecasted as one of three grades. The range of rainfall was chosen depending on the historical data. The membership functions of the fuzzy sets were also designed. Feng L. and Gaung X[13] described the model of fuzzy self-regression. The main steps were the making of the form of self-related sequence number according to the observed number, the calculation of self-related coefficient and the ascertaining of the forecasting model of fuzzy self-regression. Ishikawa M. and Moriyama T[14] have presented various methods of learning and the process of predicting time series analysis, which were ranged from traditional time series analysis to recent approaches using neural networks. It has described that back propagation learning had a difficulty in interpreting hidden inputs. In order to solve these problems, a structural learning method was proposed which was based on an information criterion.

A comparative study was made among gaussian, triangular and trapezoidal functions for using the function for fuzzification[16] and it was observed that gaussian function was the most suitable function for fuzzification. A Rule Base was constructed for a Personnel Selection System using Fuzzy Expert methodology [17]. A comparison was made among the fuzzy time series and markov model [18] for the purpose of manpower prediction and it was found that fuzzy time series method was more preferable than markov model.

From the study of several research papers, journals etc and it has been found that a lot of research work have been carried out in the field of Prediction ([1] - [5], [7] - [9], [11] - [14]), out of these certain work, some of them have been done using fuzzy logic ([1] - [5], [11] - [13]). Research work using neural networks has been done ([6], [8] - [10], [14]). A few research works have been carried out in Prediction for a particular field such as the growth of mustard plant ([16]-[19]).

In this paper, fifteen different time series data set have been predicted based on fuzzy system. The errors have been calculated between the original data and predicted data based on particular membership function. On the basis of error analysis, a membership function has been selected based on minimum error. The same method will be repeated on fifteen data sets. Finally, one membership function has been selected which has given minimum error in maximum cases. The work related to the selection of membership function for variety of data sets have not been done so far, that is the reason for making the effort in this paper.

2. Theory

2.1. Fuzzy Logic System

In contrast with "crisp logic", where binary sets have binary logic, fuzzy logic variables may have a truth value that ranges between 0 and 1 and is not constrained to the two truth values of classic propositional logic. A fuzzy set is a set without a crisp, clearly defined boundary [20]. It can contain elements with only a partial degree of membership. The process of generating membership values for a fuzzy variable using membership functions is termed as fuzzification. The process of transforming a fuzzy output of a fuzzy inference system into a crisp output is known as defuzzification. The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number.

2.2 Membership Functions

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept ([20], [21]).

For any set X, a membership function on X is any function from X to the real unit interval [0, 1]. The membership function which represents a fuzzy set is usually denoted by μ_A. For an element x of X, the value $\mu_A(x)$ is called the membership degree of x in the fuzzy set. The membership degree $\mu_A(x)$ quantifies the grade of membership of the element x to the fuzzy set. The value 0 means that x is not a member of the fuzzy set; the value 1 means that x is fully a member of the fuzzy set. The values between 0 and 1 characterize fuzzy members, which belong to the fuzzy set only partially.

The Fuzzy Logic includes 11 built-in membership functions. These 11 functions are, in turn, built from several basic functions: piecewise linear functions, the Gaussian distribution function, the sigmoid curve, and quadratic and cubic polynomial curves.

2.2.1. Types of Membership Function

The Fuzzy Logic includes 11 built-in membership function types. These 11 functions are, in turn, built from several basic functions: piecewise linear functions, the Gaussian distribution function, the sigmoid curve, and quadratic and cubic polynomial curves.

The simplest membership functions are formed using straight lines. Of these, the simplest is the triangular membership function, and it has the function name trimf. It is nothing more than a collection of three points forming a triangle. The graphical representation of triangular and trapezoidal membership functions are given in Fig.1 and Fig 2.

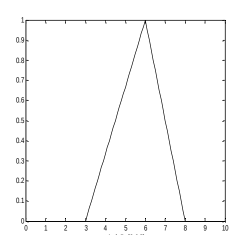

Fig. 1: Triangular MF

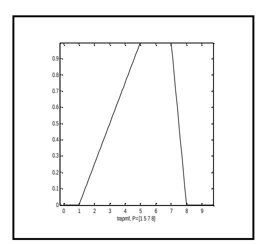

Fig. 2: Trapezoidal MF

Two membership functions gaussmf and gauss2mf are built on the Gaussian distribution curve are illustrated in the Fig 3 & Fig 4 respectively.

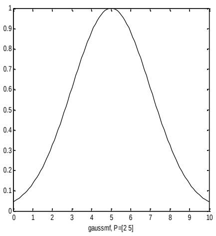

Fig 3: Gaussian MF

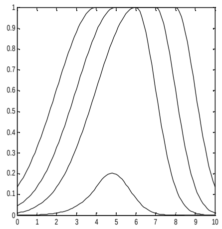

Fig 4: Gaussian2 MF

The generalized bell membership function (Fig 5) is specified by three parameters and has the function name gbellmf. The bell membership function has one more parameter than the Gaussian membership function

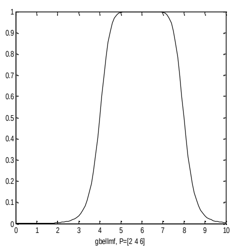

Fig 5: Gbell MF

Although the Gaussian membership functions and bell membership functions achieve smoothness, they are unable to specify asymmetric membership functions, which are important in certain applications. Next we define the sigmoidal membership function (Fig 6), which is either open left or right.

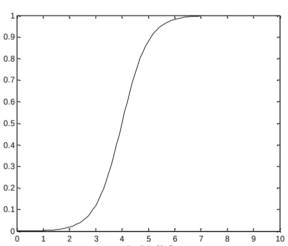

Fig 6: Sigmoidal MF

Asymmetric and closed (i.e. not open to the left or right) membership functions can be synthesized using two sigmoidal functions, so in addition to the basic sigmf, we also have the difference between two sigmoidal functions, dsigmf (Fig 7), and the product of two sigmoidal functions psigmf (Fig 8).

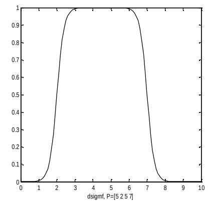

Fig. 7: Dsigmoidal MF

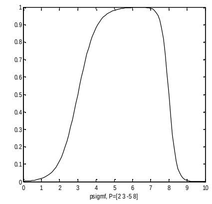

Fig. 8 : PSigmoidal MF

Polynomial based curves account for several of the membership functions in the toolbox. Three related membership functions are the Z, S, and Pi curves, all named because of their shape. The function zmf (Fig 9) is the asymmetrical polynomial curve open to the left.

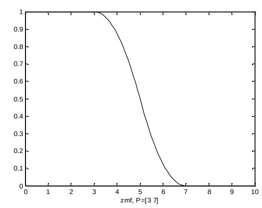

Fig. 9 : Z-shaped MF

Smf (Fig 10) is the mirror-image function that opens to the right, and pimf (Fig.11) is zero on both extremes with a rise in the middle.

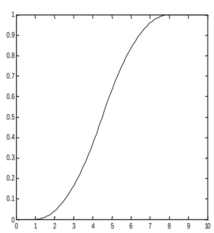

Fig. 10: S-shaped MF

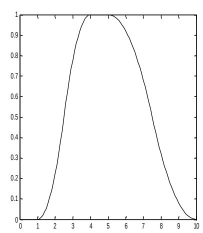

Fig. 11: Pi-shaped MF

2.3. Predicted Error and Average Predicted Error

The Predicted error and average Predicted error are calculated using the formula:-

Predicted error = | (Predicted value - actual value)| / (actual value) * 100 %

Average Predicted error = (sum of Predicted errors) / (total no of errors).

2.4. Time Series Data

Time series data occurs wherever the same measurements are recorded on a regular basis. Time series data is a series of statistical data that is related to a specific instant or a specific time period as shown in Fig 12.

2.5. Data used in this paper

The fifteen data sets have been used in this paper collected from the Book ‘Predicted: Methods and Applications (3rd edition) by Makridakis, Wheelwright and Hyndman, 1998 [22].’We also have taken help from the website *http://robjhyndman.com*[24].

3. Proposed Algorithm based on Fuzzy Logic System

3.1. Algorithm

Input: Time series Data
Output: Selected fuzzy membership function
Methods:
Step 1: One time series data will be taken as Input
Step 2: Define the universe discourse and fuzzy sets
Step 3: One fuzzy membership function will be selected
Step 4: Each data element will be fuzzyfied based on selected membership function and the fuzzy set will be selected in which the value of membership function is maximum
Step 5: Derived the fuzzy relationship by union of all selected fuzzy sets based on fuzzy MAX-MIN function
Step 6: Predict the data elements using the fuzzy relation and previous data elements
Step 7: The average error will be calculated based on original data and predicted data based on selected membership function.
Step 8: The step3 to step 7 will be repeated for all available fuzzy membership functions
Step 9: Particular membership will be selected based on minimum average error in prediction of data set.
Step 10: The step 1 to step 8 will be repeated for 15 time series data set.
Step 11: The fuzzy membership function will be selected which will be given minimum value in maximum time series data.
Step 12: Stop

4. Implementation

To implement this method, Matlab 7.1 has been used. Winning times for the men's 400 m final in each Olympic Games from 1896 to 1996 has been used as first data set. All fuzzy membership functions have been used on this data set.

4.1 Prediction Using Gaussian Membership Function

The prediction using Gaussian membership function has been narrated by step.
Step 1. The universe U is partitioned into four equal length (5) intervals. The intervals have been chosen as u1= [40, 45], u2 = [45, 50], u3 = [50, 55], u4 = [55, 60]
Step 2. The available data has been fuzzified based on Gaussian function is furnished in Table 1 . The graphical representation has been given in fig 13.

Table 1 : Actual Data and Fuzzy Set

Actual Data	A1	A2	A3	A4	Fuzzy Set
54.2	0.0000	0.0027	0.2905	0.9561	A4
49.4	0.0020	0.2575	0.9751	0.1111	A3
49.2	0.0027	0.2905	0.9561	0.0947	A3
50	0.0009	0.1735	1.0000	0.1735	A3
48.2	0.0090	0.4880	0.7969	0.0392	A3
49.6	0.0016	0.2270	0.9889	0.1296	A3
47.6	0.0175	0.6227	0.6679	0.0216	A3
47.8	0.0141	0.5773	0.7124	0.0265	A4
46.2	0.0676	0.9040	0.3636	0.0044	A2
46.5	0.0518	0.8541	0.4239	0.0063	A2
46.2	0.0676	0.9040	0.3636	0.0044	A2
45.9	0.0872	0.9448	0.3079	0.0030	A2
46.7	0.0430	0.8167	0.4662	0.0080	A2
44.9	0.1859	0.9993	0.1616	0.0008	A2
45.1	0.1616	0.9993	0.1859	0.0010	A2
43.8	0.3636	0.9040	0.0676	0.0002	A2
44.66	0.2184	0.9919	0.1356	0.0006	A2
44.26	0.2804	0.9624	0.0994	0.0003	A2
44.6	0.2270	0.9889	0.1296	0.0005	A2
44.27	0.2787	0.9633	0.1002	0.0003	A2
43.87	0.3501	0.9144	0.0719	0.0002	A2
43.5	0.4239	0.8541	0.0518	0.0001	A2
43.49	0.4259	0.8523	0.0513	0.0001	A2

Step 3. The historical knowledge from Table 1 about the evolution of the shoot length is obtained to set up the Predicted model. The available data are transformed into linguistic values. Using the symbols of Song and Chissom [3], all the fuzzy logical relationships from Table 1 has been furnished in table 2.

Table 2. Fuzzy Logical Relationships

A4----->A3, A3 ----->A3 , A3 ----->A4, A4 ----->A2, A2 ----->A2.

It is to note that the repeated relationships are counted for only once.

Step 4. By definition a time-invariant fuzzy time series has been developed ([1], [3], [5]).Let us define an operator ' X ' of two vectors. Suppose C and B are row vectors of dimension m and D = (d_{ij}) = C^T X B. Then the element d_{ij} of matrix D at row i and column j is defined as d_{ij} = min (C_i, B_j) (i, j = 1... m) where C_i and B_j are the i-th and the j-th element of C and B respectively.

Let R1 = $A4^T$ X A3, R2 = $A3^T$ X A3, R3 = $A3^T$ X A4, R4 = $A4^T$ X A2, R5 =$A2^T$ X A2.

Now a relation matrix R has been formed as R(t, t - 1) = R = U Ri where U is the union operator. The value of R as follows (Table 3):-

Table – 3 : The value of R

0.4239	0.4239	0.0518	0.0001
0.4259	0.8541	0.0518	0.0001
0.0719	0.0719	0.0518	0.0001
0.0002	0.0002	0.0002	0.0001

Using R, the predicted model is Ai = Ai – 1. R where Ai -1 is the actual data of reading i - 1 and Ai is the Predicted data of reading i and '. 'is the max - min operator.

Step 6: The predicted output has been interpreted which are all fuzzy sets. Now it has been translated into a regular number (defuzzification). The predicted values for the given data are furnished in Table 4.

Table – 4 : Output Fuzzy Value And Estimated Value

Actual Value	Output Fuzzy Value	Predicted Value
54.2		
49.4	0.4259 0.8541 0.2905 0.9561	48.5161
49.2	0.4259 0.8541 0.9751 0.1111	46.6299
50	0.4259 0.8541 0.9561 0.0947	46.5436
48.2	0.4259 0.8541 1.0000 0.1735	46.8769
49.6	0.4259 0.8541 0.7969 0.0392	46.0616
47.6	0.4259 0.8541 0.9889 0.1296	46.7138
47.8	0.4259 0.8541 0.6679 0.0216	45.7237
46.2	0.4259 0.8541 0.7124 0.0265	45.8404
46.5	0.4259 0.9040 0.3636 0.0044	44.8422
46.2	0.4259 0.8541 0.4239 0.0063	45.0309
45.9	0.4259 0.9040 0.3636 0.0044	44.8422
46.7	0.4259 0.9448 0.3079 0.0030	44.6671
44.9	0.4259 0.8541 0.4662 0.0080	45.1605
45.1	0.4259 0.9993 0.1616 0.0008	44.1725
43.8	0.4259 0.9993 0.1859 0.0010	44.2621
44.66	0.4259 0.9040 0.0676 0.0002	43.7194
44.26	0.4259 0.9919 0.1356 0.0006	44.0694
44.6	0.4259 0.9624 0.0994 0.0003	43.9048
44.27	0.4259 0.9889 0.1296 0.0005	44.0443
43.87	0.4259 0.9633 0.1002 0.0003	43.9089
43.5	0.4259 0.9144 0.0719 0.0002	43.7477
43.49	0.4259 0.8541 0.0518 0.0001	43.5962

Step 7. Finally the predicted error and average predicted error are calculated and furnished in Table 5.

Table – 5 : Predicted Error Calculation based on Gaussian MF

Actual Value	Predicted Value	Predicted Error (%)
54.2		
49.4	48.5161	1.7892
49.2	46.6299	5.2239
50	46.5436	6.9129
48.2	46.8769	2.7451
49.6	46.0616	7.1339
47.6	46.7138	1.8617
47.8	45.7237	4.3437
46.2	45.8404	0.7783
46.5	44.8422	3.5651
46.2	45.0309	2.5305
45.9	44.8422	2.3045
46.7	44.6671	4.3531
44.9	45.1605	0.5802
45.1	44.1725	2.0565
43.8	44.2621	1.0550
44.66	43.7194	2.1061
44.26	44.0694	0.4306
44.6	43.9048	1.5587
44.27	44.0443	0.5099
43.87	43.9089	0.0886
43.5	43.7477	0.5695
43.49	43.5962	0.2443

Average Error 2.29%

The same effort has been applied using bell shaped, s-shaped, trapezoidal, triangular membership functions. The results and average errors are furnished from table 6 to 15 as follows:-

Table – 6 : Predicted Error Calculation for Gauss2mf MF

Actual Value	Predicted Value	Predicted Error (%)
54.2		
49.4	50.6002	2.4296
49.2	49.6976	1.0114
50	49.7544	0.4912
48.2	50.0374	3.8121
49.6	49.7397	0.2817
47.6	50.1756	5.4110
47.8	49.8202	4.2264
46.2	49.9850	8.1927
46.5	49.7096	6.9023

46.2	49.9046	8.0187
45.9	49.9525	8.8290
46.7	50.0023	7.0713
44.9	50.3490	12.1357
45.1	49.9983	10.8610
43.8	50.1909	14.5912
44.66	49.9657	11.8802
44.26	50.3519	13.7640
44.6	50.3827	12.9658
44.27	50.6293	14.3647
43.87	50.6838	15.5318
43.5	50.7182	16.5936
43.49	50.7619	16.7208

Average Error: 8.52%

Table –7 : Predicted Error Calculation based on Dsigmoidal MF

Actual Value	Predicted Value	Predicted Error (%)
54.2		
49.4	44.75	9.3993
49.2	44.78	9.0310
50	44.76	10.4865
48.2	44.78	7.1437
49.6	44.74	9.7646
47.6	44.72	5.9732
47.8	44.72	6.3666
46.2	44.68	3.1239
46.5	44.71	3.7489
46.2	44.78	3.1239
45.9	44.75	2.4907
46.7	44.78	4.1611
44.9	44.7568	0.3190
45.1	44.73	0.7611
43.8	44.76	2.1844
44.66	44.72	0.2167
44.26	44.69	1.1224
44.6	44.70	0.3515
44.27	44.61	1.0995
43.87	44.23	2.0213
43.5	44.8	2.8891
43.49	44.7	2.9128

Average Error: 3.85%

Table – 8: Predicted Error Calculation based on Gbell MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	50.1	1.2146
49.2	50.3	1.6260
50	50.6	1.62
48.2	50.12	3.7344
49.6	50.5	0.8065
47.6	50.7	5.0420
47.8	50.03	4.6025
46.2	50.35	8.2251
46.5	50.6	7.5269
46.2	50.18	8.2251
45.9	50.32	8.9325
46.7	50	7.0664
44.9	50.45	11.3586
45.1	50.32	10.8647
43.8	50.6	14.1553
44.66	50.7	11.9570
44.26	51	12.9688
44.6	51.2	12.1076
44.27	51.3	12.9433
43.87	50	13.9731
43.5	50	14.9425
43.49	50.3	14.9690

Average Error : 8.14%

Table –9 : Predicted Error Calculation based on Pi-Shaped MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	49.6269	0.4592
49.2	47.2212	4.0219
50	47.1204	5.7593
48.2	47.5221	1.4064
49.6	46.6192	6.0097
47.6	47.3230	0.5820
47.8	46.3218	3.0925
46.2	46.4219	0.4803
46.5	45.6208	1.8907
46.2	45.7713	0.9278
45.9	45.6208	0.6083
46.7	45.4735	2.6263
44.9	45.8720	2.1649
45.1	44.9761	0.2747
43.8	45.0738	2.9082
44.66	44.4308	0.5131
44.26	44.8574	1.3498
44.6	44.6565	0.1267
44.27	44.8274	1.2591
43.87	44.6615	1.8041
43.5	44.4652	2.2189
43.49	44.2812	1.8193

Average Error: 1.83%

Table –10 : Predicted Error Calculation base on Psigmoidal MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	49.0000	0.8097
49.2	46.5000	5.4878
50	46.5000	7.0000
48.2	46.7576	2.9926
49.6	46.0000	7.2581
47.6	46.5000	2.3109
47.8	45.5000	4.8117
46.2	45.5000	1.5151
46.5	45.0000	3.2258
46.2	45.0000	2.5974
45.9	45.0000	1.9608
46.7	44.5037	4.7031
44.9	45.0000	0.2227
45.1	44.0041	2.4300
43.8	44.4966	1.5905
44.66	43.5000	2.5973
44.26	44.0000	0.5874
44.6	44.0000	1.3453
44.27	44.0000	0.6099
43.87	44.0000	0.2963
43.5	43.5011	0.0025
43.49	43.5000	0.0230

Average Error: 2.36%

Table –11 : Predicted Error Calculation S-Shaped MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	50.193	1.6053
49.2	50.194	2.0184
50	50.193	0.3861
48.2	50.192	4.1349
49.6	50.193	1.1956
47.6	50.194	5.4476
47.8	50.193	5.0063
46.2	50.193	8.6429
46.5	50.193	7.9420
46.2	50.192	8.6429
45.9	50.194	9.3530
46.7	50.191	7.4797
44.9	50.193	11.7885
45.1	50.192	11.2928
43.8	50.194	14.5960
44.66	50.193	12.3892
44.26	50.193	13.4050
44.6	50.193	12.5404
44.27	50.193	13.3793
43.87	50.192	14.4131
43.5	50.194	15.3863
43.49	50.196	15.4128

Average Error: 8.54%

Table 12 : Predicted Error Calculation Based on Sigmoidal MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	49.0	0.8097
49.2	49.03	0.4065
50	49.16	2.0000
48.2	49.06	1.6598
49.6	49.08	1.2097
47.6	49.24	2.9412
47.8	49.19	2.5105
46.2	49.03	6.0606
46.5	49.20	5.3763
46.2	49.31	6.0606
45.9	49.30	6.7538
46.7	49.16	4.9251
44.9	48.0	9.1314
45.1	49.7	8.6475
43.8	49.3	11.8721
44.66	49.5	9.7179
44.26	47.4	10.7094
44.6	47.3	9.8655
44.27	49.0	10.6844
43.87	49.0	11.6936
43.5	49.3	12.6437
43.49	49.6	12.6696

Average Error: 6.45%

Table – 13 : Predicted Error Calculation based on Trappezoidal MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	49.9390	1.0910
49.2	49.0097	0.3868
50	48.9732	2.0535
48.2	49.1228	1.9144
49.6	48.7944	1.6241
47.6	49.0468	3.0394
47.8	48.6896	1.8610
46.2	48.7244	5.4640
46.5	48.4591	4.2132
46.2	48.5073	4.9941
45.9	48.4591	5.5754
46.7	48.4111	3.6641
44.9	48.5392	8.1050
45.1	48.2626	7.0123
43.8	48.2915	10.2545
44.66	48.1105	7.7261
44.26	48.2286	8.9665
44.6	48.1726	8.0104
44.27	48.2201	8.9228
43.87	48.1740	9.8109
43.5	48.1197	10.6199
43.49	48.0713	10.5342

Average Error: 5.47%

Table 14 : Predicted Error Calculation based on triangular MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	44.8889	9.1318
49.2	46.8354	4.8060
50	46.7532	6.4935
48.2	47.0588	2.3676
49.6	46.2687	6.7164
47.6	46.9136	1.4421
47.8	45.9016	3.9715
46.2	46.0317	0.3642
46.5	44.6809	3.9121
46.2	45	2.5974
45.9	44.6809	2.6561
46.7	44.3182	5.1003
44.9	45.1923	0.6510
45.1	42.6471	5.4389
43.8	43.0556	1.6996
44.66	40.0000	10.4344
44.26	42.0886	4.9060
44.6	40.9420	8.2017
44.27	41.9355	5.2734
43.87	40.9747	6.5997
43.5	40	8.0460
43.49	40	8.0248

Average Error : 4.73%

Table 15 : Predicted Error Calculation based on Z-Shaped MF

Actual Value	Predicted Value	Predicted Error(%)
54.2		
49.4	47.9213	2.9933
49.2	45.5503	7.4181
50	45.4511	9.0978
48.2	45.8571	4.8607
49.6	44.9809	9.3127
47.6	45.6511	4.0944
47.8	44.7219	6.4396
46.2	44.8061	3.0171
46.5	44.1148	5.1295
46.2	44.2687	4.1804

45.9	44.1148	3.8894
46.7	43.9402	5.9097
44.9	44.3602	1.2021
45.1	43.3709	3.8340
43.8	43.4791	0.7325
44.66	42.8146	4.1321
44.26	43.2438	2.2960
44.6	43.0388	3.5005
44.27	43.2125	2.3888
43.87	43.0438	1.8833
43.5	42.8478	1.4992
43.49	42.6758	1.8722

Average Error: 3.89%

5. Result

The average errors of the first data set based on various types of membership functions have been summarized in table 16. From the first data set, it has been proved that pi-membership function has been given the minimum error. The same method has been applied on fifteen different data sets and the average errors have been summarized into table 17. In this table, the minimum error among the all applied membership functions for particular data set has been made bold.

The graphical comparison between eleven membership function in first ten data series have been furnished by bar chart in Fig 14. In the Fig : 14 the X-axis represents the membership functions and Y-axis represents the error for first ten data set . The average error comparison of eleven membership functions has been shown in Fig. 15. In the Fig: 15 the X-axis represents the membership functions and Y-axis represents the number of occurrences of minimum error.

6. Conclusion and future work

From the table 16, it has been observed that the Pi-membership function has been given minimum error. In this data set, the performance of Pi-membership function is better than others. But, after application the same procedure in fifteen data sets furnished in table 17, it has been observed that triangulated member ship function has been given minimum error in most cases. So, triangulated membership function can be used in prediction of time series data. In this paper, fifteen data sets have been tested but in future more data set will be tested to predict the suitable membership function in prediction of time series data.

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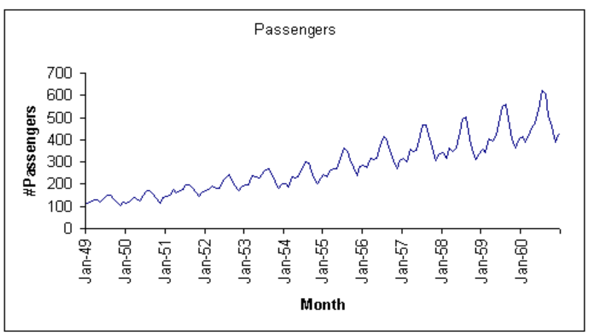

Fig: 12 : Time Series Data

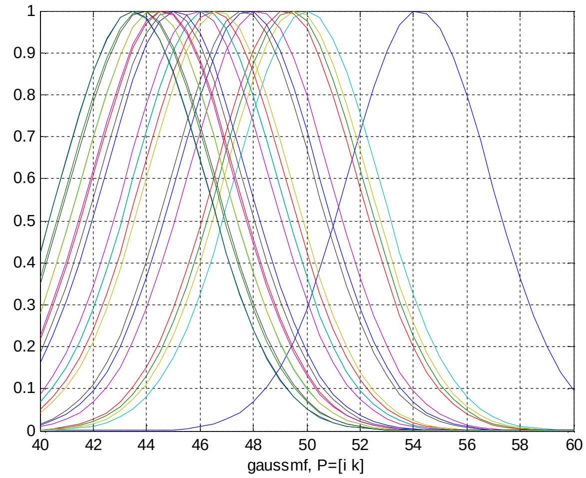

Fig: 13 : Plotting the fuzzified value of Gaussian MF

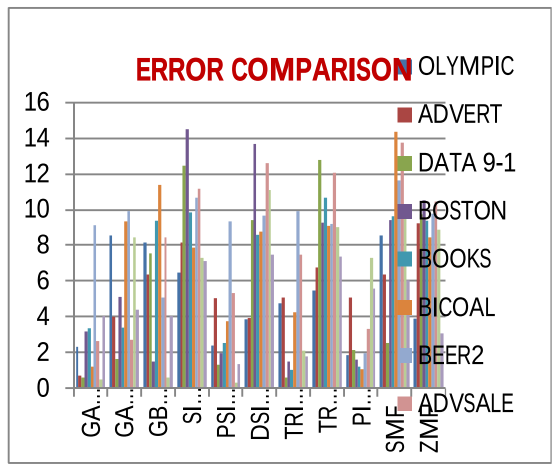

Fig. 14 : The graphical comparison between eleven MF

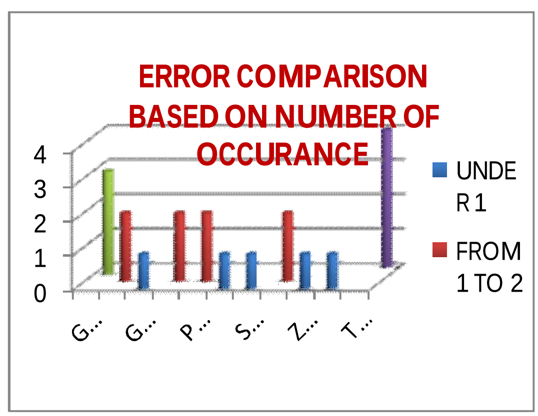

Fig. 15: The average error comparison of eleven MF

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Table – 16: Predicted Error Calculation

Error Calculation										
Gauss	**Gauss2**	**Gbell**	**Dsig**	**Pi**	**Psig**	**Smf**	**Sig**	**Trap**	**Tri**	**Zmf**
2.29	8.52	8.14	3.85	**1.84**	2.36	8.54	6.45	5.47	4.73	3.89

Table – 17 : Error Calculation on Fifteen Data Set

Data Set	**Error Calculation**										
	Gauss	Gauss2	Gbell	Dsig	Pi	Psig	Smf	Sig	Trap	Tri	Zmf
1	2.29	8.52	8.14	3.85	**1.84**	2.36	8.54	6.45	5.47	4.73	3.89
2	**0.68**	3.97	6.35	3.90	5.08	5.01	6.35	8.16	6.76	5.07	9.22
3	0.6	1.61	7.52	9.41	2.13	1.30	2.52	12.49	12.81	**0.58**	9.75
4	3.18	5.09	1.49	13.71	1.57	1.93	9.38	14.51	9.27	**1.47**	10.54
5	3.35	3.39	9.36	8.58	1.18	2.51	9.66	9.87	10.70	**1.0**	9.36
6	1.18	9.32	11.39	8.75	**1.05**	3.73	14.39	7.85	9.08	4.25	8.44
7	9.12	9.93	10.3	9.68	9.15	9.32	11.67	10.69	9.19	9.93	9.78
8	**2.63**	2.69	8.42	12.61	3.29	5.32	13.77	11.17	12.08	7.46	10.48
9	0.48	8.42	0.58	11.13	7.37	**0.30**	9.67	7.28	9.02	2.09	8.87
10	4.01	4.37	4.01	7.48	5.58	**1.34**	6.03	7.10	7.35	1.78	3.07
11	9.10	8.75	12.26	**8.47**	11.47	9.70	13.87	9.72	10.82	9.14	14.85
12	7.84	**7.01**	7.06	8.4	8.82	9.08	8.64	9.77	7.45	7.64	7.59
13	**7.94**	8.98	8.75	8.93	8.85	8.92	8.49	8.46	8.11	8.71	8.38
14	7.12	9.82	12.43	8.75	7.20	7.30	8.35	11.64	9.05	**7.07**	8.07
15	1.09	3.72	4.73	9.37	3.80	3.96	13.46	11.75	3.46	**0.49**	12.70