Development and Comparative Analysis Of Fuzzy Inference Systems for Predicting Customer Buying Behavior

Gaurav Kumar Nayak, Swathi J Narayanan, Ilango Paramasivam
School of Computing Science and Engineering
VIT University
Vellore
gauravkrnayak@gmail.com , swathi.jns@gmail.com , pilango@vit.ac.in

***Abstract*— The fuzzy inference system (FIS) has been developed for predicting customer buying behavior. Three different methods: (grid partitioning, fuzzy c-means, subtractive) have been used to get the membership values during the fuzzification of inputs which is the first step in the creation of FIS. For each method, two different FIS models (Mamdani-type FIS and Sugeno-type FIS) have been developed. ANFIS training is also done on the Sugeno-type FIS to tune the FIS parameters using the input/output training data. Finally, the comparison table has been prepared to list out the efficiencies in terms of accuracy for the different techniques used and thus finds out which method is the best for the particular system.**

Keyword— Fuzzy Inference System (FIS), Grid Partitioning, Fuzzy C-means, Subtractive, Mamdani, Sugeno, ANFIS.

I. INTRODUCTION

Fuzzy inference is the process of making a mapping system from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns can be discovered [14].Fuzzy inference systems have been correctly applied in many fields such as automatic control, data classification, decision analysis, expert systems, and computer vision [14].One of the traditional ways of classifying the input data is to use data mining technique called Naïve Bayesian classifier in which the probability of input data to be classified is calculated for each output classes and thus the output class having the higher probability is made as final output.

The reasons for using fuzzy logic in predicting customer buying behavior are [15]:

- Fuzzy logic is conceptually easy to understand.
- Fuzzy logic is flexible.
- Fuzzy logic is tolerant of imprecise data.
- Fuzzy logic can model nonlinear functions of arbitrary complexity.
- Fuzzy logic can be built on top of the experience of experts.
- Fuzzy logic can be blended with conventional control techniques.
- Fuzzy logic is based on natural language.

The customer buying prediction has got a lot of importance in data analytics through which a lot of companies use that information to see when and under what conditions the customer buys a particular product. Depending on that information the company gives offer in order to maximize their sales.

The rest of the paper is organized as follows: Section II deals with different approaches in making FIS. Section III shows different steps involved in fuzzy inference process. Section IV gives the information about the fuzzy rule base. Section V, gives results and discussions and section VI conclusions.

II. DIFFERENT APPROACHES IN MAKING FIS

There are two approaches or the ways to make a fuzzy inference system.

(1) Mamdani :

The Mamdani method has several advantages like [18]

- Mamdani method is widely accepted for capturing expert knowledge.
- It allows us to describe the expertise in more intuitive, more human-like manner.
- Mamdani-type FIS uses the technique of defuzzification of a fuzzy output.

- Due to the interpretable and intuitive nature of the rule base, Mamdani-type FIS is widely used in particular for decision support application.
- Mamdani FIS has output membership functions.

Demerits of this method are:

- Mamdani FIS is less flexible in system design
- Mamdani-type FIS entails a substantial computational burden.

(2) Sugeno :

The Sugeno method has several advantages like [18]

- Sugeno method is computationally efficient and works well with optimization and adaptive techniques, which makes it very attractive in control problems, particularly for dynamic nonlinear systems.
- Sugeno-type FIS uses weighted average to compute the crisp output.
- Sugeno has better processing time since the weighted average replace the time consuming defuzzification process.

The demerits of this method are:

- The expressive power and interpretability of Mamdani output is lost in the Sugeno FIS since the consequents of the rules are not fuzzy.
- Sugeno FIS has no output membership functions

The Sugeno type FIS can be trained using ANFIS which is also called as Adaptive Neuro Fuzzy Inference System (ANFIS).

ANFIS is helpful in tuning the membership function parameters by using either a backpropagation algorithm alone or in combination with a least squares type of method to model a given set of I/O data.

III. FUZZY INFERENCE PROCESS

Fuzzy inference process consists of five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules, and Defuzzification [16].

1. Fuzzify Inputs

   The first step is to take the inputs and determine the degree of membership to which they belong to each of the appropriate fuzzy sets [16]. In order to do this, any one of the below methods can be used:

   - grid partitioning
   - fuzzy c-means
   - subtractive clustering

2. Apply Fuzzy Operator
3. Apply Implication Method
4. Aggregate All Outputs
5. Defuzzify

IV. FUZZY RULE BASE

All the attributes are classified as numerical or categorical.

Input attributes are:

- Age-Numerical attribute
- Income-Numerical attribute
- Student-Categorical attribute
- Credit Rating-Numerical attribute

Output attributes are:

- Buys-Numerical attribute

Numerical attributes are those where each input data in an attribute has non zero membership values for each of the clusters formed for an attribute. Their values have range [0,1].

Categorical attributes are those where each input data in an attribute has only a single non zero membership value for one of the clusters and zero membership values for the other clusters. They take the values as either zero or one.

Here the number of membership functions for each input is:

- Age - 3
- Income -3
- Student -2
- Credit Rating -2

TABLE I. RULE BASE FOR THE FIS [5]

RID	Age	Income	Student	Credit Rating	Buys
1	<=30	high	no	fair	no
2	<=30	high	no	excellent	no
3	31…40	high	no	fair	yes
4	>40	medium	no	fair	yes
5	>40	low	yes	fair	yes
6	>40	low	yes	excellent	no
7	31…40	low	yes	excellent	yes
8	<=30	medium	no	fair	no
9	<=30	low	yes	fair	yes
10	>40	medium	yes	fair	yes
11	<=30	medium	yes	excellent	yes
12	31…40	medium	no	excellent	yes
13	31…40	high	yes	fair	yes
14	>40	medium	no	excellent	no

If the fuzzy inference system is Mamdani then the number of membership functions for the output would be taken as two.

The type of membership function is taken as:

For Mamdani-

- Input attributes-gaussmf
- Output attribute-gaussmf

For Sugeno-

- Input attributes-gaussmf
- Output attribute-constant/linear

For the above mentioned rule base, the rule list to be added in the FIS is taken as:

TABLE II. MAMDANI AND SUGENO RULE LIST

Mamdani rule list	Sugeno rule list
ruleList=[... 1 3 2 1 2 1 1 1 3 2 2 2 1 1 2 3 2 1 1 1 1 3 2 2 1 1 1 1 3 1 1 1 1 1 1 3 1 1 2 2 1 1 2 1 1 2 1 1 1 1 2 2 1 2 1 1 1 1 1 1 1 1 1 3 2 1 1 1 1 1 1 2 1 2 1 1 1 2 2 2 2 1 1 1 2 3 1 1 1 1 1 3 2 2 2 2 1 1]	ruleList=[... 1 3 2 1 1 1 1 1 3 2 2 2 1 1 2 3 2 1 3 1 1 3 2 2 1 4 1 1 3 1 1 1 5 1 1 3 1 1 2 6 1 1 2 1 1 2 7 1 1 1 2 2 1 8 1 1 1 1 1 1 9 1 1 3 2 1 1 10 1 1 1 2 1 2 11 1 1 2 2 2 2 12 1 1 2 3 1 1 13 1 1 3 2 2 2 14 1 1]

In order to measure the accuracy, the testing data along with the expected output considered is given in Table III.

TABLE III. TESTING DATA WITH EXPECTED OUTPUT

Age	Income	Student	Credit Rating	Expected buys
12	3	2	1	2
19	3	2	2	2
30	3	2	1	2
42	2	2	1	1
25	3	2	1	2
19	3	2	2	2
35	3	2	1	1
38	3	2	1	1
39	3	2	1	1
41	2	2	1	1
42	1	1	1	1
45	1	1	1	1
46	1	1	2	2
45	1	1	2	2
32	1	1	2	1
30	2	2	1	2
25	2	2	1	2
25	1	1	1	1
43	2	1	1	1
46	2	1	1	1
20	2	1	2	1
25	2	1	2	1
35	2	2	2	1
38	2	2	2	1
39	3	1	1	1
40	3	1	1	1
45	2	2	2	2
43	2	2	2	2
24	3	2	1	2
44	2	2	2	2

The range of an attribute is taken as minimum and maximum value available in the column of that particular attribute in testing data.

V. RESULTS AND DISCUSSIONS

Anfis training for Sugeno type FIS is done for one epoch. If the output value is greater than 1.5 then it is categorized in the second cluster else it is categorized in the first cluster. The accuracy is calculated based on the formula: Accuracy= [(Number of outputs correctly classified) / (Total number of outputs)]*100. The FIS results obtained using Grid partitioning is given in TABLE IV.

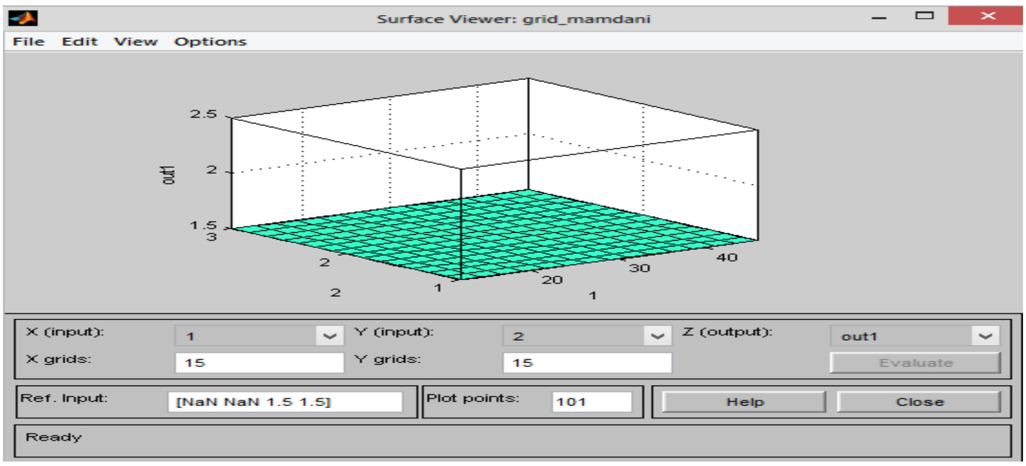

Fig.1. Surface view of grid based Mamdani

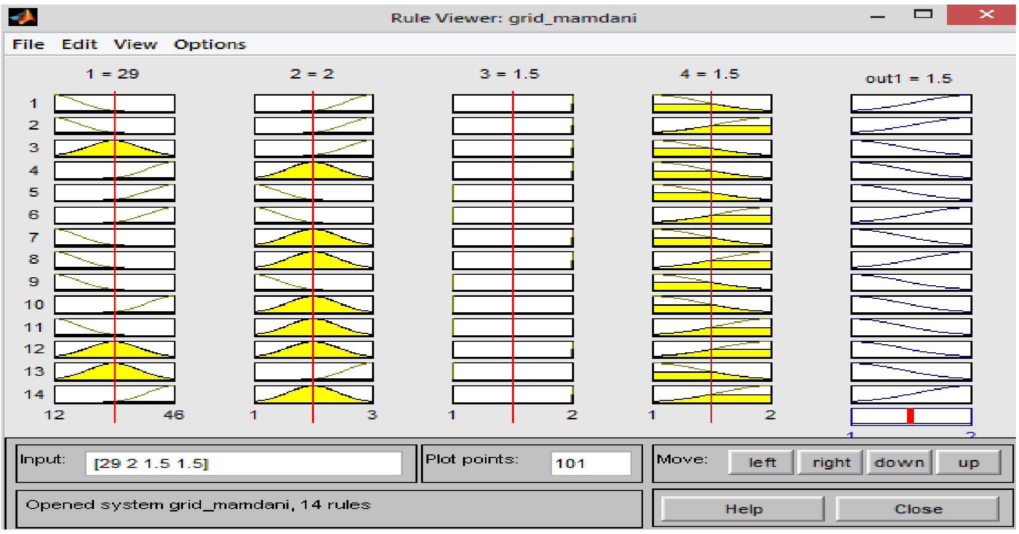

Fig.2. Rule view of grid based Mamdani

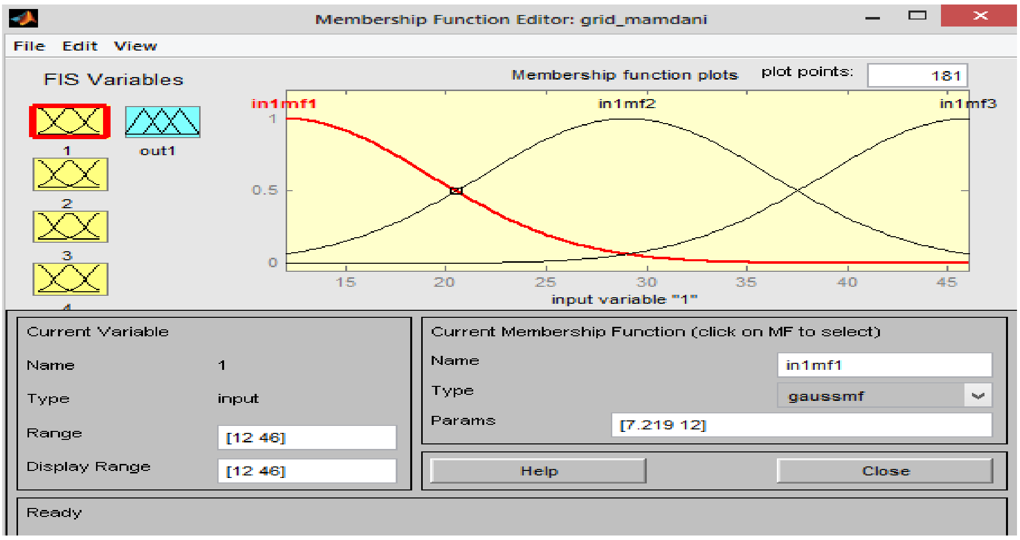

Fig.3. Age membership functions

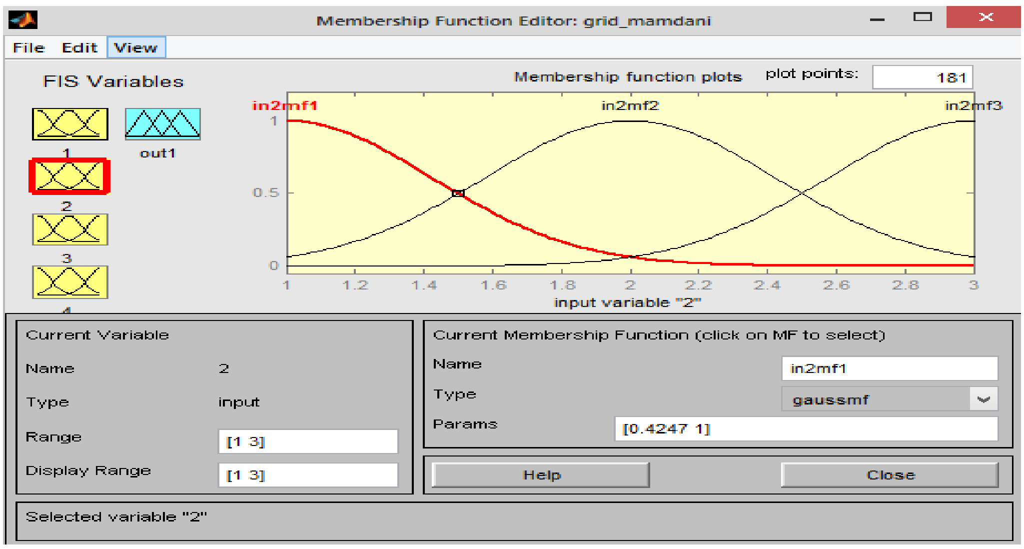

Fig.4. Income membership functions

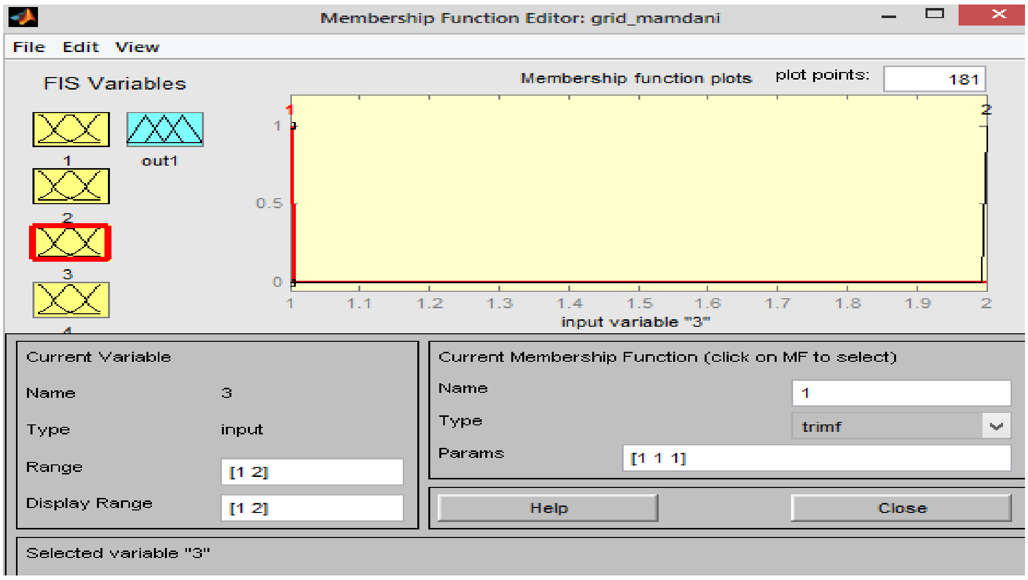

Fig.5. Student membership functions

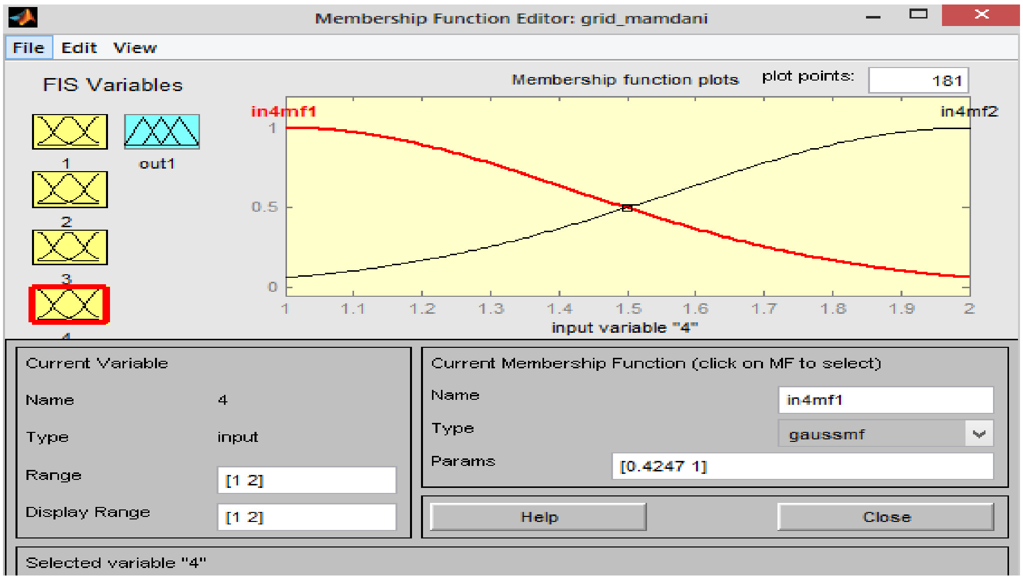

Fig.6. Credit Rating membership functions

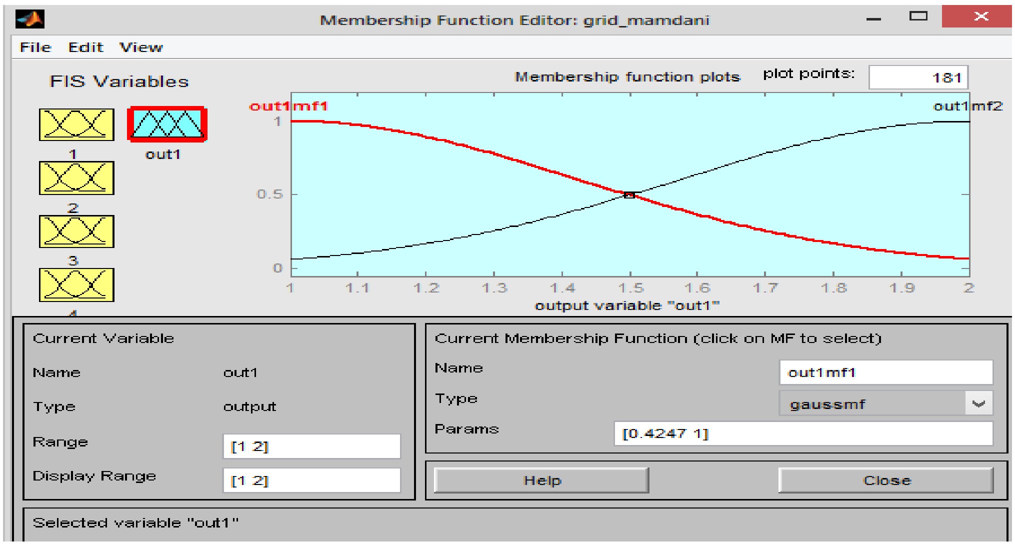

Fig.7. Output membership function for grid based Mamdani

TABLE IV. MAMDANI AND SUGENO GRID PARTITIONING BASED FIS COMPARISON

	Mamdani	Sugeno
andMethod	Min	Prod
orMethod	Max	Max
defuzzMethod	Centroid	Wtaver
impMethod	Min	Prod
aggMethod	Max	Max
Accuracy (in %)	76.666667	output membership function type :linear Before training-56.66% After anfis training-100% output membership function type :constant Before training-56.66% After anfis training- 93.33%

The graphs generated for FIS with grid partitioning after ANFIS Training is given in Fig 8-Fig10.

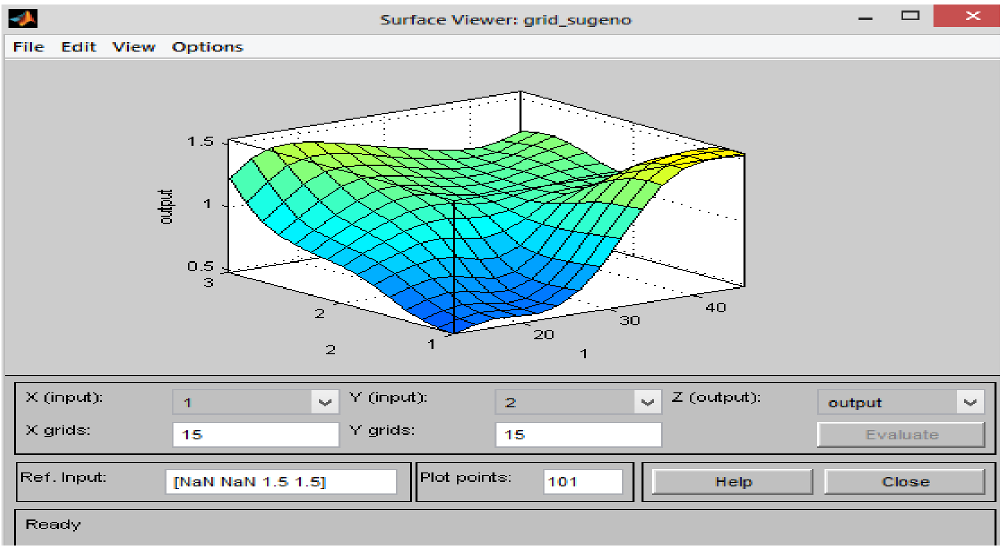

Fig.8. Surface view of grid based Sugeno

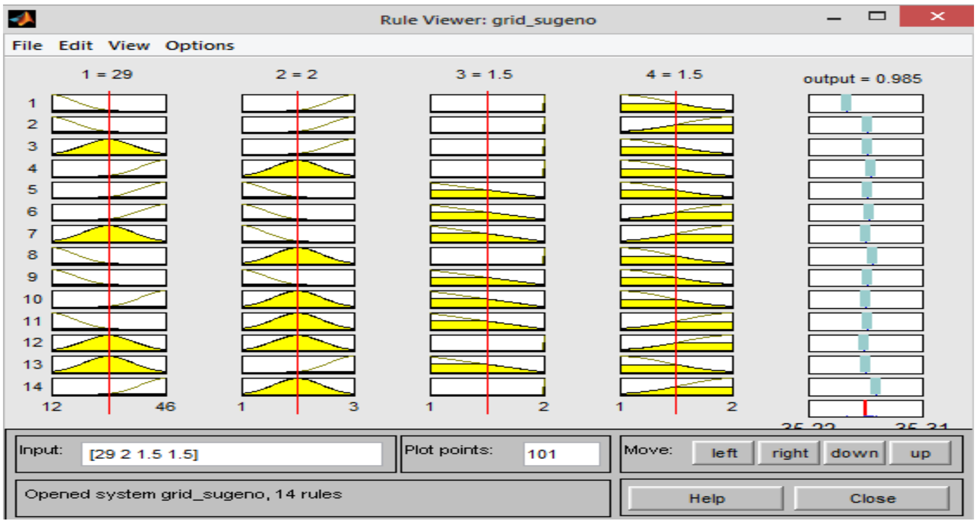

Fig.9. Rule view of grid based Sugeno

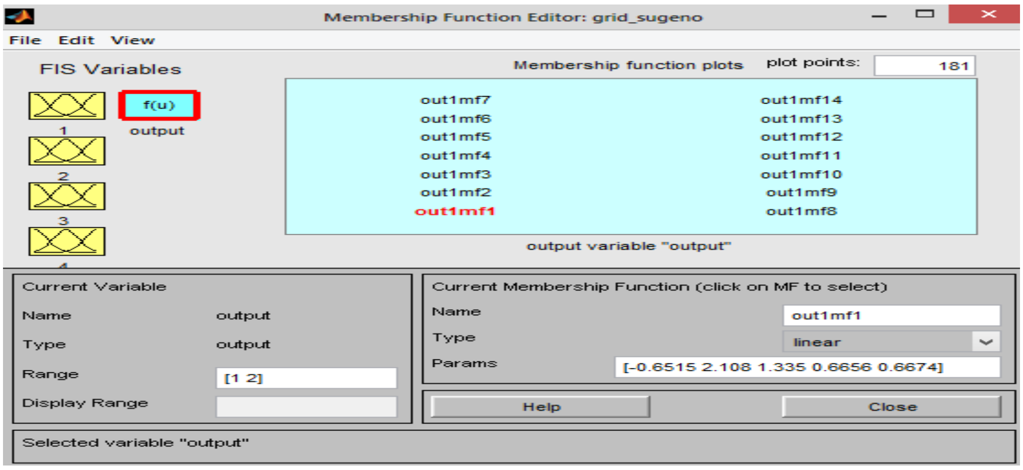

Fig.10. Output membership function for grid based Sugeno

The Second experiment is developing FIS using Fuzzy c-means[5]. The results obtained using FUZZY c-means is given in TABLE V.

In order to get non zero sigma value and avoid the occurrence of 'NaN' values, the maximum number of iterations has been set for different input attributes in the fcm options as:

- Age-100 iterations (same as default)
- Income-5 iterations
- Student-4 ieartions
- Credit Rating-4 iterations

For the Mamdani type FIS, the maximum number of iterations taken for the output attribute is two.

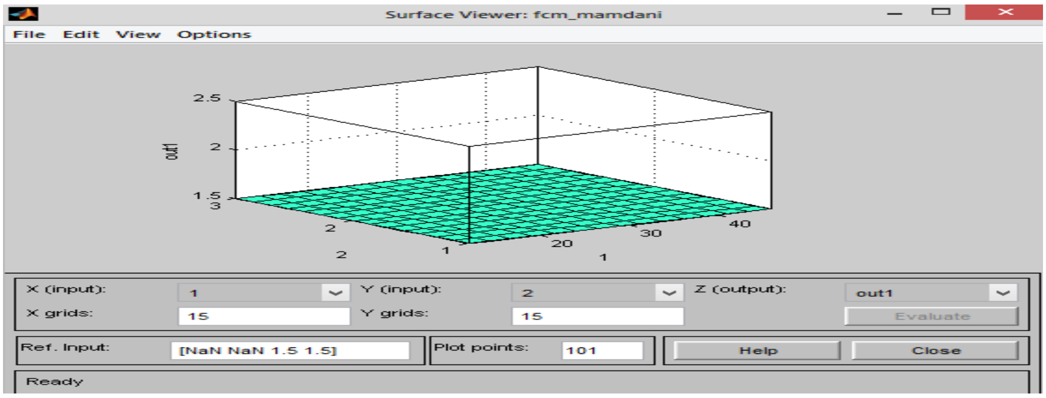

Fig.11. Surface view of fcm based Mamdani

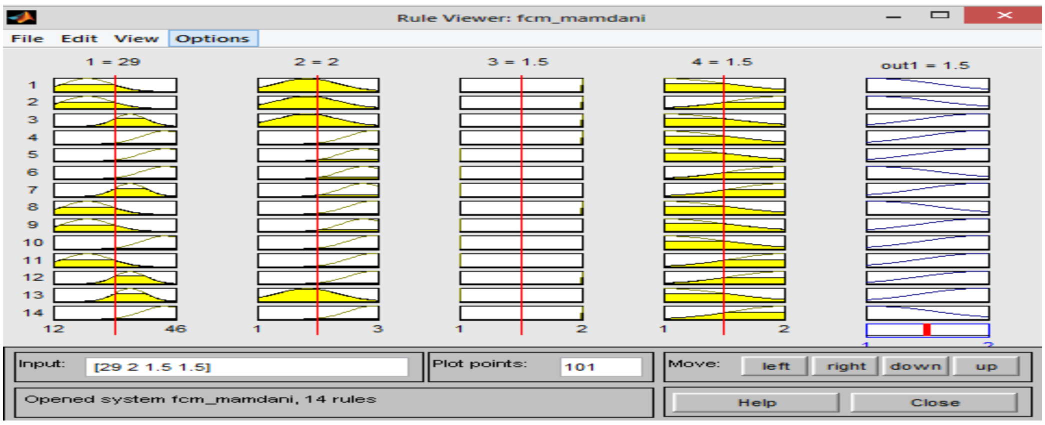

Fig.12. Rule view of fcm based Mamdani

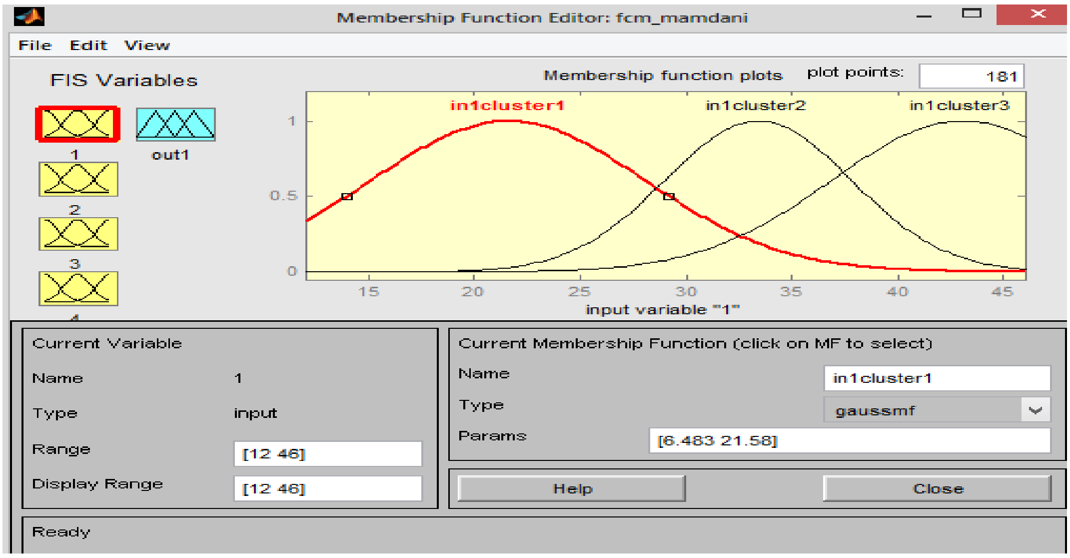

Fig.13. Age membership functions

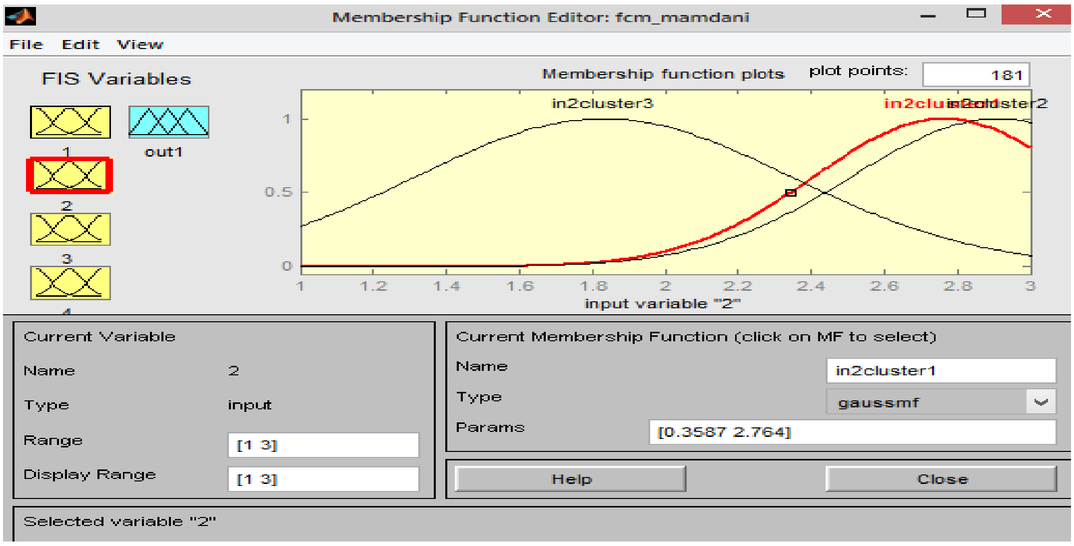

Fig.14. Income membership functions

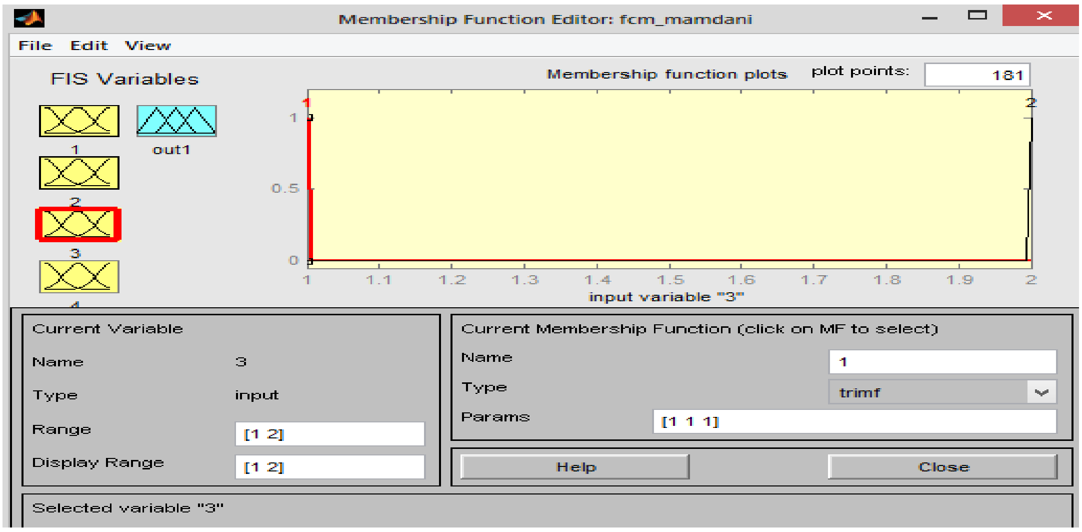

Fig.15. Student membership functions

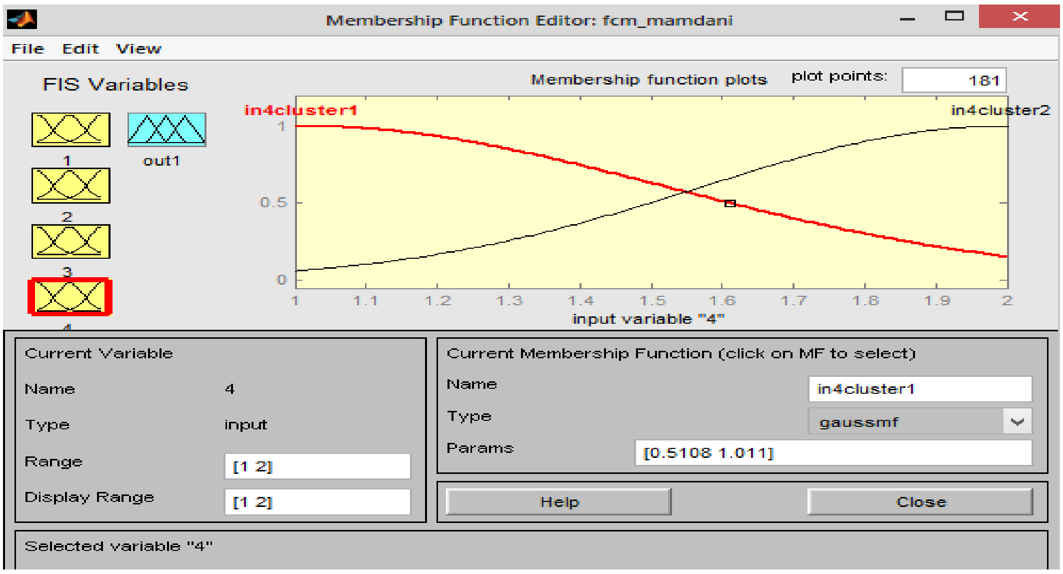

Fig.16. Credit Rating membership functions

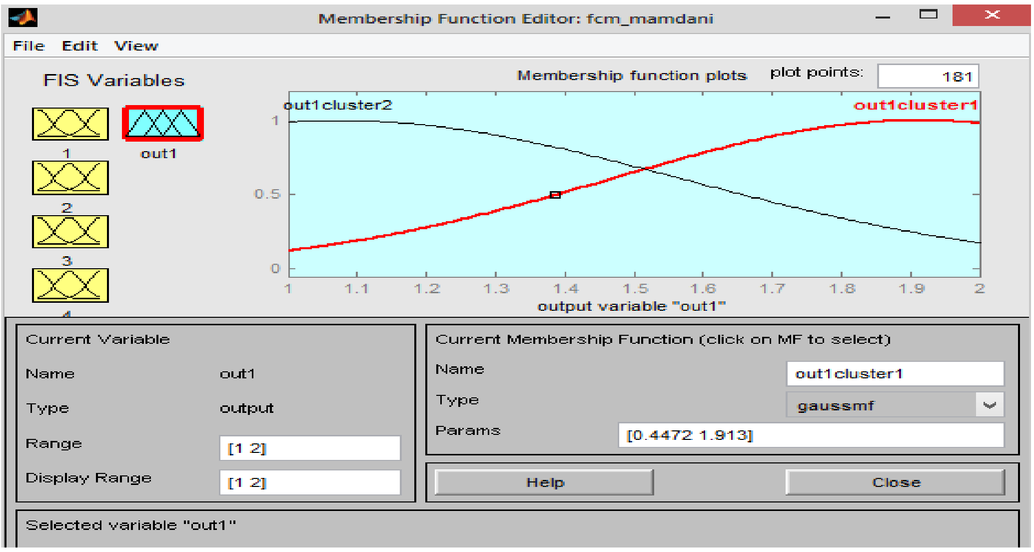

Fig.17. Output membership function for fcm based Mamdani

TABLE V. MAMDANI AND SUGENO FCM BASED FIS COMPARISON

	Mamdani	Sugeno
andMethod	Min	Prod
orMethod	Max	Probor
defuzzMethod	Centroid	Wtaver
impMethod	Min	Prod
aggMethod	Max	Sum
Accuracy (in %)	36.666667	output membership function type :linear Before training-56.66% After anfis training-100% output membership function type :constant Before training-56.66% After anfis training- 96.66%

The graphs generated for FIS with Fuzzy c-means partitioning after ANFIS Training is given in Fig 18- Fig 20.

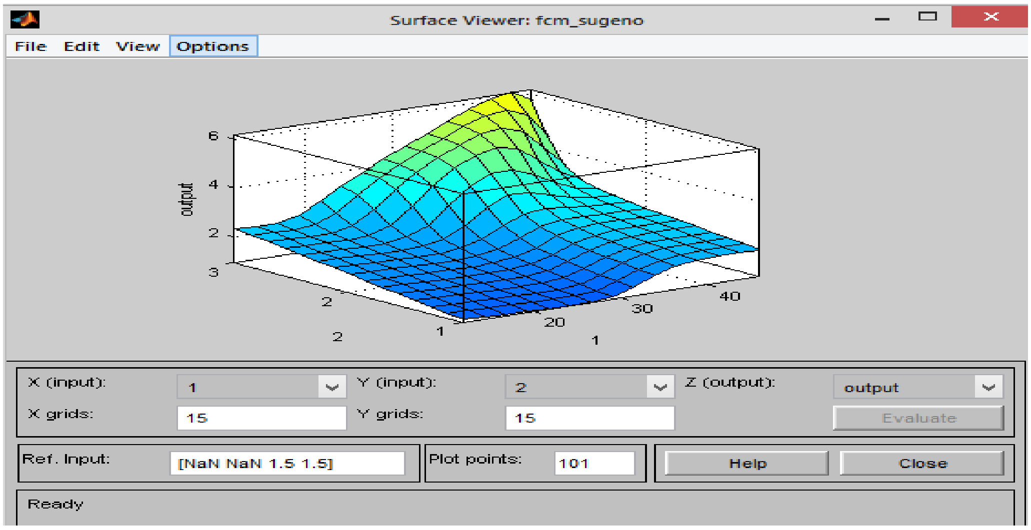

Fig.18. Surface view of fcm based Sugeno

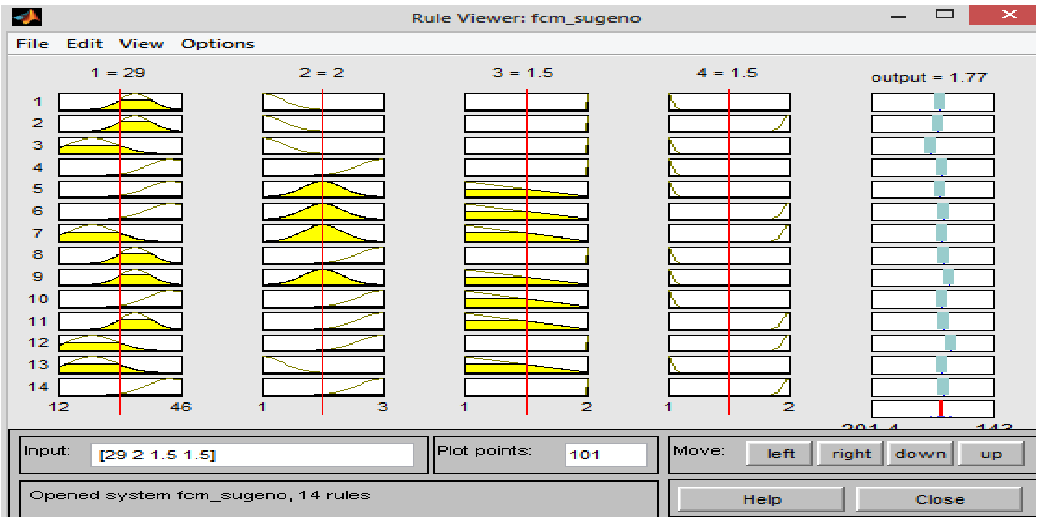

Fig.19. Rule view of fcm based Sugeno

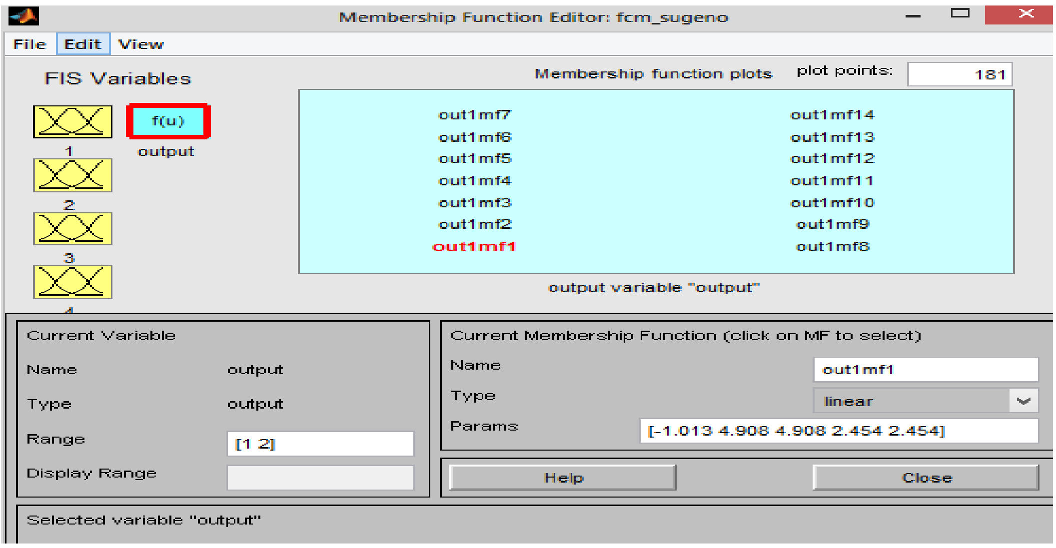

Fig.20. Output membership function for fcm based Sugeno

The third experiment is developing FIS using membership values generated by subtractive clustering. The FIS results obtained using subtractive clustering is given in TABLE VI.

In order to get a proper number of membership functions for an attribute which would be easier to map on the fuzzy rule list for the FIS defined earlier, the cluster radius for each of the input attribute has been chosen as:

- Age-0.25
- Income-0.3
- Student-0.3
- Credit Rating-0.3

For the Mamdani type FIS, the cluster radius for the output attribute is taken as 0.3

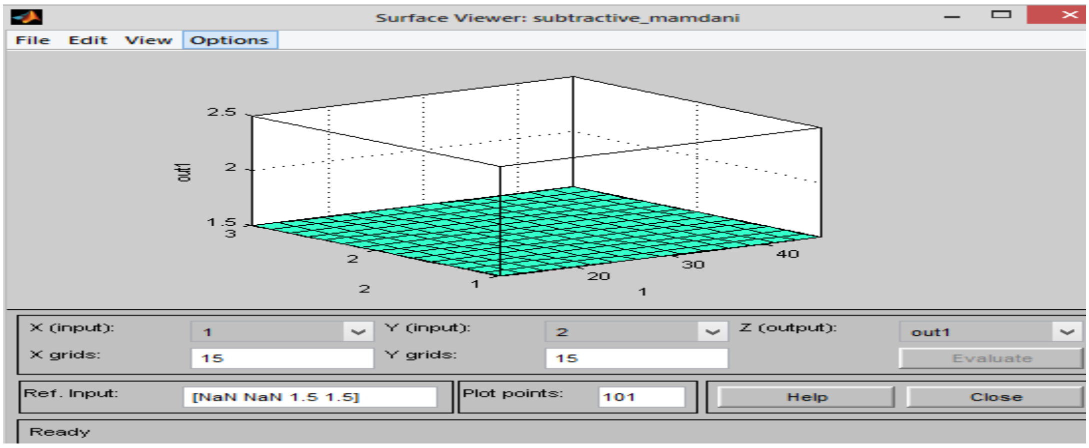

Fig.21. Surface view of subtractive based Mamdani

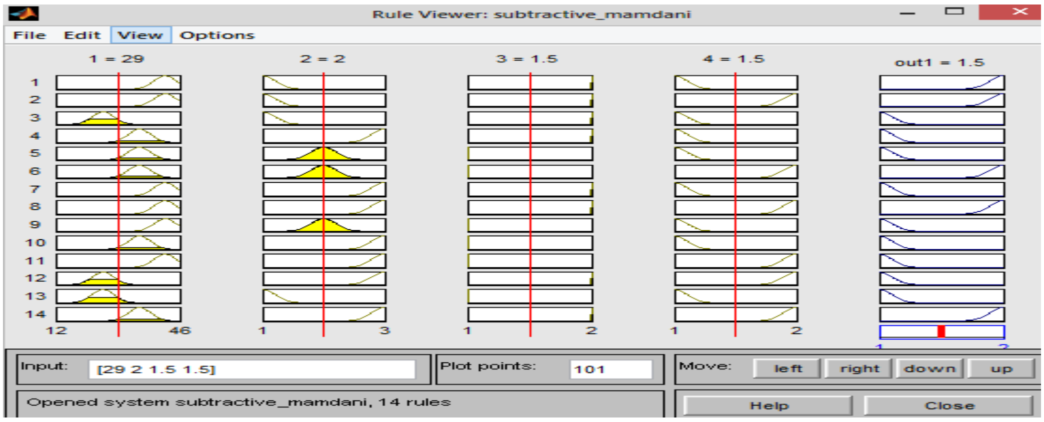

Fig.22. Rule view of subtractive based Mamdani

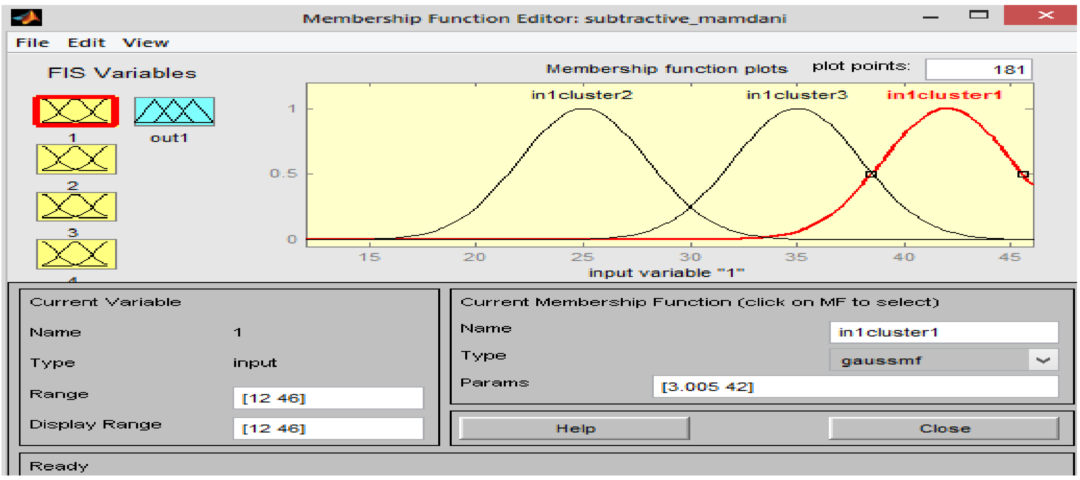

Fig.23. Age membership functions

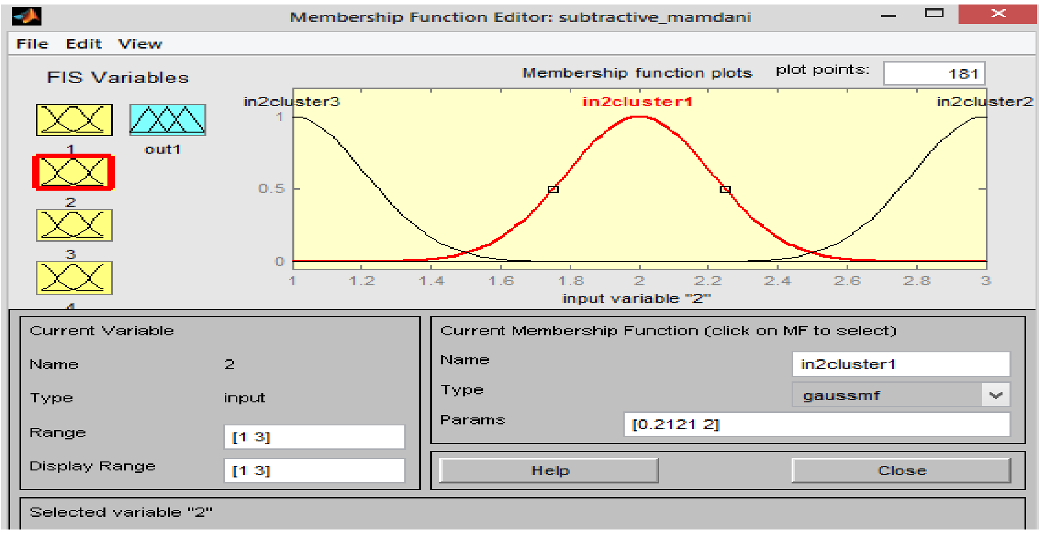

Fig.24. Income membership functions

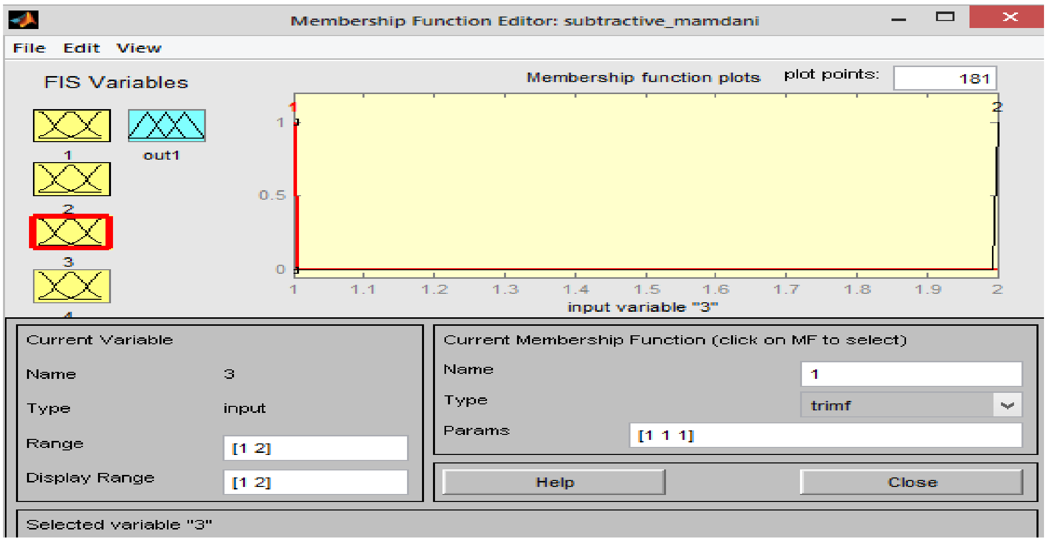

Fig.25. Student membership functions

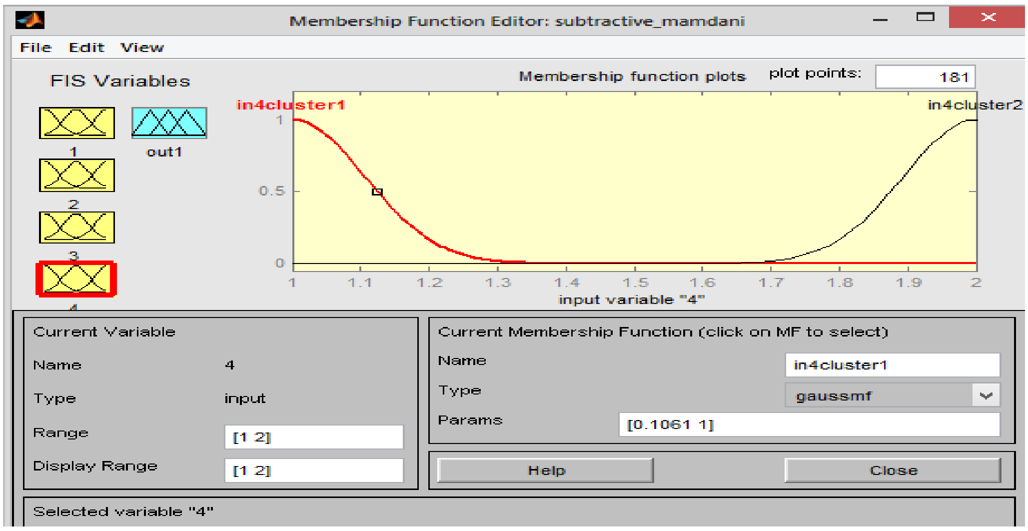

Fig.26. Credit Rating membership functions

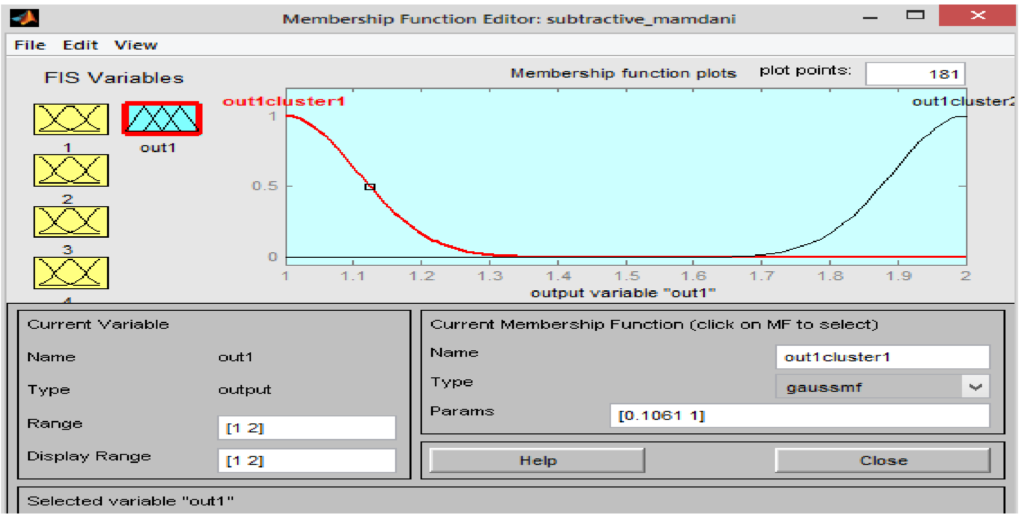

Fig.27. Output membership function for subtractive based Mamdani

TABLE VI. MAMDANI AND SUGENO SUBTRACTIVE BASED FIS COMPARISON

	Mamdani	Sugeno
andMethod	Min	Prod
orMethod	Max	Probor
defuzzMethod	Centroid	Wtaver
impMethod	Min	Prod
aggMethod	Max	Max
Accuracy (in %)	53.333333	output membership function type :linear Before training-56.66% After anfis training-100% output membership function type :constant Before training-56.66% After anfis training- 93.33%

The graphs generated for FIS with subtractive clustering after ANFIS Training is given in Fig 28-Fig 30.

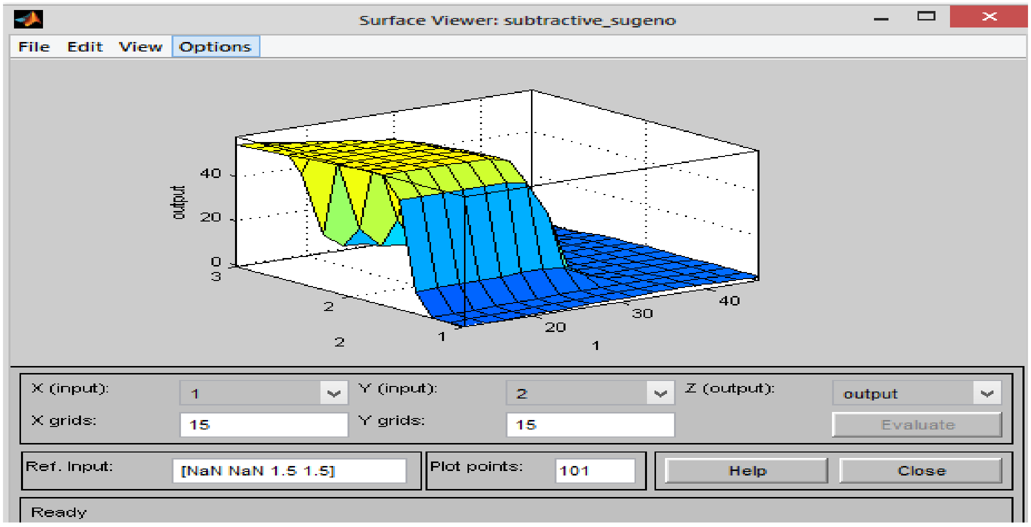

Fig.28. Surface view of subtractive based Sugeno

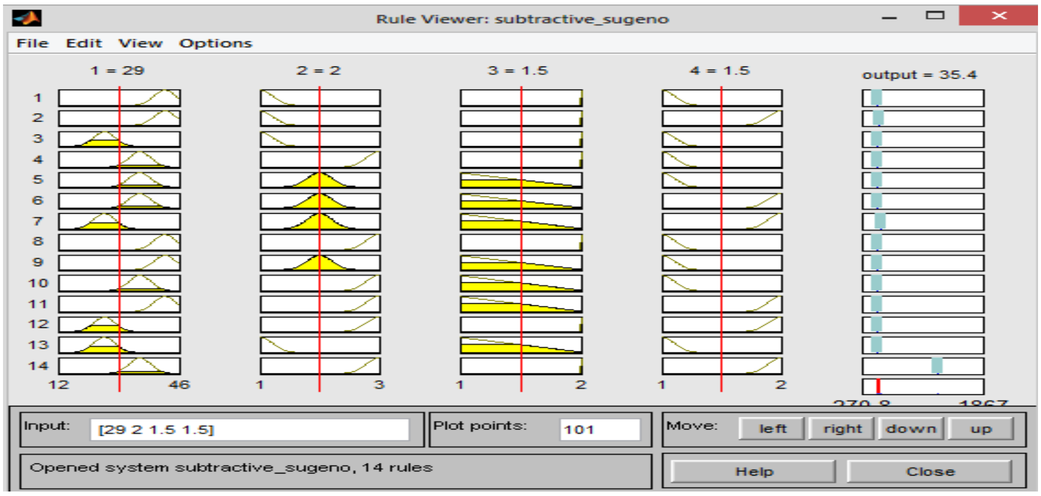

Fig.29. Rule view of subtractive based Sugeno

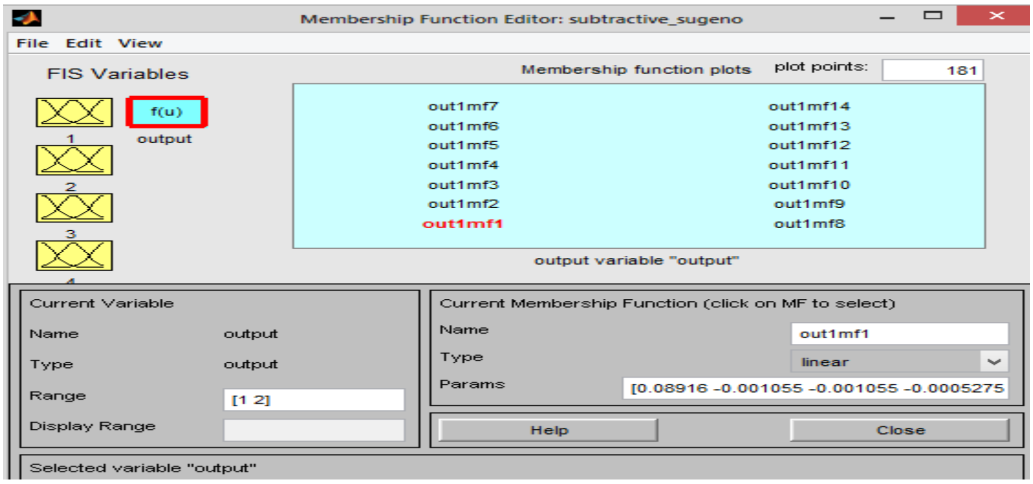

Fig.30. Output membership function for subtractive based Sugeno

Finally GUI is prepared for the end user where the customer details like age, income ,student , credit rating can be entered and used by the developed FIS to predict whether the customer would buy a particular product or not.

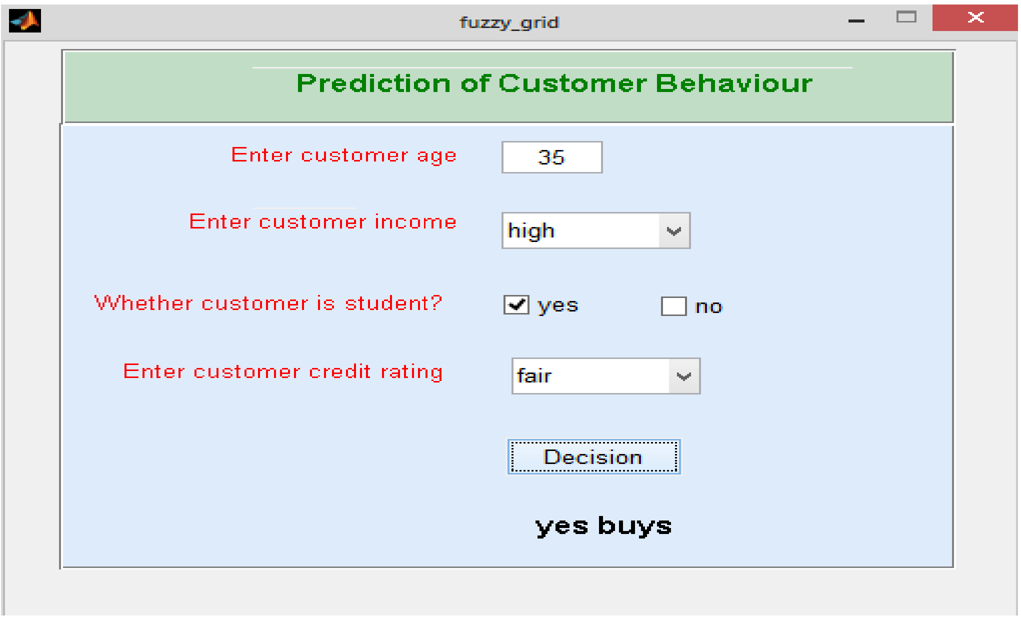

Fig.31. GUI for the end user

VI. CONCLUSION

The performance of Fuzzy Inference system depends on the FIS approach chosen like Mamdani, sugeno and also on choosing appropriate fuzzy partitioning technique. In this paper we have done several experiments with all combinations of FIS approaches and fuzzy partitioning techniques. For the Sugeno type systems, the experimental results for predicting customer buying behavior show that, all three fuzzy partitioning techniques namely grid partitioning, fuzzy c-means, and subtractive clustering play a significant role. ANFIS training has further improved the accuracy when tuned with output membership function type as linear. Among the Mamdani-type FIS, grid partitioning method gave better accuracy than subtractive and fuzzy c-means clustering techniques.

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