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Modeling Academic Performance Evaluation Using Hybrid Fuzzy Clustering Techniques

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ABSTRACT

The paper describes two novel models: hybrid SC-FCM (Subtractive Clustering-Fuzzy C-Means) and SC-ANFIS (Subtractive Clustering-Adaptive Neuro Fuzzy Inference System) models for determining students' academic ranks. Hybrid SC-FCM model use SC to form initial cluster and cluster centers, also referred to as groups, of students having almost similar academic ranks. In hybrid SC-FCM and SC-ANFIS models, a Fuzzy Inference System (FIS) inferred the students' academic ranks. For hybrid SC-FCM and SC-ANFIS models, we developed fuzzy rules from fuzzy-membership values of a student that we obtained by computing a function of the distance between his/her term-wise marks and clusters. The Hybrid SC-FCM and SC-ANFIS methods not only regulates the division of fuzzy inference system input and output space and determines the relative member function parameters, but also overcomes the impacts of initial values on academic performance evaluation. We have tested the performance of these models and discovered the hybrid SC-ANFIS model performed better against the statistical techniques and hybrid SC-FCM models.

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INTRODUCTION

Commonly, we use GPA (Grade Point Average) as an API, which is computed from student's aggregated numeric grade using some statistical measures. The aggregation does not reflect some data such as student's Continuous Performance Assessments (CPA) data. Also, the statistical measures, like average, may lead to a wrong conclusion. For example, consider a scenario where two student**'s** score**s** are 50, 60, 70, and 70, 60, 50 in three tests respectively. The average mark obtained by each is 60. Can we conclude, from the average, that intelligence level of both the students are same? Of course not! The data indicates that one student is improving while the other is deteriorating consistently-it may imply that one student is learning consistently from his experience. Despite these limitations (Oyelade, O.J., *et al*., 2010), the GPA is almost the only instrument that academic planners are using in (Sansgiry, S.S., *et al*., 2010).

We can make an API more realistic if we estimate it from homogenous student groups. The student homogeneity based on intelligence level (or other measures) would make academic performance indicators robust, fairer and comparable. Moreover, factors other than academic ones, creates/poses barrier to students attaining and maintaining their high performance. Therefore, grouping or clustering of students using cognitive as well as affective factors into homogenous groups may make an API even more realistic.

In their recent work reported in (Mankad, K., *et al*., 2011) have reported an evolving rule based model for identification of multiple intelligence. Their genetic-fuzzy hybrid model identifies human intelligence. Zukhri and Omar (2008) have reported successful application of Genetic Algorithm for solving difficult optimization problems in new students' allocation problem. Sreenivasarao *et al* (2012); Gupta and Dhawan (2012); Pavani, Gangadhar and Gulhare (2012); Chaudhari, Khot and Deshmukh (26); Stathacopoulou, Magoulas, Grigoriadou and Samarakou (2005); Upadhyay (2012), have developed models for improving academic performance evaluation of students based on data warehousing and data mining techniques that use soft-computing intensively. Their analysis indicates that the group homogeneity improves students' academic performance and enhances education quality.

An Artificial Neural Network (ANN) model reported in Ayodele *et al*. (2010); Mullier (2002) that along with computation also derives meaning from imprecise data, extracts patterns and detects trends. This ability has

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added new dimensions in comprehending the complex phenomena that is buried in students' data otherwise might have gone unnoticed using hard computing techniques.

In practice, whether phenomena discovery or performance indicator computation, their accuracy depends on the data quality that in turn depends on the accuracy of data collection process and representation techniques. In order to address the data related issues, in education domain, Biswas (1995), suggested use of fuzzy sets, Zadeh (1965) in students' answer-sheets evaluation. Wang and Chen (2007) have recommended the use of vague sets instead of fuzzy sets to represents the vague marks of each question where the evaluator can use vague values to indicate the degree of the evaluators' satisfaction for each question.

In fuzzy sets the membership evaluation (characteristics function definition) is a major issue. In order to apply the fuzzy set in education domain effectively, there have been a lot of efforts in defining the effective membership. In Bai and Chen (2008) have defined the fuzzy membership functions for fuzzy rules; Law (1996) has used fuzzy numbers, and for more information on this issue consult in: Chen and Lee (1999); Wang and Chen (2006); Neogi, Mondal and Mandal (2011); Stathacopoulou *et al*. (2005); Guh, *et al*. (2008); Gokmen *et al*. (2010); Daud, Aziz and Sakib (2011); Hameed (2011); Baylari and Montazer (2009); Posey and Hawkes (1996); Yadav and Singh (2011); Stathacopoulou *et al*. (2007); Bhatt and Bhatt (2011); Zhou and Ma (2000); Voskoglou (2012); Guh, Yang, Po and Lee (2009). The research works cited in the preceding paragraph indicates that the fuzzy logic, neural network and fuzzy neural network have already been employed in student modeling systems but almost nothing or very little has been mentioned about automatic generation of fuzzy membership function. This paper describes two methods for automatic generation of membership function for student academic performance evaluation by using Subtractive Clustering and Adaptive Neuro Fuzzy Inference System. For this purpose we have used Subtractive Clustering technique for automatic generation of membership function and evaluation of student academic performance evaluation. In order to obtain the homogeneous clusters (or classes) of students, we have studied the performance of Subtractive clustering technique for student population clustering. For this purpose, we have developed students' academic performance evaluation models.

The methods presented in Biswas (1995); Law (1996); Rasmani and Shen (2006); Chen and Lee (1999) will show that fuzzy approaches are potentially useful for student performance evaluation. It can be observed that these methods also have several common shortenings. Firstly, these methods produce a new total score in terms of crisp values before a new grade can be awarded. This can be a substantial setback as the difference of the new total score with the original score may be very large and thus create confusion for the user, especially the students. Secondly, all the methods are wholly based on expert opinions without offering the possibility of making direct use of information gathered from data. Yadav and Singh (2012) have recommended the use of Fuzzy C-Means for student's academic performance. Consisting of a number of input-output linear regression models in each subspace, a T-S model can be built by means of fuzzy rule based on descriptions of input-output measurements of the academic performance evaluation. We conclude that the FCM technique is an effective way to establish fuzzy inference rules. However, due to multiple iterations employed and a large number of Eigen vectors computed, the FCM technique suffers heavy computational burdens, becoming very time-consuming. Additionally, it is strongly sensitive to the initialization treatment, which usually requires a priori knowledge of the cluster numbers to form the initial cluster centers. To our disappointment, in appropriate initial values readily lead to an undesired local minimum or suboptimal solution. Newly developed hybrid SC-FCM and SC-ANFIS models approaches should look into ways of avoiding, or at least reducing such disadvantages. The proposed SC-ANFIS model has learning capability due to neural network techniques. So, the SC-ANFIS model is more suitable for academic performance.

The paper, besides introduction, has five sections. The next Section describes Fuzzy Logic for academic performance evaluation. Section three describes the architecture of proposed Hybrid SC-FCM and SC-ANFIS model. Section four describes the experimental results of proposed hybrid SC-FCM and SC-ANFIS models. We conclude and future works of paper with section five.

2. Fuzzy Logic for Academic Performance Evaluation:

2.1. Fuzzy Logic:

Fuzzy logic is branch of logic specially designed for representing knowledge and human reasoning in such a way that it is amenable to processing by a computer. Thus, it is applicable to artificial intelligence, control engineering, and expert systems. The more traditional propositional and predicate logic do not allow for degrees of imprecision, indicated by words of phrases such as poor, average and good. Instead of truth values such as true or false, it is possible to introduce a multi valued logic consisting of Unsatisfactory, Satisfactory, Average, Good, and Excellent. Fuzzy systems implement fuzzy logic, which uses sets and predicates of this kind. As the classic logic is the basic of ordinary expert logic, fuzzy logic is also the basic of fuzzy expert system. Fuzzy expert systems, in addition to dealing with uncertainty, are able to model common sense reasoning which is very difficult for general systems. One of the basic limitations of classic logic is that it is restricted to two values, true or false and its advantage is that it is easy to model the two-value logic systems and also we can have a precise deduction. The major shortcoming of this logic is that, the number of the two-value subjects in the real world is few. The real world is an analogical world not a numerical one. We can consider fuzzy logic as an extension of a multi-value logic, but the goals and application of fuzzy logic is different from multi-value logic since fuzzy logic is a relative reasoning logic not a precise multi-value logic. In general, approximation or fuzzy reasoning is the deduction of a possible and imprecise conclusion out of a possible and imprecise initial set.

2.2. Fuzzy Set:

A fuzzy set A in a universe of discourse X is defined as the following set pairs

$$A = \{\mu_A(x) : x \epsilon X\} \tag{1}$$

Where, $A = \{\mu_A(x) : x \epsilon X\}$ is a mapping called the membership function of fuzzy set *A* and $\mu_A(x)$ is called the degree of belongingness or membership value or degree of membership of $x \epsilon X$ in the fuzzy set *A*. We write (1) in the following form:

$$A = \left\{\frac{\mu_A(x)}{x} : x \epsilon X\right\} \tag{2}$$

For brevity; however, we often equate fuzzy sets with their membership functions, i.e., we will often say fuzzy sets.

Example: Suppose *X = {6, 2, 0, 4}*. A fuzzy set of *X* may be given by *A = {0.2/6, ½, 0.8/0, 0.1/4}*.

2.3. Membership Functions:

In this paper we have used the triangular and trapezoidal membership function for converting the crisp set into fuzzy set. The triangular and trapezoidal membership functions are specified by three parameters *(a, b, c)* and four parameters *(a, b, c, d)* as follows (2011):

$$triangular(x, a, b, c) = \max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{3}$$

$$trap(x, a, b, c, d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{4}$$

A Gaussian membership function is specified by two parameters $(m,\ \sigma)$ as follows:

$$gaussian(x: m, \sigma) = exp\left(-\frac{(x-m)^2}{\sigma^2}\right) \tag{5}$$

Where m and σ denote the center and width of the function respectively. We can control the shape of the function by adjusting the parameter.

Due to their simple formula and computational efficiency, the Gaussian membership function has proven popular with fuzzy logic and has been used extensively in academic performance evaluation (Yadav, R.S. and V.P. Singh, 2011). In this paper, we have used this membership function for antecedent and consequent part in IF-THEN rule to predict the academic performance evaluation.

3. Architecture of Hybrid SC-FCM and SC-ANFIS Models:

3.1. FCM Based T-S Model:

Tskagi-Sugeno (T-S) fuzzy model has been one of the most popular fuzzy types model in problem solving domain. Consider a non-linear multiple input single output (MISO) system with *p* inputs: $u \in U \subset R^p$, and *1* output, $y \in U \subset R$,. The corresponding T-S fuzzy models is expressed as *n* rules, in which, the i^{th} for k^{th} time instant data is described as follows (1993):

$R^i : if\ x_1\ is\ A_1^i, x_2\ is\ A_2^i, \dots \dots, x_m\ is\ A_m^i$

$$\begin{aligned} then\ y^i(k) &= p_0^i + p_1^i x_1 + p_2^i x_2 + \cdots + p_m^i x_m \\ &= p_0^i + \textstyle\sum_{j=1}^m p_j^i x_j,\ i = 1,2,\dots,n \end{aligned} \tag{6}$$

where A_j^i is the fuzzy set of the j^{th} input variable of the antecedent of the i^{th} fuzzy rule; $x(k) = [x_1, x_2, \dots., x_m]$ is the vector of the input variables; y^i is the output variable of i^{th} rule; p_j^i are the consequent parameters.

The final output of T-S model can be expressed by a weight mean defuzzification at *kth* time as follows:

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$$y = \frac{\sum_{i=1}^{n} \mu^i y^i}{\sum_{i=1}^{n} \mu^i} \tag{7}$$

Where *n* corresponds to the number of fuzzy rules, y^i is the output variable of *ith* rule; μ^i represents the firing strength of *ith* rule, which is defined as:

$$\mu^i(x) = \prod_{j=1}^{m} A_j^i(x_j) \tag{8}$$

Where Π is the fuzzy operator, usually performing minimizing or product operation; $A_j^i(x_i)$ is the grade of membership function

Note $\beta_i \triangleq \frac{\mu^i}{\sum_{i=1}^{n} \mu^i}$ (9)

The current estimated output may be expressed generally as follows:

$$y = \frac{\sum_{i=1}^{n} \mu^i y^i}{\sum_{i=1}^{n} \mu^i} \tag{10}$$
$$= \sum_{i=1}^{n} \beta_i y^i = \sum_{i=1}^{n} \beta_i\left(p_0^i + p_1^i x_1 + \cdots + p_m^i x_m\right), i = 1, 2, \ldots, n$$

Regarding T-S models, both the clusters (fuzzy regions) and the linear sub-models' parameters valid are requested. By premise structure identification, we mean to determine the specific input variables and partition the input space properly. The clusters can be identified using clustering algorithms such as fuzzy C-Means.

The objective function of the FCM is defined by:

$$f_b(U, Z) = \sum_{i=1}^{c} \sum_{k-1}^{N} (\mu_{ik})^m \|x_k - z_i\|^2 \tag{11}$$

Where x_k signifies the point in data space, $k = 1,2, \ldots, N$; N signifies the number of data points;z_i stands for the final cluster center, $i = 1,2, \ldots, c$; c corresponds to the number of fuzzy rules; $\mu_{ik} \epsilon [0, 1]$ is the fuzzy membership degree of the k^{th} data pair pertaining to the i^{th} fuzzy subset. It is assumed that μ_{ik} is constrained with following equation:

$$\sum_{i=1}^{c} \mu_{ik} = 1,2, \ldots., N \tag{12}$$

The C-Means algorithm for clustering in *n* dimensions produces C-Means vectors that present c classes of data. The problem of finding the fuzzy clusters in the data set is now solved as a constrained optimization problem using FCM algorithm, considering the minimization of the function in equation (11) over the domain data set and taking into account the constrained in equation (7). The results of FCM imply the clustering centers together with the corresponding membership degrees. The main steps for identifying the T-S fuzzy model based on FCM are given as follows:

Step1: Given c, m and the initial clustering centers for all $k = 1,2, .. N$ and $i = 1,2, \ldots. c$. Set an initial fuzzy c-partition $U = [\mu_{ik}]$ to indicate the membership value for the i^{th} cluster representatives.

Step 2: Calculate the following equation:

$$z_i = \frac{\sum_{k=1}^{N} z_k (\mu_{ik})^m}{\sum_{k=1}^{N} (\mu_{ik})^m}, \ i = 1,2, \ldots. c \tag{13}$$

Step 3: Update U to adjust:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{x_k - z_i}{x_k - z_j}\right)^{\frac{2}{m-1}}\right]^{-1}, i = 1,2, \ldots., c;$$

$k = 1,2, \ldots N$ (14)

Step 4: Check for termination. If

$$\|U_k - U_{k-1}\| < \varepsilon \tag{15}$$

Stop; otherwise, let $k = k+1$ and return to step 2.

Step 5: Identify the consequent parameters using orthogonal least-squares (OLS) method. Rewrite equation (10) in a vector form:

$$y = \phi\theta \tag{16}$$

Where, $\phi = [\beta_1, \ldots, \beta_n, \beta_1 x_1, \ldots., \beta_n x_m]$,

$\theta = [p_0^1, \dots, p_m^1, p_0^2, \dots, p_m^2, \dots, p_0^n, \dots, p_m^n]^T$, signifies the consequent parameters. In regard to the least squares solutions:

$$\theta = (\phi^T \phi)^{-1} \phi^T y, \tag{17}$$

We convert $[\phi^T \phi]$ into an orthogonal matrix$[W^T W]$. By implementing iteration and conversion algorithms, the $[m+1]*n$ coupled equations become mutually independent, thereby calculating the consequent parameters θ.

3.2. Subtractive Clustering Technique:

Subtractive Clustering (SC) is an effective method that searches for the number of clusters and cluster centers, which starts off with generating a number of clusters in the dimensional input space. The aim of the clustering approach is to group data by using a similarity measurement which is to assume each data point is a potential clustering center and calculates a measure of the likelihood that each data point would define the clustering center based on the density of surrounding data points. Each point of the input vector $[x_1, x_2, \dots, x_N]$ is considered as a potential clustering center. The density measurement at a data point x_i is calculated by:

$$D_i = \sum_{j=1}^{N} exp\left(-\frac{\|x_i - x_j\|^2}{(r_a/2)^2}\right) \tag{18}$$

Where N is the total number of data points; $[x_1, x_2, \dots, x_N]$ are data points;$r_a \epsilon\ [0, \infty]$ is the neighborhood range of the cluster implying the radius of hypercube cluster in data space. Thus, the potential associated with each cluster depends on its distance to all points, leading to cluster with high potential where neighborhood is dense. The density value of ith data pint will be larger one if it has many neighboring data points and the distance between the data points and its location is small. The first clustering center is defined as x_{c1} which has the largest density value D_{c1}. For the second and other cluster centers, the effect of the first cluster centering is updated in determination of the new density values, as follows:

$$D_i = D_i - D_{c1} \sum_{j=1}^{N} exp\left(-\frac{\|x_i - x_{c1}\|^2}{(r_b/2)^2}\right) \tag{19}$$

where $r_b \epsilon [0, \infty]$ has measurable reduction in density measurement. Typically, $r_b = 1.5 r_a$. According to equation (18), the data points which are near the first center x_{c1} will have reduced the density measurement strongly, and the probability for those points to be chosen as the next cluster is lower. This procedure selecting centers and reducing their potential is carried out iteratively until the stop criterion is satisfied. Additionally two threshold levels are defined. If the one is greater than a higher threshold, then the *i*th data is selected for a clustering center. If the one is below the lower threshold, the point is rejected.

3.3. Proposed Hybrid SC-FCM Algorithms:

Step1: According to the specific system, the number of data points, the radius of neighborhood and the error should be given.

Step 2: Calculate the density of every data point, and the highest density of the point is chosen as x_{c1}.

Step 3: According to equation (14), the density of all data points are updated. The data point x_{c2} which corresponding to the larger density value is chosen as the second cluster center. The selection is carried out iteratively, until the stopping criteria achieved. The results of the clustering are clustering number and cluster centers, all of which are adaptive formulated according to the effect of the cluster centers in each dimension.

Step 4: The results of aforementioned including the clustering number and cluster centers are chosen as the FCM initial values. The initial fuzzy partition matrix *U(0)* is also set contemporaneously as follows:

$$\mu_{ik}(0) = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ik}}{D_{jk}}\right)^{\frac{2}{m-1}}}, i = 1,2, \dots c; k = 1,2, \dots N \tag{20}$$

Where D_{jk}, which is calculated firstly, signifies the distance between *k*th data point and jth initial cluster center.

Step 5: Calculate the center values according to equation (13).

Step 6: Update the fuzzy partition matrix *U(k)* according to equation (14).

Step 7: If equation (10) is satisfied, then stop;

Otherwise, *k = k+1*, return to step (5).

Step 8: The consequent parameters are identified using orthogonal least-square method (OLS), eventually resulting in the T-S methods.

3.4. Proposed Hybrid SC-ANFIS Algorithms:

The most important reason for combining fuzzy systems with neural networks is to use the learning capability of neural network. Neuro-fuzzy system is based on linguistic rules, so we can easily integrate prior knowledge into the system, and this can substantially shorten the learning process. One of the popular integrated systems is an ANFIS, which is an integration of a fuzzy inference system with a back-propagation algorithm. There are two types of fuzzy inference systems that can be implemented: Mamdani-type and Sugeno-type. Because the Sugeno system is more compact and computationally more efficient than a Mamdani system, it lends itself to the use of adaptive techniques for constructing the fuzzy models. Fig. 1 shows the Architecture of SC-ANFIS model.

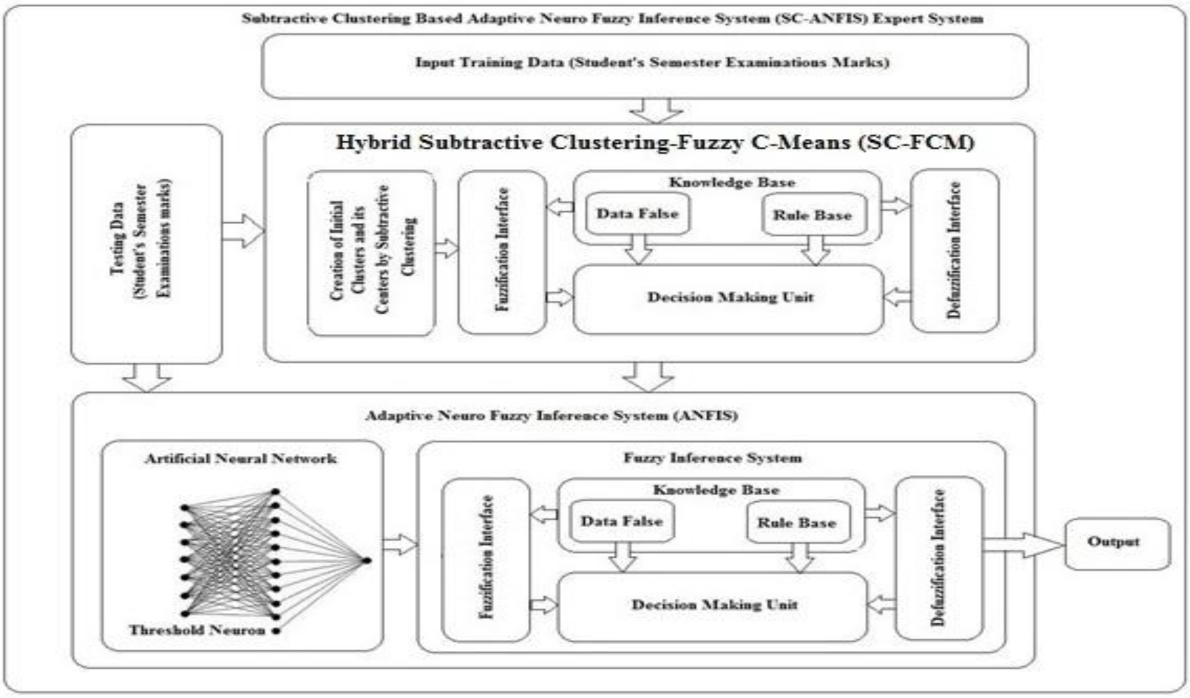

Fig. 1: Architecture of Hybrid SC-ANFIS Model

Architecture of ANFIS: Adaptive-network-based fuzzy inference system (ANFIS) was proposed by Jang (1993), which is a fuzzy inference system, implemented in the framework of adaptive networks. The architecture of a typical ANFIS with two inputs X_1 and X_2, two rules and one output *f*, for the first order Sugeno fuzzy model, where each input is assumed to have two associated membership functions (MFs). For a first-order Sugeno fuzzy model a typical rule set with two fuzzy if–then rules can be expressed by Jang (1993):

Rule (1): If X_1 is $A_1$and X_2 is B_1 then $f_1 = m_1X_1 + n_1X_2 + q_1$

Rule (2): If X_1 is A_2 and X_2 is B_2 then $f_2 = m_2X_1 + n_2X_2 + q_2$

where m_1, n_1, q_1 and m_2, n_2, q_2 are the parameters of the output function. The architecture of the proposed model (ANFIS) contains five layers where the node functions in the same layer are from the same family. Inputs, outputs and implemented mathematical models of the nodes of each layer are explained below.

Layer 1: The node function of every node *i* in this layer take the form:

$$O_i^1 = \mu_{A_i}(X) \tag{21}$$

where X is the input to node *I*, $\mu_{A_i}(X)$is the membership function (which can be triangular, trapezoidal, Gaussian functions or other shapes) of the linguistic label A_i associated with this node and O_i is the degree of match to which the input *X* satisfies the quantifier A_i. In the current study, the Gaussian shaped MFs defined below are utilized.

$$\mu_{A_i}(X) = exp\left\{-\frac{1}{2}\frac{(X-c_i)^2}{\sigma_i^2}\right\} \tag{22}$$

where, $\{c_i, \sigma_i\}$ the parameters of the MFs governing the Gaussian are functions. The parameters in this layer are usually referred to as premise parameters.

Layer 2: Every node in this layer multiplies the incoming signals from layer 1 and sends the product out as follows:

$$w_i = \mu_{A_i}(X_1) \times \mu_{B_i}(X_2),\ i = 1,2 \tag{23}$$

where the output of this layer *(w_i)* represents the firing strength of a rule.

Layer 3: Every node i in this layer is a node labeled N, determine the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths as:

$$w = \frac{w_i}{w_1+w_2} \tag{24}$$

where, the output of this layer represents the normalized firing strength.

Layer 4: Every node i in this layer is an adaptive node with a node function of the form:

$$o_i^4 = wf_i = w(m_iX_1 + n_iX_2 + q_i), i = 1, 2 \tag{25}$$

where w is the output to layer 3, and *{m_i, n_i, q_i}* is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: There is only a single node in this layer that computes the overall output as the weighted average of all incoming signals from layer 4 as:

$$O_i^5 = \sum_i wf_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1, \tag{26}$$

4. Experimental Results:

4.1. Normalized the Data Sets of Mark:

In this study, 50 data sets (Table 1) was selected from the total 100 data sets for the purpose of training in hybrid SC-FCM and SC-ANFIS and 50 data sets (Table 2) was selected from the total 100 data sets for the purpose of testing in hybrid SC-FCM and SC-ANFIS. The marks obtained by each student appeared in Sem-1, Sem-2 and Sem-3 examinations; have to be converted to the normalized values. Normalized value is referred to a range of [0, 1]. It can be obtained by dividing the mark for each semester examination with the total mark. The normalized value will be the input value of this evaluation. Table 3 shows the marks and their associated original grade and their level of achievement namely Cluster-1, Cluster-2, Cluster-3, Cluster-4 and Cluster-5. Table 4 shows 15 new students' marks for testing purpose of the proposed models.

Table 1: Student Training Data Set

S.No.	Sem-1	Sem-2	Sem-3	Final Marks	Observed output	Grade
1.	0.05	0.37	0.18	0.2000	0.25	E
2.	0.10	0.23	10.6	0.1633	0.25	E
3.	0.15	0.13	0.06	0.1133	0.25	E
.	.	.	.	.	.	.
.	.	.	.	.	.	.
49.	0.90	0.93	0.94	0.9233	1.00	A
50.	1.00	0.83	0.98	0.9367	1.00	A

Table 2: Student Testing Data Set

S.No.	Sem-1	Sem-2	Sem-3	Final Marks	Observed output	Grade
1.	0.05	0.34	0.16	0.1833	0.25	E
2.	0.02	0.45	0.46	0.3100	0.45	D
3.	0.23	0.45	0.19	0.2900	0.45	D
.	.	.	.	.	.	.
.	.	.	.	.	.	.
49.	0.37	0.59	0.57	0.5100	0.55	C
50.	0.06	0.45	0.03	0.1800	0.25	E

Table 3: Marks and Their associated original grade and level of achievement

S. No.	Marks	Grade	Level of Achievement
1.	0.00-0.25	E	Cluster-1
2.	0.26-0.45	D	Cluster-2
3.	0.46-0.55	C	Cluster-3
4.	0.56-0.75	B	Cluster-4
5.	0.76-1.00	A	Cluster-5

Table 4: Data Set of Students' Score in Sem.-1, Sem.-2 and Sem.-3

S.No.	Sem-1	Sem-2	Sem-3	Statistical method	Grade
1.	0.10	0.2333	0.2000	0.1778	E
2.	0.50	0.1667	0.1200	0.1122	E
3.	0.15	0.1333	0.1800	0.1544	E
4.	0.45	0.2667	0.4000	0.3722	D

5.	0.35	0.3333	0.3000	0.3278	D
6.	0.35	0.5000	0.3800	0.4100	D
7.	0.45	0.4333	0.5400	0.4744	C
8.	0.50	0.4000	0.5000	0.4667	C
9.	0.45	0.5000	0.5800	0.5100	C
10.	0.50	0.7000	0.6200	0.6067	B
11.	0.65	0.7000	0.7400	0.6967	B
12.	0.85	0.6000	0.7600	0.7367	B
13.	0.95	0.7667	0.8600	0.8589	A
14.	0.85	0.8333	0.9600	0.8811	A
15.	0.90	0.9000	0.9800	0.9267	A

4.2. Experimental Result of Hybrid SC-FCM:

The proposed hybrid SC-FCM model was trained on 50 training data sets and tested on 50 testing data sets (Table 1 and Table 2). Let us consider, 15 new students' marks obtained by Semester-1, Semester-2 and Semester-3 examination which are shown in Table 4. The proposed model hybrid SC-FCM model was tested of this 15 new data set marks. It consists of 15 instances, involving three conditional attributes: Sem-1, Sem-2 and Sem-3, and five possible classification outcomes: Cluster-1, cluster-2, Cluster-3, Cluster-4 and Cluster-5. The primary assumption is that the partitions chosen by Subtractive clustering are those best possible to represent the training data. Clearly, Subtractive clustering has given better fuzzification, if available will help improve the experimental results reported below. Note that the given definition of the fuzzy sets is obtained solely on the basis of the normal distribution of the crisp marks given. This ensures their comparison with other approaches. Fig. 2 shows the hybrid SC-FCM model for academic performance evaluation. This hybrid SC-FCM model has three inputs namely Sem-1, Sem-2 and Sem-3, one output namely Academic Performance and it has five rules. The membership functions of hybrid SC-FCM model are shown in Fig. 3, 4 and 5.

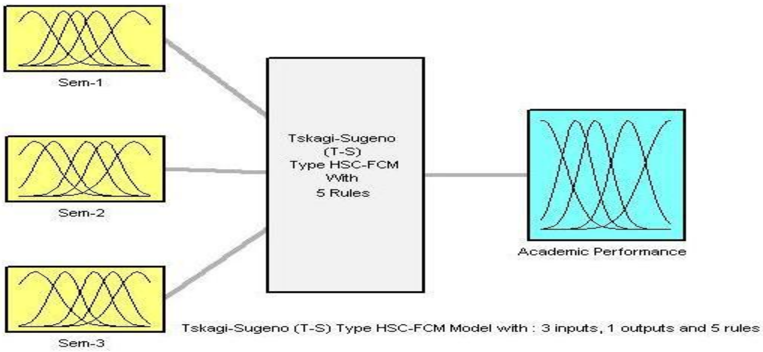

Fig. 2: Hybrid SC-FCM Model

We applied hybrid SC-FCM model to deal with 15 new data points which are generated randomly within [0, 1] by in two-dimensional space. The radius of hybrid SC-FCM model was specified as 0.5; the weighting exponent m = 2; a termination criterion minimum improvement = 0.0000001. The hybrid SC-FCM model automatically generates appropriate clustering numbers according to the impacts of each dimension of data on cluster centers, rather than demands the number of clusters ahead. The clustering number of hybrid SC-FCM model was initiated to 5, which means 5 rules are available. Fig. 6 shows the clustering of hybrid SC-FCM model.

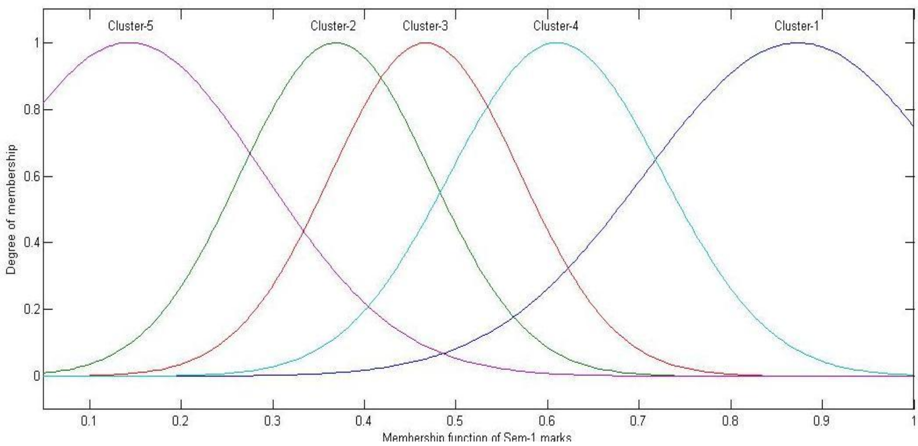

Fig. 3: Membership function of Sem-1 marks

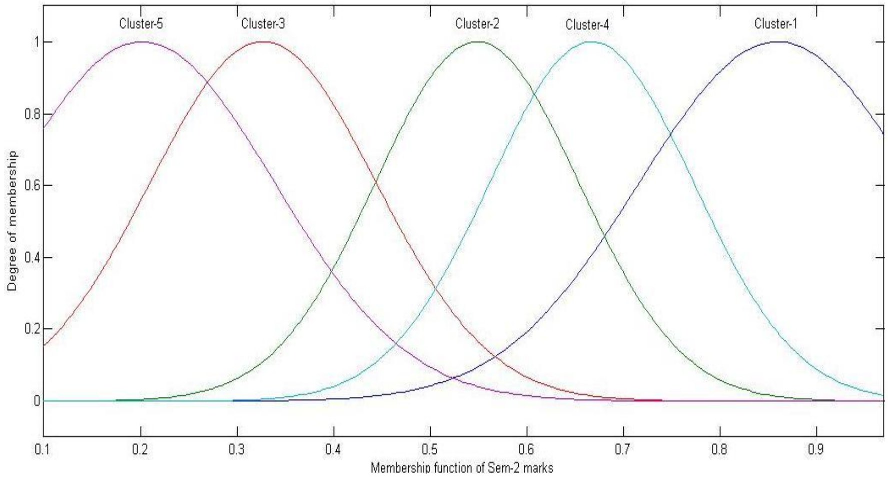

Fig. 4: Membership function of Sem-2 marks

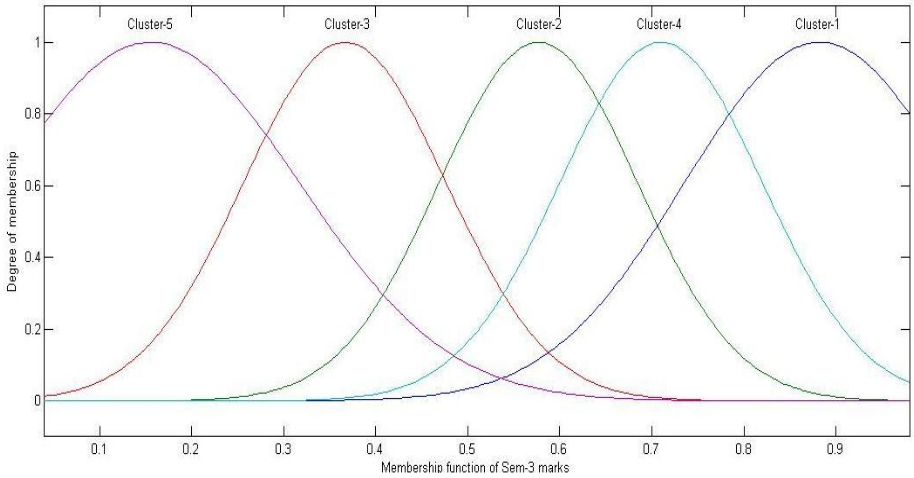

Fig. 5: Membership function of Sem-3 marks

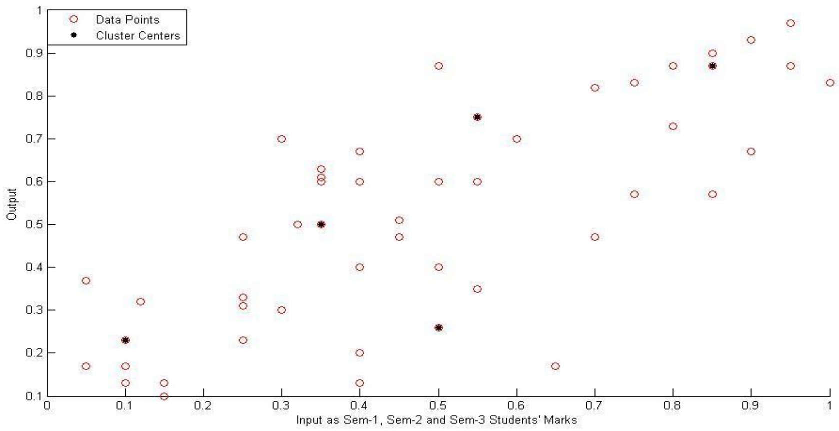

Fig. 6: Clustering results of SC-FCM

The classification of the grades in this experiment is based on maximum value of mark that refers to the level of performance given by experts as shown in Table 3. To facilitate a fair comparison, the same dataset consisting of 15 instances and having the same features as the training dataset is used for the both methods. Table 5 shows the cluster centers of hybrid SC-FCM model

Table 5: The cluster centers of Cluster-1, Cluster-2, Cluster3, Cluster-3 and Cluster5 for SC-FCM model

Cluster Number	Sem-1	Sem-2	Sem-3	Output
Cluster-1	0.100	0.230	0.159	0.250
Cluster-2	0.349	0.500	0.579	0.550
Cluster-3	0.500	0.260	0.380	0.450
Cluster-4	0.549	0.750	0.760	0.750
Cluster-5	0.849	0.870	0.880	1.000

The following five rules generated by hybrid SC-FCM model are given below:

R1: If Sem-1 is in cluster-1 and Sem-2 is in Cluster-1 and Sem-3 is cluster-1 then academic performance is in cluster-1.

R2: If Sem-1 is in cluster-2 and Sem-2 is in Cluster-2 and Sem-3 is cluster-2 then academic performance is in cluster-2.

R3: If Sem-1 is in cluster-3 and Sem-2 is in Cluster-3 and Sem-3 is cluster-3 then academic performance is in cluster-3.

R4: If Sem-1 is in cluster-4 and Sem-2 is in Cluster-4 and Sem-3 is cluster-4 then academic performance is in cluster-4.

R5: If Sem-1 is in cluster-5 and Sem-2 is in Cluster-5 and Sem-3 is cluster-5 then academic performance is in cluster-5.

The first rule can be explained simply as follows: If the inputs to the hybrid SC-FCM model, Sem-1, Sem-2 and Sem-3, strongly belong to their respective Cluster-1 membership functions then the output of Student Performance strongly belong to its Cluster-1 membership function. The significance of the rule is that it succinctly maps Cluster-1 in the input space to Cluster-1 in the output space. Similarly the other four rules map Cluster-2, Cluster-3, Cluster-4 and Cluster-5 in the input space to Cluster-2, Cluster-3, Cluster-4 and Cluster-5 in the output space. If a data point closer to the first cluster, or in other words having strong membership to the first cluster, is fed as input to hybrid SC-FCM model then rule 1 will fire with more firing strength than the other four rules. Similarly, an input with strong membership to the second cluster will fire the second rule will with more firing strength than the other four rules and so on. The outputs of the rules (firing strengths) are then used to generate the output of the hybrid SC-SCM model through the output membership functions. The one output of the hybrid SC-SCM model, student performance, has five linear membership functions representing the five cluster identified by Subtractive clustering. The coefficients of the linear membership functions though are not taken directly from the cluster centers. Instead, they are estimated from the dataset using least squares estimation technique in T-S model.

Table 6: Students' Academic Performance Results Using Subtractive Clustering Techniques

S.N	Sem-1	Sem-2	Sem-3	Statistical Method	Grade	Output of Hybrid SC-FCM Model	Grade
1.	0.10	0.2333	0.2000	0.1778	E	0.354	D*
2.	0.05	0.1667	0.1200	0.1122	E	0.469	C*
3.	0.15	0.1333	0.1800	0.1544	E	0.357	D*
4.	0.45	0.2667	0.4000	0.3722	D	0.457	C*
5.	0.35	0.3333	0.3000	0.3278	D	0.449	D
6.	0.35	0.5000	0.3800	0.4100	D	0.500	C*
7.	0.45	0.4333	0.5400	0.4744	C	0.556	B*
8.	0.50	0.4000	0.5000	0.4667	C	0.517	C
9.	0.45	0.5000	0.5800	0.5100	C	0.609	B*
10.	0.50	0.7000	0.6200	0.6067	B	0.686	B
11.	0.65	0.7000	0.7400	0.6967	B	0.765	A*
12.	0.85	0.6000	0.7600	0.7367	B	0.783	A*
13.	0.95	0.7667	0.8600	0.8589	A	0.876	A
14.	0.85	0.8333	0.9600	0.8811	A	0.865	A
15.	0.90	0.9000	0.9800	0.9267	A	0.870	A

*improve grade

Table 6 shows that if a 1st has got 0.10 marks in sem-1, 0.2333 marks in sem-2 and 0.2000 marks in sem-3 than the performance of that student is 0.1778 in Statistical method model and 0.354 in hybrid SC-FCM model. Similarly 5th has got 0.35 marks in sem-1, 0.3333 in sem-2 and 0.3000 marks in sem-3 than the performance of that student is 0.3278 in Statistical method model and 0.449 in hybrid SC-FCM model. Table 7 shows the RSME of hybrid SC-FCM model.

Table 7: RMSE of Hybrid SC-FCM Model

Model Number	Number of Clusters	MF Type	Optimize Method	Training (RMSE)	Testing (RMSE)
Hybrid SC-FCM	5	Gaussian	Hybrid SC-FCM	0.0881	0.1051

Here, Root Mean Square Error (RMSE) is employed to evaluate the accuracy of the model identification. Table 7 shows the RMSE of hybrid SC-FCM model. It reveals that RMSE of hybrid SC-FCM is 0.0881 and 0.1051 for training and testing data set.

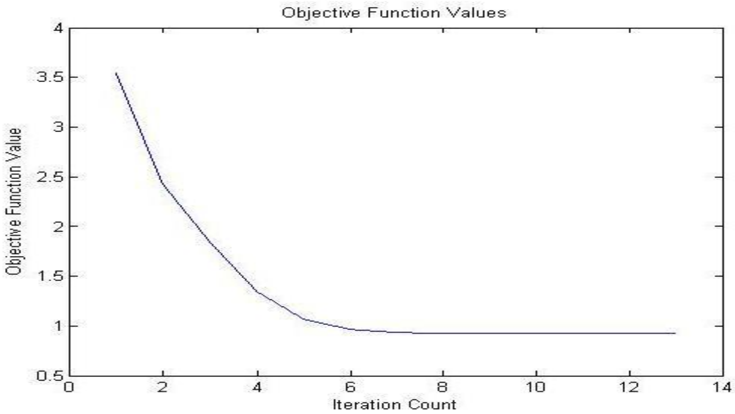

Fig. 7: Objective function profiles of the Hybrid SC-FCM Model

The objective function evolutions associated with the hybrid SC-FCM model is shown in Fig. 7, which indicates that hybrid SC-FCM model not only performs less iteration, but also achieves smaller value of objective function, implying that hybrid SC-FCM model conducts faster convergence and higher accuracy for student academic performance evaluation. The hybrid SC-FCM model also removes the most of the problem described in Yadav and Singh (2012). We conclude that the proposed hybrid SC-FCM model have given better performance in comparison to FCM model and other existing model for student academic performance evaluation in educational domain.

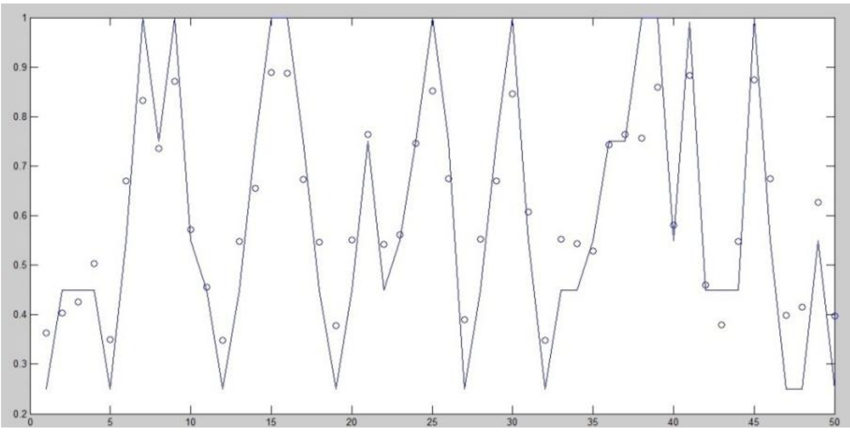

Fig. 8: Hybrid SC-FCM Model Output and Testing Data

Fig. 8 shows the model output and testing data shown by circles and line, respectively. It also shows that the model does not perform well on the testing data. At this point, we use the optimization capability of hybrid Subtractive Clustering-Adaptive Neuro Fuzzy Inference Systems (SC-ANFIS) to improve the proposed model.

4.3. Experimental Results of SC-ANFIS Algorithm:

The proposed hybrid SC-ANFIS model was trained on 50 training data sets and tested on 50 testing data sets (Table 1 and Table 2). In some cases, data is collected using noisy measurements, so model validation is needed to cross validate the fuzzy inference system using testing data set. The testing data set is useful to testing the generalization capability of the resulting Tskagi-Sugeno (T-S) fuzzy model. That is why the other 50 sets were then used for testing after training was completed to verify the accuracy of the predicted values of academic performance evaluation. Here, Sem-1, Sem-2 and Sem-3 are the inputs and the maximum values of the classification of marks shown in Table 3 and Table 4, are the outputs of the system. Gaussian shapes are used for the membership function distribution for the input variables. The three inputs of the fuzzy inference are classified into 5 fuzzy sets. Therefore maximum number of fuzzy rules for this system can be five. During training in hybrid SC-ANFIS, 50 sets of experimental data were used to conduct 20 epoch of learning.

A hybrid SC-ANFIS based on first order Sugeno fuzzy inference system is used to evaluate the student academic performance in semester examinations. By employing the hybrid or back-propagation learning algorithm, hybrid SC-ANFIS can obtain the optimal Gaussian membership functions.

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Student academic performance values predicted by hybrid SC-ANFIS are compared with the student performance values derived from the SC method in order to determine the RMSE of hybrid SC-ANFIS. The RMSE of academic performance values predicted by hybrid SC-ANFIS is 0.0203 for training data and 0.0874 for testing data. In contrast, the RMSE by hybrid SC-FCM model is 0.0881 for training data and 0.1092 for testing data. The comparison indicates that the address of combine techniques of Subtractive clustering and ANFIS achieved much satisfactory results in comparison to hybrid SC-FCM method for student academic performance evaluation. The hybrid SC-ANFIS achieves slightly higher prediction accuracy than hybrid SC-FCM model. Table 8 shows that the comparison of student's academic performance evaluation using hybrid SC-FCM and SC-ANFIS.

Table 8: Comparison of Students' Academic Performance Results Using hybrid SC-FCM and SC-ANFIS

S.No.	Sem-1	Sem-2	Sem-3	Output of SC-FCM Model		Output of SC- ANFIS Model	
				Output	Grade	Output	Grade
1.	0.10	0.2333	0.2000	0.345	D	0.238	E*
2.	0.05	0.1667	0.1200	0.349	D	0.243	E*
3.	0.15	0.1333	0.1800	0.348	D	0.237	E*
4.	0.45	0.2667	0.4000	0.455	C	0.464	C
5.	0.35	0.3333	0.3000	0.441	D	0.430	D
6.	0.35	0.5000	0.3800	0.524	C	0.508	C
7.	0.45	0.4333	0.5400	0.560	B	0.519	C*
8.	0.50	0.4000	0.5000	0.508	C	0.510	C
9.	0.45	0.5000	0.5800	0.600	B	0.568	B
10.	0.50	0.7000	0.6200	0.678	B	0.733	B
11.	0.65	0.7000	0.7400	0.788	A	0.768	A
12.	0.85	0.6000	0.7600	0.821	A	0.757	A
13.	0.95	0.7667	0.8600	0.874	A	0.988	A
14.	0.85	0.8333	0.9600	0.880	A	1.000	A
15.	0.90	0.9000	0.9800	0.900	A	1.000	A

*Improve grade

By using a given input/output data set, the hybrid SC-ANFIS constructs a Tskagi-Sugeno (T-S) fuzzy model whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least squares type of method. An important advantage of using a clustering method to find rules is that the resultant rules are more tailored to the input data rather than in a FIS generated. This reduces the problem of an excessive propagation of rules when the input data has a high dimension. Table 9 shows the RMSE of testing and checking data sets of hybrid SC-FCM and SC-ANFIS model. This table also shows that the RMSE of training and testing data sets are reduced against hybrid SC-FCM model. Thus hybrid SC-ANFIS gives better result in comparison to hybrid SC-FCM model for academic performance evaluation. Fig. 9 shows the comparison of output of hybrid SC-FCM and SC-ANFIS models for testing data set.

Table 9: Comparison of RMSE of hybrid SC-FCM and SC-ANFIS for Testing Data Sets

S.No.	Training and Testing (RMSE)	Hybrid SC-FCM Model	Hybrid SC-ANFIS Model
1.	Training (RMSE)	0.0881	0.0203
2.	Testing (RMSE)	0.1051	0.0874

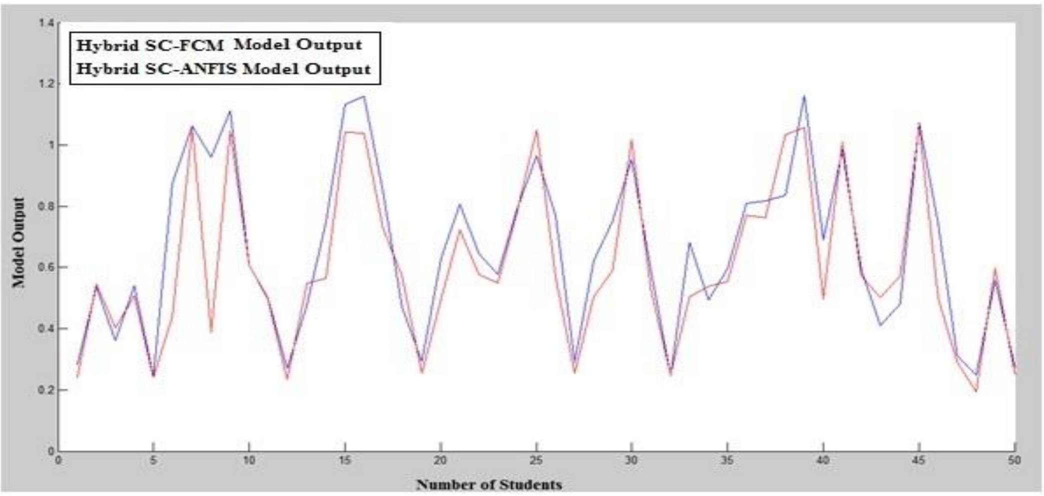

Fig. 9: Comparison of output of Hybrid SC-FCM and SC-ANFIS Techniques for Testing Data Sets

According to the discussion in section 4 of the implementation of the two data clustering techniques and their results, it is useful to summarize the results are shown in Table 8 for academic performance evaluation.

Table 9 also shows that the RMSE hybrid SC-FCM are 0.0203 and 0.0874 for training and testing data set, respectively. These values are low in comparison to K-Means, FCM, Subtractive and hybrid SC-FCM clustering techniques. Therefore, we conclude that the hybrid SC-ANFIS gives better results for academic performance evaluation. Fig. 9 shows the comparative study of hybrid SC-FCM and hybrid SC-ANFIS model for academic performance evaluation. It is clearly evident from Fig. 7 shows that the hybrid SC-ANFIS technique as the better academic performance evaluation comparison to statistical and hybrid SC-FCM models. The hybrid SC-ANFIS model also removes the most of the problem described in Yadav and Singh (2012); Biswas (1995); Law (1996); Rasmani and Shen (2006); Chen and Lee (1999).

5. Conclusion and Future Work:

According to the results shown in this paper shows that the proposed hybrid SC-ANFIS approach has several advantages like learning capability, initial cluster center computed by the subtractive clustering and automatic generation of membership function compared to existing fuzzy techniques for the evaluation of student academic performance. In hybrid SC-ANFIS model, the uses of fuzzy membership values are very helpful to the users to understand why the new grade was awarded. The proposed method has the potential to be developed further to use an extended method of evaluation by providing new grades that refers to achievements of other groups. The experimental results also show that the proposed hybrid SC-ANFIS model can evaluate academic performance more stable than statistical model, FCM and hybrid SC-FCM models.

Further, we have observed that the hybrid SC-ANFIS model is used for the first time and best model for modeling academic performance in educational domain. Therefore, hybrid SC-ANFIS model serves as a good benchmark to monitor the progression of students modeling in educational domain. It also enhances the decision making by academic planners semester by semester by improving on the future academic results in the subsequence academic session.

It worth of future research to use combine technique of Subtractive clustering technique, Genetic Algorithm and Artificial Neural Network techniques called hybrid Fuzzy Expert System to evaluate student and teacher academic performance and also develop adaptive learning system and Intelligent Tutoring System for Internet based education like Distance Education, instructional design and e-learning in educational domain.

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