

EVALUATION OF STUDENT ACADEMIC PERFORMANCE USING ADAPTIVE NEURO-FUZZY APPROACH

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ABSTRACT

The Fusion of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) has attracted a growing interest of researchers in various scientific and engineering areas. Due to the growing need for adaptive intelligent systems to solve real world problems. ANN learns by adjusting the interconnections between layers. FIS is a popular computing framework based on the concept of fuzzy set theory and fuzzy if-then rules. The advantages of the combination of ANN and FIS are apparent. The developed method uses a fuzzy system to support neural networks to enhance some of its characteristics like flexibility, speed and adaptability which is called the Adaptive Neuro-fuzzy inference system (ANFIS). Evaluating and assessing the student academic performance is not an easy task, especially when it involves many attributes or factors. Moreover, the knowledge of the human experts is acquired to determine the criteria of students' academic performance and the decisions about their level of assimilation but most of the information is incomplete and vague. To overcome the problem, this work evaluates the student's academic performance based on ANFIS tools which was implemented on MATLAB 7.6.0 (R2008a). The method produces crisp numerical outcomes that evaluate the student's academic performance. The student performance after the training of the two inputs was at the average for semester1 and semester 2.

Keywords: Adaptive, Artificial Neural Network, Fuzzy, Performance

INTRODUCTION

Evaluation of students' academic performance is the process of determining the performance levels of individual students in relation to educational objectives. A high quality evaluation system which is able to provide grounds for individual improvement and ensures that all students receive fair evaluation so as not to limit students' present and future opportunities is required and very important.

The use of fuzzy logic approach for aca-

demic performance evaluation has reached a wide range of application areas in educational systems in addition to evaluation of student academic performance, including the evaluation of curriculum and that of the educators (e.g. lecturers and tutors) (Bai and Chen, 2006). In student performance evaluation in particular, fuzzy techniques have been adapted for evaluation based on numerical scores obtained in an assessment and for assessing prior educational achievement based on evidence such as academic certificates. Much attention has also been given to

adopting fuzzy approaches for the evaluation of teaching using a computer, in particular in Intelligent Tutoring Systems (ITS) and Computer Assisted Instruction (CAI) (Yadav and Singh, 2011). Saleh and Kim (2009) proposed that the fuzzy system should regularly be reviewed and improved to ensure that it is precise, fair and beneficial to all students.

According to Yadav and Singh (2011), evaluation of student academic performance usually consists of several components, each involving a number of judgments often based on imprecise data. This imprecision arises from human (teacher) interpretation of human (students) performance. Arithmetical and statistical methods have been used for aggregating information from these assessment components. These methods have been accepted by many educational institutions around the world although there are limitations with these traditional approaches.

The current methods of classifying and grading students' academic performance using arithmetical and statistical techniques does not necessarily offer the best way to evaluate human acquisition of knowledge and skills. It is expected that adaptive neuro-fuzzy systems will provide an alternative way of handling various kinds of imprecise data (e.g. bad, good, very good, excellent etc.), which often reflects the way people think and make judgments.

Neuro-fuzzy Inference System (NFIS) can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate stipulated input-output pairs (Jang, 1993). According to Abraham and Nath (2000), a Neuro-Fuzzy (NF) System is a combination of Artificial

Neural Network (ANN) and Fuzzy Inference System (FIS) in such a way that ANN learning algorithms are used to determine the parameters of FIS. ANN and FIS are both very powerful soft computing tools for solving a problem without having to analyze the problem itself in detail.

Generally, the adaptive neuro-fuzzy inference system (ANFIS) is a hybrid intelligent system. ANFIS combines a neural network with a fuzzy system. An artificial neural network is good in learning but acts as a black-box and it learns without the human intervention. Similarly, fuzzy inference system can be built if knowledge is expressed in linguistic rules but the fuzzy system lack the ability to learn and the fuzzy system cannot adjust itself to a new environment. By combining both of them, the neural networks become more transparent and the fuzzy systems become capable of learning (Negoita *et al.*, 2005).

ANFIS technique was used to evaluate student's academic performance and to overcome the uncertainty and imprecise information (Rasmani, 2002).

Need for Evaluation of Students' Academic Performance

There are several reasons for the evaluation of students' academic performance and these include the following:

- (a) The evaluated level of performance can be used as an indication of a student's level of assimilation or understanding. This is important in providing information for teachers to take further action if necessary, such as planning remedial activities, or planning further instruction. This information is also very useful to enable students to overcome any weak-

- nesses. Besides this, students who succeed in examinations may be motivated to learn more.
- (b) Assessment is important for the purpose of making academic decisions about the students now, or in the future. For example, students who do not achieve a certain level have to repeat the course while other students will proceed onto the next stage. Assessment is also important to indicate the level of assimilation and performance for graduation purposes, and this usually has a permanent effect on the future career of students (Ashworth, 1982)
- (c) Assessment is important to provide information about the teacher's ability to instruct and the 'system' being practiced.
- In addition, (Atkins *et al.*, 1993) also stated that the reasons for assessing students include:
- (i) to give staff feedback on the effectiveness of their teaching,
 - (ii) to determine the extent to which course aims have been achieved,
 - (iii) to obtain information on the effectiveness of the learning environment, and
 - (iv) to monitor standards over time.

METHODOLOGY

Architecture of the Proposed Adaptive Neuro-Fuzzy System

The architecture of the proposed adaptive neuro-fuzzy system for evaluating student academic performance is as shown in Figure 1.

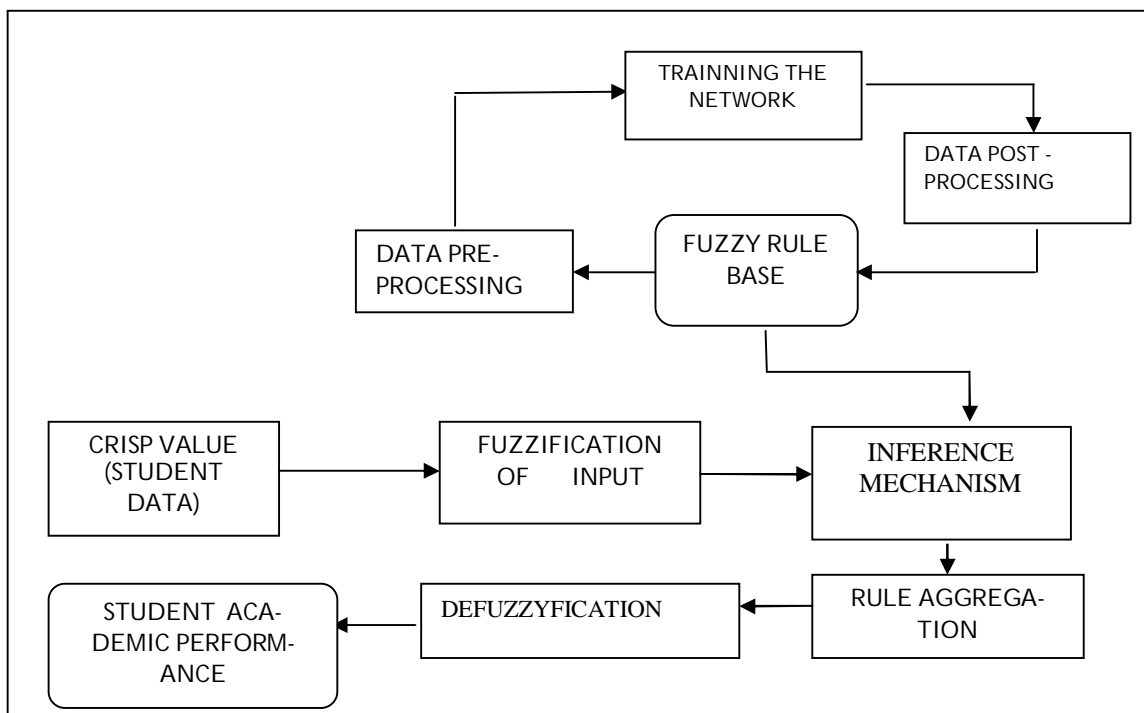


Figure 1: The architecture of the proposed neuro-fuzzy systems for evaluating student academic performance

a. Crisp Values

Crisp values: crisp value is the student score obtained in both semesters' examination. Table 1 shows the dataset of each semester.

Table 1: Dataset for the Session

Semester 1			Semester 2		
Courses	Unit (Weight)	Score Obtained	Courses	Unit Weight	Score Obtained

(b) Fuzzyfication

Fuzzyfication means crisp value (student score) is converted into fuzzy value with the help of suitable membership function or linguistic variable. Each input variable has six linguistic variables and the corresponding linguistic values as stated in Table 2.

Table 2 : Fuzzification Table

Linguistic Variable	Notation	Linguistic Value (Crisp)	Fuzzy Value (Interval)
Extremely Low	EL	0-39	- 0.39
Very Low	VL	40-44	0.40 - 0.44
Low	L	45-49	0.45 - 0.49
High	H	50-59	0.50 - 0.59
Very High	VL	60-69	0.60 - 0.69
Extremely High	EH	70-100	0.70 - 1.0

Each of the two input variables has six linguistic variables and the corresponding linguistic values as stated in Table 3.

Table 3: Fuzzy Set of Input Variables

Semester 1 (X)		Semester 2 (Y)	
Extremely Low (EI)	A6	Extremely Low (EI)	B6
Very Low (VI)	A5	Very Low (VI)	B5
Low (L)	A4	Low (L)	B4
High (H)	A3	High (H)	B3
Very High (VI)	A2	Very High (VI)	B2
Extremely High (Eh)	A1	Extremely High (Eh)	B1

The fuzzy set of the output variables obtained from the input variables in Table 3 are shown in Table 4.

Table 4: Fuzzy Set of Output Variables

Linguistic Variables	Linguistic values	Normalized Values
Extremely Unsuccessful(EU)	C6	0.0-0.39
Very Unsuccessful (VU)	C5	0.40-0.44
Unsuccessful(U)	C4	0.45-0.49
Successful(S)	C3	0.50-0.59
Very Successful (VS)	C2	0.60-0.69
Extremely Successful (ES)	C1	0.70-1.00

(c) Rule Mechanism

This defines different types of fuzzy rules (“if - then “rules) for the evaluation of students’ academic performance.

Table 5: Defining the Rules For Semester 1 (X) and Semester 2 (Y)

X	Y					
	EL	VL	L	H	VH	EH
EL	EU	EU	VU	U	U	S
VL	EU	VS	U	U	S	S
L	VU	U	U	S	S	S
H	U	U	S	S	VS	VS
VH	VU	S	S	VS	VS	ES
EH	S	S	S	VS	ES	ES

These rules determine the input and output membership function that will be used in the inference process. These rules are linguistics and are called IF-THEN-RULES.

(d) Applying the ANFIS approach on the evaluation of students’ academic performance

This stage of evaluation is very crucial because an ANFIS model will be constructed to evaluate students’ performance. The ANFIS approach is proposed to form a complete fuzzy rule base system so that all possible input conditions of the fuzzy rules can be generated. Figure 1 shows that there are three additional phases in ANFIS approach (Norazah, 2005):

- data pre-processing
- training the network and
- data post-processing

If X is A6 and Y is B6 THEN SAP is C6
If X is A6 and Y is B5 THEN SAP is C6
If X is A6 and Y is B4 THEN SAP is C5
If X is A6 and Y is B3 THEN SAP is C4
If X is A6 and Y is B2 THEN SAP is C4
If X is A6 and Y is B1 THEN SAP is C3
If X is A5 and Y is B6 THEN SAP is C6
If X is A5 and Y is B5 THEN SAP is C5
If X is A5 and Y is B4 THEN SAP is C4
If X is A5 and Y is B3 THEN SAP is C4
If X is A5 and Y is B2 THEN SAP is C3
If X is A5 and Y is B1 THEN SAP is C3
If X is A4 and Y is B6 THEN SAP is C5
If X is A4 and Y is B5 THEN SAP is C4
If X is A4 and Y is B4 THEN SAP is C4
If X is A4 and Y is B3 THEN SAP is C3
If X is A4 and Y is B2 THEN SAP is C3
If X is A4 and Y is B1 THEN SAP is C3
If X is A3 and Y is B6 THEN SAP is C4
If X is A3 and Y is B5 THEN SAP is C4
If X is A3 and Y is B4 THEN SAP is C3
If X is A3 and Y is B3 THEN SAP is C3
If X is A3 and Y is B2 THEN SAP is C2
If X is A3 and Y is B1 THEN SAP is C2
If X is A2 and Y is B6 THEN SAP is C5
If X is A2 and Y is B5 THEN SAP is C3
If X is A2 and Y is B4 THEN SAP is C3
If X is A2 and Y is B3 THEN SAP is C2
If X is A2 and Y is B2 THEN SAP is C2
If X is A2 and Y is B1 THEN SAP is C1
If X is A1 and Y is B6 THEN SAP is C3
If X is A1 and Y is B5 THEN SAP is C3
If X is A1 and Y is B4 THEN SAP is C3
If X is A1 and Y is B3 THEN SAP is C2
If X is A1 and Y is B2 THEN SAP is C1
If X is A1 and Y is B1 THEN SAP is C1

The data pre-processing phase prepares the input patterns for both the training and testing operations of the training in the neural network by using the back propagation method.

The training network consist of three op-

erations which are: determining a suitable and appropriate network structure, training the operation of the network and the last phase is the validation of result.

The data post-processing phase converts the output generated from the neural network

phase into complete fuzzy rules and stores it in fuzzy rule base. Then the complete fuzzy rule will be used in the neuro-fuzzy inference system for the rule evaluation stage.

(e) **Aggregation of rules**

When there are many rules active for the same membership function, only one membership value is chosen. This process is known as fuzzy decision or fuzzy inference. Several methods have been proposed by different author such as Mamdani, Takagi, Zadeh and so on (Jang, 1993). Sugeno method is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in

control problems, particularly for non linear systems. A nonlinear system is one that does not satisfy the [superposition principle](#) or one whose output is not [directly proportional](#) to its input. The consequent part of IF-THEN rules is a linear combination of input variables and a constant term and the final output is the weighted average of each rule's output. In this work, first order sugeno inference system was used and is stated below.

The output (student academic performance) was calculated using the first-order Sugeno fuzzy model (Sugeno and Kang, 1988). A typical rule set with one fuzzy if-then rule can be expressed as:

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } y = P_1X + Q_1Y + r_1$$

Where $P_1 = w_i x_i$, $i = 1 \dots n$, $Q_1 = w_j x_j$, $j = 1 \dots m$, X and Y are the two input with six linguistic variable denoted with (A6.....A1) and (B6.....B1) respectively. $r_1 = bk$ referred to as the bias value (the value used are constant).

The input information P_i is aggregated, by addition, to produce the input

$$\text{net} = p_1 + p_2 = W_{11}X_{11} + W_{12}X_{12}$$

to the neuron. The neuron uses its transfer function f , which could be a sigmoid function,

$$f(x) = (1 + e^{-x})^{-1},$$

to compute the output $y = f(\text{net}) = (w_1x_1 + w_2x_2)$.

(f) **Defuzzification**

The last stage is the defuzzification stage which produces the output as a crisp value, that is, calculating the performance value with the help of suitable defuzzification method.

IMPLEMENTATION AND RESULT

In this research work, the proposed Adaptive Neuro-fuzzy inference System for student academic performance evaluation was implemented in MATLAB (version 7.8) and ANFIS tool was used. MATLAB is a high-level technical computing language and interactive software environment for algorithm development, data visualization, data analysis and numerical computation that can easily be used to implement neuro-fuzzy (i.e. fuzzy logic and neural network).

The proposed Adaptive Neuro-fuzzy Inference System was tested with student's marks obtained from semester-1 and semester-2 examinations in the Department of Computer Science, Federal University of Agriculture Abeokuta. For each student, both semester examination scores were fuzzified by means of the triangular membership functions. Active membership functions were calculated according to rule table, using the Sugeno method. The output (Performance Value) was calculated and then defuzzified.

This sequence was repeated using the semester examination scores for each student. This sequence was repeated using the semester examination scores for each student. This sequence was repeated using the semester examination scores for each student. This sequence was repeated using the semester examination scores for each student.

Visualizing the Results

Figure 2 shows the result of the fuzzy inference system (FIS) with two input variables and one output using the Sugeno method.

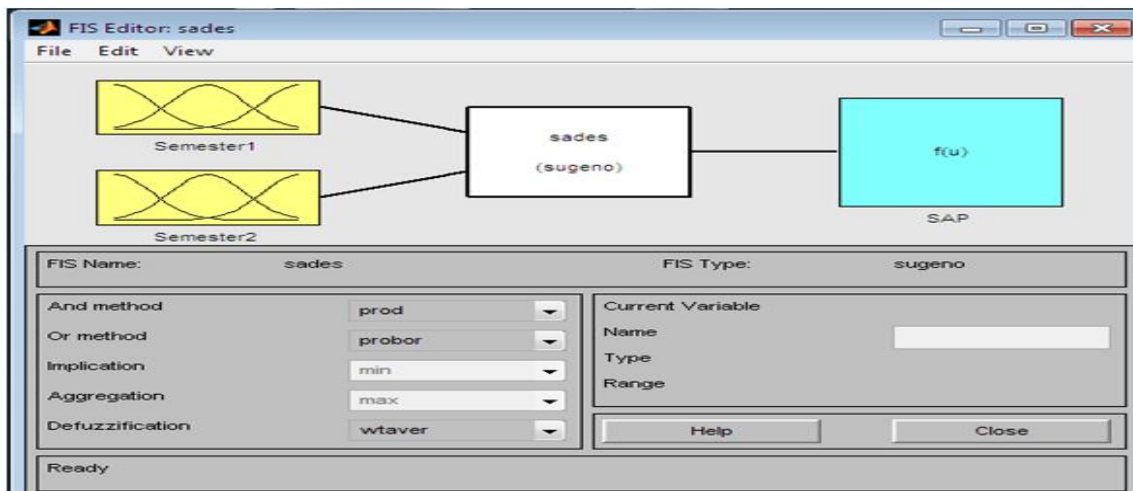
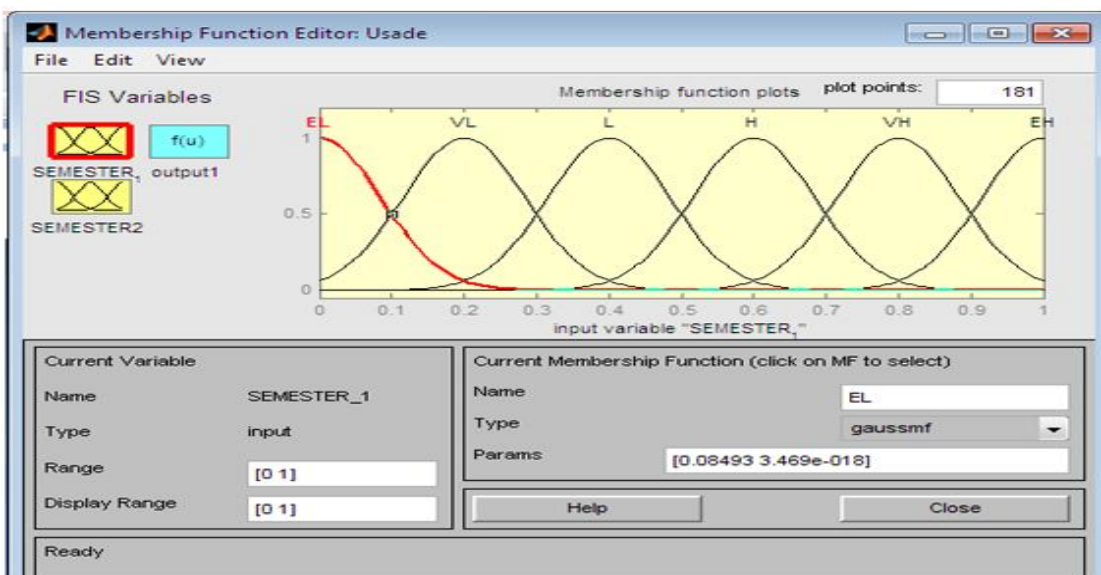
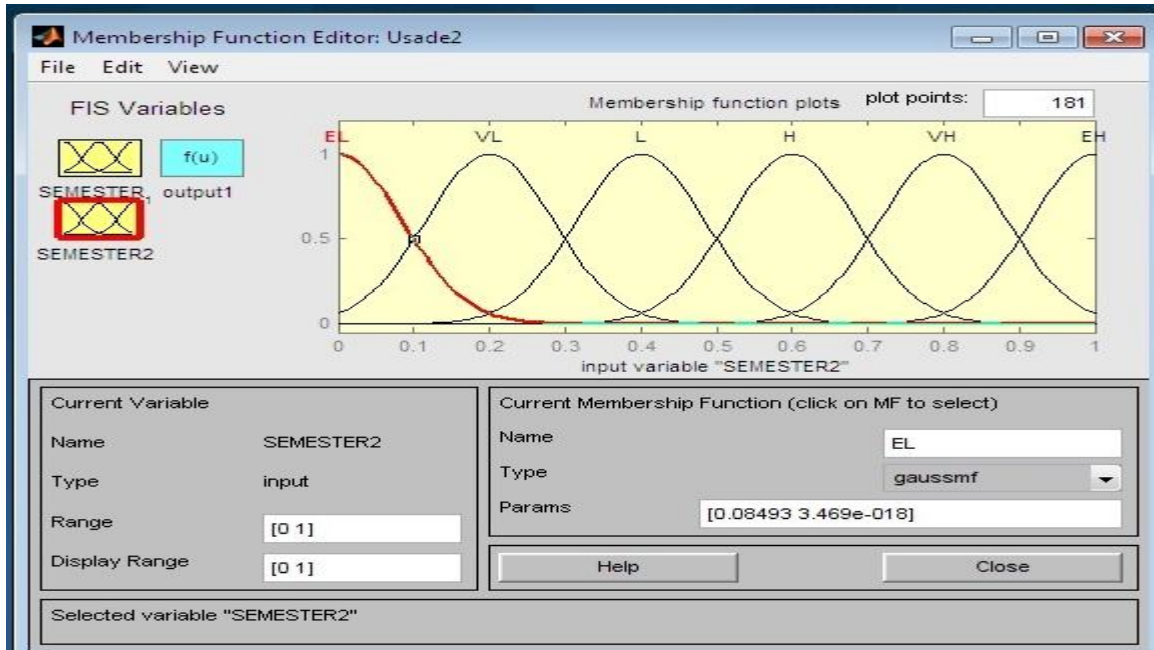


Figure 2: Screen shot of FIS with two input variables and one output

Figure 3 shows the student score (crisp value) for semester 1 and 2 which were converted into fuzzy value with the help of the membership function.



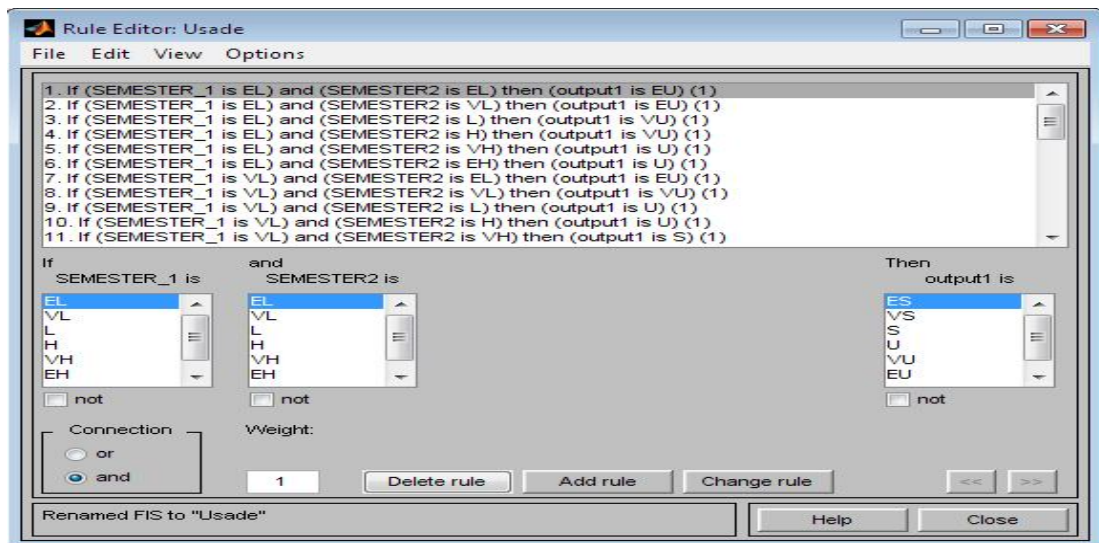
(a)



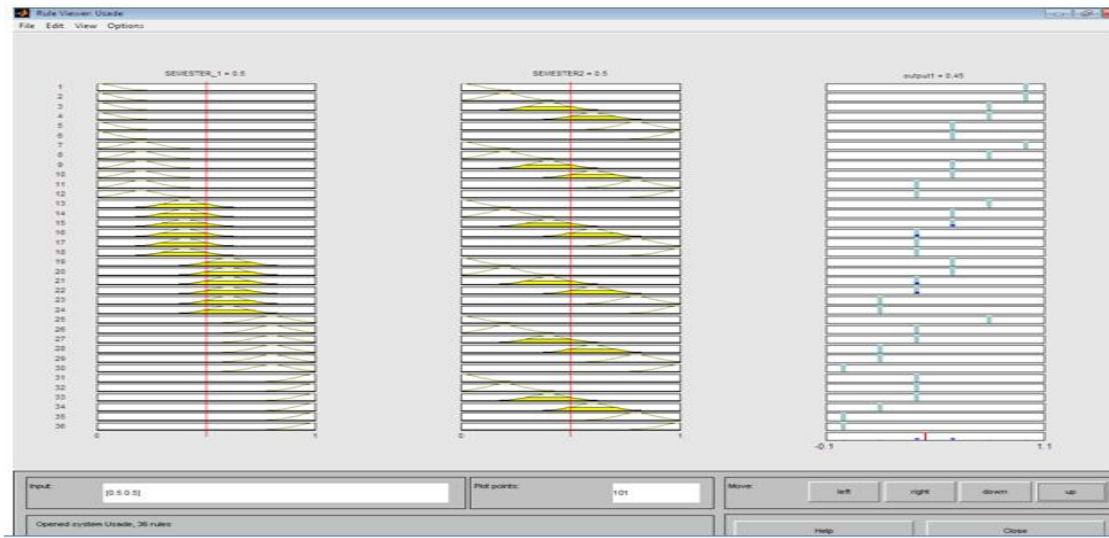
(b)

Figure 3 (a & b): Screen shot of linguistics variables for each semester (semester 1 and 2)

Fuzzy reasoning is an inference procedure that derives conclusions from the set of fuzzy If-Then rules and known facts. Figure 4 presents the two inputs and one output reasoning of the students' academic performance procedure for Sugeno fuzzy model. This figure shows the rules which determine the input and output membership function that were used in the inference process to evaluate the student academic performance.



(a)



(b)

Figure 4 (a & b): Screen shot showing the thirty six rules for evaluation of student academic performance and the equivalent rule viewer

Figure 5 represents three dimensional plots for the two-input one-output system.

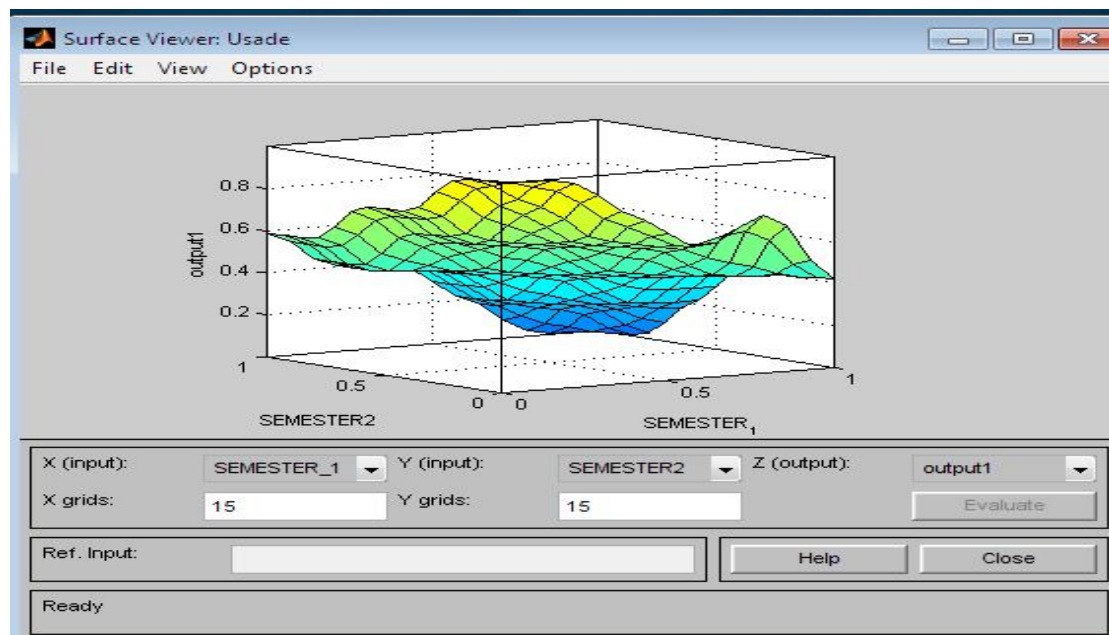
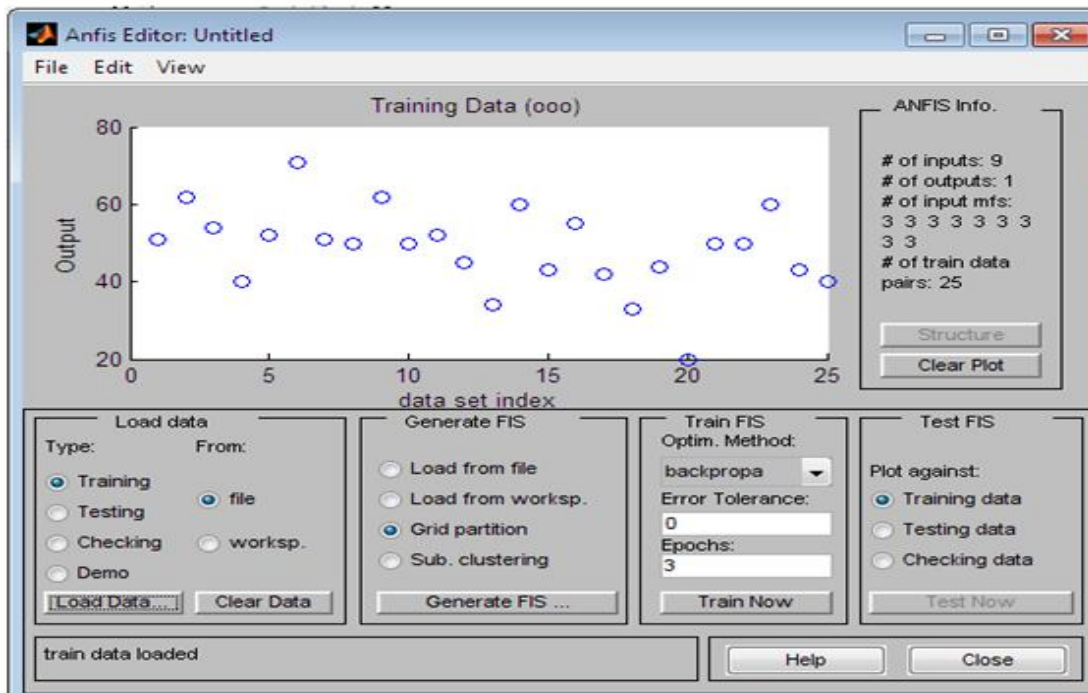
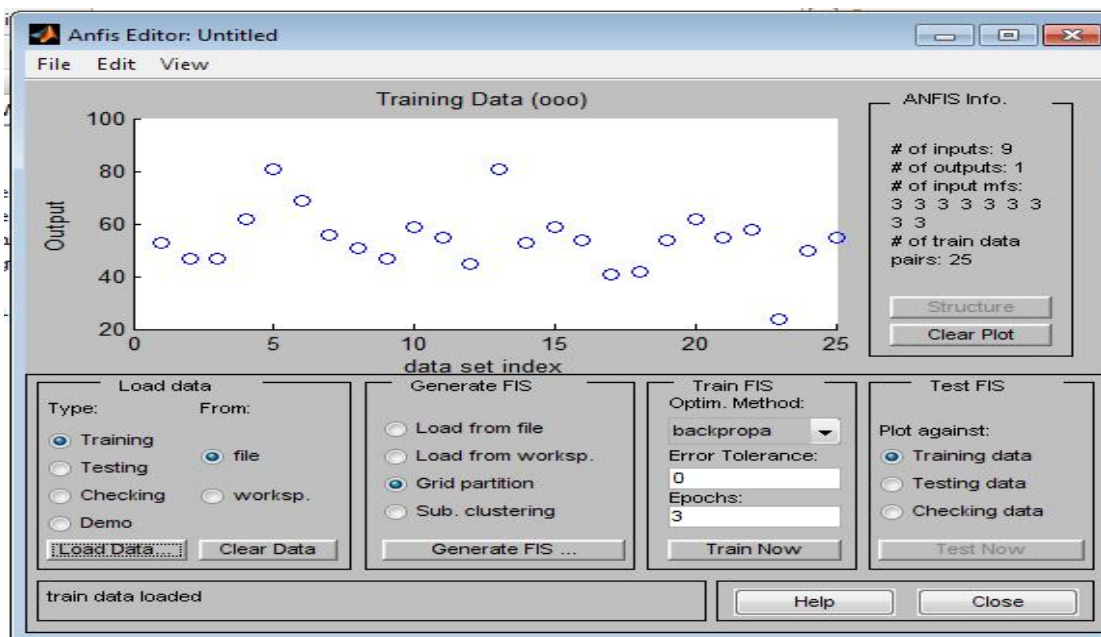


Figure 5: The surface viewer of the inputted rules

Figure 6 shows how the linguistic variable for semesters 1 and 2 are trained and tested in the ANFIS editor.



(a)



(b)

Figures 6 (a & b): Training and testing of semester 1 and semester 2 in the ANFIS editor

Figure 7 shows the ANFIS architecture that corresponds to the first-order sugeno fuzzy model. The ANFIS has two inputs – semester 1 and semester 2, and one output – performance

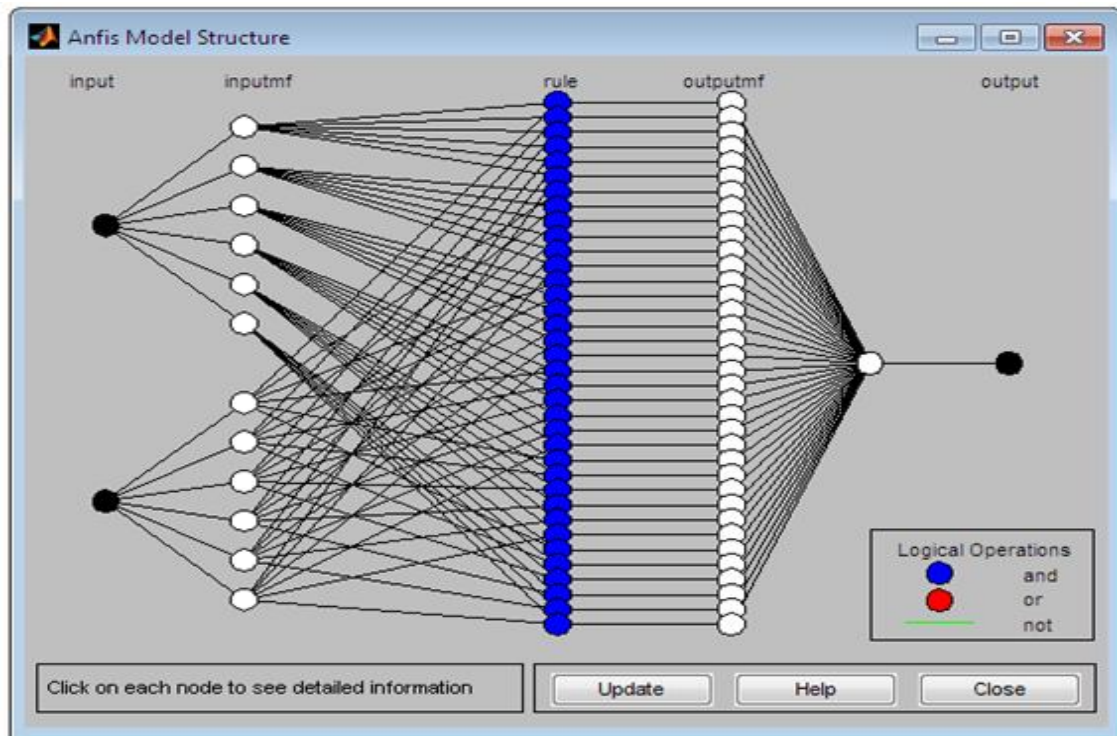


Figure 7: ANFIS model structure showing the two input variable (semester 1 and semester 2) with the corresponding linguistics variables and the output membership function

CONCLUSION

Neuro-fuzzy is a soft computing tool and is considered as one of the most promising tools for evaluation of students' academic performance. In this work, fuzzy inference models provided an efficient and effective way to evaluate students' academic performance in a quantitative way. However, the number of fuzzy rules acquired from the human experts has always been incomplete and inconsistent. The adaptive neuro-fuzzy approach with sufficient training data sets determines the performance level. When the first input (semester1) was trained, it was observed that the student

academic performance was 60% which was above average and when the second input (semester2) was also trained, it was 40% which was below average. Therefore, the student academic performance after the training of the two inputs was at the average for semester1 and semester 2. The ANFIS approach has successfully solved the problem of incompleteness in the decision made by human experts. It has a remarkable ability to generalize and converge rapidly. This is particularly important in on-line learning. The proposed approach produces decisions that could not previously be determined.

REFERENCES

- Abraham, A., Nath, B.**, 2000. Evolutionary design of neuro-fuzzy systems.
- Ashworth, A. E.**, 1982. Testing for Continuous Assessment, Evans Brothers Limited, London.
- Atkins, M. J., Beattie, J., Dockrell, W. B.** 1993. Assessment Issues in Higher Education, Employment Department Group: United Kingdom.
- Bai S. M., Chen S. M.**, 2006. "A new method for students' learning achievement evaluation using fuzzy membership functions," *Proceeding of the 11th Conference of Artificial Intelligence and Applications, Kaohsiung, Taiwan, Republic of China*, 177-184.
- Jang, J. S. R.**, 1993. ANFIS: Adaptive Network-based Fuzzy Inference Systems, *IEEE Transactions on Systems, Man and Cybernetics*, 23(3), 665-685.
- Negoita, M., Neagu, D., Palade, V.**, 2005. Computational Intelligence: Engineering of Hybrid Systems. Berlin Heidelberg, New York : Springer.
- Norazah, Y.** 2005. Student Learning Assessment Model Using Hybrid Method. Ph.D. Thesis. Universiti Kebangsaan Malaysia, Malaysia.
- Rasmani K. A.**, 2002. A Data-Driven Fuzzy Rule-Based Approach for Student Academic Performance Evaluation, Centre for Intelligent Systems and their Applications.
- Saleh I, Kim, S. I.**, 2009. A fuzzy system for evaluating student's learning achievement. *Expert systems with Applications*. 36, 6236-6243.
- Sugeno, M. and Kang, G. T.** (1988). Structure identification of fuzzy model. *Fuzzy Sets and Systems*, 28:15-33.
- Yadav R. S., Singh V. P.**, 2011. Modeling academic Performance Evaluation using Soft Computing Techniques: A Fuzzy Logic Approach.

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