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Integrating Neuro-Fuzzy Systems to Develop Intelligent Planning Systems for Predicting Students' Performance

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ABSTRACT

This paper presents a simulation of Neuro- Fuzzy application for analyzing students' performance based on their CPA and GPA. This analysis is an attempt for extension of Analysis on Student's Performance Using Fuzzy Systems. This paper focuses to support the development of Intelligent Planning System (INPLANS) using Fuzzy Systems, Neural Networks, and Genetic Algorithms which will be used by the Academic Advisory Domain in educational institutions by evaluating and predicting students' performance as well as comparing the results with the previous study. The Neuro-Fuzzy model is feed-forward architecture with five layers of neurons and four connections. System evaluation has been done for about 20- 26 cases of students' results. The results depict that there has been a significant improvement in the performance of students' as compared to the prediction of the same case using Fuzzy Systems.

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1. INTRODUCTION

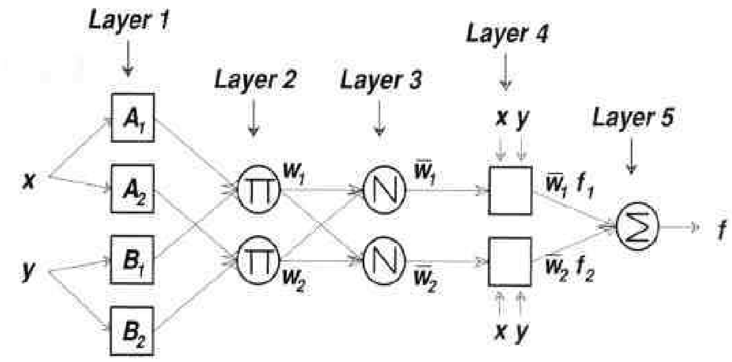
In case of Academics the evaluation system plays an important role in guiding and monitoring student's performance based on the learning process inspired by the simulations of study planning program. One of the most important roles to be played by an academic advisor is to advice the students in study planning, such as choosing the subjects that need to be taken, and total credits that need to be fulfilled. The academic advisor also monitors the student's program and suggests for amendments to the original planning when needed [1]. Basically, each student registers the subjects for each semester based on a Faculty's Program Planning. This planning consists of a flowchart of subjects that need to be taken throughout the program. Therefore, students with good results will not have a problem to follow the planning. The problem arises when students with moderate or poor results want to register the same total credit hours and subjects offered as in the planning. This kind of approach will not help in improving the student's performance. Therefore, the intelligent planning system (INPLANS) should be able to help the academic system in generating a planning based on the student's performance. In order to generate an automatic program planning based on student's abilities, the student's performance was analyzed using a Neuro-Fuzzy method. In [2], the student's performance was evaluated using a Fuzzy method and proved that the fuzzy method could predict a student's performance based on his/her learning abilities. However, the Neuro-Fuzzy method was introduced to improve the accuracy of the results. In order to produce accurate results, several criteria were taken into account. The criteria include the output value of student's performance, the class of student's performance, the corresponding Fuzzy inference rule, the Neural Network training goal performance, and error rate between the result value of this method and the previous method [2]. This Neuro-Fuzzy model was used in the third phase of the INPLANS development. This paper is organized as follows. Sections 2 and 3 present the basic system design and method of the Neuro-Fuzzy. Section 4 discusses the findings. Conclusion is presented in Section 5.

2. NEURO-FUZZY SYSTEMS

Neuro-Fuzzy has been used in various areas, such as emotion recognition [3], control engineering [4], decision support systems [5], civil engineering [6], etc. Fuzzy Systems and Neural Networks are efficient and effective methods to analyze the uncertainty in education assessment. For instance, Neural Networks have been used by many researchers in solving prediction problems which require function approximations [7] and Fuzzy Systems have been used in application of education assessment [8 – 12]. The advantage of Neural Networks is it has the learning capability to adapt new data. On the other hand, Fuzzy Systems has the capability to handle numerical data and linguistic knowledge simultaneously. However, both methods have some limitations, for example; even though Fuzzy Systems can perform inference mechanism under cognitive uncertainty, it does not have learning and adaptation capabilities that are crucial in the development of INPLANS. Therefore, to enable INPLANS to deal with cognitive uncertainties in a manner more like humans, the concept of Fuzzy System is incorporated into Neural Networks, which is called Neuro-Fuzzy must be implemented.

A. Neuro-Fuzzy Model

A neural network model consists of a network of neurons; each neuron is associated with an input vector, a weight vector corresponding to the input vector, a scalar bias, a transfer function and an output vector [13]. A neural network may consist of one or more layers of neurons with one or more neurons in each layer. In a network, the final layer is called the output layer and all previous layers are called hidden layers. In the hidden layers, the output of a layer becomes the input of the following layer. The operation function of a neuron converts the input to the output of the neuron. In this analysis, the Neuro- Fuzzy model is a connectionist of feed-forward architecture with five layers of neurons and four layers of connections. Figure 1 shows the architecture of the Neuro-Fuzzy model used in this study. A Neuro-Fuzzy model has input and output layers and three hidden layers that evaluate membership function and explain the fuzzy rules.

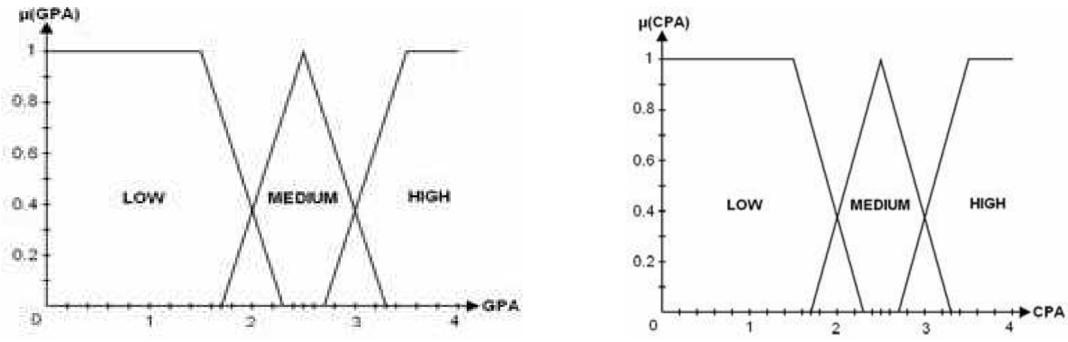


Layer-1: Input to the system
Layer-2: Production of the intermediate result
Layer-3: Normalization to remove anomalies in the data, if any
Layer-4: Summation
Layer-5: Defuzzified output

Figure 1. Neuro-Fuzzy architecture

This paper encompasses the input of Neuro-Fuzzy System as students' Grade Point Average (GPA) and Cumulative Grade Point Average (CPA). The GPA is the grade point for the current semester, while CPA is the cumulative point for the last semester. This system can only be used starting from the second semester. The GPA and CPA have values from 0 to 4.0 and were fuzzified using Gaussian formulation as fuzzy membership function (Figure 2).

The input and output variables show three possibilities for evaluating performance; low, medium, and high following the range of 0 to 2.3, 1.7 to 3.3 and 2.7 to 4.0 respectively. The relationships between the CPA and the GPA are described as in Table 1 and Table 2.



(a) (b)

Figure 2. Membership function of (a) GPA and (b) CPA

Table 1. Fuzzy Rules Matrix

CPA\GA	GL	GM	GH
CL	L	L	M
CM	L	M	H
CH	M	H	H

Table 2. List of Detail Rules

R1 : IF G is L and C is L then SP is L
R2 : IF G is L and C is M then SP is L
R3 : IF G IS L and C is H then SP is M
R4 : IF G is M and C is L then SP is L
R5 : IF G is M and C is M then SP is M
R6 : IF G is M and C is H then SP is H
R7 : IF G is H and C is L then SP is M
R8 : IF G is H and C is M then SP is H
R9 : IF G is H and C is H then SP is H

Matrix defines GL as GPA Low, GM as GPA Medium, GH as GPA High, CL as CPA Low, CM as CPA Medium, CH as CPA High, L as Low, M as Medium and H as high.

The first layer of this model is called crisp input where the neuron receives the GPA and CPA as inputs. Each neuron in this layer transmits external crisp signal directly to the next layer. The second layer of neurons is the input membership function layer, in this analysis there are 251 neurons. This layer calculates the fuzzy membership degrees to which the input values belong to predefined output membership functions, i.e. low, medium and high. Neurons in this layer represent fuzzy sets used in the antecedents of fuzzy rules. A fuzzification neuron receives a crisp input and determines the degree to which the input belongs to the neuron's fuzzy set. The third layer is the fuzzy rules where the rules represent associations between the input membership function and output membership function. Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule receives input from the fuzzification neurons that represent fuzzy sets in the rule antecedents. Other than that, it is important to note that the weights between Layer 3 and Layer 4 represent the normalized degrees of confidence of the corresponding fuzzy rules. The weights are adjusted during training of the Neuro- Fuzzy systems, from these fuzzy rules, the fourth layer of the Neuro-Fuzzy systems which is output membership functions layer calculates the degrees to which output membership functions are matched by the input data. An output membership neuron receives input from the corresponding fuzzy rule neurons and combines them using fuzzy operation union. In this study, the probabilistic AND has been used as a fuzzy operation union. Lastly, the fifth layer or defuzzification layer does defuzzification or in other words, it calculates values for the output variable. Each neuron of this layer represents a single output of the Neuro-Fuzzy systems. The output of the Neuro- Fuzzy systems is crisp, and thus a combined output fuzzy set must be defuzzified.

3. INVESTIGATION AND FINDINGS

MATLAB 7.0 simulator is used to program the scenario; Figure 3 shows the comparison of fuzzy sets for GPA and CPA of Neuro-Fuzzy systems with fuzzy sets of Fuzzy Systems. The curves represent Neuro- Fuzzy and Fuzzy Systems membership functions. From the graph, it shows that the degree of membership function for Neuro-Fuzzy systems is not exceeding the maximum degree, which is 1. Therefore, this system produces smaller range of degree of membership functions, which is more precise and accurate compared with the Fuzzy Systems. Based on the distribution of the membership functions, there are two intersections; low/medium intersection and medium/high intersection. Figures 4, 5 and 6 show the rules evaluations which produce low, medium and high set of output membership functions. In comparison with the results of [2], this process produces similar results in terms of which rules that produce those sets of output membership functions. Based on the analysis, rule numbers 1, 2, and 4 produce low sets of output membership functions. Rules 3, 5 and 7 produce medium sets of output membership functions.

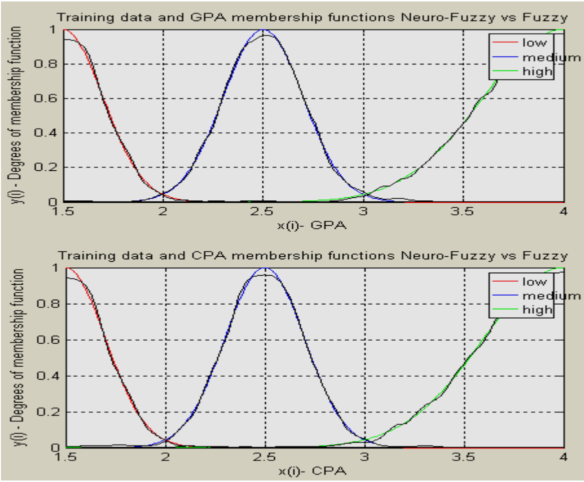


Figure 3. GPA and CPA membership functions of a Neuro-Fuzzy systems versus Fuzzy Systems

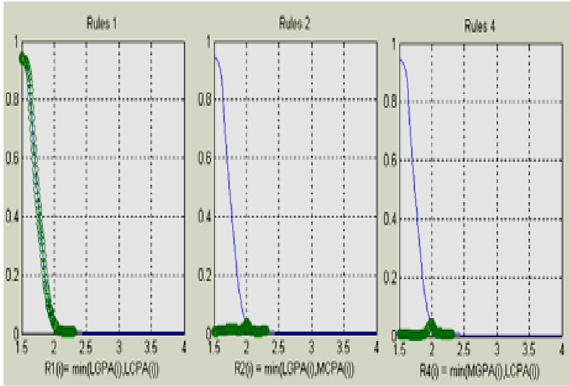


Figure 4. Rules evaluations which produce low sets

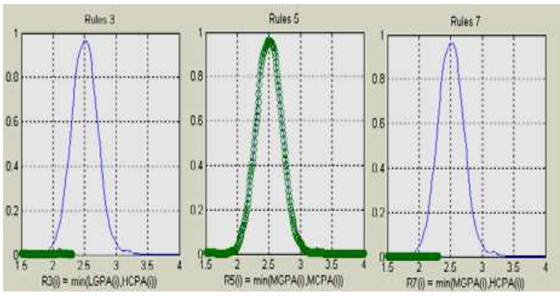
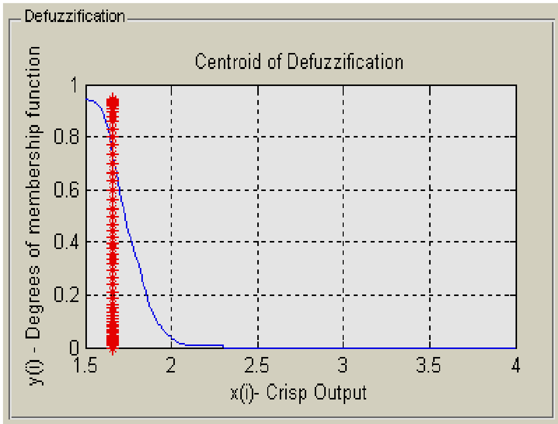
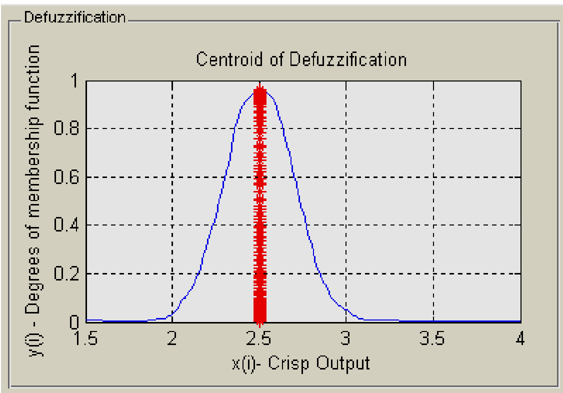


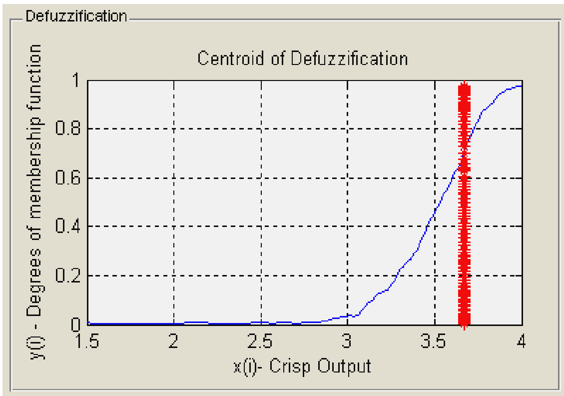
Figure 5. Rules evaluations which produce medium sets and high sets



(a)



(b)



(c)

Figure 6. Defuzzification of output fuzzy sets (a) Low output, (b) Medium output, and (c) High output.

Meanwhile, rules 6, 8 and 9 produce high sets of output membership functions. Then, all the data for each set of output membership function was aggregated, which is a process of unification of the outputs of the corresponding rules. In this study, outputs of rules 1, 2 and 4 were combined to be low sets. Outputs of rules 3, 5, and 7 were combined to be medium sets. Outputs of rules 6, 8, and 9 were combined to be high sets.

The aggregate output fuzzy set in layer 4 is transferred to the layer 5 of Neuro-Fuzzy systems for the defuzzification process. The output of the Neuro- Fuzzy systems is crisp, and thus a combined output fuzzy set must be defuzzified. Here, we apply centroid technique to determine the output. It finds a point, called the centre of gravity (COG) of the fuzzy set. Here the vertical line of COG would slice the aggregate set into two equal masses. Figure 6 shows the defuzzication for each output fuzzy set.

The result shows the Neuro-Fuzzy systems produced the crisp output very well. The Neuro-Fuzzy gives a small error value compared to Fuzzy Systems. It is clear that the Neuro-Fuzzy systems produce more accurate and reliable results compared to [2]. In order to prove that Neuro-Fuzzy can predict students' performance more accurately, the Neuro- Fuzzy and Fuzzy Systems results of 26 cases of CPA and GPA were compared .On the other hand, Neuro-Fuzzy produced different output values for both cases which are more reliable and accurate. In case number 16 and 19, Fuzzy Systems also produced similar output value which are 2.4967 for different input values for both cases, but Neuro-Fuzzy produced different output values which are more reliable and accurate. The same kind of error also occurred for case number 23 and 25, but by implementing Neuro-Fuzzy, the error was corrected. It is clear that Neuro-Fuzzy has improved the predicted output of students' performance to become more reliable and accurate when compared to the predicted output of the same cases using Fuzzy Systems. To assess the model's ability to determine the student's performance into low, medium, and high, the predictive ability of the model was compared with several alternative methods, namely, statistical models, neural networks, machine learning combination, and heuristics. In this research, regression analysis indicates the single most important variable is the cumulative GPA. Statistical analysis only focused on determining the factors responsible for the performance and based on that information, it finds ways to improve it. Whereas, in our research we have used Neuro-Fuzzy method to generate the assumption results for the coming semester based on the previous CPA and current GPA. A combination of machine learning technique, named genetic algorithm and decision tree is used by Dimitris Kalles and Christos Pierrakeas [16] to analyse the students' performance in Hellenic Open University (HOU). The analysis was focused on the problem of predicting students' performance and the problem on adult students learning at a distance. It was measured by the homework assignments and attempted to derive short rules that explain and predict success or failure in the final exam on a specific module. The result obtained were more accurate analysis of the students' performance compared to the conventional decision tree classifiers. The genetic algorithm and decision tree focused only on predicting the possibility of students on passing the final exam based on a specific module. In our research, as stated earlier, the neuro- fuzzy method was used to analyze the students' performance for the coming semester based on the previous CPA and current GPA.

However, this method has a limitation where it only works for certain grades and not for all grades. Compared with our research, it shows that our research used different approaches to analyze students' performance, which then produced different results.

4. CONCLUSION

In this paper, we presented an analysis of students' performance using Neuro-Fuzzy systems. The main focus of this study is to prove that Neuro-Fuzzy systems can improve the output of student performance prediction to be more accurate compared with the output from [2]. Therefore, this system has been tested using the same data from our previous study. The system was modeled and trained based on a connectionist of feed-forward architecture. The experiment and analysis of this system was on the role of students' CPA and GPA. By entering their GPA and CPA, the simulation application with Neuro- Fuzzy engine will process the results and calculate the output of the students' performance and classify the students' performance into three different categories. The system modeled the training data very well because it gives small error values compared with the Fuzzy Systems. This system has been tested on various student results, and the experimental results have demonstrated this system as fast, reliable and accurate.

REFERENCES

[1] *Buku Panduan Sistem Penasihatan Akademik* (Pejabat Pengurusan Akademik KUiTTHO, 2005.

[2] Khalid Isa, Shamsul Mohamad and Zarina Tukiran, "Development of Intelligent Planning Conference on System (INPLANS): An Analysis of Student's Performance Using Fuzzy Systems", IASTED International Artificial Intelligence and Applications (AIA 2007), Austria, 2007.
[3] Spiros V. Ioannou, Amaryllis T. Raouzaiou, Vasilis A.Tzaouvaras, and et. al, "Emotion Recognition Through Facial Expression Analysis Based on a Neurofuzzy Network", NeuralNetwork, Elsevier, 2005, vol. 18, pp 423-435.
[4] Xiang-Jie Liu, Felipe Lara-Rosano, C.W. Chan, "Neurofuzzy Modelling and Control of Steam Pressure in 300 MW Steam- Boiler System", Engineering Application of Artificial Intelligence, Elsevier, 2003, Vol. 16, pp 431- 440.
[5] Tran, C., Abraham, A., and Jain, L, "A concurrent fuzzy- neural network approach for decision support systems". FUZZ apos; 03. The 12th IEEE International Conference, vol2, 25-28 May 2003, pp. 1092 – 1097.
[6] Barai S. V. and Nair R. S, "Neuro-Fuzzy Models For Constructability Analysis". ITcon, vol 9, 2004, pp 65-73..
[7] Kosko B., Neural Networks and Fuzzy Systems, A Dynamic Systems Approach to Machine Intelligence', Prentice Hall, 1992.
[8] James R. Nolan, A Prototype Application of Fuzzy Logic. and Expert Systems in Education Assessment, Proceedings Fifteenth National Conference on Artificial Intelligence (AAAI-98), Menlo Par, CA, USA, 1998, 1134.
[9] James R. Nolan, An Expert Fuzzy Classification System for Supporting the Grading Student Writing Samples, Expert Systems with Applications, 1998, Vol. 15, Iss. 1, 59-68.
[10] Jian Ma and Duanning Zhou, Fuzzy Set Approach to the Assessment of Student-Centered Learning, IEEE Transaction on Education, 2000, Vol. 43, No. 2.
[11] Echauz, J. R. and Vachtesvanos, G. J., Fuzzy Grading System, IEEE Transaction of Education, 1995, Vol. 38, No.2, 158-164.
[12] Ranjit, B., An Application of Fuzzy Set in Students Evaluation", Fuzzy Sets and Systems, 1995, Vol. 74, pp 187-194.
[13] Demuth, H. and Beale, M. "Neural Network Toolbox: User's Guide", Natick, MA: Mathworks, Inc., 1995.
[14] Merry McDonald, Brian Dorn, and Gary McDonald, A Statistical Analysis of Student Performance in Online Computer Science Courses. *Proc. 35th SIGCSE Technical Symposium on Computer Science Education*, Norfolk, Virgina, USA, 2004, 71-74.
[15] Bijayananda Naik & Srinivasan, Using Neural Network to Predict MBA Student Success, *College Student Journal*, March 2004, 1-4.
[16] Dimitris Kalles & Christos Pierrakeas, Analyzing Student Performance in Distance Learning with Genetic Algorithm and Decision Trees. Hellenic Open University, 2005.
[17] Murat Gunel, Recai Akkus, Liel Hohenshell & Brian Hand, Improving Student Performance On Higher Order Cognitive Questions Through The Use of The Science Writing Heuristics. *Annual Meeting of the National Association of Research in Science Teaching*, Vancouver, Canada, 2004, 1-22.