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ALGORITHM TO OPTIMIZE THE FUZZY MODEL OF ACADEMIC PERFORMANCE USING TWO VARIABLES "ELECTRO 2018"

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ABSTRACT

This paper presents a *Genetic Algorithm to optimize a Fuzzy Sets that model a phenomenon using Two Variables* (GAFSP2V). The Academic Student Performance has been considered as an application phenomenon that is estimated by the average grade of the first-semester university that represents the output variable. The two input variables are: 1) the *Average of high School* (AS) and 2) *the Aptitude Test* (AT). Three fuzzy sets described the above variable. An individual (solution) is a set of fuzzy sets that are optimized by using a *Genetic Algorithm* (GA). The GAFSP2V can be extended such that more than two input variables can also be applied in some other areas, i.e., social, economic, and engineering, just for mentioning a few of them.

Keywords: Genetic Algorithms, Fuzzy Sets, Modeling

RESUMEN

En este artículo se presenta el *Algoritmo Genético para optimizar los Conjuntos Difusos que modelan un fenómeno a partir de dos variables (*GAFSP2V). Se toma como fenómeno de aplicación el Rendimiento Académico de estudiantes, el cual es estimado por las calificaciones del primer semestre que representan la variable de salida. Las variables de entrada son: 1) el *promedio de procedencia* (AS) y 2) *la prueba de aptitud* (AT). Cada variable es descrita por tres conjuntos difusos. Entonces, un individuo (solución) es un conjunto de conjuntos difusos los cuales son optimizados empleando un Algoritmo Genético. El GAFSP2V puede extenderse para considerar más de dos variables de entrada y además puede aplicarse en otras áreas, p. ej., las sociales, económicas, e ingeniería, por citar solo algunas.

Palabras Clave: Algoritmos Genéticos, Conjuntos Difusos, Modelado

1. INTRODUCTION

Many techniques related with *artificial intelligence* as *Fuzzy Logic* (FL) [1][2], *artificial neural networks* [3], *evolutionary algorithms* [4][5], *expert systems* [6], Etc. are attractive due to its effectiveness in solving some complex problems in areas of control [7], engineering [8], optimization [9], linguistic [10], and others. *Academic Performance* (AP) is a complex educational topic due it is a multifactorial and nondeterministic phenomenon [11]. Also, it is well known that the administrative policy of any higher-education institution requires to improve terminal efficiency [12] that it is AP's consequence. It is convenient to obtain an AP model that helps to identify and opportunely take care of some problems related to students' academic attention [13]. When academic problems are identified, it can be facilitated by the activation of institutional support mechanisms to minimize student's failure [14]. The concept model is defined as a representation of an object, system, or an idea [15]. In this sense, models are used in communication, entertainment, instruction, prediction and experimentation [16]. In education, some models are used to classify learning styles [17] that identify the weaknesses of students on early stages of study [18]. Other approaches focus on using student models to coordinate the computer systems that help students, known as intelligent tutors [19]. GA and FL techniques are used in this work to obtain an AP model. GA is an evolutionary algorithm that proposes the use of solutions' population that is refined. The idea is that the ancestors can pass the best characteristics to their descendants from generation to generation [20]. Therefore, is acceptable to think that the GA is

robust, efficient and effective to solve some complex problems and achieve optimized solutions [21].

On the other hand, FL has the facility to process data, according to linguistic variables and degree of memberships [22]. FL can model imprecise reasoning and complex systems [23]. Specific problems are resolved with a hybrid theory like GA and FL [24] [25]. In this work, an extension of [26] is presented. The enhancement considers two variables to describe the AP phenomenon. These variables know as *input variables* or *explanatory variables* are the AS and the AT.

This work is organized as follows. Section 2 provides the theoretical fundament for the development of GAFSP2V, and Section 3 describes the GAFSP2V. An example of the application of GAFSP2V is showed in Section 4. Finally, conclusions and future work are presented in Section 5.

2. BACKGROUND

Below it is presented the most relevant concepts of the theoretical framework used to address the problem of modeling. The FL is a type of logic that allows an approximation of human reasoning through *Fuzzy Sets* (FS) and *Logical Rules* (LR) [27]. GA addresses the optimization problem [28].

2.1. Fuzzy Logic

FL, unlike bi-valued logic, is based on the idea that every statement is valid but with a degree of membership whose variation is between zero and one [29]. The description of a variable is done with a series of FS, where they are associated to a linguistic label. These labels are qualifiers that involve *possibilistic uncertainty* that refers to the fact of boundaries between the qualifiers related for describing something that is not well defined. The FL attends to the statement that there is not a reasonable number that says when a person is considered high or low. FS's make the graphic representation between the qualifier and a degree of membership for a given value, where trapezoidal and triangular are most common forms. In this work, triangular FS's are used because they are the simplest and with enough characteristics to describe the qualifiers used in the AP's variables. The features of the FS are shown in Figure 1. Each FS has an associated label with it. The membership function is on the ordinate axis, and it indicates the degree of membership of x in the FS. The intersection of FS is defined as [30],

$$(A^1 \cap A^2) = min\left(\propto (A^1(x)), \propto (A^2(x))\right) \Big| x \in X \qquad (1)$$

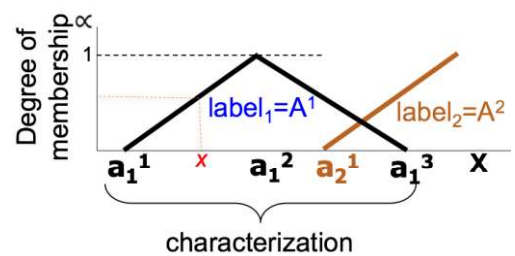

Fig. 1. FS Features [32]

2.2. Genetic Algorithm

GA is a formal approach to the evolutionary concept. The GA used as a base is presented in [26], and that is referred here as GA^{AP}. GA^{AP} seeks individuals whose characteristics make a better description of the AP phenomenon.

GA^{AP} is described as follows. The initial population is a set of individuals. Each one of them is a candidate solution to the search that is done. The individual that best describes the phenomenon is searched. The population is updated in each iteration (generation), and the individuals of the new population are the best after they are subjected to a filter that evaluates their adjustment measure. In each iteration, the individuals are undergoing to the recombination and alteration of characteristics. The recombination occurs with the parent's individuals characteristics to generate a child. The modification of characteristics occurs randomly throughout the population and creates mutated individuals. Among the parents, the children, and the mutated individuals, those with better features are chosen, in an amount equal to the size of the initial population. Then, the proportion of the population remains invariant in each generation.

2.3. Adjustment Measurement Function

To make the adjustment measurement the magnitude of the error, least squares, Etc., can be used. This type of analysis is also known as a performance measure or error measurement. In this work, the *Relative Error Magnitude* (REM) is used [31],

$$REM = \frac{|MAP - EAP|}{EAP} \tag{2}$$

where MAP is the *Measured AP*, and the EAP is the *Estimated AP*. The average operation is done for the calculation of REM over multiple registers,

$$REMM = \frac{1}{N}\sum_{i=1}^{N} REM_i \tag{3}$$

where N is the records number.

3. DESCRIPTION OF MODEL AND GAFSP2V

The *Model of Academic Performance of student from Two Explanatory Variables* (MAP2V) has been described previously to facilitate the GAFSP2V explication.

3.1. MAP2V description

Model MAP2V is defined in general terms as the model presented in [32],

$$MAP2V = \begin{matrix} f(EV, var_explained, LR) \\ f(EV, AP, LR) \\ f(AT, AS, AP, LR) \end{matrix} \tag{4}$$

The MAP2V is based on **I)** a set of fuzzy sets with labels that describe *Explanatory Variables* (EV) and AP, and **II)** a set of logical rules of *if-then* type.

I) Each variable is described by three FS's distributed in interest range.

$$\begin{aligned} AT &= \{FS^{AT1}, FS^{AT2}, FS^{AT3}\} \\ AS &= \{FS^{AS1}, FS^{AS2}, FS^{AS3}\} \\ AP &= \{FS^{AP1}, FS^{AP2}, FS^{AP3}\} \end{aligned} \tag{5}$$

Each FS is described by three parameters,

$$FS^{Ayx} \equiv \left(a_1^{Ayx}, a_2^{Ayx}, a_3^{Ayx}\right) | y = T, S, P; x = 1,2,3 \tag{6}$$

where

$$a_1^{Ayx} < a_2^{Ayx} < a_3^{Ayx} \tag{7}$$

Each FS has a label associated with it.

$$\begin{aligned} &FS^{AT1}, FS^{AS1} \equiv small && FS^{AP1} \equiv low \\ &FS^{AT2}, FS^{AS2} \equiv medium && FS^{AP2} \equiv average \\ &FS^{AT3}, FS^{AS3} \equiv big && FS^{AP3} \equiv high \end{aligned} \tag{8}$$

For the FSs proposed in Fig. 2, the medium qualifier and the big qualifier describe a 60 score on the AT. The degree of membership for the *medium* is higher than the degree of membership for the *big*.

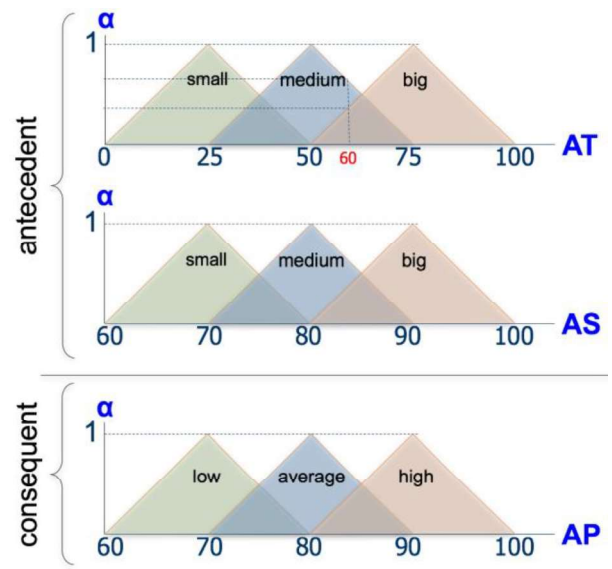

Fig. 2. FS that describe individual characteristics [32].

II) EV and the AP are in the antecedent and consequent of the logical rules, respectively. The logical rules are generated with statements of the form,

R1) The student with a *small* score in the AT *and* the student with a *small* score in the AS have a *low* AP
R2) …
R5) …
R9) The student with a *big* score in the AT *and* the student with a *big* score in the AS have a *high* AP

So, the MAP2V rules are like as,

R1) *if* FS^{AT}(small) and FS^{AS}(small) *then* FS^{AP} (low) (9)
R2) *if* FS^{AT}(small) and FS^{AS}(medium) *then* FS^{AP} (low)
R3) *if* FS^{AT}(small) and FS^{AS}(big) *then* FS^{AP}(average)
R4) *if* FS^{AT}(medium) and FS^{AS}(small) *then* FS^{AP}(low)
R5) *if* FS^{AS}(medium) and FS^{AT}(medium) *then* FS^{AT}(average)
R6) *if* FS^{AT}(medium) and FS^{AS}(big) *then* FS^{AP}(high)
R7) *if* FS^{AT}(big) and FS^{AS}(small) *then* FS^{AP}(average)
R8) *if* FS^{AT}(big) and FS^{AS}(medium) *then* FS^{AP}(high)
R9) *if* FS^{AT}(big) and FS^{AS}(big) *then* FS^{AP}(high)

Since the rules do not change, different solutions are available for a_x^{Ayx} variations.

3.2. GAFSP2V description

The algorithm is an extension of [26]. The matrix *M* is a member (*individual*) of the population *P*, i.e., $M \in P$. Each member *M* has FSs, which are involved in rules (9), and it is defined as,

$$M = \left(FS^{AT}, FS^{AS}, FS^{AP}\right) \equiv \begin{bmatrix} a_{1,1} & \cdots & a_{1,9} \\ a_{2,1} & \cdots & a_{2,9} \\ a_{3,1} & \cdots & a_{3,9} \end{bmatrix} \equiv \begin{bmatrix} a_{small}^{AT} & a_{small}^{AS} & a_{low}^{AP} \\ a_{medium}^{AT} & a_{medium}^{AS} & a_{average}^{AP} \\ a_{big}^{AT} & a_{big}^{AS} & a_{high}^{AP} \end{bmatrix} \tag{10}$$

where, for example,

$$a_{small}^{AT} = \left[a_{1,1}, a_{1,2}, a_{1,3}\right] \tag{11}$$

Each *M* is a *candidate solution*. The *M* can be as two blocks of fuzzy sets. In the first, *antecedent* fuzzy sets are included. The second has *consequent* fuzzy sets, i.e., $M \equiv [\tilde{a}_A, \tilde{a}_C]$. This representation is used to compute crosses. Then, the genetic representation (genotype, (*G*)) has the form,

$$G = \begin{bmatrix} g_{1,1} & \cdots & g_{1,9} \\ g_{2,1} & \cdots & g_{2,9} \\ g_{3,1} & \cdots & g_{3,9} \end{bmatrix} \equiv \begin{bmatrix} g_{small}^{AT} & g_{small}^{AS} & g_{low}^{AP} \\ g_{medium}^{AT} & g_{medium}^{AS} & g_{average}^{AP} \\ g_{big}^{AT} & g_{big}^{AS} & g_{high}^{AP} \end{bmatrix} \tag{12}$$

where $g_{i,j} \mid i = 1\ldots3,\ j = 1\ldots9$ is a specific gene that has a binary value. The *G* is represented by antecedent and consequent genotype, i.e., $G \equiv [g_A, g_C]$. This *genotype* representation is used to compute the mutation.
The population is defined as,

$$P = \begin{bmatrix} M_1 \\ \vdots \\ M_n \end{bmatrix} \tag{13}$$

where *n* is the *population size*.
The parameters of each fuzzy sets are on a specific *search space*, and constraints bound these spaces. These constraints are convenient because the convergence could be fast, but this is not strictly necessary for other problems. The following description is FS^{AT}'s constraints that they are equivalent for FS^{AS} and FS^{AP}.

$$\begin{aligned} &a_{1,1} = lower\ bound \equiv 0 \\ &a_{3,3} = upper\ bound \equiv 100 \\ &a_{1,1} \le a_{1,3} \le \frac{3}{4}[a_{3,3} - a_{1,1}] \\ &a_{1,1} \le a_{1,2} \le a_{1,3} \\ &\tfrac{1}{4}[a_{3,3} - a_{1,1}] + a_{1,1} \le a_{3,1} \le a_{3,3} \\ &a_{3,1} \le a_{3,2} \le a_{3,3} \\ &a_{1,1} \le a_{2,1} \le a_{1,3} \\ &a_{3,1} \le a_{2,3} \le a_{3,3} \\ &a_{2,1} \le a_{2,2} \le a_{2,3} \end{aligned} \tag{14}$$

The initial population *P(0)* is randomly ordered *P´(0)*, and this makes sure a cross of features among the population's members.

$$P'(0) = \begin{bmatrix} M_1' \\ \vdots \\ M_n' \end{bmatrix} \equiv \begin{bmatrix} \tilde{a}_{A_1}' \ \tilde{a}_{C_1}' \\ \vdots \\ \tilde{a}_{A_n}' \ \tilde{a}_{C_n}' \end{bmatrix} \tag{15}$$

In the *crossover* step, a new population of sons M^c is generated. Two parents generate two sons. Sons have genes crossed of the parents as,

$$M^c = \begin{bmatrix} \tilde{a}_{A_1}' \ \tilde{a}_{C_2}' \\ \tilde{a}_{A_2}' \ \tilde{a}_{C_1}' \\ \vdots \\ \tilde{a}_{A_{k-1}}' \ \tilde{a}_{C_k}' \\ \tilde{a}_{A_k}' \ \tilde{a}_{C_{k-1}}' \end{bmatrix} \tag{16}$$

M^c is added to parent population *P´(0)*, and it generates *P´´(0)*.

$$P''(0) = \begin{bmatrix} P'(0) \\ M_1^c \\ \vdots \\ M_k^c \end{bmatrix} \equiv \begin{bmatrix} M_1'' \\ \vdots \\ M_m'' \end{bmatrix} \mid m = m + k \tag{17}$$

$$k = n \text{ if } n \text{ is even number}$$
$$k = n - 1 \text{ if } n \text{ is odd number}$$

The mutate step generate a new population of sons M^d that is added to $P''(0)$

$$P'''(0) = \begin{bmatrix} P''(0) \\ M_1^d \\ \vdots \\ M_m^d \end{bmatrix} \equiv \begin{bmatrix} M_1''' \\ \vdots \\ M_q''' \end{bmatrix} \mid q = 2m \tag{18}$$

The mutation is operated over g_A, and $g_C \in G$. In this step each $M \in P''(0)$ could be mutated in $\tilde{a}_A''$ and/or $\tilde{a}_C''$ with 0.3 of probability predefined in this case. Finally, n best individuals are selected from $P'''(0)$ using the measurement function (2). Here, the rules (9) are used with each register and they generated a number. The sum of this numbers (3) is the indicator to select a new generation $P(1)$ that have the minimum values. $P(0)$'s process is reproduced for $P(1)$. The loop procedure stops if the best individual does not change in eight generations.

4. APPLICATION CASE

A case where the GAFSP2V is applied is shown. The data are obtained of a database of a participated higher education school. Here, 57 registers are got. Each register has data about a student of his AT, AS, and AP. For example, one student that has 48.4 in AT and 69.1 of AS, obtained 76.29 in AP, Fig. 3.

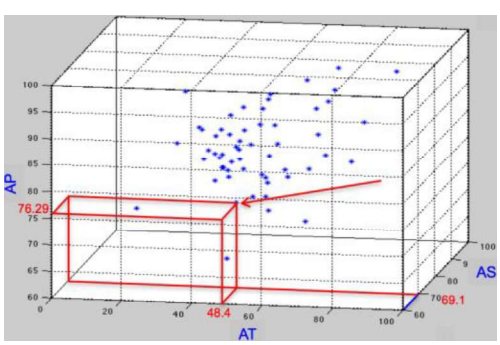

Fig. 3. Data to analysis

FS with the best characteristics to describe MAP2V are obtained (^{S}MAP2V), Fig. 4. The characterization of each FS is marked with correspondent numbers. The numbers are organized in a matrix shown in each figure in order not to confuse the FS's values.

The ^{S}MAP2V exhibits a *solution surface* (SS) in 3D space. The SS is the one that best traces the AP records shown in Fig. 3. Figure 5 shows the SS, and the point corresponded with the AP obtained using specific AT and AS values. For example, a student who has 69 from AS and got 48.4 in AT, then the real amount of AP is 76.29 (Fig. 3), and the estimated value is 78.5 (Fig. 5). As it is observed, the SS presents areas with pronounced slopes. The above is because there are no records to obtain the model that are located in those coordinates.

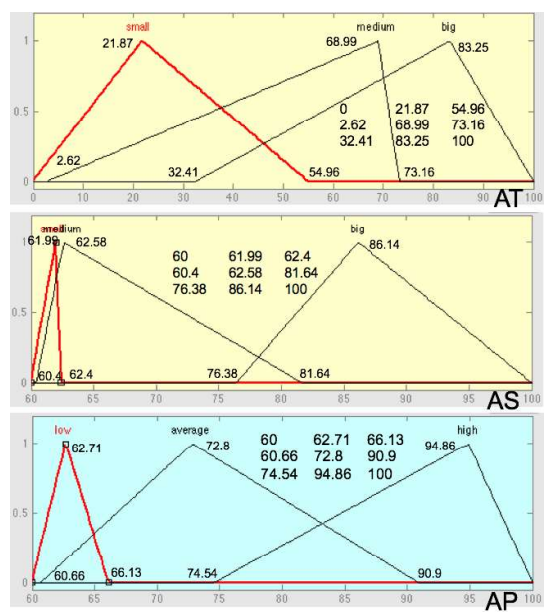

Fig. 4. Optimized FSs of MAP2V

The equation (3) is the criterion that guarantees the search of the best approximation of the MAP2V to all the registers (real values) used in it, obtaining in this case an MMER = 0.0537. Forty five records are used (different from those shown in Figure 3) to validate MAP2V and got an MMER = 0.066.

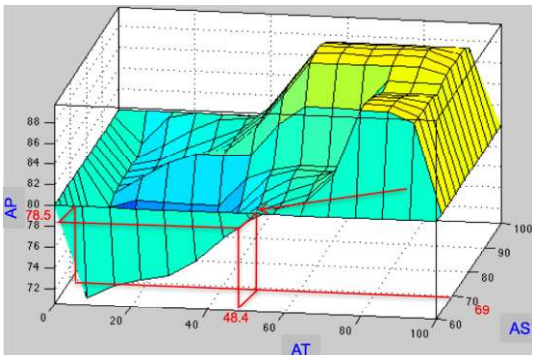

Fig. 5. Solution surface (SS)

5. CONCLUSIONS

The GAFSP2V gives the best FS to describe the AP phenomenon. The performance indicator measurement has been improved, although it penalizes a little on such action using the model obtained with the test data. The GAFSP2V can be used in other study areas since the rules can be expanded and the restrictions of the FSs placed in GA^{AP} can be modified.

6. REFERENCES

[1] J. Mendel, "Fuzzy Logic Systems for Engineering: A tutorial", *Proceeding of the IEEE,* vol. 83, no. 3, pp. 345-377, March 1995.

[2] M. Algazar, H. AL-Monier, H. Abd EL-Halim, M. Ezzat El Kotb Salem, "Maximum Power point tracking using fuzzy logic control," *International Journal of Electric Power & Energy System*, vol. 39, no. 1, pp. 21-28, July 2012.

[3] M. Frega, "Neuronal Network Dynamics in 2D and 3D In Vitro Neuroengineered Systems". [S.l.]: *Springer*, 2018.

[4] G. di Tollo, F. Lardeux, J. Maturana, F. Saubion. "An Experimental Study of Adaptive Control for Evolutionary Algorithms", *Applied Soft Computing*, vol. 35, pp. 359-372, October 2015.

[5] K.S. Tang, K.F. Man, S. Kwongs. "Genetic Algorithms and their applications". *IEEE Signal Processing Magazine*, vol. 13, no. 6, pp. 22-37. November 1996.

[6] Y. Yuan, S. Liang, S. Gan, J. Zhong and Q. Xiong. "Expert control system–based multimode hybrid switching control strategy for microwave lignite drying", *An International Journal of Drying Technology*, vol. 35, no. 12, pp. 1468-1480, June 2017.

[7] L. Zhi, L. Han-Xiong. "A probabilistic Fuzzy System for Modeling and Control", *IEEE Transactions on Fuzzy Systems*, vol. 13, no. 6, December 2006.

[8] P. Rowcliffe, J. Feng. "Training Spiking Neuronal Networks With Applications in Engineering Tasks". IEEE Transactions on Neural Networks, vol. 19, no. 9. September 2008.

[9] J. M. Rendel, S. P. Flassse. "Hybrid Methods Using Genetic Algorithms for Global Optimization". *IEEE Transactions on Systems, Man and Cybernetics-Part B: Cybernetics*, vol. 26, no. 2, April 1996.

[10] M. Gen, R. Cheng. *Genetic Algorithms and Engineering Optimization (Engineering Design and Automation)*. Wiley-Interscience, 1999.

[11] J. I. Rotgans, H. G. Schmidt. "The Intricate Relationship Between Motivation and Achievement: Examining the Mediating Role of Self-Regulated Learning and Achievement-Related Classroom Behaviors". *International Journal of Teaching and Learning in Higher Education*, vol. 24, no. 2, pp. 197-208, 2012.

[12] A. Toscano, A. Vergara, C. Ochoa-Zezzatti, J. Ponce, R. Betancourt, S. Olivares. "QUALITY ANALYSIS IN EDUCATION: TERMINAL EFFICIENCY IN EDUCATION PROGRAM INFORMATION TECHNOLOGY", pp. 169-198, June 2015.

[13] J. M. Cunha, T. Miller, "Measuring value-added in higher education: Possibilities and limitations in the use of administrative data", *Economics of Education Review,* vol. 42, pp. 64-77, October 1994.

[14] C. Márquez-Vera, A. Cano, C. Romero, S. Ventura, "Predicting student failure at school using genetic programming and different data mining approaches with high dimensional and imbalanced data", *Springer US,* vol. 38, no. 3, pp. 315-330, April 2013.

[15] R. E. Shannon, F. A. Bernal, Simulación de sistemas: Diseño, Desarrollo e implantación. México: Trillas, 1988.

[16] E. Tarifa. *Teoría de Modelos y Simulación*. Facultad de Ingeniería: Universidad de Jujuy. 2001.

[17] E. Durán, R. Costaguta, "Minería de datos para descubrir estilos de aprendizaje", *Revista Iberoamericana de Educación,* no. 42, Marzo 2007.

[18] L. Chun-Teck, N. Lik-Neo, C. H. Mohd, G. Wei-Wei, L. Check-Yee, I. Noradzilah, "Predicting Pre-university Student's Mathematics Achievement", *Procedia-Social and Behavioral Sciences*, vol. 8, pp. 299-306, 2010.

[19] M. Larrañaga, J. A. Elorriaga, U. Rueda, A. Arruarte, "Modelado de grupos en actividades de aprendizaje basado en mapas conceptuales", *Inteligencia artificial Revista Iberoamericana de Inteligencia Artificial*, 8(24), pp. 131-148, Enero 2004.

[20] A. Petrowski, S. Ben-Hamida and Z. Michalewicz. *Evolutionary Algorithms*. London: John Wiley & Sons, Inc. 2017.

[21] J. Guo, J. White, G. Wang, J. Li, Y. Wang, "A genetic algorithm for optimized feature selection with resource constraints in software product lines", *Journal of Systems and Software*, vol. 84, no. 12, pp. 2208-2221, December 2011.

[22] H. Nguyen and E. Walker. *A first course in fuzzy logic*. Boca Raton: Chapman & Hall/CRC, 2006.

[23] L. Wang, R. Langari, "Complex Systems Modeling via Fuzzy Logic", *Proceedings of 1994 33rd IEEE Conference on Decision and Control*, August 2002.

[24] M. J. Varnamkhasti, L. S. Lee, M. R. Abu Bakar, W. J. Leong, "A Genetic Algorithm with Fuzzy Crossover Operator and Probability", *Hindawi Publishing Corporation Advances in Operations Research*, vol. 12, article ID 956498. 2012.

[25] J. C. González-Castolo, S. Ramos-Cabral, S. Hernánez-Gallardo, "Construcción de un modelo difuso optimizado del aprovechamiento académico de estudiantes en educación superior," *Revista Iberoamericana para la Investigación y el Desarrollo Educativo*, no. 12, Enero 2014.

[26] S. Ramos-Cabral, J. C. González-Castolo, S. Hernánez-Gallardo "Algorithm to optimize a fuzzy model of students academic achievement in higher education", *Revista Iberoamericana para la Investigación y el Desarrollo Educativo*, no. 2, January 2015.

[27] G. Chen, T. T. Pham, *Introduction to fuzzy sets, fuzzy logic and fuzzy control systems*. Boca Raton (Florida): CRC, 2001.

[28] H. Iba, T. K. Paul, Y. Hasegawa, *Applied genetic programming and machine learning*. Boca Raton, Fla: Taylor & Francis, 2010.

[29] G. Klir and B. Yuan, *Fuzzy sets and fuzzy logic*. [Taipei]: Pearson Education Taiwan Ltd., 2002.

[30] J. Gonzalez-Castolo and E. Lopez-Mellado, "Approximating State of DES Using Fuzzy Timed Petri Nets", *2007 IEEE International Conference on Automation Science and Engineering*, 2007.

[31] B. Seref, N. Barisci "Software Effort Estimation Using Multilayer Perceptron and Adaptive Neuro Fuzzy Inference System", *International Journal of Innovation, Management and Technology*, 2014.

[32] J. C. González-Castolo, S. Ramos-Cabral, S. Hernández-Gallardo, "Modelo Difuso del Rendimiento Académico Bi-explicado", *Revista de Gestión Educativa,* vol. 4, no. 13, pp. 55-64, Diciembre 20.