COMPETENCY ASSESSMENT MODEL FOR A VIRTUAL LABORATORY SYSTEM AT DISTANCE USING FUZZY COGNITIVE MAP

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ABSTRACT
With the development of Information Technology and Communications (ICT) are increasingly knowledge areas within it. The automatic control has contributed its Systems of Virtual Labs at Distances (SLVD) in order to share precious resources from the Internet technology which would be very difficult to generalize its cost of implementation. However the absence of a professor for monitoring control strategies designed by students, it is possible that not competent persons can assess the platform and generate a malfunction in their workstations. This paper describes a solution to the issue raised from the implementation of a model for the assessment of competitions which bases its operation on fuzzy cognitive map and operators of aggregation of information as a regulatory mechanism for access control practices in SLVD.A case study is implemented through which it is possible to determine the rate of student skills and support the decision making process for access to running practice.

KEYWORDS*:* Aggregation of information; assessment of competitions; fuzzy cognitive map; making decisions.

MSC: 90C70

RESUMEN
Con el desarrollo de las Tecnologías de la Información y Comunicaciones (TICs), son cada vez más las áreas del conocimiento que la integran. El control automático ha aportado sus Sistemas de Laboratorios Virtuales y a Distancias (SLVD) con el fin de compartir preciados recursos tecnológicos desde Internet los cuales serían muy difícil de generalizar por su costo de implementación. Sin embargo al no existir un profesor supervisando las estrategias de control diseñadas por los estudiantes, es posible que personas no competentes accedan a la plataforma y puedan generar un mal funcionamiento en sus estaciones de trabajo. La presente investigación describe una solución a la problemática planteada a partir de la implementación de un modelo para la evaluación de competencias el cual basa su funcionamiento en mapa cognitivo difuso y operadores de agregación de la información como mecanismo regulatorio para el acceso a las prácticas de control en un SLVD. Se implementa un estudio de caso mediante el cual es posible determinar el índice de competencias del estudiante y apoyar el proceso de toma de decisiones para el acceso a la ejecución de la práctica.

1. INTRODUCTION

The new way to manage everyday processes from the introduction of Information Technology and Communications (ICT) integrates all areas of knowledge where the teaching-learning process in its various functions incorporated in its action innovative technologies. The teaching of the Automatic Control has provided its systems of Virtual Labs at Distance (SLVD) in order to share precious resources from the Internet technology which would be very difficult to generalize its implementation cost.

A System Laboratory Distances can be defined as a tool that uses a communication network, where users and laboratory equipment are separated geographically and communications technologies are used to access these devices [14], [20].

The working philosophy of a SLVD is based on sharing resources from a technological point of view, possess high complexity where reproduction would be very costly especially in public institutions budgeted by the state. The main objective is based on achieving an availability of 24 hours throughout the week [27] with a global accessibility which would facilitate that students were not restricted to one place or time to make an oriented task [4].

However the absence of a professor for monitoring control strategies designed by students, it is possible that not competent persons can assess the platform and generate a malfunction in their workstations. In this sense, competency assessment would allow the prediction of future functionality problems or indicate the need to return to train again.

The above analysis can identify that at the present the assessment of competitions constitute an element to deepen, identifying the following dissatisfactions:

- It is lacking of mechanisms for assessing the competence of practitioners students.
- The uncertainty in determining whether a person is suitable for a certain practice.

Taking as a case of study the process of evaluation of competencies, it is proposed as a general objective of the research: to develop a model for assessment of competitions with the implementation of fuzzy cognitive map and operators of the aggregation of information as a regulatory mechanism of the access control practices for Virtual Laboratory System and Distance.

2. MATERIALS AND METHODS

In this session the inference process is described for making decisions about competency assessments and raises the general characteristics of the model to facilitate understanding of the proposal.
The model for the assessment of competencies is geared to support making decisions for a system of virtual laboratories and distance, it is based on three basic stages: input, processing and output of information. Figure 1 shows a general outline of the proposal.

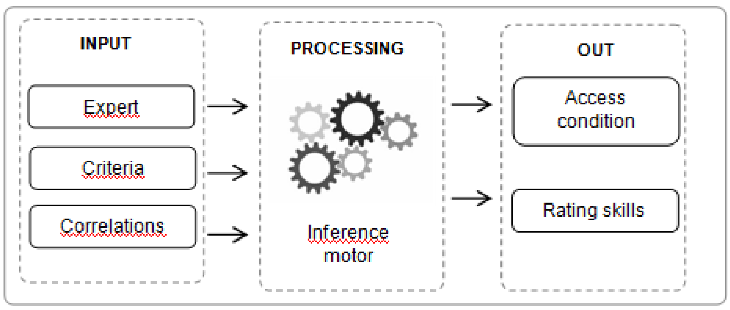

Figure 1: General scheme of the proposed model

Description of model stages

Data Entry: The process by which the model takes the data required for processing [28].In the proposal, there are manually managed data are those provided directly by the user as management experts, indicators and causal relationships.
Information processing: Capability of the model to perform calculations according to a predetermined sequence of operations that allows data transformation of low interpretability in organized information.
The inference process and organization of the information is guided by using fuzzy cognitive maps.
Fuzzy cognitive maps (MCD) are fuzzy models with feedback to represent causality.
They combine theoretical tools of cognitive maps, fuzzy logic, neural networks, semantic networks, expert systems and nonlinear dynamic systems [7], [17].
This technique allows to model the feedback system with diffuse degrees of causality in the interval [0,1], where each node represents a fuzzy set or event that occurs to some degree. The nodes are causal concepts and can model events, actions, values, goals or processes. By using this technique are also obtained the benefits of the visual modeling, the simulation and the prediction [24].
In the MCD there are three possible types of causal relationships between concepts:

- $W_{ij} > 0$ indicates a positive causality between C_i and C_j concepts. That is, the increase (or decrease) in the value of C_i leads to increase (or decrease) in the value of C_j.
- $W_{ij} < 0$ indicates a negative causality between C_i and C_j concepts. That is, the increase (decrease) in the value of C_i leads to a decrease (increase) in the value of C_j.
- $W_{ij} = 0$, indicates the absence of relationship between C_i and C_j.

A MCD can be represented by a digraph in which nodes represent concepts and arcs indicate causal relation.
The intensity of the causal relationship is represented by fuzzy values [22].The values of the concepts are calculated at each step of the simulation. According to the initial vector of the MCD will converge to a fixed point, limit cycle or chaotic attractor.

The MCDs can be represented by an adjacency matrix which is obtained from the values assigned to the arcs, it can be written as:

$$E = \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & w_{ij} & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix}$$

When involved a group of experts (k), the adjacency matrix is formulated by equation (1).

$$E = \frac{1}{K}\left(E_1 + E_2 + \ldots + E_k\right) \quad (1)$$

This aggregation of knowledge allows to improve the reliability of the final model, which is less susceptible to potentially erroneous beliefs of a single expert [31]. However, the arithmetic mean is very sensitive to the presence of outliers.

One thing to keep in mind are the mistakes that experts commit for determining the sign accompanying causation [6], besides using the arithmetic mean , the magnitude of weight vanishes. Methods have been proposed that attempt to minimize the error which require some consensus are reached [2] or subsequent interaction with the expert [9] which, while desirable, is not always possible.

Departure information: The output is the ability of the model to represent the data processed and decide alternatives [26]. For the proposed model the fundamental informations are the access condition for executing control practices and the system of personal competencies.

Structure of proposed model

For the selection process, decision and interpretation of the behavior reflecting reasoning [1], [29] the intensity is processed of casual relationships [3] allowing the system to model with feedback of diffuse degree of causality [16].The authors propose a model for decision making, which is based on multi-criteria approach [12] with the use of fuzzy cognitive maps [19] and consists of the following steps:

Step 1: Identify the evaluative indicators.
Step 2: Determine the relationships between indicators.
Step 3: Obtaining of MCD.
Step 4: Static Analysis.
Step 5: Evaluation of the practitioners.

Then each of the steps are described:
Step 1: Identify the evaluative indicators
Identifying indicators to value it is based on the selection of factors involved in auto engineering skills.
Must be complied that:
Assigned indicators or criteria meet the following condition expressed in equation (2).

$$I = \{I_1 \ldots I_n\}(n \geq 2) \quad (2)$$

The domain of criteria I is finite.

Step 2: Determine the relationships between indicators

An multi-expert approach is applied where it is recommended to 7-13 experts in the area of knowledge of the subject matter, the MCDs can be integrated into one single model [15].This aggregation of knowledge allows to improve the reliability of the final model, to make it less susceptible to potentially erroneous beliefs of a single expert [8]. It asks each expressing the correlation of the indicators to which the defined scale is taken in Table 1, where positive values show a direct correlation and negative values as the inverse correlation such as shown.

Value	Impact
-1	Negatively extremely important
-0,75	Negatively strongly important
-0,50	Negatively very important
-0,25	Negatively important
0	Without importance
0,25	Important
0,50	Very important
0,75	Strongly important
1	Extremely important

Table 1: Domain linguistic variable and the corresponding real values causal

The absolute value of MCD is obtained by averaging based on a valuation prepared by experts as expressed in equation (3).

$$VA = \frac{\sum_{i=1}^{n} W_{ij}}{E} \qquad (3)$$

Where:
AV: Absolute value.
E: Number of experts involved in the process.
W_{ij}: Vector correlation given by experts to the I_{ij} indicators.
In the adjacency matrix $E_{ij} = E(I_i I_j)$ being causal function value of the arc, the node I_i imparts I_j. I_i. Causally increases I_j if $E_{ij} = -1$, and it does not impart causality if $E_{ij} = 0$.
Table 2 shows the absolute values that are obtained in the adjacency matrix are displayed.

	I$_1$	**I$_2$**	**I$_3$**	**I$_n$**
I$_1$	0	VA(1,2)	VA(1,3)	VA(1,n)
I$_2$	VA(2,1)	0	VA(2,3)	VA(2,n)
I$_3$	VA(3,1)	VA(3,2)	0	VA(3,n)
I$_n$	VA(n,1)	VA(n,2)	VA(n,3)	0

Table 2: Matrix of adjacency

Step 3: Obtaining of MCD

Figure 2 shows directed graph, called causal graph. There are different types of causality that can be expressed graphically [11], where each causal model can be represented by a graph.

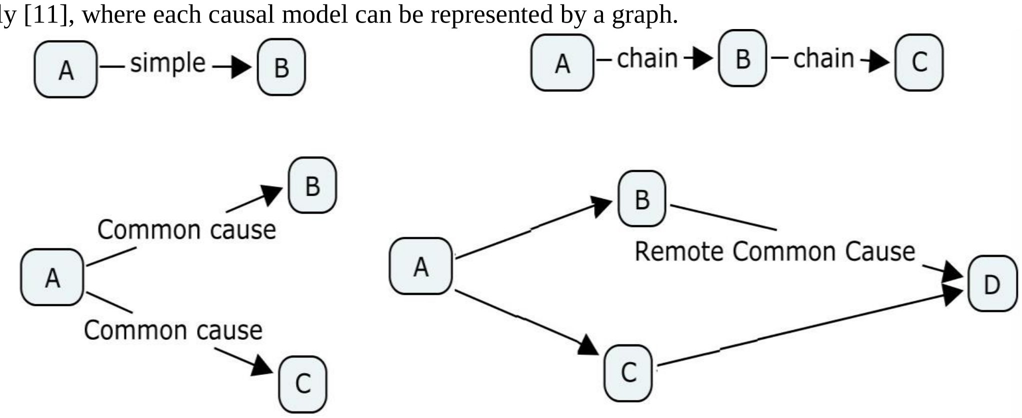

Figure 2: Scheme of causal graph

The absolute values obtained from the experts grouped by the adjacency matrix, make the connection with their respective weights between nodes [23], which in turn shape the overall fuzzy cognitive map [32].

Step 4: Static Analysis

Cognitive maps are very useful for generating knowledge since causality is diffuse, accommodate their knowledge base according to experts [13], so that its outcome will depend on a lot of knowledge expressed by experts [21]. Static analysis provides causal conceptual centrality of cognitive maps is defined with the components of the adjacency matrix. The model parameters are: output degree OD, ID input level and the centrality C [25] Degree of output obtained by the equation (4)

$$od_i = \sum_{i=1}^{n} \left\| I_{ij} \right\| \tag{4}$$

Input level obtained by equation (5)

$$id_i = \sum_{i=1}^{n} \left\| I_{ji} \right\| \tag{5}$$

Centrality obtained by equation (6)

$$C_i = od_i + id_i \tag{6}$$

Step 5: Evaluation of practitioners

In the evaluation process, it is selected as an instrument a questionnaire previously developed which has a set of questions with possible answers output which in turn are evaluated by numerical scale normalized giving as a result a vector of activation with the result obtained assigned turn the powers present in the exercise which is assessed. The decisional process is performed by the operator of information aggregation OWA, Ordered Weighted Averaging, ordered weighted average [30].This method unifies the classical criteria of decision uncertainty in a single expression [5].With the application of the aggregation process information obtained through major role, the vector competence for a hopefully analyzed by equation (7) scenario is generated.

$$F(p_1, p_2, ..., p_n) = \sum_{j=1}^{n} w_j b_j \tag{7}$$

Where:

P: Set of preferences $P = \{p_1, .., p_n\}$on the assessment of the questions asked by the students to the questionnaire

b_j: It is the largest of the jth p_j ordered.

W : Important vector obtained by static analysis with outdegree parameter sorted in descending order so that meets: Equation (8).

$$W \in [0,1]_{\mathrm{y}} \quad \sum_{j=1}^{n} W_j = 1 \tag{8}$$

Once obtained vector competencies, there is the initial vector representing the stage for the simulation and knowledge representation system based on a decision tree it arises. Figure 3 shows the tree of decision of inference whereby it is possible to express a set of rules [10].

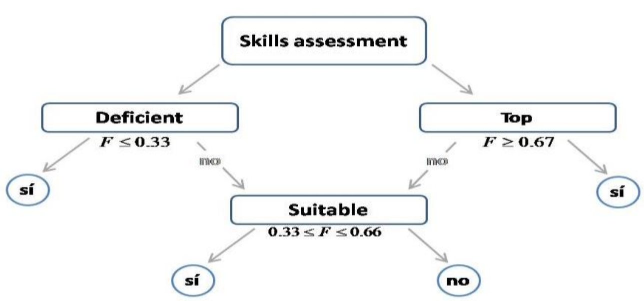

Figure 3: Tree of decision of inference

The tree can be expressed by the following set of rules:

R1: If F ≥ 0.67 Then competency assessment = Top; R2: If F ≤ 0.33 Then competency assessment E = Deficient; R3: If F ≤ 0.66 y F ≥ 0.34 Then competency assessment = Suitable
Concluding that the inference is true decisional "Yes" the result is the value consulted, otherwise it continues to consult rules until a true value.
To make the simulation of the stage, the influence of interconnected concepts to the specific item is calculated according to equation (9) using F(x)= tanh(h)expressed as follows:

$$A_i^{(K+1)} = f\left(A_i^{(K)} \sum_{i=1;\, j\neq i}^{n} A_i^{(K)} * W_{ji}\right) \tag{9}$$

Where:

$A_i^{(K+1)}$ **:** is the value of the concept C_i in step k+1 of the simulation

$A_i^{(K)}$: is the value of the concept C_j in step k of the simulation

Wji: It is the weight of the connection from concept C_j to concept C_i y f (x) is the activation function [29], [33].

3. RESULTS AND DISCUSSION

The assessment of competencies has many applications in practical life, especially when you want to predict behavior inadequate in the future .The proposed model integrates a SLVD where the process is implemented taking an example of using as a case study, which was developed with a student selected at the Central University of Las Villas. A description of the results is performed.

Steps of the implement the case of study
Step 1: Identify indicators.
To determine the evaluative indicators taken as a basis, the doctoral research by Santana [27] which proposes the following indicators:

1. Fundamentals of automation and control methods.
2. Ability to model and simulate systems.
3. Automatic regulation and control techniques.
4. Principle and application of robotic systems.
5. Applied knowledge of industrial computing and communications.
6. Design of automated control systems.
7. Principles of automatic regulation and its application to industrial automation.

Step 2: Determine the relationships between indicators.
In the process to determine the relationship between indicators from the function (1), involving seven experts, they were obtained 7 MCD being built by the function (3). Table 3 shows the adjacency matrix obtained as a result.

	I_1	**I_2**	**I_3**	**I_4**	**I_5**	**I_6**	**I_7**
I_1	0.00	0.75	0.71	1.00	0.96	0.92	0.75
I_2	0.39	0.00	0.50	1.00	0.50	0.96	0.50
I_3	0.32	0.92	0.00	0.92	0.50	0.96	0.50
I_4	0.32	0.50	0.75	0.00	0.75	0.75	0.50
I_5	0.89	0.50	0.75	0.75	0.00	1.00	0.50
I_6	0.78	1.00	0.92	0.96	0.96	0.00	0.50
I_7	0.25	0.75	0.75	1.00	0.75	0.50	0.00

Table 3: Adjacency matrix

Step 3: Obtaining of MCD.
General MCD represents the causal relationships expressed in graphical form on the assessments issued by the experts with their respective causes. Figure 4 displays the causal relationships obtained adjacency matrix Table 3.

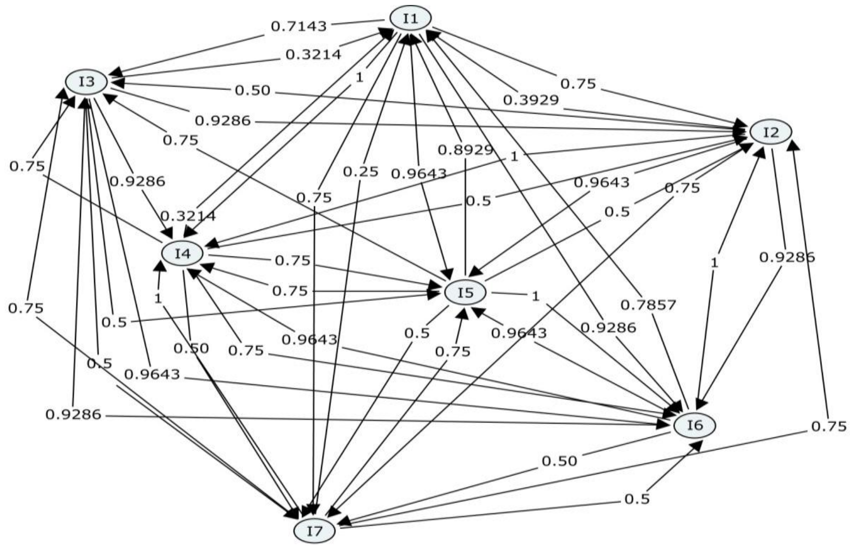

Figure 4: General fuzzy cognitive map obtained

Step 4: Static Analysis.

Given the knowledge base stored in the adjacency matrix table 3, applying the function (4), (5). Table 4 shows the static analysis obtained.

No	**Indicators**	**id**	**od**	**c**
6	Design of automated control systems.	5.11	5.14	10.25
4	Principle and application of robotic systems.	5.64	3.57	9.214
5	Applied knowledge of industrial computing and communications.	4.43	4.39	8.821
3	Automatic regulation and control techniques.	4.39	4.14	8.535
2	Ability to model and simulate systems.	4.43	3.86	8.285
1	Fundamentals of automation and control methods.	2.96	5.11	8.071
7	Principles of automatic regulation and its application to industrial automation	3.25	4.00	7.250

Table 4: Static Analysis

Source: presentation of the authors.

The fundamental result of the static analysis of the system formed by the evaluative indicators shows that the three most important indicators in descending order are: design of automated control systems, principle and application of robotic systems, industrial applied computing and communications knowledge.

Step 5: Evaluation of practitioners

In the evaluation process, is selected as an instrument a questionnaire previously developed which has a set of questions with possible answers which in turn are evaluated by numerical scale standard managed by SLVD giving as a result a role competency representing vector of initial activation. Table 5 shows the results of evaluation practitioners.

Stage	Results of the questionnaire	Important vector	Activation vector
Case 1	1; 1; 0.5; 0.25; 0.5; 0; 0	0.17; 0.169; 0.145; 0.137; 0.132; 0.127; 0.118	0.170; 0.169; 0.072; 0.034; 0.033; 0; 0

Table 5: Dynamic Analysis

Applying the simulation process using equation (9) an attractor reached iteration 9 returning the output vector C9 = [0.89; 0.97; 0.97; 0.99; 0.97; 0.98; 0.98.

After performing the process of inference applied to the major role (7) on the set of rules derived from the decision tree, is obtained as a result the assessment of competencies where proficiency rate of 0.48 considered is obtained according to the rules inference competencies as appropriate index. It is proposed that the user can access the control practices requested.

4. CONCLUSIONS

With the development of research, a model for the assessment of competencies based on indicators of competency by MCD and OWA operators is presented. A case study of its application, where it was possible to demonstrate the applicability of the model is applied.
With the implementation of the proposed model, a fuzzy cognitive map is built from experts formalizing the critical indicators for assessing competencies.
Once applied the study of case, it is possible to assume a pattern of behavior on an environment of high uncertainty determining the proficiency rate of practitioner proposing the implementation of practices in the SLVD.

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