# MODEL FOR DECISION-MAKING ON ACCESS CONTROL TO REMOTE LABORATORY PRACTICES BASED ON FUZZY COGNITIVE MAPS

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**ABSTRACT**
The operations of Industrial systems require to maintaining the stability of certain operation parameters. With this aim were developed the control systems. They allow the operation of processes automatically, replacing human procedures of measurement and intervention. Development of automation on facing the demands of the different industrial processes that required modern methods of control. Training the professionals to meet the demands of automation in Cuba is carried out from the Automation Engineering. In this context, the Control Systems is a critical discipline in the academic formation of graduated ones. For the correct development of the Control Engineering matter included into the Control Systems discipline, laboratory practices as a kind of lesson play an important role. The user (student) can do the practices in two platforms: by using physical laboratories with equipment related to the received subject, and/ or using a distance or remote way. The use of a Remote Laboratory System for laboratory practices introduces problems in terms of supervising the work carried out by the students, because is not possible to have a full-time supervisor for this function. This research presents a model for decision-making on access control to laboratory practices. The proposal is described through a workflow with four components. Artificial intelligence techniques were used to model causal knowledge using Fuzzy Cognitive Maps. For the validation of the model, several methods and techniques were used. The proposed experimental design demonstrated the correlation of the research variables.

**KEYWORDS*:*** Control Systems, Control Engineering Matter, Remote Laboratory System, Fuzzy Cognitive Maps, Decision making.

**MSC**: 90C70

**RESUMEN**
Las operaciones de los sistemas industriales requieren mantener y estabilizar ciertos parámetros de operación. Con este objetivo se desarrollaron los sistemas de control. Estos permiten la operación de procesos de forma automática, reemplazando los procesos humanos de medición e intervención. El desarrollo de la automatización asumió las exigencias de los diferentes procesos industriales que requerían de modernos métodos de control. La formación de profesionales para atender las demandas de la automatización en Cuba se realiza desde la carrera de Ingeniería en Automatización. En este contexto, la disciplina Sistemas de Control es crítica en la formación académica. Para el correcto desarrollo de la materia Ingeniería de Control incluida en la disciplina Sistemas de Control, se realizan prácticas de laboratorio como forma de clase. El usuario (alumno) puede realizar las prácticas en dos plataformas: utilizando laboratorios físicos con el equipamiento requerido, y/o utilizando la modalidad a distancia o remota. El hecho de utilizar un Sistema de Laboratorio Remoto para las prácticas introduce una dificultad en cuanto a la supervisión del trabajo realizado, porque es complejo contar con un supervisor a tiempo completo para esta función. Esta investigación presenta un modelo para la toma de decisiones sobre el control de acceso a las prácticas de laboratorio. La propuesta se describe a través de cuatro componentes. Se utilizan técnicas de inteligencia artificial para modelar el conocimiento causal utilizando mapas cognitivos difusos. Para la validación del modelo se combinaron varios métodos y técnicas. El diseño experimental propuesto demostró la correlación de las variables de investigación.

**PALABRAS CLAVES:** Sistemas de Control, Asignatura de Ingeniería de Control, Sistemas de Laboratorios Remotos, Mapas Cognitivos Difusos, Toma de Decisiones.

## 1. INTRODUCTION

The technological development achieved by society outcome a mechanization of industrial processes with the aim of simplifying the physical work. For this purpose, ingenious instruments and machines have been developed and used as tools in many industrial processes. Mechanization was undoubtedly a significant step of technological development, but increasing productivity involved new challenges. Industrial systems emerge from energy development and motorization of mechanical processes, allowing the serial production with a significant efficiency. For their operations these systems require to maintain the stability of certain operation parameters. With this aim were developed the control systems. They allow the operation of processes automatically, replacing human processes of measurement and intervention. Automation was quickly introduced in the essential processes of science and technology. Development of Automation science assumed the demands of the different industrial processes that required modern methods of control.

Training the professionals on facing the demands of automation in Cuba is carried out from the Automation Engineering degree. In this context, the Control Systems (CS) is a critical discipline in the academic curriculum of graduated ones. CS discipline contains a group of matters that makes up the basic curriculum, such as: Modeling and simulation, Electrical Machinery, Control Engineering (I and II), Processes, and Control of Process (I and II). Particularly, training the contents of Control Engineering matter, laboratory practices are carried out as a kind of lesson. In this context, the student can carry out the practices in two platforms: by using physical laboratories with equipment related to the received subject, and/ or using distance or remote way. For implementing the last way, users (students) access to centralized physical equipment using remote laboratories. The fact of using a Remote Laboratory System (RLS) for laboratory practices introduce several problems in terms of supervising the work carried out by the students, because of this, it is not possible to have a full-time supervisor for this function. On the other hand, the development of skills and self-preparation of students is a continuous training and it is difficult to have certainty about their preparation to assume the successful development of laboratory practices during all the process.

A student without previous training to carry out laboratory practice begins a trial process looking for a possible answer for the technical problem to be assessed. The problem mentioned previously causes an environment of uncertainty and, subsequently, a poor preparation causes the following insufficiencies during the practice:

- Unnecessary operating time for physical devices used in the laboratory practices.
- Generation of random solutions through a trial-and-error process.

Taking into account these challenges, an analysis that guides the successful development of laboratory practices is considered appropriate. From the current state of the process, it can be defined as a decision-making problem where:

- There is a set of alternatives that represent the students who access the RLS, in order to carry out the laboratory practices.
- It is required a classification method that allows diagnosing the skills of the alternatives to establish access control to the available laboratory practices.

Decision-making problems similar to the above mentioned have been addressed in the scientific literature from the application of artificial intelligence techniques [1]. The representation of the causal knowledge with the use of Fuzzy Cognitive Maps (FCM) would allow the inference of the behavior of the students’ skill based on establishing the control of access to the laboratory practices.

An alternative to solve the problem of the access to RLS would consist of establishing a satisfactory access control mechanism. For this, a skills diagnosis would represent the inferential base of the access control. Through the study of the scientific literature on RLS for Control Engineering practices, the following insufficiencies were found [2]:

- The RLS do not have techniques to diagnose the skills of the students who carry out the laboratory practices.
- The RLS do not have access control mechanisms based on the students' abilities to access the laboratory practices.

In this paper we introduce a model based on FCM for decision-making on access control for the successful development of Control Engineering II laboratory practices. We establish as a hypothesis that: if a model based on FCM is developed, decision-making on access control will be guaranteed for the successful development of Control Engineering II laboratory practices.

## 2. MATERIALS AND METHODS

The proposed model is aimed at supporting the workflow for access control to laboratory practices through skills diagnosis. It integrates in its structure the four components that make it up. The model is based on linguistic preference relationships [3], reasoning behavior [4] and the management of causal relationships [5] based on the selection of skills.

For the modeling, the causal feedback of fuzzy graphs was used as a reference [6]. It is based on a multi-criteria multi-expert approach [7], represented by FCM [8]. As a result, the model for decision-making on access control to laboratory practices was obtained from the skills diagnosis based on its components [9-11]. For each component, is made a textual description based on the mathematical model that supports the decision-making process. In Figure 1, we present a general outline of the proposed model.

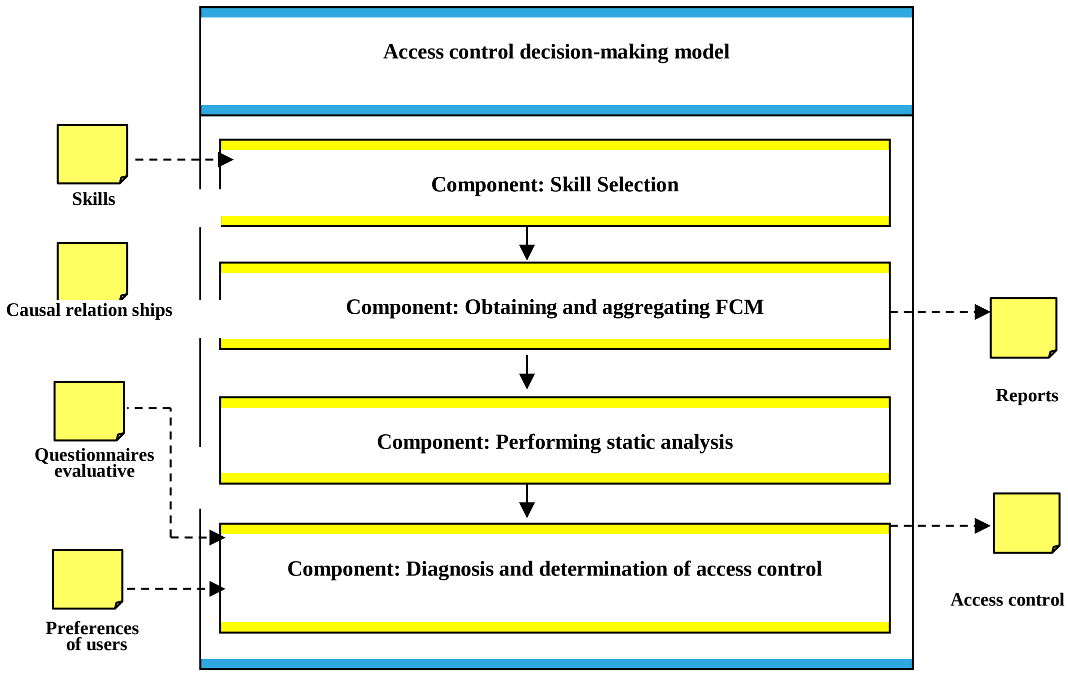



**Figure 1.** General outline of the model's operation

### 2.1 Component: Selection of skills

The skill selection component is defined as the tuple $\{E, H\}$, where:

- $E$: represents the non-zero set of experts involved in the process for selecting skills.
- $H$: represents the set of requirements or skills to be identified in the study plan and consultation with experts.

For the group of experts involved in the identification of skills and their causal relationships, it must be met as a necessary condition that the domain of values that represents the experts is not null. Several authors have theorized about the optimal number of experts to use in processes of this type [12,13]. Based on these authors, it is assumed as a threshold that the domain of the$E_i \rightarrow \exists, 7 \leq i \leq 15$ and is expressed by equation 1:

$$E_i = \{Hp_1, Hp_2, \ldots, Hp_r\}, r \geq 1, r \in \mathbb{N}, r \neq \infty \tag{1}$$

For the selection of skills, the Delphi method was used, through which the knowledge of the experts was obtained in conditions of anonymity, guaranteeing a geographical dispersion of the participants [14]. For applying the Delphi the Delphi method, it is necessary to identify the experts in the field of Automation and Computer Systems. For this, the following criteria were considered:

- Candidates must be Assistant Professor at least.
- Candidates have at least five years of experience as a university professor linked to Automation or Computer Systems.
- Candidates have more than 5 years of work experience in industrial processes.
- Candidates have published their research results in scientific journals.
- The participation of at least two national institutions was guaranteed.

For the expert’s selection, a curricular synthesis of candidates was reviewed. Subsequently, nine experts were selected. The characteristics of this group endorses their academic background for our research: 100% come from the Cuban Educational System, 100% are Full or Associate professor, 66.6% have worked in industrial processes, 100% have published at least five scientific articles in scientific journals of Automation and Computer Systems. For the selection of skills, a study was carried out as an initial basis for Cuban curriculum in Automatic Engineering degree, as well as the teaching experiences with the help of experts, using the Delphi method in its first round. The results obtained were submitted to an exploratory focus group where the proposal was enriched. As a result, a set of skills and recommendations used to enrich the research was obtained.

### 2.2 Component: Obtaining and aggregating Fuzzy Cognitive Maps

This component aims at representing the causal knowledge expressed by experts about the skill set. Figure 2 shows the workflow for obtaining the causal model.

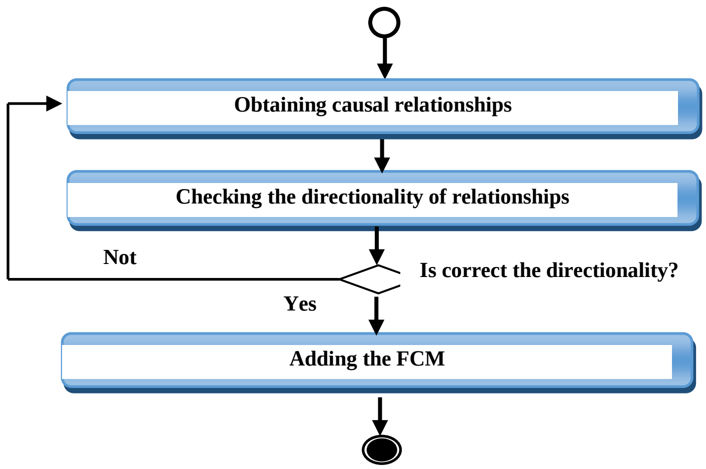



**Figure 2.** Workflow for obtaining the causal model

The workflow for obtaining the causal model is the following:

1. Obtaining the causal relationships: based on the assessment issued by the experts on the different concepts, the causal relationships are established, obtaining the causal influence. The influence can be represented positive or negatively, as well as the weight of the relationships, for which the 2-linguistic tuple method is used in the representation proposed by Pérez [15].
2. Checking the directionality of relationships: It allows, based on the evaluations issued by experts, to determine if an expert did not correctly insert the direction of causal relationships.
3. Adding FCMs: Aggregation allows, once consensus among experts is obtained, to add the proposed individual causal models in a single representation. The aggregate representation constitutes the idealization of the knowledge expressed in the causal relationships of all the experts who participate.

The fuzzy linguistic approach with 2-tuples is used to characterize causal relationships [3, 16]. This approach makes it easier for experts to represent causal knowledge. Obtaining FCMs can be formalized as a decision-making problem in group. The set of experts uses a linguistic context to express the causality between the different concepts such that

$$E_i = \{e_1, \dots, e_n\} \quad (2)$$

Where,
$E_i$: represents the domain of experts involved. The group of individual mental models is expressed via a set of fuzzy linguistic terms *S* in agreement to Pérez [15], (see table 1).

**Table 1.** Set of linguistic terms used

$$S_i = \{s_0, \dots, s_k\} \quad (3)$$

| Variable | Linguistic terms | Value |
|---|---|---|
| $S_0$ | Negatively very strong | (-1,-1;-0,75) |
| $S_1$ | Negatively strong | (-1;-0,75;-0,50) |
| $S_2$ | Negatively average | (-0,75;-0.,0;-0,25) |
| $S_3$ | Negatively weak | (-0.50,-0.25, 0,0) |
| $S_4$ | Zero | (-0,25;0,0;0,25) |

| | | |
|---|---|---|
| $S_5$ | Positively weak | (0,0;0.25;0,50) |
| $S_6$ | Positively average | (0,25;0,50;0,75) |
| $S_7$ | Positively strong | (0,50;0,75;1) |
| $S_8$ | Positively very strong | (0,75;1;1) |

To represent the causal correlations between the concepts involved [17] and that represent the grouping of $H$ skills, we define:

$$H = \{H_1, \dots, H_r\}, r \geq 1, r \in \mathbb{N}, r \neq \infty \tag{4}$$

The weight of the concepts´ connections that go from the concept $H_1$ to the concept $H_r$, expressed by the experts $E$, it is represented by linguistic 2-tuples as expressed by equation 5 [18].

$$w_{ij}{}^{E} = (s_u, \alpha)_{ij}^{E} \tag{5}$$

Where,
$w_{ij}$: represents the correlation vector expressed by the experts.
$s_u$: represents the value of the linguistic term pointed to by u defined in Table 1
α : represents a symbolic translation.
Verification of the relationship's directionality consists in validating if the causal relationship expressed by the group of experts $E$ from ($E_1$ to $E_k$ ) have the same causal meaning. The causal relationships expressed by the experts $E_i$ on the concept $H_r$ with respect to the concept $H_r + 1$ must have the same sense of implication. If during the process of checking directionality inconsistencies are identified in the relationships expressed by an expert $E_i$, with respect to the rest of the experts $E_n$, the directionality expressed by this should be assessed.

The aggregation of the FCM consists of the fusion of the causal knowledge expressed individually by the experts to represent the relationships between the concepts [19]. The aggregation of knowledge allows improving the reliability of the final model, making it less susceptible to errors [20].

The aggregation process takes place from the establishment of an average function of the matrices that represent the causal knowledge of the experts, as shown in equation 6.

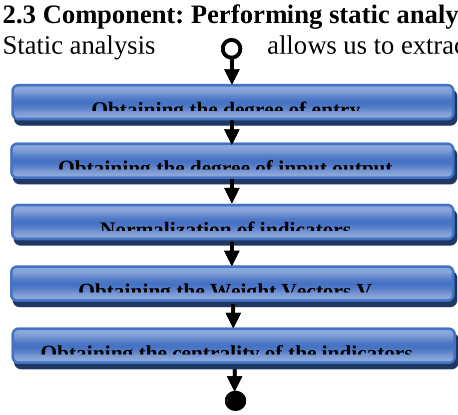
$$VA_{ij} = \frac{\sum_{i=1}^{n} W_{ij}}{E} \tag{6}$$

Where:
$VA_{ij}$:represents the added value.
$E$: number of experts participating in the process.
$W_{ij}$:correlation vector expressed by experts for the criteria $H_{ij}$ .

The aggregated values issued by the experts grouped via the adjacency matrix, make up the relationships with the weights of the nodes, through which the resulting FCM is generated [21].

**2.3 Component: Performing static analysis**

Static analysis allows us to extract a set of information that is useful about causal relationships. From this processing it is possible to extract hidden knowledge so far.



The workflow to perform static analysis is described below:

1. **Obtaining the degree of entry:** the activity consists of determining the group of values that represent the nature of the entry. The degree of entry is obtained from the behavior reflected in the adjacency matrix.
2. **Obtaining the degree of exit:** represents the activity that allows obtaining the parameters attributed to the relative weights of the behavior of the skills.

**Figure 3.** The proposed workflow for performing static analysis

3. **Normalization of indicators:** during the activities to obtain both the entry and the exit degree are normalized the vectors related to the indicators in domain [0; 1].
4. **Obtaining the weight vector:** the weight vector *V* attributed to the importance of skills is determined from the normalization activity and is subsequently used in other components of the model.
5. **Obtaining the centrality of indicators:** it allows determining how strongly one node is related to another from its direct connections.

Figure 3 shows the defined workflow for performing static analysis.

The input degree (*id*) represents an array of values that expresses a comparison function of an indicator $H_i$ with respect to the rest of the indicators $H_j$. Here, $H_j$ expresses the vertical displacement on the elements traveled by $_j$ (equation 7).

$$id_i = \sum_{i=1}^{n} \left\| H_{ji} \right\| \tag{7}$$

The degree of output (*od*) represents an array of values that expresses a comparison function of an indicator $H_j$ with respect to the rest of the indicators $H_i$. $H_i$represents the horizontal displacement on the elements traveled by *i* (equation 8).

$$od_i = \sum_{i=1}^{n} \left\| H_{ij} \right\| \tag{8}$$

The normalization of the indicators takes place since the values obtained by $od_i, id_i$, They represent vectors that are not in a discrete value domain $\in \neq$ [0,1]. Normalization is represented by an average function such that $od_i, id_\mathrm{i} \in \mathbb{R}, 0 \leq od \leq 1$.

After the normalization process, the weight vector *V* of the indicators is reached. The vector denotes the absolute values attributed to the skills that are obtained from the normalized degree of exit. Once the parameters obtained with the output degree $od$ and the input degree Id have been extracted, the centrality *C* of the indicators is determined [22].

From the analysis of centrality *C* is possible to determine how strongly one node is related to another via equation 9.

$$C_i = od_i + id_i \tag{9}$$

### 2.4 Component: Diagnosis and determination of access control to laboratory practices

The diagnosis and determination of access control is the component of the model that interacts directly with students or alternatives. The activity consists of determining if the person who is accessing the RSL coherently reacts from the application of a set of verification questionnaires. These questionnaires are designed to measure the abilities of the students. Figure 4 shows the workflow defined for the component.

The workflow to diagnose and determine access control to laboratory practices includes six activities:

1. Defining the base of evaluation questionnaires: the activity consists of creating a set of evaluation questionnaires that contribute to the generation of an evaluation base.
2. Developing the skills present in each questionnaire: from the definition of the evaluation questionnaires, it is determined for each one of them what are the skills that are in each evaluation quiz.
3. Creating and assigning questionnaire package: the activity consists of generating a random grouping of questionnaires to be evaluated, from the base of existing questionnaires.

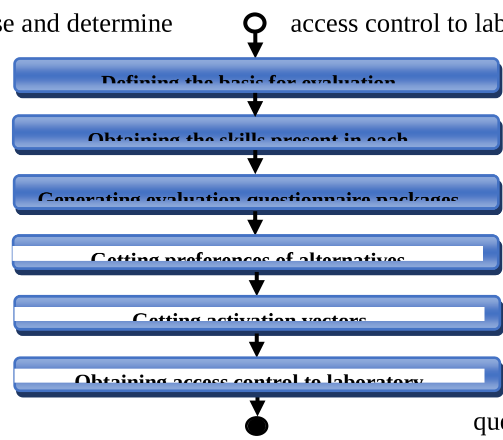


**Figure** 4. Workflow diagnoses and access control.

4. Obtaining references of the alternatives: the preference is obtained from evaluating the responses made to the questions in the questionnaires by the students.
5. Obtaining the activation vector is an intermediate activity; it represents an input parameter for the operation of the model in generating recommendations.
6. For obtaining the control of access to laboratory practices: based on the results of the preferences obtained, an ordering of the alternatives is carried out. With the use of operators for the aggregation of information, it is determined if the alternative is within the threshold allowed to carry out the laboratory practice. Otherwise, the necessary recommendations are generated and a new evaluation questionnaire is assigned.

For the proposal of the assessment questionnaires, the classification proposed by Cueto is assumed [23,24], which states that a questionnaire may have low or high involvement. For the diagnosis of skills, the implication in the results is high. Besides, determining the level of alternative regarding skills, it defines access to laboratory practices. For determining the skills in each questionnaire, in the process of preparing them, they are introduced as a configuration parameter of the model. The skills that a student should know and apply for the proposed instrument are determined. The process of generating and assigning questionnaire packages is a part of the set of the set of assessment questions that are grouped in the $Ce$ as expressed in equation 10.

$$Ce = Ce_1, \dots, Ce_n \tag{10}$$

A grouping of the questionnaires is obtained from a random value generation function, as shown in equation 11.

$$Group\{Pa_1, \dots, Pa_n\} = \sum_{i=1}^{t} Random\ Ce_j \tag{11}$$

Where:
*Group*: represents the function resulting from the grouping of the questionnaires
$Pa$: stores the t questionnaires generated by $Random\ Ce$
$Random\ Ce$: function of generating random values between 1 and the total of 1 and the total of $Random \in \mathbb{N}, 1 \leq Random \leq$ n.

The obtained $Pa$ are assigned to the set of alternatives that request laboratory practices according to equation 12.

$$A = \{a_1, a_2, \dots, a_m\} = Grup\{Pa_1, \dots, Pa_n\} \tag{12}$$

The preferences of the alternatives are obtained from the evaluation obtained from the answers to the questionnaires and is calculated using equation 13

$$A[Pa_x] = [Pre_y] \tag{13}$$

An alternative *A* is matched by a packet of questionnaires packet $Pa_x$ which, once answered, returns an $Pre_y$ arrangement with preferences for skills.

$[Rre_y]$: resulting arrangement as a preference of the alternatives with respect to a set of elaborated $Pre \in \mathbb{N}$, questionnaires $[0,1]$.The value of$Pre_y$ is used as an activation vector that represents an input parameter for the operation of the model in the simulation of sceneries.

For the inference process on access control to laboratory practices, we start from equation 14

$$A[Pa_x] = [Pre_y, ME], \longrightarrow \propto \tag{14}$$

Where:
$\propto$: represents the threshold on skills.
$ME$ : represents the aggregation and classification method to use.

The classification method for access control inference uses the $\mathrm{Rre_y}$ resulting from the skills diagnosis. The processing employs information aggregation operators. Aggregation operators are mathematical functions used in decision-making processes [25], they combine values *(x, y)* in a domain *D* and return a unique value.

Among the main operators for the aggregation of information is the arithmetic mean and weighted mean [15] as expressed in the definition:

Definition 2.1. An operator WAWA has associated a vector of weights$V$, with $\mathrm{v_i} \in [0,1]$and$\sum_1^n v_i = 1$, expressed in equation 15.

$$WA(a_1, \dots, a_n) = \sum_{i=1}^{n} v_i a_i \tag{15}$$

Where $v_i$ represents the importance of the source $a_i$.

An information aggregation operator (OWA), proposed by Yager [26], allows the classic criteria of uncertainty decision to be unified in an expression [27].

Definition 2.2. An OWA operator is a function $F: \mathbb{R}^n \rightarrow \mathbb{R}$ of dimension $n$ if it has an associated vector W of dimension n with $w_j \in [0, 1]$ y $\sum_{j=1}^{n} w_j = 1$, so such that:

$$F(a_1, a_2, \dots, a_n) = \sum_{j=1}^{n} w_j b_j \tag{16}$$

Where $b_j$ is the $j$-th largest of the $a_j$.

Each family of operators is used in different contexts. There are several formulations of aggregation operators that unify the WA and OWA operators combining the advantages of both [8, 28]. For the present investigation, the operator Weighted Sum Ordered Weighted Ordered (OWAWA) was used due to its high flexibility [29]. It unifies the OWA and WA arithmetic mean operators, [30]. Here we extend the definition of the OWAWA operator for working with multiple input functions $\Delta_{x\_}OWAVA$:

Definition 2.3. Let $Odn = (Odn_1, \dots, Odn_n)$ be a vector of weights of dimension n such that $\sum_{j=1}^{n} Odn_j = 1$ and $Odn_j \in [0,1]$, related to the WA operator and $\propto$ a weight vector of dimension $n$, with a configuration function $\nabla x \in [1, n]$, such that:

$$\propto_{\nabla x} (Odn_1, Odna_2, \dots, Odn_n) = \sum_{j=1}^{n} w_j b_j \, , Conf \tag{17}$$

Where:

$\propto_{\nabla x}$: Represents the resulting function influenced by an initial configuration function ∇x for the attributes of $Odn_n$.

*Conf*: represents the behavior assumed by the $W_j$, $Odn_n$ from the ∇x configuration.

$W_j$ : vector of weights of dimension influenced by the configuration function ∇x of the $Odn_n$.

$b_j$: is the j-th influenced by an initial configuration function $\nabla x$ of the $Pre_j$.

The configuration function ∇x represents a grouping of classic criteria for decision-making and behaves as follows:

For $\nabla x$=1: represents an optimistic state and is determined as referred to by equation 18

$$Decision = \mathrm{Max}\left\{ \mathrm{E_i} \right\} = \mathrm{Max}\left[ \mathrm{Max}\left\{ \mathrm{a_j} \right\} \right] \tag{18}$$

For $\nabla x$=2: represents the pessimistic or Wald state and is determined as reported by equation 19 [31].

$$Decision = Max\left\{ E_i \right\} = Max\left[ Min\left\{ a_j \right\} \right] \tag{19}$$

From the obtaining of $\propto_{\nabla x}$, it is determined if the threshold on skills is above the mean such that $\propto_{\nabla x} \in \mathbb{R}, 0.50 \leq \propto_{\nabla x} \leq 1$, making it correspond to the expressed linguistic values in figure 5. Otherwise, access to the requested laboratory practice is denied.

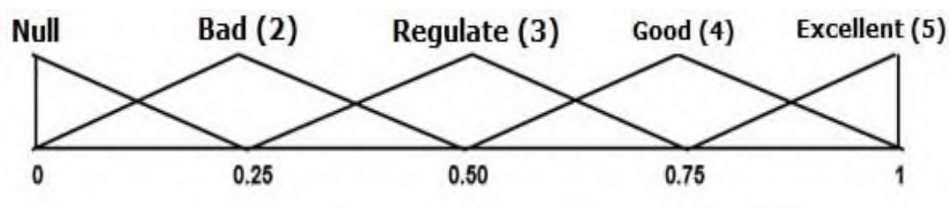



**Figure 5.** Linguistic variable used to express the evaluation

## 3. RESULTS AND DISCUSSION

### 3.1 Validation of the model

In order to validate the research, was carried out a study that involves the intentional manipulation of an action to analyze its possible result or effect known in the scientific literature as an experiment. The experimental design proposal was conducted by a sequence of steps proposed by Grau& Correa [32]. The steps proposed to carry out an experiment are described below:

Step 1: Decide how many (and which) independent and dependent variables are included in the experiment.

In order to identify the variables of the research, we start from the approach carried out in the theoretical design, where it is defined as a hypothesis: if a model based on FCM is developed, the decision-making on access control will be guaranteed for the successful development of the practices of Control Engineering II laboratories in a Remote Laboratory System. It is possible to identify in the context of the present investigation the following variables:

- Independent variable: model based on FCM.
- Dependent variable: access control for the successful development of Control Engineering II practices.

Step 2: Choose the manipulation levels (measurement level) of the independent variables and translate them into experimental treatments (convert theoretical variables to manipulate into groups or treatments).

This step is not applicable in the investigation in question, since manipulation of the independent variable is not desired.

Step 3: Choose or develop an instrument to measure the dependent variables.

The measuring instruments used for the pre-test and post-test measurement were supported on the SPSS v13.0 computer software.

Step 4: Select the experimental design to perform. In the case of true experiments, decide if the participants are randomized or mated with respect to some variable (s).

The pre- and post-test type pre-experiment with a single group is selected.

$$G O_1 X O_2$$

Where:

G: represents the experimental group used.

X: experimental condition (independent variable of the hypothesis).

$O_1$ , $O_2$: measurement of the dependent variable of the hypothesis ($O_1$ , pretest $O_2$ , posttest).

For the proposed design, you do not want to manipulate the independent variable, so the introduction of a control group is not necessary. The experimental result expresses the variation of the dependent variable in relation to its history.

Step 5: Select a sample of people to perform the pre-experiment.

For experimentation there are implementation rules that work with the Control Engineering II subject of Study Plan D, in the Automation Engineering degree. The experimental design proposed was applied to 4th year students of the Automation Engineering degree who receive the Control Engineering II course at the Central University "Marta Abreu" in Las Villas during the school year 2018-2019. A population of 38 students was identified, of which they participate in pre-experiment 28 for 73.7% representativeness.

Pre-test $O_1$ , experimental condition ($X$) and Post-test $O_2$ :

G: 28 access controls representing the 28 students analyzed as case studies.

$O_1$ : measurement of the dependent variable of the hypothesis on the application of the model.

X: application of the model.

$O_2$: measurement of the dependent variable of the hypothesis after the application of the model.

In the analysis of the results, the non-parametric Wilcoxon signed rank test was used as the statistical method.

Step 6: If it's about subjects, recruit them. This implies having contact with them, giving the necessary explanations and quoting them. Provide facilities and motivate them.

Step 7: Apply pre-tests, treatments and post-tests.

**Declaration of pre-experiment 1**

The pre-experiment is designed to compare the total access control and the access control inferred by the proposed model. Their objective is to demonstrate that the total access control and the access control inferred by the model differ statistically. The method is applied to determine that there is a significant statistical difference between total access control and inferred access control by means of the non-parametric test of the Wilcoxon signed ranges.

Step 1: Collect the data and analyze it with the relevant statistical tests for pre-experiment one.

According to the pre-experiment performed, total access control and access control inferred by the model were verified for 28 case studies using the non-parametric Wilcoxon signed rank test.

Measurement

1. Full access control (pre-test).
2. Access control inferred by the model (post-test).

Wilcoxon test hypothesis

$H_0$: There is not difference between the measure of total access control and the access control inferred by the model.
$H_1$: There is a difference between the measure of total access control and the access control inferred by the model.
Decision rule: If $P \geq 0,05$ hypothesis $H_0$.

**Table 2.** Statistics of related samples from experiment 1

| Pair | N | Z | (p_value) |
|---|---|---|---|
| Full access control<br>Access control inferred by the model | 28 | 1,637 | 0,009 |

The experimental results show a p_value<0.05 as evidenced in Table 2, the rest of the processing is performed for the pre-experiment in the SPSS statistician. From the obtained p_value, the null hypothesis is rejected, which indicates that "there is no significant statistical difference between the values of total access control and the access control inferred by the model". $Z$ = 1,637, p_value = 0.009. Summing up, the statistical difference is significant. From the statistical analysis, it can be concluded that there is a set of students who accessed the RLS and the model classification method infers that they do not have the necessary skills to access the laboratory practices. The importance of having included a control mechanism to validate access to laboratory practices in the RLS is demonstrated through the experiment.

**Declaration of pre-experiment 2**

The pre-experiment is designed to compare the results of the laboratory practices carried out satisfactorily with respect to the access control inferred by the proposed model. Its objective is to demonstrate that the access control inferred by the model does not differ statistically with respect to the satisfactory development of laboratory practices. The method allows determining that there is no significant statistical difference between the access control inferred by the model and the satisfactory development of laboratory practices by means of the non-parametric test of the Wilcoxon signed ranges.
Step 1: Collect the data and analyze it with the relevant statistical tests for pre-experiment two.
According to the pre-experiment one carried out, it was verified that of the 28 case studies, the classification method used by the model infers that 24 can access the development of laboratory practices, representing the value of the data for the application of pre-experiment two, using the Wilcoxon nonparametric signed rank test.
Measurement
1. Access control inferred by the model (pretest).
2. Satisfactory development of laboratory practices (post-test).
Wilcoxon test hypothesis
$H_0$: There is no difference between the measure of access control inferred by the model and the satisfactory development of laboratory practices.
$H_1$: There is a difference between the measure of access control inferred by the model and the satisfactory development of laboratory practices.
Decision rule: If $P \geq 0.05$ hypothesis $H_0$.

**Table 3.** Statistics of related samples from experiment 2

| Pair | N | Z | (p_value) |
|---|---|---|---|
| Access control inferred by the model<br>Satisfactory development of laboratory practices | 24 | -1,722 | 0,085 |

The experimental results show a p_value> 0.05 as evidenced in Table 3, the rest of the processing is performed for the pre-experiment in the SPSS statistician. Based on the obtained p_value, the null hypothesis is not rejected, which indicates that there is no significant statistical difference between the access control values inferred by the model and the satisfactory development of laboratory practices. Z = -1,722, p_value = 0.0857. The statistical difference is not significant; it shows that the inference model on the control of access to laboratory practices with respect to the satisfactory development of laboratory practices does not differ, or what is the same, that the students who access the practices Laboratories possess the set of skills to perform them successfully.

## 4. CONCLUSIONS

The use of a RLS for laboratory practices introduces problems in terms of supervising the work carried out by the students, because of this, it is not possible to have a full-time supervisor for this function. An alternative to solve the problem of the access to RLS would consist of establishing a satisfactory access control mechanism. Here, we

introduced a new model based on artificial intelligence techniques from the representation of causal knowledge through FCM for the diagnosis of skills, guaranteed decision-making on access control to the laboratory practices. The proposal was described through a workflow with four-components. The components of the proposed model are: Skill Selection, Obtaining and aggregating FCM, Performing static analysis and Diagnosis and determination of access control. A key point of the model is the diagnosis and determination of access control, this component interacts directly with students. For each component of the model, we defined the workflow and the activities to be carried out.
The experimental design proposed was applied to 4th year students of the Automation Engineering degree who receive the Control Engineering II course at the Central University "Marta Abreu" in Las Villas during the school year 2018-2019. Two pre-experiments were designed. A population of 38 students was identified, of which they participated in pre-experiment 28 for 73.7% representativeness. The application of the experimental design through the pre-experiment allowed corroborating the existing correlation between the variables of the research design, as well as the demonstration of the research hypothesis. The proposed model could be useful for suitable and safe access control of users to RLS in different academic matters.

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