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A Fuzzy Logic Approach to Decision Support in Collaborative E-Learning

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***Abstract*— Research works presented in this article are dedicated to the automation of learners support in collaborative e- learning. In this paper we present an intelligent multi-agent system for supporting learners in collaborative learning environment. The aim of our system is to analyze the interaction among learners and the calculation of socials indicators. The system then proposes automatically particular recommendations for the learners. The automation of the tutor roles is achieved by an agent that uses fuzzy logic techniques for its machine learning**.

***Keywords*—artificial intelligence, collaborative learning Fispro, fuzzy logic, indicators, machine learning, multi-agent system.**

I. INTRODUCTION

Collaborative learning is any learning activity realized by a group of learners who have a common purpose, each one is being a source of information, motivation, interaction, mutual aid, and contributing to the benefit of others, synergy of the group. The help of a tutor tends to facilitate the individual and collective learning[1]. The problem that arises in the case of E-learning is how to support the collaborative leaning taking into consideration the separation in space and time between the various participants

Several research works have been focusing on the support of collaborative E-learning to suggest solutions that allow better collaboration between learners within the groups and avoid their isolation.

Soller proposed a model of collaborative learning that is designed to help the intelligent collaborative learning systems to detect the problems of interaction between the members of the Workgroup [2]. Two tools are proposed to automate the coding, the analysis of the interactions, and the activities of the learners. The first tool is a shared space which allows learners to realize jointly a model OMT (technical Object modelling) from an enunciated exercise. The second tool is an interface of semi-structured communication which allows four learners to discuss. This structuring suggests for the learners to select an opener of sentence to begin their interventions.

This model describes some indicators to have an effective collaborative learning. For each indicator, strategies to allow the improvement of the interactions are proposed.

MBALA proposed a multi-agents system (MAS) intended to be coupled with platforms of e-learning to implement features that allow to estimate the state of the group: present, absent, still persons; the state of the group according to the percentage of active people; the productivity of a given learner; the level of realization of an activity [3].

Israel describe an Intelligent Collaborative Support System (ICSS) that supports a collaborative effort by analyzing and modifying the collaborative process dynamically while employing a web-based interface[4]. Based upon principles rooted in Computer-Supported Cooperative Work (CSCW), Intelligent Tutoring Systems (ITS) and Cooperative Learning (CL), this system extends the Group Leader paradigm to assist students working together in collaborative groups. Discussion skills are supported by examination of sentence openers chosen from a menu, keywords found in free-text sentence closers, student and group models, and historical database files. Groups are categorized and guided toward the optimal category of a high-performing cooperative group with positive interdependence. The use of the dialogue designated as creative conflict is mediated by an agent to assist in formulating a constructive discussion, serving as an instructional tool. Conflicts in the categorization of discussion skills exhibited in the sentence openers versus the sentence closers are resolved.

Djouad proposed a method and tools to calculate the indicators of collaborative activities in a computing environment for human learning having Trace-Base Management System. The method is based on the engineering managed by the models (modelled interactions traces), and leans on sequences of transformations of traces model and the associated instances allow to collect necessary observable for an explicit calculation of collaborative activities indicators[5].

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Within our lab (LASTID), a similar work was realized with the aim of assisting the on-line collaborative learning. A multi-agents system (SYSAT[i]) is realized for supporting the learner collaborative activities [6]. The mission of system is to analyze the interactions in order to aid the tutor in the follow-up of the learners and the groups. The interactions are estimated by tutor based on certain indicators stemming from the analysis of automatic interactions, examples: the semi structuring of messages, centrality of group, the cognitive activities... These indicators allow the tutor to optimize and to target more effectively their interventions to the students who present most risk to fall down

II. PROBLEM

The perception that emerges from the tutor's role in collaborative e-learning environments defines certain qualities among tutors, including;

- Very short reaction time: tutor must intervene in fairly short time.
- Appropriateness of interventions: tutor must send appropriate recommendations and comments to each learner.

However, in front of the quantity of information exchanged during a learning session, it seems extremely difficult for the tutor to meet the requirements; hence it becomes necessary to set up an automatic support system.

For the realization of our intelligent system, we propose to use multi-agent systems SMA because of their ability to provide robustness and efficiency. They also enable interoperability of existing systems, and solve problems with data, the expertise (knowledge) , and control that are distributed.

The automation of tutor role in collaborative E-learning requires to providing the agents of our system with capacities of reasoning and decision-making, with indistinct and incomplete knowledge under uncertainties by using the fuzzy logic techniques. The choice of the fuzzy logic significantly permits the artificial agents of our machine learning to have the most effective means taking into account the indistinctness and the uncertainty of information with the aim of formalizing the processes of reasoning and decisions making [7]. An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. INTELLIGENT MULTI-AGENTS SYSTEM FOR SUPPORTING THE ON-LINE COLLABORATIVE LEARNING

3.1 Support model for collaborative e-learning

Our idea consists of exploiting the data of interactions between the learners during the process of learning to improve the level of collaboration. These data will be analyzed and stored in the form of indicators in the learning profile. Based on these indicators, the system estimates the state of the learner collaboration, and afterward proposes automatically recommendations that allow improving the collaboration.

The process of supporting consists of two stages:

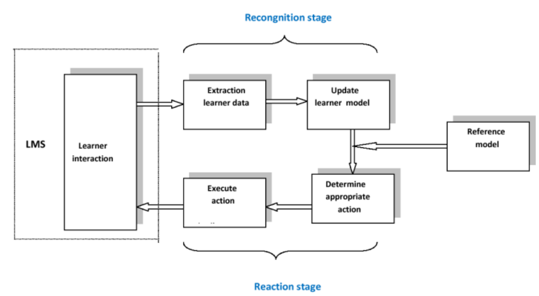

Fig 1: Support model

- The recognition stage: the system receives the collaborative activities of the learner. such as participation in forums, sending messages, sharing documents …. These activities will be analyzed and stored in the learner profile as indicators.
- The reaction stage: during this stage, the system determines the appropriate instructions and recommendations to the learners in order to improve their level of collaboration.

Based on the model of support of the on-line collaborative learning (see fig1), we want to propose an intelligent multi-agent system whose mission is the automation of the role of the tutor. The automation of the system will be realized relying on the fuzzy logic technique.

3.2 Fuzzy Logic

3.2.1 Introduction

Fuzzy logic is an extension of Boolean logic, it was proposed by Zadeh [8] to model natural language and to account for the vague knowledge that we humans manipulate every day.

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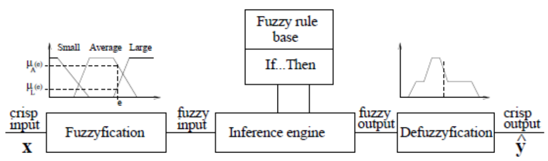
He introduced the concept of fuzzy set to address the problems in many complex systems that need to process information that is imperfect nature, its basic concept is to graduate membership of a set, allowing to take into account the imprecision in knowledge and formalizing the process of human reasoning.

A fuzzy inference system is composed of three blocks, as shown in Figure 2:



A

Fig 2:fuzzy inference system

The first block is the fuzzification block. It transforms numerical values into membership degrees to the different fuzzy sets of the partition. The second block is the inference engine, with the rule base.

IF (condition_1 [and / or] condition_2 [and / or] ... [and / or] Condition) THEN (actions in output variables)

3.3 MAS[ii] and E-learning

An agent is an autonomous entity, capable of communicating with other agents, as well as of perceiving and of representing his environment. Every agent makes specific actions according to the perception of his environment. A set of agents in interaction forms a multi-agents system.

Two categories of agents can be distinguished: the reactive agents and the cognitive agents[9].

The agents in a multi-agent system have several important characteristics [10]:

- *Autonomy:* the agents are at least partially independent, self-aware, and autonomous.
- *Local views:* no agent has a full global view of the system, that is to say the system is too complex for an agent to make practical use of such knowledge.
- *Decentralization:* there is no designated controlling agent.

The use of the intelligent multi-agents system in E-learning field allows to solve some pedagogic problems by taking advantage of some characteristics. Examples: adaptation of the courses of learning [11], [12]; the design of collaborative learning platform [13][14]; the individualization of the learning[15]; the support of the learners and the tutor [16].

By studying these works, we noticed that any process of adaptation is based on a model of the learner, a representation of its characteristics which the system takes into account

This modelling allows to give a description as complete as possible of all the aspects related to the behaviour of this user. In this work, we suggest bringing assistance to the community of learning on the basis of social behavioural side more than cognitive one. So, we use indicators which inform about the behavioural profiles (social) of the learners.

In the next section we present the architecture of an intelligent multi-agent system for supporting learners in a Collaborative e-Learning Platform.

3.4 Architecture design

Based on the support model of learner, the architecture system consists of three layers (see Figure 3.):

The learning layer: is the interface interaction between the learner and the system.

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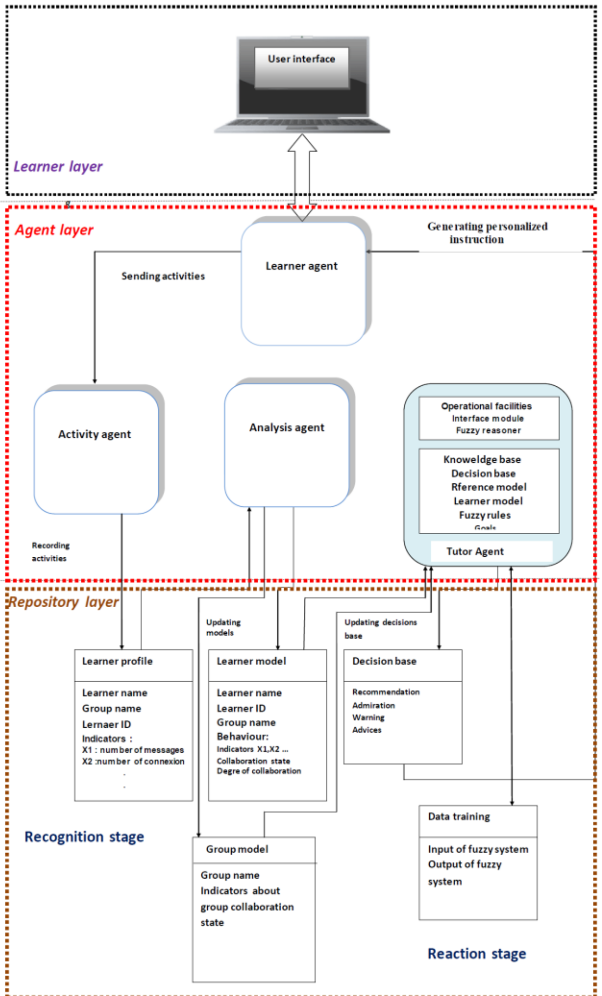

Fig 3. Architecture system

Agent Layer: contains a number of cognitive and reactive agents:

- *Activity Agent:* a reactive agent, from the collaborative activities of the learner, such as participation in forums, message exchange, the depositing of documents, it calculates indicators that will be stored in the profile learner
- *Modelling agent:* a reactive agent, it supplies and updates the model of learning based on the learner profile.
- *Tutor agent:* cognitive agent is responsible for the automation of learner support (see paragraph 4). Its role is to assess the state's collaborative learning based on the learner model, and submit appropriate recommendations to each learner. It also updates the database rules.
- *Learner agent:* produces a suitable interface for each student where he can receive messages, warning …based on the basis of decisions.

The repository Layer: This layer contains five components:

- *The learner profile:* includes static data of the learner, such as: name, code, and dynamic: indicators about social behaviour.
- *The learner model:* contains information about Collaborative behaviour of the learner: the state of collaboration, degree of involvement....
- *The model group:* contains information about the collaborative behaviour of workgroups.
- *Decisions base:* Contains the appropriate decisions to the various scenarios of behaviour, and will be subject to the learners according to the state of their collaboration
- *Training data:* includes data about the inputs and outputs of the fuzzy system. The tutor agent is based on the training data to generate the rule base

IV. Fuzzy Logic Inference To Evaluate The Learner Involvement In A Collaborative Online Learning

We aim to have a fuzzy system which leads to estimate the degree of collaboration of every learner, or working groups in an on-line collaborative learning. The system is based on indicators stemming from the analysis of the learner activities. The collaborative indicators represent the input of our fuzzy system.

Let $A = \{A_1, A_1 \ldots\ldots A_i, \ldots\ldots A_k\}$ the set of learner's collaborative actions .For each type of actions $A_i (i = 1,2, \ldots\ldots k)$, a measured numeric value $x_i (i = 1,2, \ldots\ldots k)$ is calculated for a student, example the action A_i : sending messages with the value x_i : number of messages sent by each student each measured numeric value

$x_i (i = 1,2, \ldots\ldots k))$ takes its values in a universe of discourse $U_i (i = 1,2, \ldots\ldots k)$

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Let $X = \{x_1, \ldots x_i \ldots x_k\}$ the input of our fuzzy system with $x_i \in U_i$, $U_i \subset IR^+$.

Let $C_j(j = 1,2, \ldots, L)$ the output of the system which represent different learning characteristics, such as level of collaboration, degree of implication

The process consists of three stages: fuzzification, inference, and defuzzification [17].

4.1 Fuzzification

This stage represents teacher's subjective linguistic $A=\{A_1, A_1 \ldots \ldots A_i, \ldots \ldots A_k\}$.Each variable $A_i(i = 1,2, \ldots k)$ can take a different number of linguistic values f_i. The number f_i of the linguistic values of each linguistic variable $A_i(i = 1,2, \ldots k)$ and their names $V_{i1}, V_{i2}, \ldots \ldots V_{if_i}$ are defined by the developer with the help from teachers, and depend on the variable $A_i(i = 1,2, \ldots k)$Let $T(A_i) = \{V_{i1}, V_{i2}, \ldots \ldots V_{if_i}\}$ the term set of $A_i(i = 1,2, \ldots k)$.

For example, let us consider the linguistic variable A_i = « time of task's execution » The corresponding term set could be:

$$\begin{aligned} T(\text{time of task'sexecution}) &= \{V_{i1}, V_{i2}, V_{i3}\} \\ &= \{\text{short}, \text{normal}, \text{long}\} \end{aligned}$$

At the fuzzification stage, the numeric input $X = \{x_1, \ldots x_i \ldots x_k\}$, where$x_1 \in U_1, x_2 \in U_2, \ldots \ldots x_k \in U_k$, and U_i is the universe of discourse of the ith input element ,$U_1, U_2, \ldots U_k \subset IR^+$is fuzzified and transformed into membership degrees to the linguistic values $V_{i1}, V_{i2}, \ldots \ldots V_{if_i}$ which describe a student's behavior A $=\{A_1, A_1 \ldots \ldots A_i, \ldots \ldots A_k\}$.

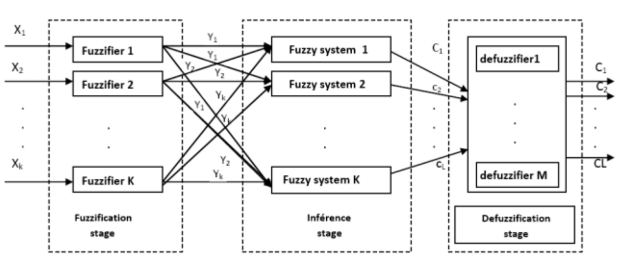

Fig.4. Inference model [17]

4.2 Inference

This stage represents teachers' reasoning in categorizing students qualitatively according to their abilities and personal characters. In particular, an approximation of fuzzy IF–THEN rules is performed, which represent teachers' reasoning in the qualitative assessment of students' characteristics.

In our model, a qualitative description of a student's characteristics $C_1, \ldots, C_j, \ldots C_l$ is performed by treating student characteristics as linguistic variables. Each linguistic variable $C_j(j = 1,2, \ldots, L)$ can take a different number of linguistic valuesm_j.

The set $T(C_j) = \{C_{j1}, C_{j2}, \ldots \ldots C_{jm_j}\}$is the term set of Cj (j = 1, 2. . . L).

For example: if we treat the linguistic variable C_j=''student interest'' using three linguistic values $(m_j = 3)$, then the term set could be: $T(C_j)$= T (student interest) = $\{C_{j1}, C_{j2}, C_{j3},\}$ = { neither interested , interested , very interested}.In this way, a mode of qualitative reasoning, in which the preconditions and the consequents of the IF–THEN rules involve fuzzy variables , is used to provide an imprecise description of teachers' reasoning:

$$\text{IF} x_1 \text{is} V_{1I_1} \text{AND} x_2 \text{is} V_{2I_2} \text{AND} \ldots \ldots x_k \text{is} V_{kI_k} \text{THEN}$$

$$C_1 \text{is} C_{1J_1} \text{AND} C_2 \text{is} C_{2J_2} \text{AND} \ldots \ldots C_L \text{ is } C_{LJ_L}$$

With $I_1 = 1,2, \ldots, f_1;\ I_2 = 1,2, \ldots f_2;\ I_k = 1,2, \ldots f_k;\ J_1 = 1,2, \ldots m_1;\ J_2 = 1,2, \ldots m_2;\ J_L = 1,2 \ldots m_L$

Let $c_j = [c_{j1}, c_{j2}, \ldots c_{jmj}](j = 1,2, \ldots, L)$ membership degree of output variable $C_j(j = 1,2, \ldots, L)$.

The inference stage, provides a fuzzy assessment $c_j = [c_{j1}, c_{j2}, \ldots c_{jmj}](j = 1,2, \ldots, L)$ of a student's characteristics,$C_1, \ldots, C_j, \ldots C_l$ by assessing membership degrees $c_{j1}, c_{j2} \ldots c_{jm_j}$ to the linguistic values$C_{j1}, C_{j2} \ldots C_{jm_j}$ of the linguistic variable $C_j(j = 1,2 \ldots; L)$that describe the characteristic $C_j(j = 1,2 \ldots; L)$

4.3. Defuzzification

This stage represents teachers' final decision in classifying a student in one of the predefined linguistic values $C_{j1}, C_{j2} \ldots C_{jm_j}$ of the characteristic$C_j(j = 1,2 \ldots; L)$. This process is performed by weighting the fuzzy assessment$c_j(j = 1,2 \ldots; L)$.The fuzzy assessments $c_j = [c_{j1}, c_{j2}, \ldots c_{jmj}](j = 1,2 \ldots; L)$ are defuzzified to non-fuzzy values, that is to say, to decisions on one of the linguistic values $C_{j1}, C_{j2} \ldots C_{jm_j}(j = 1,2 \ldots; L)$ of the learning characteristic$C_j(j = 1,2 \ldots; L)$.

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V. APPLICATION

Our system's mission is to automate the intervention of a tutor on distance learning. As mentioned above, we propose to analyze the collaborative actions executed by learners, and calculate indicators associated. These indicators represent the inputs of the proposed fuzzy system.

In this section, we present the implementation of the introduced fuzzy model detailed in the previous paragraph.

Let A $=\{A_1, A_2 \ldots\ldots.. A_i, \ldots\ldots A_k\}$ set of collaborative activities

We take 3 actions (k=3).

A_1 : sending messeages by learner
A_2 : Participations in forum
A_2: the connection
The inputs of the fuzzy system
x_1: is the number of messages sent by the learner during an activity;
x_2: number of participations in forum;
x_3: The number of connections of each learner.

For outputs of fuzzy system we consider $C_j(j = 1,2, \ldots\ldots, L)$ that represent collaborative assessment characteristics of each learner. Based on these evaluations, the system sends the appropriate recommendations to each learner to improve its level of engagement and involvement.

We consider two outputs (L = 2)

C_1: is the output variable denoting the level of collaboration of the learner;
C_2: Degree of presence.

We propose two fuzzy systems FIS1 and FIS2. The first system infers the degree of collaboration of the learner according to the number of messages and the number of its participations in the forums, the second infers the degree of presence of the learner based on number of its connections

The simulation results have been obtained by using fispro software that allows creating fuzzy inference system (FIS) from digital data observed (the training data)[18].

Training data in our example are variablesx_1 ,x_2 ,x_3 C_1 , C_2 that represent the results of the experiment SYSAT in Ibn Tofail University[16].

As described in the introduction, SYSAT is an automated system whose goal is the calculation of indicators that allow tutors to assess the collaborative behavior of learners during a collaborative activity. Thex_1 ,x_2 ,x_3 indicators are calculated by sysat C_1 , C_2marks given by tutor evaluation

5.1 Fuzzification

This operation consists of specifying the domain of variation of variables: the universe of discourse, which we divide into intervals (under fuzzy sets, or linguistic values). This distribution consists of fixing the number of these values and distributing them on the universe of discourse. It is realized on the basis of the expert knowledge.

We determine linguistic values for each variable:

– x_1 is described with five linguistic values (f_1=5) and by the term set :

$$T(x_1) = \{V_{11}, V_{12}, V_{13}, V_{14}, V_{15}\}$$
$$= \{\text{very weak, weak, average , high, very high}\}$$

The choice of f_1=5 is justified by the nature of the values of $x_1$which are very scattered.

The universe of discourse of x_1 is: $U_1 = [2,\ 208]$

– x_2 is described with three linguistic values (f_2=3) and by the term set:

$$T(x_2) = \{V_{21}, V_{22}, V_{23}\} = \{\text{weak, avearge , high}\}$$

The universe of discourse of x_2 is: $U_1 = [2,\ 8]$

– x_3 is described with five linguistic values (f_3=5) and by the term set :

$$T(x_3) = \{V_{31}, V_{32}, V_{33}, V_{34}, V_{35}\}$$
$$= \{\text{very weak, weak, average , high, very high}\}$$

For outputs, C_1 , C_2 are continuous outputs that represent marks between 0 and 20

– C_1 is described with four linguistic values and by the term set (m_1=4) :

$$T(C_1) = \{C_{11}, C_{12}, C_{13}, C_{14}\}$$
$$= \{\text{insufficient , average , sufficient, very sufficient}\}$$

– C_2 is described with four linguistic values and by the term set (m_1=4) :

$$T(C_1) = \{C_{21}, C_{22}, C_{23}, C_{24}\}$$
$$= \{\text{insufficient , average , sufficient, very sufficient}\}$$

The membership functions are explained in the following figures:

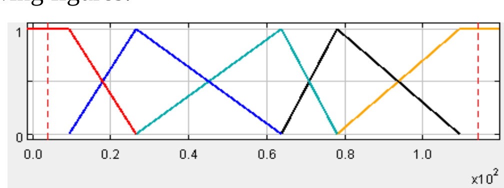

Fig 5: membership function of x_1

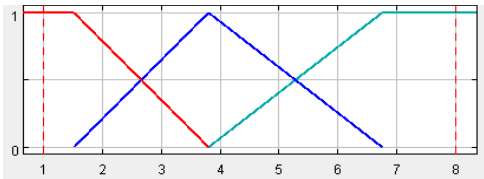

Fig 6: membership function of x_2

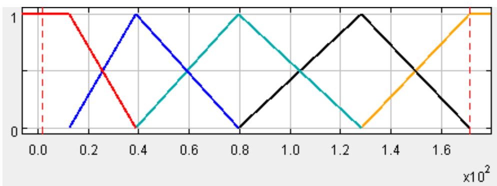

Fig 7: membership function of x_3

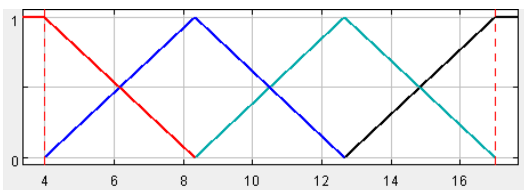

Fig 8: membership function of C_1

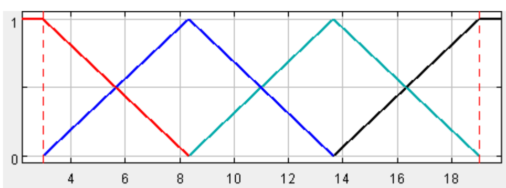

Fig 9: membership function of C_2

5.2 Fuzzy rules

The design of a fuzzy rule basis is an interactive process. The most important working part is the stage that concerns the collection of the expert. Thus, using the data corresponding to different inputs and outputs, the teacher - expert provides a series of combinations that approximates its reasoning.

One of the advantages of fuzzy logic is the ability to validate the basic rules to those who provided expertise, before testing it in a real system.

FisPro can generate all possible rules corresponding to all possible combinations of inputs from a data file that represents the knowledge of the expert.

Rules induction

We used the FPA (The Fast Prototyping Algorithm) method to generate the rule base of our fuzzy system [19].

The inference by fuzzy logic allows in the example treated here determining the level of involvement of the learner in a collaborative activity. Therefore, the system sends the appropriate recommendations to each learner.

The rule base corresponding to our application is as follows:

Rule	x1	x2	C1
1	very weak	weak	average
2	very weak	average	average
3	very weak	high	average
4	weak	weak	average
5	weak	average	sufficient
6	weak	high	sufficient
7	average	weak	sufficient
8	average	average	sufficient
9	average	high	sufficient
10	high	average	very sufficie...
11	high	high	very sufficie...
12	very high	average	very sufficie...
13	very high	high	very sufficie...

Fig 10: Fuzzy rules of FIS1

Rule	x2	C2
1	very weak	insufficient
2	weak	average
3	avreage	sufficient
4	high	very sufficie...
5	very high	very sufficie...

Fig 11: Fuzzy rules of FIS2

5.3 Defuzzification

At the end of the inference, the fuzzy output is determined, but it is not directly used. It is necessary to pass the "fuzzy world" to "the real world" that is the defuzzification. We present two main methods of deffuzification: the Mean of Maximum (MOM), and the centroid (C).

The defuzzification MOM defines the output as the average of the abscissas of the maximum from fuzzy conclusions aggregation.

The defuzzification (C) is most commonly used. It sets the output to correspond to the abscissa of the centroid of the surface of the membership function from fuzzy set that characterizes the aggregation results. This definition avoids discontinuities that could appear in the defuzzification MOM, but it is more complex as it requires important calculations

Once assessed by following the rules, then "defuzzified" output gives an estimate of the level of the learner

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For our purposes, we used the centroid method.

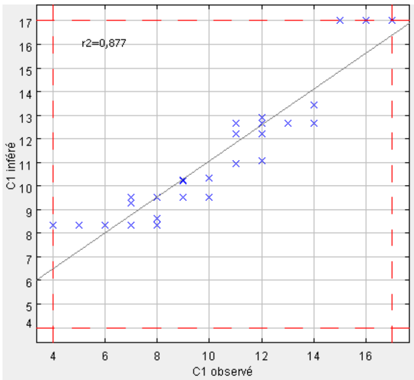

Fig 12: C_1results « degre of collaboration »

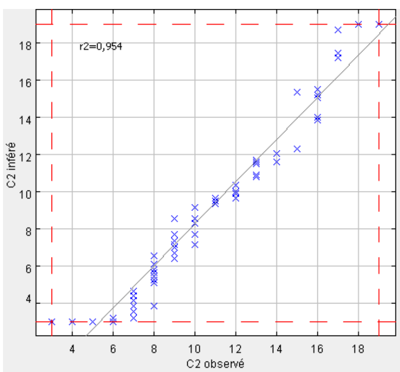

Fig 13: C_2results « degre of presence »

The results of SIF1 represent a comparison between marks given by the tutor to assess the degree of collaboration and marks returned by the fuzzy inference system (FIS1). The dispersion observed around the regression line is due to the wide dispersion of values x_1, denoting the number of messages sent by each learner. Indeed, the participation of learners is very unbalanced, and very few students participate (some messages sent over the whole period) and others are involved in the group activity (some hundreds of messages).

For FIS2 results, the degree of presence depends on the number of connections of each learner, as most learners logs regularly, so no significant dispersion was observed. This result expresses a good agreement between the observed and the inferred evaluation.

VI. The Evaluation Criteria

The coverage index and the performance indices, which are different for regression and classification cases, will be used as evaluation indices to assess the prediction capabilities of a FIS for a given data set.

Denoted by(x_i,y_i) the ith row of the data set, where x_i is a multidimensional input vector and y_i is the corresponding output

6.1 Coverage index

Data rows are labeled active or inactive for a given rule base. A row is active if its maximum matching degree over all of the rules is greater than a user defined threshold, otherwise it is inactive. Following this definition, a coverage index value is calculated by applying the formula

$$CI = \frac{A}{n}$$

A is the number of active rows, and N is the size. The coverage index value is a quality index that is complementary to the classical accuracy index

6.2 Performance index

They are calculated using only active examples. Three are available for continuous output

$$PI = \frac{1}{A}\sqrt{\sum_{i=1}^{A} \|\hat{y}_i - y_i\|^2}$$

PI is the performance index of Fispro,

$$RMSE = \sqrt{\frac{1}{A}\sum_{i=1}^{A} \|\hat{y}_i - y_i\|^2}$$

RMSE signify Root Mean Squared Error, and *MAE* is Mean Absolute Error.

$$MAE = \frac{1}{A}\sum_{i=1}^{A} \|\hat{y}_i - y_i\|$$

$\hat{y}_i$:Designates the output inferred by the FIS.
y_i: refers to the mark given by the tutor.

We obtained results

Table 1:
Performance index and coverage index of FIS1 and FIS2

	PI	$RMSE$	MAE	CI
SIF1	0,278	1,689	1,374	100%
SIF2	0,237	2,08	1.686	100%

VII. Simplification And Optimization

7.1 Simplification

Simplification principles are presented in [20]. It aims to eliminate the less useful variables from the rules of a fuzzy inference system.

This procedure is applicable to any fuzzy inference system, especially those built by learning.

7.2 Optimization

This procedure allows to optimize different parts of the FIS: FLS placement of fuzzy partitioning of the inputs and outputs values conclusion of rules. Whatever part of the optimized FIS, this optimization is based on an improvement in performance of the FIS. FisPro contains an optimization module. The optimization algorithm is based on the work of Solis and Wets [21] and Glorennec [22]

After the application of these two procedures on our system we found the following results

Rule	x1	x2	C1
1	trés élevé		tres bien
2	moyen		bien
3	trés faible		moyen
4		élevé	bien
5		moyen	moyen

Figure 14 fuzzy rules of SIF1 after simplification

Rule	x2	C2
1	high	very sufficie...
2	average	sufficient
3	weak	average
4	very weak	insufficient

Figure 15: fuzzy rules of SIF2 after simplification

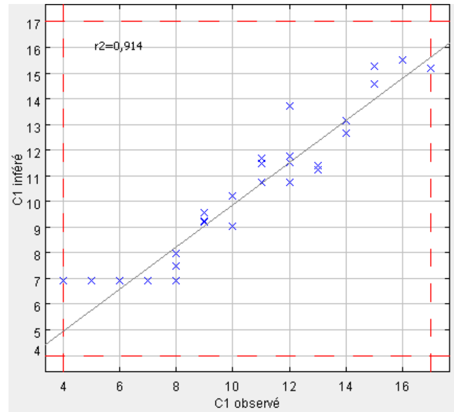

Figure 16: C_1 results after optimization

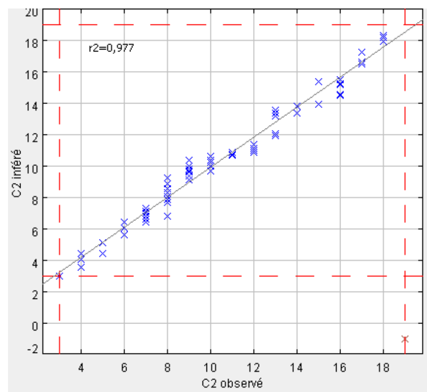

Figure 17: C_2 results after optimization

Table 2
Performance index and coverage index of SFI1 and SFI2 after optimization

	PI	$RMSE$	MAE	CI
SIF1	0,169	1,027	0,751	100%
SIF2	0,07	0,61	0,474	98%

The process of simplification has reduced the number of rules for the SIF1 from 13 to 5. The number of rules used has allowed characterizing the overall system operation; its local operation depends on the maximum number of simultaneously releasable rules.

For our example, the process of simplification and optimization has brought improved results as PI performance index increased from 0.278 to 0.169.

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VIII. Conclusion

In this paper we presented the design of an intelligent multi-agent system that assists learners during collaborative E-learning. We started by describing fuzzy logic technique, and presenting our fuzzy inference model that allows to evaluate the degree of collaboration for each learner in an E-collaborative learning. This model describes all the steps of inference: fuzzification, inference, and defuzzification. We presented the architecture of our intelligent system. The system aims to generate some recommendations, in an automatic manner, that are suitable for every learner then it represents an automation of mission of natural tutor. Finally, we finish by making a simulation by Fispro to build a fuzzy inference system for evaluation collaborative activities.

This automation presents many advantages like supporting a large quantity of information, stemming from a lot of learners interaction, sending recommendations and remarks to each student, intervention in good deadlines.

As future work we will implement the multi agent system proposed in this paper. We have chose to base on jade platform, and we aim make experiences to determine the advantage of our system .

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[i] **system for Supporting Learners and Tutors**

[ii] **Multi-agent system**