Utilization of a Neuro Fuzzy Model for the Online Detection of Learning Styles in Adaptive e-Learning Systems

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***Abstract*—After conducting a historical review and establishing the state of the art of the various approaches regarding the design and implementation of adaptive e–learning systems —taking into consideration the characteristics of the user, in particular their learning styles and preferences in order to focus on the possibilities for personalizing the ways of utilizing learning materials and objects in a manner distinct from what e–learning systems have traditionally been, which is to say designed for the generic user, irrespective of individual knowledge and learning styles— the authors propose a system model for the classification of user interactions within an adaptive e–learning platform, and its analysis through a mechanism based on backpropagation neural networks and fuzzy logic, which allow for automatic, online identification of the learning styles of the users in a manner which is transparent for them and which can also be of great utility as a component of the architecture of adaptive e–learning systems and knowledge-management systems. Finally, conclusions and recommendations for future work are established.**

***Keywords*—e-Learning; learning style identification; backpropagation neural network; fuzzy logic; neuro fuzzy systems**

I. Introduction

Learning is not a process of accumulation of representations of the external environment. Rather, it is a continuous process of behavioral transformation by way of continuous change in the capacity of the nervous system to synthesize new information. Memory does not depend on the indefinite retention of an invariant structure representing an entity (e.g., an idea, image, or symbol), but rather the functional ability of the system to create when certain recurrence conditions are given, for example, a behavior that satisfies recurrent demands or one that the observer would classify as a reactivator of a previous behavior.

For Dittus and Vasquez [1], "one commonly has the idea that the nervous system is an instrument which obtains information from the environment that the organism subsequently utilizes in order to construct a model of the world". Every autopoietic unit is unique because it is characterized by the phylogenetic inheritance of its ancestors, as well as its life history or ontogeny [2], defined as "the history of structural change of a unit, without which it loses its organization". It is in this way that different human beings possess different ways of learning. Some can construct knowledge in a more optimal way when they receive information through auditory pathways, while others do so visually or through other senses. However, for Alshammari [3], e-learning systems do not consider the diversity of learning types, learners' abilities, learners' knowledge, or the learning context.

Nowadays, in many teaching/learning activities, be they traditional or the utilization of technological resources or emergent media, learner differences in the classroom, such as the different learning styles [4], they may possess, tend to be ignored or simply not considered. This fact tends to result in the stardardization of methodologies, strategies, and techniques for different kinds of students, and this is understandable because it is extremely difficult for a teacher to apply multiple teaching strategies in the classroom. Currently, adaptive e-learning provides new ways of focusing traditional models of education, thus making possible the personalization of characteristics and educative experiences for each type of learner [5]. Among these characteristics, learning styles are one of the most important factors in learning. Adaptive systems focus on the transformation of learning from the passive receptor of information to collaborator in the educative process.

For Joy and Kolb [6], the types of learning styles indicate the differences in perspective regarding learning, based on individual preferences and considering the dialectical combination of those modalities. Learning styles are the cognitive, affective, and physiological traits which serve as relatively-stable indicators of how students perceive interactions and respond to their learning environments. They describe a learner in terms of the educative conditions which are more favorable for his/her learning. In this sense, the identification of student's learning styles is considered a vital element, and diverse perspectives for the identification of them have been developed.

In this paper, a model is proposed based on an analysis of user interactions within an e-learning platform, utilizing the concepts of 'fuzzy logic' and 'neural networks' with the objective of identifying individual learning styles and adapting the contents of the platform to the demands, preferences, and learning styles of each user.

II. Theoretical Framework

In this section, the authors conduct a historical review, identifying the state of the art and exploring the theoretical foundation of the research project.

A. e- Learning systems

The diversity and heterogeneity of resources available on the internet, the newest trends in methodologies and teaching/learning tools, and the current needs of the users make it indispensable to have at one's disposal virtual learning environments which possess the characteristics of adaptation and content personalization, as well as virtual assistants, among other tools. In this context, one of the lines of research which has recently seen a lot of activity is that of e-learning. According to H. Hashim and Z. Tasir [7], "an e-learning platform is that which applies and utilizes electronic media and information and communication technology (ICTs)". E-learning can imply other alternative terms, such as 'online education', 'computer-based, e-learning systems', and others. If the root of the word is taken as a reference, e-learning is translated as electronic learning, and in such a way, in its broadest conceptualization, it can encompass virtually any educative activity that utilizes electronic media in order to realize all or part of a learning process. This particular reference has arisen due to other online services, for example, e-business or e-commerce.

The following are components of an e-learning course, complementary to the instructional strategy: objectives; study cases; readings; centers of knowledge; conceptual maps; complementary, instructional materials and elements of interactivity and evaluation, for example, animations, simulations, interactive tasks, glossaries, biographies, self-evaluation exercises, and open-ended question exercises; material format: slides, media clips, linear text, multimedia, graphics, digital video, and audio; navigation tools, such as arrows for going forward or back; print copies; online help; site maps; filters; chat applications; forums; and email; some of which can better attend to the demands and preferences of the users.

Morales [8] establishes e-learning participants and their respective responsibilities in the following manner:

1) Teachers/tutors: Their role is to facilitate learning, for which they have to supply the tools so that the student learns autonomously and is capable of constructing his/her own knowledge in an active and responsible manner.

2) Students: The students need to have planning capability; flexibility to adapt to new and different ways of learning, as well as the traditional modalities; the capability to participate/integrate in the virtual group; technical competency in the navigation and use of new technologies, as well as a favorable attitude towards them; and time availability for learning within or apart from the work schedule, depending on the case.

According to Alshammari et al. [3], in e-learning systems, the learner may be overwhelmed by the great quantity of information that he/she encounters. The student might make poor decisions in relation to the subjects or material under study. Learning may demand a lot of time or create confusion and/or frustration, so for this reason, it might not be very effective. One of the modifications for the development of e-learning systems consists of being familiar with the differences among students, as well as their indvidual needs, with the objective of providing a personalized learning system that gives better relevance to the instructional material in accordance with the demands and needs of the student.

Adaptive e-learning systems based on different learning styles generally use different learning-style models. This raises the issue of which models and theories are most suitable and effective as components of these environments. An adaptive e-learning system based on knowledge level and learning style has been designed and implemented by Alshammari et al. [3]. This system facilitates personalized-learning pathways through the organization of material links according to their relevance to a particular learner; it also provides adaptive guidance and feedback to support learner-system interaction goals. Using a standard usability instrument, an experimental evaluation concerning learners' perception of usability was conducted to compare the adaptive e-learning system with a non-adaptive version, which yielded favorable results for the former.

In other words, understanding the needs of the students and identifying their learning patterns and preferences is crucial with regard to the design of e-learning-systems material in accordance with distinct learning styles, in this manner closing the resulting breach in relation to the members of the triangular community, which is to say the students, instructors, and adaptive contents online. It is necessary to establish what is required in order to capture the attention of each student and satisfy the demands and needs of his/her natural learning style so that what is learned is retained over the long term. Therefore, for Abdullah [9], identifying the learning styles is considered a vital element in the design of e-learning systems.

Lo and Shu [10] point out that the majority of authors in the field concur that the consideration of learning styles in the pedagogical process can increase the efficiency and efectiveness of learning. In this sense, diverse approaches have been developed for the identification of learning styles. Particularly, in the current paper, individual learning styles are identified in order to focus on subsequently the adaptation of platform content in accordance with the demands, preferences, and learning and thinking styles of each user, attempting in this way to supply the particular learning resources and objects that the student prefers.

B. Proposal for e-Learning Adaptive System Architecture

The authors propose an adaptive-system architecture based on autonomous intelligent agents for the implementation of a virtual-learning platform, given that this has proven itself to be the approach with the most potential in the field. Among their principle advantages are:

- They permit the modelling of individual profiles for each student, thus facilitating tasks such as the search for information and contents.
- They facilitate the incorporation of a knowledge-representation model and can facilitate the tasks of adaptation and personalization of contents in the proposed platform.
- They permit the incorporation of machine-learning characteristics in conjunction with other approaches and techniques of artificial intelligence.
- They can be equipped with various characteristics, such as autonomy, initiative, mobility (including among distinct platforms), and adaptability, among others.

The architecture of the proposed mulit-agent model, as with the description of its components, can be found in Alfaro et al. [11], which is shown in Figure 1.

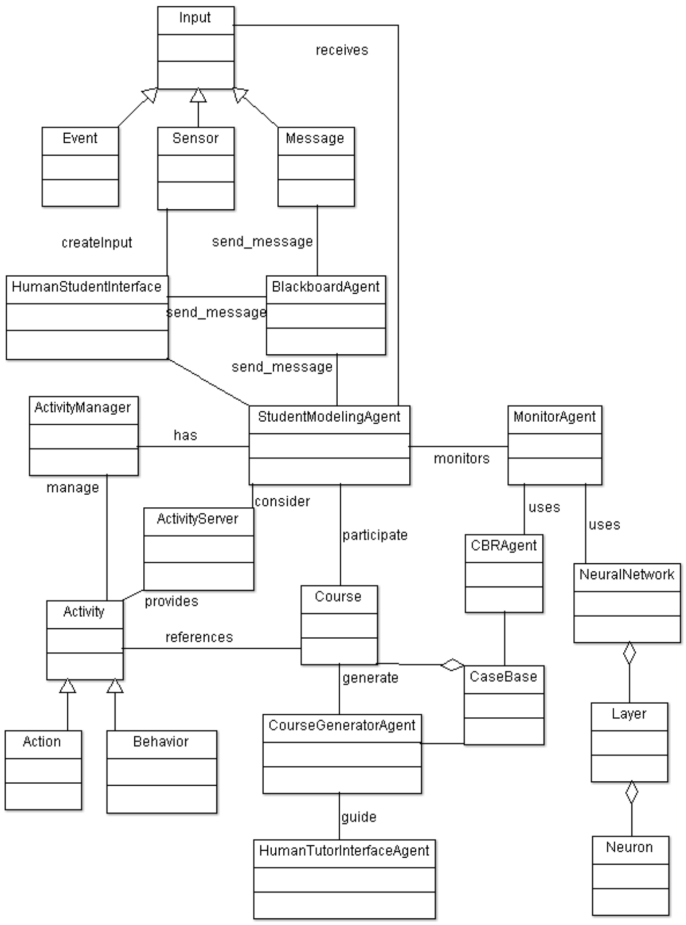

Fig. 1. Architecture of the multi-agent system [11]

The implementation of the proposed intelligent agents was realized utilizing the JADE platform, which is an agent platform distributed with a container for each host, in which the agents are executed and which possesses storage for diverse languages and ontologies, complying with FIPA (Foundation for Intelligent Physical Agents) specifications, for which developed agents can easily be integrated in other languages and platforms, including owners.

The originality of this hybrid proposal resides in the fact that it incorporates diverse artificial-intelligence techniques, such as 'intelligent agents', a 'backpropagation neural network', 'fuzzy logic', and 'case-based reasoning'. It also incorporates the 'learning-based-on-projects' paradigm.

The current proposal principally focuses on the model possessing a high degree of adaptability to the student's demands.

C. Backpropagation Neural Networks - RNAs

Backpropogation is a training method used for a multi-layer neural network. It can be thought of as a generalization of the "Delta Rule" for direct networks with more than two layers. In this case, at least one layer of neurons is not involved with the input or output and is, therefore, internal to the network. This layer and its connections, when it learns to effectuate a function, acts as if there were an internal representation of the problem's solution. Without going in to detail, backpropagation is a supervised learning rule. If an example is presented to the network, and the network output is verified, it is compared to the expected output, yielding an error. The gradient of this error is calculated in relation to to the synaptic values of the output layer, which is then updated by a selected step. The output error of the penultimate layer can, therefore, be calculated, and in this manner, starting at the front, the error (origin of the name 'backpropagation') propagates backwards through all the connection layers.

RNAs possess innumerable algorithms for pattern recognition: Kohonen, Perceptron, Adaline, and many others, each with its own specificities. For R. Lanelhas [12], the principle advantage of using RNA backpropagation is that it works with multiple layers and solves 'non-linearly-separable' problems that some algorithms cannot solve. Therefore, they can be counted among the networks proposed by Honey and Munford for the identification of learning styles.

Another important characteristic is that backpropagation is feedforward, which means that the connnection between neurons is not cyclic.

The RNA backpropagation is multi-layered, as it has a minimum of three layers. There are many calculations involved in the process so that the weight is adequately readjusted.

The RNA theory has provided an alternative to classical computation for those problems for which traditional or common methods have yielded not-very-convincing or disappointing results. This project in particular focuses on the online identification of learning styles, which has to do with pattern recognition within imprecise limits. Its degree of complexity made posible the incorporation of 'fuzzy logic', which, upon conducting the experimentation and corresponding tests, permitted the obtainment of superior results, as is discussed in the corresponding section.

D. Fuzzy Logic

For Timothy [13], fuzzy logic can be seen as a formalization mode of imprecise reasoning that represents certain human capacities to make approximate inferences and judgements within conditions of uncertainty.

According to Ozdemir et al. [14], determining the learning style most adequate to the individual capacities of the student is very important for quick, easy, and effective learning. However, the quantification of said capacities and the rules to follow in order to determine the most convenient learning style are of an imprecise nature, for which any approach one wishes to follow should incorporate fuzzy-logic techniques. In the particular case of the perspective developed by the aforementionded authors, an 'expert system' is proposed, in which the membership or belonging functions, as well as each one of the inputs and outputs of the inferrence rules, employ concepts of fuzzy logic.

Palomino et al. [15] part from the premise from which it is possible to define much more practical mechanisms adjusted to the real educative action for the detection of learning styles,

utilizing techniques associated with fuzzy logic. The proposed approache is based on the concept of learning pathways as a way to establish the type of preference that the learners possess with respect to how they perceive and process information, where the inputs are defined by fuzzy combinations.

Stathacopoulou et al. [16] point out that the neuro-fuzzy approaches are capable of handling imprecise information in a fashion superior to computational methods, for which this approach is utilized for diverse tasks.

E. Learning Styles

For Alonso et al. [4], "learning styles are the cognitive, affective, and physiological traits which serve as relatively-stable indicators of how students perceive interactions and respond to their learning environments". "The learning style describes a learner in terms of the educative conditions that are more conducive to favoring his/her learning. (....) certain educative approximations are more effective than others for him/her".

The learning style can predict the behavior of the student and, in this way, constitute itself as a good indicator of effective distance learning. The majority of the research that has been conducted in this area is based on learning styles because these are more dynamic, and they yield superior results if they are adequately attended to.

Cognitive traits have to do with the way in which students structure contents, form and utilize concepts, interpret information, solve problems, select representational modalities (e.g., visual, auditory, kinesthetic), etc. Affective traits are linked to the motivations and expectations that influence learning, while physiological traits are related to the biotype and biorhythm of the student [17].

For Joy and Kolb [6], the learning-style types indicate the differences in approaches with regard to learning, based on individual preferences and considering the dialectical combination of those modalities. There are four learning-style modalities, which are: divergent, assimilating, convergent, and accommodating. Divergent learners prefer to make greater use of concrete experiences and reflexive observation. Those of the assimilating type prefer to learn by way of reflexive observation and abstract conceptualization. Those of the convergent type prefer to engage in abstract conceptualization and active experimentation, while those of the accommodating type utilize active and concrete experimentation.

Not all learning-style models are ideal for the development of educative materials within adaptive, hyper-media systems. The approach most used by many adaptive-system researchers is Honey and Mumford's model [18], because it is centered on how information is perceived and processed. Nonetheless, other models are based on aspects that are not very relevant to development in web environments.

In practice, the majority of learners tend to display the characteristics of one style without either affirming or setting aside the other styles. According to the preferred style, the same content will turn out to be easier (or more difficult) to learn, depending on how it is presented to the learner and how it is dealt with in the classroom.

Optimal learning requires the four stages of Kolb's wheel, for which it is necessary to enforce discipline in such a way that activities that cover all the stages are guaranteed. With this, on the one hand, the learning of all students will be facilitated, whichever their preferred style may be, and, moveover, the stages will be strengthened for those who are less comfortable with the content. The stages mentioned are: active, reflexive, teoric, and pragmatic.

The review realized in this part of the paper allows the authors to provide the teoric basis that is required for the development of the online model for the identification of students' learning styles, which is presented in the next section of this paper.

F. Related Work

Research into e-learning systems is currently poised for continued growth due to the fact that there are currently important educative-system demands, which require high degrees of adaptation and intelligence from those systems to be able to provide students with more personalized attention according to their particular requierments. In this part of the paper, the authors attempt to establish the state of the art regarding the research subject.

For Maldonado-Perez [19], "in the learning model based on projects one finds the essence of problematic teaching, thus showing the student the way towards the obtainment of concepts." The contradictions that arise and the ways leading to their solution contribute to this object of pedagogical influences becoming an active subject. This learning model demands that the professor be a creator as well as a guide, who stimulates the students to learn, discover, and feel satisfied by the accumulated and adequately-operated and utilized knowledge, which can be achieved if teaching-based-on projects is correctly applied.

It is worth pointing out the majority of e-learning tools found on the market and based on web platforms are not naturally compatible with the Project-Based-Collaborative-Learning paradigm (PBCL), for which Abdallah et al. [20] proposes a general meta-model that permits the adapatation of existing platforms to this paradigm, taking as a case study the adaptation of the Moodle platform.

It is worth indicating that the traditional approaches already mentioned were based on the previous identification of the learning style of each participant through the application of surveys and other tests. Nevertheless, there are currently techniques for the automatic identification of the learning style of each individual, such as the proposal of Klansja-Milicevic et al. [21], based on a hybrid, recommendation system that combines clustering and data-mining techniques, and also that of Lo and Shu [10], in which neural networks are utilized for the identification of learning styles starting from the monitoring of the user's behavior on the platform.

On the other hand, the possibility of integrating diverse types of actors with well-defined roles and their capacity to handle heterogeneous resources has been addressed principally through approaches based on multi-agent systems, where variations have been observed, such as the execution of interactions through the use of the XML standard [22], delivery of contents

and distribution of roles in a dynamic and adaptive way [23]. According to Azambuja and Vicari [24], the application of multi-agent architectures allows for improvement in the interactivity of e-learning platforms, such as described in their proposal based on JADE architecture.

There is, moreover, a set of techniques from diverse areas that can be applied to the improvement of the proposed models. One example is implementation of the use of rubrics for the evaluation of complex, imprecise, and subjective areas [25]; the utilization of reasoning-based-on-cases techniques [26], applied to the evaluation and selection of projects according to the characteristics of the audience and learning environments, among other factors.

The vast quantity of projects in the area makes it possible to establish as fact that there are different proposals for the architecture and modelling of adaptive, e-learning systems that utilize diverse artificial-intelligence approaches in order to develop systems with a high degree of personalization and a high capacity to adapt to the learners' personal requirements and expectations.

III. Model System Development

Next, we will describe the different elements that were developed, as well as the procedural steps that were followed in order to build the adaptative e-learning-model system.

A. Traditional Detection of Learning Styles

The proposed model utilizes as a reference the classification of learning styles proposed by Honey and Mumford [18]. For the experimental data collection, a survey was applied to a group of 34 pregraduate students from the Professional School of Marketing at Saint Augustine National Univeristy of Arequipa, Peru during the second academic semester of 2017.

The student responses were systematized and tabulated on a digital spreadsheet designed for the purpose with the objective of facilitating the couting of responses, independently from the number of students, considering future tests and the possible scaling of the developed platform. Table I shows the summary of responses from the group of students, where the following facts must be considered:

- The cells highlighted in yellow correspond to students for which one solitary preferred learning style can be identified in a clear manner.
- The cells highlighted in grey correspond to cases in which it is not possible to identify only one learning style, either due to the possible mixed preferences of some students or deficiencies in the application of the aforementioned survey.

These facts, although they will only be pointed out here, are analyzed in greater detail in section IV, where they possess greater relevance with regard to the implementation and tests of the proposed model. However, it should be mentioned that traditional methods (e.g., surveys), although they are the most accepted, are also far from infallible in terms of the identification of learning styles or the other cognitive characteristics of the students.

TABLE I. Data obtained from the traditional method

Student	Activist	Reflector	Theorist	Pragmatist
1	11	16	13	10
2	15	15	13	15
3	13	13	12	9
4	13	16	12	17
5	9	18	17	15
6	13	18	14	14
7	15	15	17	17
8	12	9	8	13
9	16	13	10	17
10	14	17	15	12
11	13	18	13	12
12	11	17	15	13
13	10	17	19	10
14	13	17	14	13
15	13	18	13	16
16	12	17	16	17
17	14	15	16	15
18	13	14	15	18
19	11	16	17	13
20	13	18	11	13
21	13	17	17	13
22	10	18	18	18
23	14	16	15	17
24	17	16	11	17
25	16	15	18	20
26	15	10	7	16
27	12	15	13	15
28	10	18	17	15
29	17	14	11	15
30	10	15	12	17
31	19	16	13	14
32	13	12	10	13
33	19	12	10	15
34	10	11	18	18
Total	3	10	3	8

The distribution of the student's preferences for distinct learning styles is shown in Figure 2, where it can be appreciated that the number of cases in which it is not possible to determine only one preferred learning style is one of the most significant groups, which represents an important fact from the point of view of educative technologies, because it indicates that the students currently adapt better to ditinct types of materials, resources and contents, as well as learning environments.

Finally, it should be indicated that the data obtained through the traditional method (surveys) will be utilized in order to compare them with the results obtained from the neural network as a way to validate them, for which the data have been divided into two sets of equal cardinality (equal number of registers), procuring that both sets retain similarity regarding the percentatge of learning styles identified in each group. These sets will be utilized as training and test sets for the implementation of the neural network.

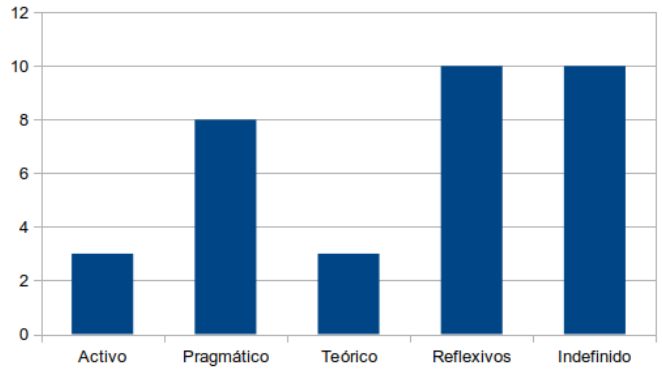

Fig. 2. Resuls of the test data obtained [27]

B. Establishment of Resource Categories and their Relation to Learning Styles

In order to classify user interactions, a list of 20 resource categories was defined, considering the types of resources existing in the Moodle platform, which was utilized for the implementation of the platform due to the fact that it is an opensource platform, subsequently relating each resource category with each one of the learning-style categories, utilizing general sets defined for that purpose (Table II).

TABLE II. RESOURCE CATEGORIES AND THEIR RELATION TO LEARNING STYLES

	Resource Type	Activist	Reflector	Theorist	Pragmatist
1	Content (Textual)	Low	High	High	Medium
2	Content (Mixed)	Medium	High	High	High
3	Content (Multimedia)	High	Medium	Medium	High
4	Content (Simulation)	High	High	Medium	High
5	Content (Url's)	Low	High	High	Low
6	Case Study (Textual)	Medium	High	High	Medium
7	Case Study (Multimedia)	High	Medium	Medium	High
8	Examples (Textual)	Medium	High	High	High
9	Examples (Multimedia)	High	High	Medium	High
10	Examples (Url's)	Medium	High	High	Low
11	Glossary (Reading)	Low	High	High	Medium
12	Glossary (Writing)	Null	High	High	Low
13	Wiki (Reading)	Medium	High	Medium	Medium
14	Wiki (Writing)	Medium	Medium	Low	Low
15	Forum (Reading)	Medium	Medium	Medium	Medium
16	Forum (Writing)	Medium	Low	Medium	Medium
17	Chat (Reading)	High	Low	Medium	Medium
18	Chat (Writing)	High	Low	Low	Medium
19	Self-assessments	Medium	High	High	Low
20	Conceptual maps	Nulo	High	High	Medium

It is important to mention that the source code of the Moodle platform was modified with the purpose of adding a log of user activity and interaction, which would store the resource selections realized by the user (by way of 'clicks') according to the type of category, which is to say a log of user behavior in the platform.

In this manner, the proposed approach permitted the attainment of the inputs (i.e., user interactions) and expected outputs of the model (i.e., learning styles identified beforehand), manually dividing the obtained data into two similar sets, making it possible for them to have the same cardinality (i.e., number of individuals) and also for them to be equally representative of the distinct learning styles in the same proportion in which they are found in the test data obtained with the traditional method.

C. Proposal and Implementation of the Neuro-Fuzzy System

Towards the identification of the learning style, a back-propagation neural network model was proposed, composed of an input layer, a hidden layer, and an output layer, such as shown in Figure 3. Upon implementation of the neural network, for the activation of the neurons, the sigmoidal function was chosen due to the fact that it permits the modeling of temporal progressions, which go from beginning levels—in which the contents are more or less generic and do not require sophisticated knowledge on the part of the users—to advanced levels, which with the passage of time, as content personalization is refined, permit the attainment of the required knowledge for a more precise identification of the user type (Figure 4).

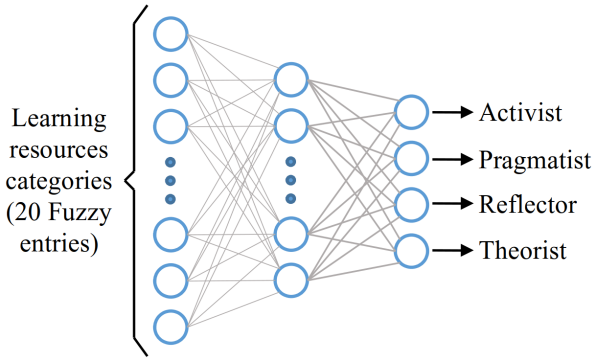

Fig. 3. Neural Network architecture

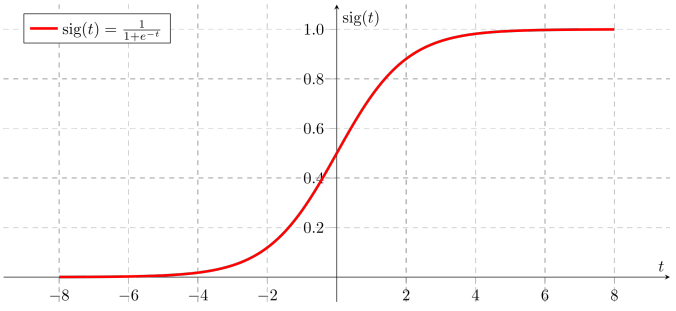

Fig. 4. Sigmoidal function

The input neurons represent each one of the platform resource categories previously defined (Figure 3), while the input values represent user preference for each of these categories. In this manner, 20 input neurons have been identified.

In the 'neural network', the hidden layer increases the processing capacity, and the number of neurons in the hidden layer directly affects the capacity of the 'neural network' for learning. In the proposed case, during the initial experimentation phase, before pre-processing the inputs (a process which will be described later), tests were conducted with distinct numbers of neurons in the hidden layer. Moreover, tests were also conducted with two intermediate layers without achieving

favorable results. In the final design of the 'neural network', a hidden layer with an equal number of neurons as the input layer was utilized, which was able to achieve the best results in an acceptable period of time.

The output layer was implemented with four output neurons that represent the four learning styles proposed by Honey [18], while the output values indicate user compatibility with said learning style.

During the initial runs of the model, some inconveniencies were found in the performance of the network, which, according to the analysis conducted, arose due to two causes:

- The level of 'noise' present in the input sets – For example, the user identified as number 23 in Table I —whose number of responses in relation to the learning styles is shown in Table III, according to the method proposed by Honey [18]—corresponds to the 'pragmatic' learning style. Nevertheless, the values are very close in each of the learning styles, complicating the establishment of a clear differentiation. This can be due to, for example, the selection of some indispensable contents for the achievement of objectives or, rather, the recommendations of other users which were finally selected by the user but do not necessarily represent the predominate learning style for him and, consequently, should not have a noticeable influence in the model.

TABLE III. ILLUSTRATION OF THE NOISE LEVEL

Activist	Reflector	Theorist	Pragmatist
14	16	15	17

- The input sets for which it is impossible to define an output –For example, as in the case of the user identified as number 2 in Table I, whose response log in relation to the learning styles is shown in Table IV, where clearly, according to the scheme proposed by Honey [18], it is not possible to identify the learning style.

TABLE IV. SPECIFIC INPUT SET

Activist	Reflector	Theorist	Pragmatist
15	15	13	15

In order to focus on these inconveniences, especially the first one, the authors opt for conducting a pre-processing of inputs through the definition of the second group of general sets, which are oriented towards achieving a better categorization of user preferences for a certain resource category, according to the percentage and relevance of their interactions in each resource category, such as shown in Figure 5.

This decision is based on the premise proposed by Palomino [15], who points out that determining a student's learning style becomes a problem of a general nature because evaluative situations and characteristics must be taken into consideration, albeit with a certain level of imprecision. These require a treatment appropriate to the nature of the problem, such that corresponds to the proposed case. Generally, the

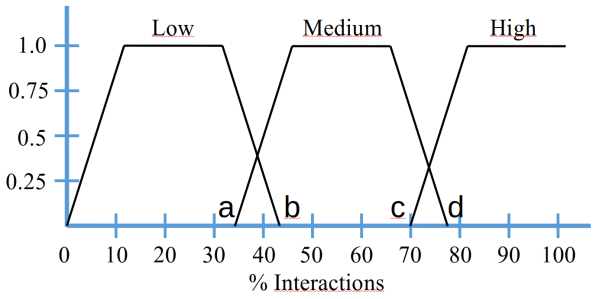

Fig. 5. Fuzzy sets for user preference for a certain resource category [27]

application of the concept of 'fuzzy logic' permits the modeling of situations which do not have precise limits, which makes for a much more realistic model, especially when having to do with cognitive and subjective aspects.

To this mechanism of 'fuzzification' —starting from the output data of the platform logs, previous to being considered as input data for the 'neural network'—the name 'preprocessing stage' of inputs is given. For the definition of the 'fuzzy sets', a trapezoidal function was utilized, defined as shown in Equation 1.

$$\mu B(x) = trapezoidal(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \quad (1)$$

Subsequent to implementing the specified criteria for this stage, the results obtained by the model are notably improved, and a superior design of the 'neural network' could be determined, with only one hidden layer remaining, as was explained previously.

It should be noted that the developed model, under an opencode platform, will allow for, in a subsequent stage, the development of a resource selection and adaptation mechanism within the platform, based on the learning style of each individual. What is more, this mechanism will also permit the validation and refinement of knowledge regarding user preferences, as well as the creation of more sophisticated user profiles.

IV. RESULTS AND DISCUSSION

For the experimentation and runs with the proposed model, the students were asked to perform some activities as part of a university course throughout the semester. It is important to note that the identification must be made throughout a period of platform-utilization time, given that the data analyzed in just one session might be seen as influenced by the time available for the identification of the style, the emotional state of that particular moment, problems in the environment, etc., making it possible for errors in the perception and identification of the learning style to arise.

For example, Figure 6, shows the identification of the learning styles of four students throughout each week of the

20-week duration of the semester, where it can be appreciated that, for example, for the 'case-1' student, the identification realized in weeks 3 and 20 might indicate that the student fits into second category. However, when the general panorama is observed, it is clear that this student instead fits into the first category.

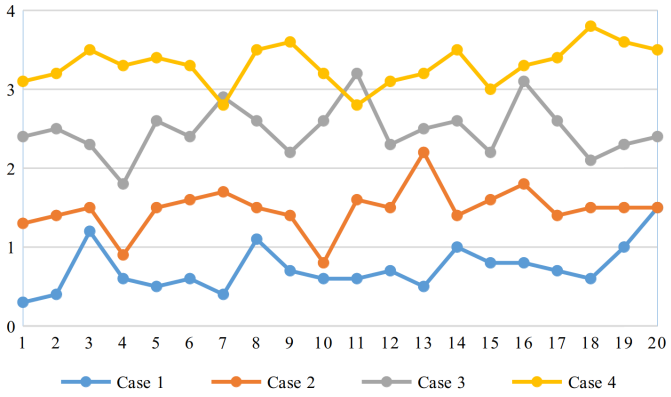

Fig. 6. Variation of user identifications through several learning sessions [27]

This phenomenon is relatively normal, given the proximity among some learning styles and the mixed preferences of some students, which also can be appreciated in Table I and Figure 6, where, for example, the set of students with mixed preferences is the second most representative, in some cases the task of identifying just one learning style being very complex.

In this sense, the most feasible option would be to identify the learning styles during some introductory course —such as 'study strategies' or previous activities before beginning to perform a content adaptation—and later validate and refine this identification in the subsequent activities or courses.

Finally, the results obtained by the neural network demonstrated a 76.5% coincidence with those obtained through the traditional method, which is to say that the learning styles of 26 of the 34 students were obtained correctly. For this reason, it can be said that the proposed model reached 76.5% efficiency with respect to the manual method proposed by Honey [18].

Table 5 shows a reasonable comparison of the different approaches for automatic, online detection of learning styles, considering the classification of learning styles used in each approach. It should be noted that in the case of approaches where efficiency was calculated for each of the learning dimensions or styles, the average of these has been considered in order to facilitate comparison with other more general approaches, such as the one proposed in the present research.

TABLE V. COMPARISON OF EVALUATED MODELS

Evaluated models	Learning Styles	Efficiency
Bayesian networks	Felder & Silverman	66%
NBTree y CRB	Felder & Silverman	67.5%
Genetic algorithms and K-NN	Ad-hoc	96%
Monitoring of interactions	Felder & Silverman	79.6%
Learning objects and time estimation	Felder & Silverman	69.6%
Neural networks and navigation maps	Vincent & Ross	90%
Stochastic models	Felder & Silverman	70%
NeuroFuzzy model (Proposal)	Honey & Mumford	77.1%

V. CONCLUSION

It has been proposed the design of an adaptive e-learning system, still in the process of implementation, which considers the characteristics of the users, in particular their learning styles and preferences, to focus on the possibility of personalizing the ways of using the objects of learning, in a different way to traditional systems, designed for generic users.

The authors also proposed a System model for the classification of user interactions, within an adaptive e-learning System platform, and whose analysis through a mechanism based on a backpropagation neural network and fuzzy logic, it allows the automatic online identification of learning styles, in a transparent way for the user, which is very useful within the platform of the adaptive e-learning system.

The determination of a student's learning style is a problem of a general nature because evaluative situations and characteristics must be considered (with a certain level of imprecision to be expected), requiring an appropriate treatment to the nature of this problem.

The identification of learning styles can not be based on a single session or user access, which can lead to errors of interpretation, but rather must be made over several sessions in order to achieve an adequate accuracy in the identification.

It is important to propose and develop the system model, which using Case Based Reasoning (CBR), establishes the correspondence between the preferences of students of different learning styles, detected with the proposed neuro-fuzzy system, with the problems formulated with the project-based learning approach, which contains the learning objects with the greatest significance for them.

It is important to continue contributing to the area with research into learning and thinking styles, whose theoretical bases must be taken seriously as important elements in adaptive, e-learning systems.

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