

# A Soft Computing Decision Support Framework to Improve the e-Learning Experience

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## Abstract

In this paper an e-learning decision support framework based on a set of soft computing techniques is presented. The framework is mainly based on the FIR methodology and two of its key extensions: a set of *Causal Relevance* approaches (CR-FIR), that allow to reduce uncertainty during the forecast stage; and a *Rule Extraction* algorithm (LR-FIR), that extracts comprehensible, actionable and consistent sets of rules describing the student learning behavior. The data set analyzed was gathered from the data generated from user's interaction with an e-learning environment. The *introductory course* data set was analyzed with the proposed framework with the goal to help virtual teachers to understand the underlying relations between the actions of the learners, and make more interpretable the student learning behavior. The results obtained improve system understanding and provide valuable knowledge to teachers about the course performance.

## 1. INTRODUCTION

The fast increasing popularity of the Internet and the advance of telecommunication technologies is determining the next generation of distance education tools. The kind of distance education that currently undergoes an important research effort is web-based education, which has revealed itself as a useful tool for course delivery and knowledge sharing. The Internet medium is used to convey content and to gathering information of student online behavior. However, a well-known problem in e-learning environments is associated with the high virtual teacher's workload. Initially, e-learning was presented as the best solution to cover the necessities of remote students and/or help the teaching-learning process, reinforcing or replacing face-to-face education. However, several real projects have failed due to the fact that a huge amount of time is needed to provide feedback to virtual learners, being necessary to

increase the number of teachers and therefore educative costs.

Moreover, one of the most difficult and time consuming activities for teachers in distance education courses is the evaluation process, due to the fact that, in this kind of courses, the review process is better accomplished through collaborative resources such as e-mail, discussion forums, chats, etc. As a result, this evaluation has usually to be carried out according to a large number of parameters, whose influence in the final mark is not always well defined and/or understood. Therefore, it would be helpful to reduce systems' dimensionality by identifying features that are highly relevant for the student evaluation. In this way, it would be possible for teachers to provide feedback to students regarding their learning activities online and in real time.

Dealing with the above problems, we develop an e-learning decision support framework that focuses on e-learning systems improvement through the analysis of the data generated by the students of virtual campus, aiming to discover their system usage patterns. The proposed framework includes a set of soft computing techniques contributing to solve the most time demanding teachers activities and therefore, alleviating the teacher workload.

Several research projects have dealt with the integration of data mining methods focusing on e-learning systems improvement. For a deeper inside into these projects the authors recommend [1, 2, 3], where an extensive and profound analysis of different learning platforms is performed, including LON-CAPA [4], AHA! [5], ALFANET [6], etc. Commonly, the existing platforms perform student's classification (using supervised neural networks, decision trees, fuzzy methods, association rules, etc.), and/or student's clustering (using Kohonen's self-organizing maps, EM, etc.), but do not study students performance from the prediction of his/her learning behavior point of view, i.e. predictive models are not included in the platforms.

The framework proposed in this paper includes as part of its skills the identification of student learning behavior models that allow both, students and teachers, to know the

future performance of the student based on the current learning behavior, allowing the teachers to give feedback to those students that need it more.

The remaining of the paper is organized as follows: section 2 presents the basics of the FIR methodology and the two extensions included in the proposed framework. The e-learning decision support framework is described in section 3. A description of the data used in this research is provided in section 4. Results from the experiments are presented and discussed in section 5. Finally, section 6 wraps up the paper with some conclusions.

## 2. THE FUZZY INDUCTIVE REASONING (FIR) METHODOLOGY

This modeling and qualitative simulation methodology is based on systems behavior rather than on structural knowledge [7]. It is able to obtain good qualitative relations between the variables that compose the system and to infer the future behavior of that system. It also has the ability to describe systems that cannot easily be described by classical mathematics (e.g. differential equations), i.e. systems for which the underlying physical laws are not well understood. FIR consists of four main processes, namely: fuzzification, qualitative model identification, fuzzy forecast and defuzzification. Figure 1 describes the structure of the FIR methodology as applied in this study.

The fuzzification process converts quantitative data stemming from the system into fuzzy data. The qualitative model identification process is responsible for finding causal and temporal relations between variables and therefore for obtaining the best model that represents the system. A FIR model is composed of an optimal mask (model structure) and a pattern rule base (behavior matrix).

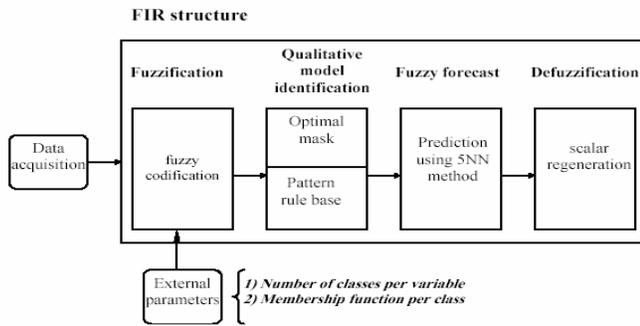


Figure 1. Fuzzy Inductive Reasoning Methodology.

The optimal mask is obtained by either a mechanism of exhaustive search of exponential complexity, or by one of various suboptimal search strategies of polynomial complexity and is based on the Shannon entropy measure. Once the best mask has been identified, it can be applied to the qualitative training data obtained from the system

resulting in a particular pattern rule base. The number of pattern rules obtained in this process has almost the same size than the training data set available and, therefore, the comprehension and understanding of the pattern rules is usually reduced.

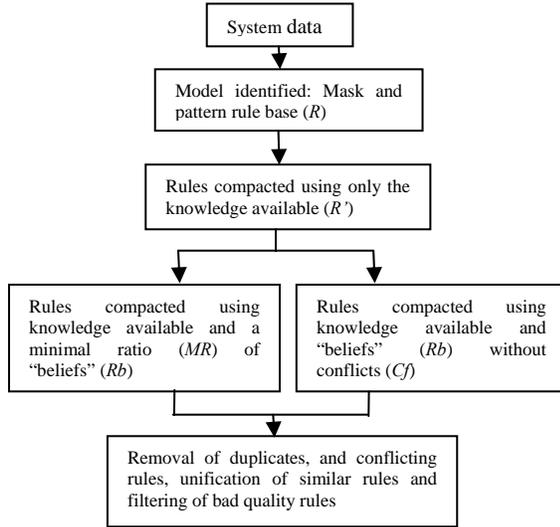
The FIR inference engine is a specialization of the k-nearest neighbor rule, commonly used in the pattern recognition field. Defuzzification is the inverse process of fuzzification. For a deeper and more detailed insight into the FIR methodology, the reader is referred to [8].

### 2.1. LR-FIR Algorithm

Figure 2 shows, in a schematic way, the main phases of the proposed algorithm. It performs an iterative process that compact the pattern rule base obtained by FIR. On the one hand, the goal is to obtain interpretable, realistic and efficient rules, describing student learning behavior. On the other hand, it is intended to compact the pattern rule base to speed up the prediction process. In order to get a set of logical rules congruent with the pattern rules previously identified by FIR, the proposed algorithm is based on FIR model initial discretization. The algorithm can be summarized as a set of ordered steps:

1. *Basic compactation.* This is an iterative step that evaluates, one at a time, all the rules in a pattern rule base. The pattern rule base,  $R$ , is compacted on the basis of the “knowledge” obtained by FIR. A subset of rules  $R_c$  can be compacted in the form of a single rule  $r_c$ , when all premises  $P$  but one ( $P_a$ ), as well as the consequence  $C$  share the same values. Premises, in this context, represent the input features, whereas consequence is the output feature in a rule. If the subset contains all legal values  $LV_a$  of  $P_a$ , all these rules can be replaced by a single rule,  $r_c$ , that has a value of -1 in the premise  $P_a$ . When more than one -1 value,  $P_{ni}$ , is present in a compacted rule  $r_c$ , it is compulsory to evaluate the existence of conflicts by expanding all  $P_{ni}$  to all their legal values  $LV_a$ , and comparing the resultant rules  $Xr$  with the original rules  $R$ . If conflicts,  $Cf$ , exist, the compacted rule  $r_c$  is rejected, and otherwise accepted. In the latter case, the previous subset,  $R_c$  is replaced by the compacted one  $r_c$ . Conflicts occur when one or more extended rules,  $Xr$  have the same values in all its premises,  $P$ , but different values in the consequence  $C$ .
2. *Improved compactation.* Whereas the previous step only structures the available knowledge and represents it in a more compact form, the improved compactation step extends the knowledge base  $R$  to cases that have not been previously used to build the model:  $R_b$ . Thus, whereas the step 1 leads to a compacted data base that only contains knowledge; the enhanced algorithm contains undisputed knowledge and uncontested belief. Two options are

studied: In the first one, using the compacted rule base  $R'$  obtained in step 1, all input features  $P$  (premises) are visited once more in all the rules  $r$  that have nonnegative values (not compacted), and their values are replaced by -1. An expansion to all possible full sets of rules  $Xr$  and their comparison with the original rules  $R$  are carried out. If no conflicts,  $Cf$ , are found, the compacted rule,  $r_c$ , is accepted, and otherwise, rejected. The second option is an extension of the basic compactation, where a consistent minimal ratio,  $MR$ , of the legal values  $LV_a$  should be present in the candidate subset  $R_c$ , in order to compact it in the form of a single rule  $r_c$ . This latter option seems more suitable because, although a consistent ratio was used to compact  $R_c$  in a single rule  $r_c$ , the assumed beliefs are minimal and do not compromise the model previously identified by FIR. Instead, in option 1, beliefs are assumed to be consistent with the original rules; nevertheless, this could compromise the agreement with model identified, especially when the training data are poor and do not describe well all possible behaviors.



**Figure 2.** Ordered steps of the rule extraction method.

The obtained set of rules is subjected to a number of refinement steps: removal of duplicate rules and conflicting rules; unification of similar rules; evaluation of the obtained rules and removal of rules with low specificity and sensitivity. These are standard metrics, described in figure 3, that assess the quality of the obtained rules. For space limitations the refinement steps can not be explained in detail in this paper.

## 2.2. Causal Relevance approaches

The idea behind causal relevance (CR) is simple and can be addressed through the following question: How much does each variable influence the prediction of the

output? If it is possible to quantify the importance of each variable with respect to the output, it becomes easier to obtain good predictions, closest to the best that can be obtained for a specific set of training data.

In this study, the Shannon entropy and the Mean Square Error (MSE) are applied to take into account the relative importance of each input feature, and a weight-Euclidean distance measure is proposed to find neighbors of a better quality.

The FIR model identification process has already selected the more relevant inputs. The question now is: Do all of these selected variables affect the prediction of the output to the same degree? In general terms, the answer should be no. Usually, some of the selected inputs are more relevant than others from the causality point of view. The CR concept addresses this issue by quantifying the influence of each selected input with respect to the output. From now on the FIR selected inputs will be referred only by inputs.

For the sake of space availability and in order to provide an essential background to understand the CR approaches proposed in this study, we only present the Euclidean distance formulae used to calculate the distances between the new input pattern and all previous input patterns, stored in the pattern rule base in equation 1, and the remaining formulas can be analyzed in [8].

$$d_j = \sqrt{\sum_{i=1}^N (psrIN_i - psrPR_{j,i})^2} \quad (1)$$

The  $psrIN$  vector represents the new input state and the  $psrPR_j$  vectors represent all previous recordings of the same input state. This kind of metrics assumes that all  $(psrIN_i - psrPR_{j,i})$  elements have the same influence on the overall distance  $d_j$ , in spite of the fact that this assumption is not very realistic when dealing with dynamical systems. Based on this idea, a new distance measure that takes these considerations into account has been proposed. The CR is used as a weight to the modified Euclidean distance formulae as presented in equation 2,

$$d_j = \sqrt{\sum_{i=1}^N ((R_{dis_i}) * (psrIN_i - psrPR_{j,i}))^2} \quad (2)$$

where  $R_{dis_i}$  is the quantified causal relevance of the  $i^{\text{th}}$  input. Using the weight-modified distance formulae of equation 2, the distances of the most relevant inputs exert a stronger influence on the overall distance of this specific input pattern, whereas the influence of the less relevant inputs is reduced with respect to the classical Euclidean distance formulae that has been used previously. Depending on the richness of the data available and the difference between the causal relevance of the inputs, the  $R_{dis_i}$  factor will select better neighbors due to the fact that it weighs the contribution of each variable. How are the  $R_{dis_i}$  weight

values computed? In the first two of the CR methods (QVAR and QNOVAR) proposed in this research, the quality of a mask,  $Q_m$ , is used to quantify the causal relevance of each input. The remaining two CR approaches are based on the prediction MSE,  $Ep$ , of a validation data set, never seen in the training data.

Equations 3 and 4 present the two CR formulas based on the quality of the mask, named from now on QVAR and QNOVAR, respectively.

$$\text{QVAR:} \quad R_{dis_i} = Q_{vari} \quad (3)$$

$$\text{QNOVAR:} \quad R_{dis_i} = 1 - Q_{no\ vari} \quad (4)$$

$Q_{vari}$  is the quality of the mask of complexity two, i.e. the mask that contains only the output and the  $i^{th}$  input. It can be interpreted as a direct causal correlation between the  $i^{th}$  input and the output to be predicted.  $Q_{novari}$  is the quality of the mask that contains the same inputs of the optimal mask but excluding the  $i^{th}$  input. It quantifies the amount of information that will be lost when the  $i^{th}$  input is eliminated from the model to be used to predict the system.

Equations 5 and 6 present the two CR formulas based on the prediction MSE of the validation data set, named from now on PVAR and PNOVAR, respectively.

$$\text{PVAR:} \quad R_{dis_i} = 1 - E_{p_i} \quad (5)$$

$$\text{PNOVAR:} \quad R_{dis_i} = \begin{cases} E_{p_i} - E_{p_m}; E_{p_i} - E_{p_m} > 0 \\ \min(E_{p_i}) * \Delta Inf; E_{p_i} - E_{p_m} \leq 0 \end{cases} \quad (6)$$

$E_{p_i}$  stands for the MSE obtained when the mask that contains only the output and the  $i^{th}$  input is used to predict the validation data set.  $E_{p_m}$  is the MSE obtained when the optimal mask, identified by FIR, is used to predict the validation data set.  $\Delta Inf$  is a factor that helps to preserve the consistency of the model identified by FIR by given a low value to  $R_{dis_i}$  when the prediction error obtained by the sub-optimal mask without the  $i^{th}$  input is lower than the prediction error obtained by the optimal mask.

Equation 7 presents the Mean Square Error in percentage (MSE) formulae, where  $y_{var}$  stands for the variance,  $y(t)$  is the real output value and  $\hat{y}(t)$  is the predicted output value.

$$MSE = \frac{E \left[ (y(t) - \hat{y}(t))^2 \right]}{y_{var}} . 100\% \quad (7)$$

### 3. THE DECISION SUPPORT FRAMEWORK PROPOSED

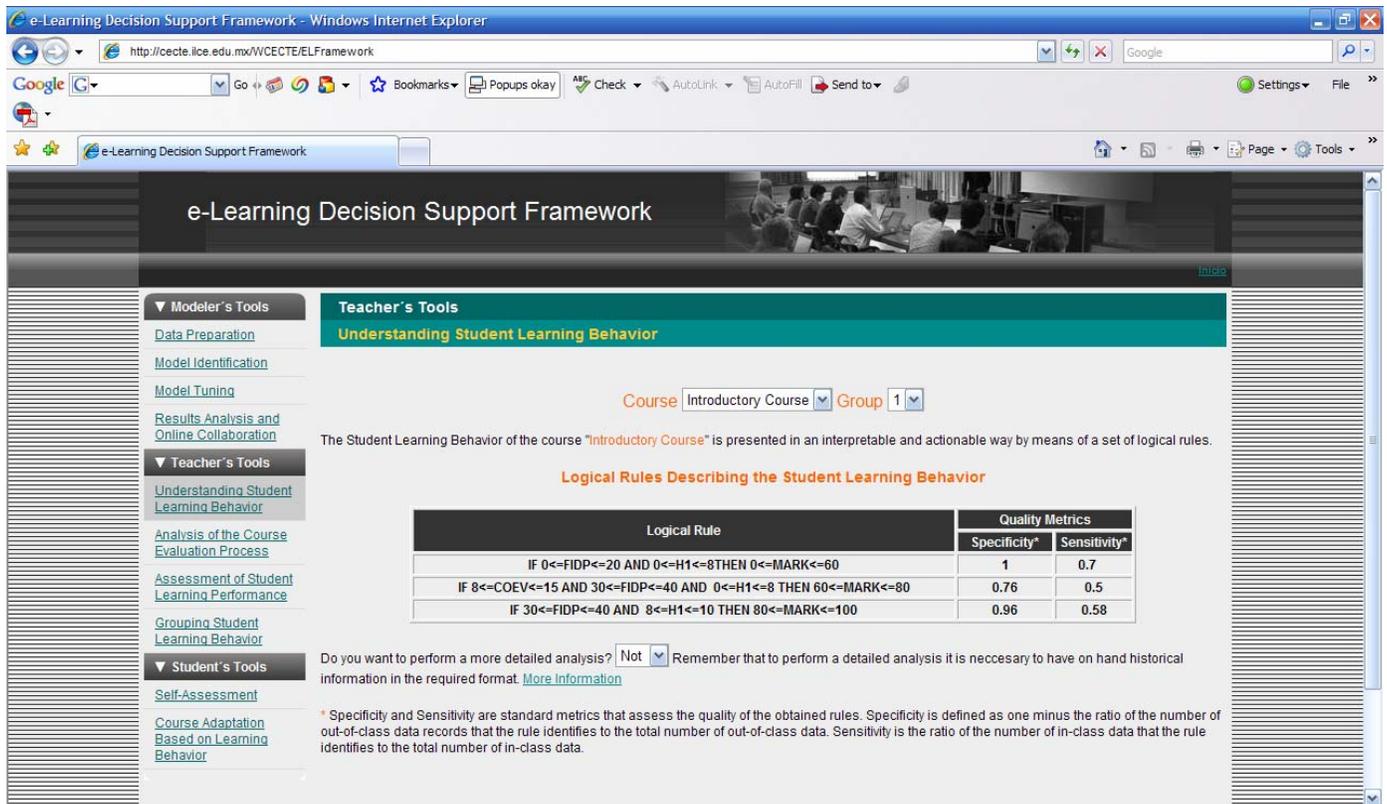
In this research the e-learning decision support framework shown in figure 3 has been developed. The main goal of the proposed framework is to discover relevant learning behavior patterns from student interaction with the educational materials. The knowledge obtained can be used

by teachers to design courses in a more effective way and to detect in time students with learning difficulties. On the other hand, it can be also helpful for the students in order to know his/her own learning performance and therefore use the educational resources more efficiently.

As can be seen in figure 3, the platform offers different functionalities for each user type (left hand side), i.e. course modeler, teacher and student. On the right hand side of figure 3 the results of the selected functionality are presented. In this case, as an example, the *understanding student learning behavior* option is selected for group 1 of the introductory course. Once the results are shown, a link to perform a deeper analysis of each e-learning topic becomes available. Notice, that only if the user has the right permissions he/she would be able to execute the desired functionality.

Modeler's options are: *Data preparation*, where the data stemming from the student portfolio and course database is loaded in the framework in a specific format; *Model identification*, where the modeler should identify the model that best represents the analyzed course by using the FIR methodology; *Model tuning*, where a selection of the best model parameters is performed and *Result analysis and online collaboration*, where an analysis of the knowledge obtained and its usefulness to improve the courses is done in an on-line collaborative way together with all the teachers.

Teacher's options are: *Assessments of student learning performance*, *Understanding student learning behavior*, *Analysis of the course evaluation process* and *Grouping student learning behavior*. The *assessments of student learning behavior* option provide a temporal learning status, in the sense that the performance of the student is evaluated during the course and not at the end. This brings the teacher the possibility to offer efficient and on time feedback to the student in order to improve his/her course performance. Moreover, the platform offers to the teacher the option to send automatically feedback to all students with bad grades in the predicted final mark, reducing his/her workload. The *understanding student learning behavior* tool provides an easy interpretable and comprehensible way to describe the student learning behavior, by means of logical rules. The rules are automatically mined from the data registered from the course. This allows knowing the course performance patterns and, therefore, to use this knowledge in future courses design or decision support. The *analysis of the course evaluation process* option improves the knowledge associated to the educative process by describing the most relevant features involved in the evaluation process. This knowledge allows teachers to confer more weight to the more important variables and don't expend much time to grade the less important variables. Moreover, if a Causal Relevance option is selected, the results of the feature relevance can help the course advisors to define a more accurate final mark equation. The *grouping student learning*



**Figure 3.** User interface of the e-learning decision support framework.

*behavior* option offers to the teachers a tool for cluster students with similar learning behavior. This option could reduce teacher workload if he/she made recommendations to all the students of a specific cluster at once.

Student's options are: *Self-assessment* and *Course adaptation based on learning behavior*. The first option allow student to know at any time his/her learning and course performance by obtaining the prediction of his/her final mark. The second option provides to the user a course adaptation based on the student profile and necessities. The learning material is then provided to the student in a customized way, based on his/her level of knowledge and learning behavior.

From all the platform functionalities, this paper is focused on those that are based on the FIR, CR-FIR and LR-FIR techniques and that are distinctive of the decision support framework developed in this research, i.e. *assessments of student learning performance, understanding student learning behavior, analysis of the course evaluation process and self-assessment*.

The LR-FIR algorithm is the core of the *understanding student learning behavior* option whereas both FIR and CR-FIR support the other three functionalities.

All the framework functionalities are implemented as a Matlab toolkit, and are exploited by Java applet modules.

#### 4. DATA SET ANALYZED FROM A REAL COURSE

The CECTE is a partially virtual campus, offering postgraduate courses and continuous education (graduate, workshops and specific courses) to Latin-American students. The CECTE is the part of the international organism known as ILCE (Latin-American Institute of the Educative Communication, in its original Spanish denomination) whose main goal is to offer postgraduate courses. The teaching-learning process is semi-presential, as students follow courses online (WCECTE) but also attend weekly TV sessions. Through WCECTE, the students can access the course materials and communicate with each other through an e-mail system and a discussion forum. The environment also includes an agenda, a news system, virtual classrooms, a digital library, interactive tutorials, and other related tools.

The CECTE *Introductory Course* was selected for the experiments performed in this study. The introductory course is mandatory for all students that want to get enrolled to any of the masters offered by the CECTE and the main objective of this course is to develop a set of competencies and skills related with communication, computation and critic thinking. A set of 146 students enrolled in the introductory course is used in this study. A 5-fold cross-

validation is chosen, where each test set is composed of 30 samples, the training set contains 100 samples and the validation set has 16 samples. The validation set is necessary to perform two of the CR methods presented in this paper. Table 1 describes the features of this course.

**Table 1.** Data features collected from the introductory course.

Feature	Description
H1	Mark obtained by the student in the homework # 1
H2	Mark obtained by the student in the homework # 2
H3	Mark obtained by the student in the homework # 3
GROUP	The group where the student was enrolled. This course has 7 groups
DPF	Mark of the forum didactic problem (referred exclusively to the didactic problem)
TF	Mark of the student's forum participation (referred to all the topics of the course)
FIDP	Mark obtained by the student in his/her final report of the didactic problem
COEV	Mark of the co-evaluation performed by the student of the work of other students
MARK	Final mark obtained by the student in the course

## 5. EXPERIMENTS: RESULTS AND DISCUSSION

In the next subsections we present the results obtained when the proposed e-learning framework is used to analyse the *introductory course* of the CECTE virtual campus. All the results obtained were evaluated and validated by educative experts of the CECTE. For the sake of space availability the framework results will be presented in tables instead of using the framework user interface.

### 5.1. Assessments of student learning performance

The main goal of this experiment is to identify and model the learning behavior of each student of the course, in order that the teacher can perform a prediction of the final mark and know their learning performance. This framework functionality is based on FIR and/or CR-FIR methodologies.

Notice that before the teachers can use this option, it is mandatory that the modeller identifies the model that best represents the course analyzed from the prediction accuracy point of view. In this sense, before the model identification process can take place, it is necessary to provide the number of classes parameter for each system variable. For the introductory course, all variables have been discretized

into 3 classes except the GROUP variable that has been discretized into 7 classes due to its specific characteristics. Once all parameters have been supplied, the next step is the identification of the best model. FIR discovered that the average mark of the co-evaluation (COEV), the final report of the didactic problem (FIDP), and the first homework (H1) are the most relevant features to predict the final mark of the course (MARK) for each student.

As was stated in section 3, the framework includes two approaches to predict the student's performance, FIR and CR-FIR. In this experiment we apply both to predict the final mark for each student. For the sake of space availability, figure 4 presents, only, the prediction results for the fold with lower error (fold #3). From figure 4, it is clear that the predicted signals (with and without causal relevance) follow very well the real signal, being able to forecast quite accurately low and high marks. However, in some cases the predictions obtained when the CR-FIR method is used are more accurate than those predictions obtained using the classical FIR inference engine.

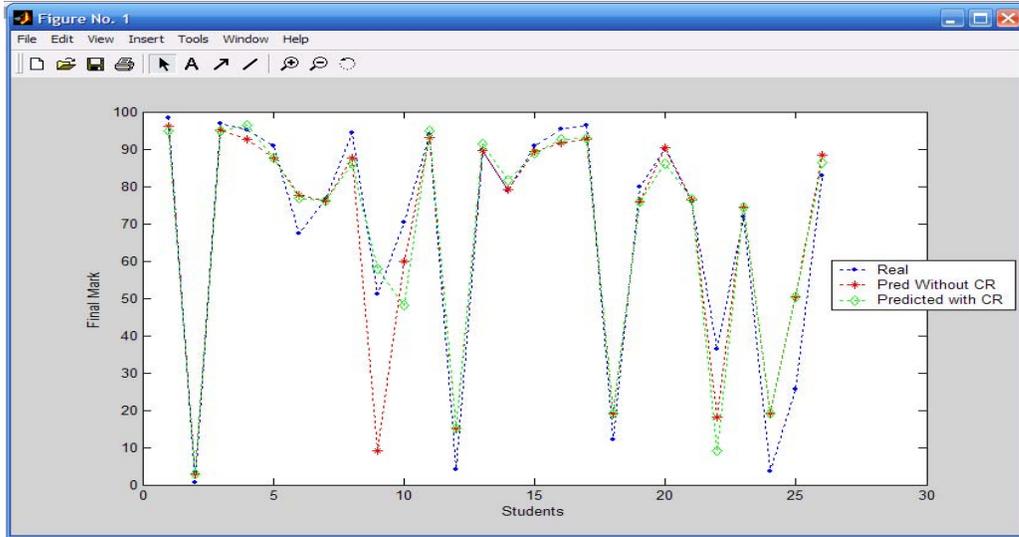
The knowledge derived from the predictions is used for teachers to automatically e-mail feedback to all students with bad grades in the predicted final mark, reducing his/her workload and increasing the course performance.

In the *self-assessment* functionality the same information offered in the *assessment of student learning performance* option is provided, but only for that specific student. Additionally, in the self-assessment option the student can analyze the e-learning platform usability and the learning patterns of successful students that have already passed the same course.

### 5.2. Understanding student learning behavior

In this study we are not only interested in the prediction of student's behavior, but we are also concerned in obtaining an accurate and simple understanding of student learning patterns.

In this experiment it is intended to identify the student learning behavior and make it available in a clear and simple format easily understandable for teachers. To this end, the *understanding students learning behavior* tool of the e-learning framework was selected. The logical rules extracted using the model previously identified are shown in table 2. Notice that the FIDP variable allows values in the range [0..40], COEV in the range [0..15], H1 in the range [0..10] and MARK in the range [0..100]. The rules describe in an easy interpretable way the student learning patterns. The extracted knowledge provides valuable information to didactic experts in the educative decision support stage.



**Figure 4.** Real and predicted signals when PNOVAR CR method and classical FIR inference engine are used (optimal mask; Fold #3).

From the rules obtained, the course teachers observed that the COEV variable has an important final mark prediction capacity, especially in medium performance students. However, COEV feature has a low weight in the final mark computation. Therefore, the course coordinator together with the teachers should perform a careful analysis to study the usefulness to modify the final mark formulae, increasing, by instance, the COEV weight.

**Table 2.** Logical rules that describe the student learning behavior for the introductory course.

Logical Rule	Quality Metrics	
	Spec.	Sens.
IF $0 \leq FIDP \leq 20$ AND $0 \leq H1 \leq 8$ THEN $0 \leq MARK \leq 60$	1	0.7
IF $8 \leq COEV \leq 15$ AND $30 \leq FIDP \leq 40$ AND $0 \leq H1 \leq 8$ THEN $60 \leq MARK \leq 80$	0.76	0.5
IF $30 \leq FIDP \leq 40$ AND $8 \leq H1 \leq 10$ THEN $80 \leq MARK \leq 100$	0.96	0.58

The obtained rules from the introductory course were validated by the course coordinator, teachers and educative experts. They conclude that the obtained results were consistent with their own perception of course student learning behavior.

### 5.3. Analysis of the course evaluation process

In this experiment, the *analysis of the course evaluation process* functionality is selected. As explained before, the evaluation process is one of the most difficult and time consuming activities for teachers in distance education courses, due to the fact that, in this kind of courses, the review process should be done using collaborative

resources. Additional problems are the usually high number of features involved and the difficulty to define their influence in the final mark. Therefore, in this experiment it is intended to reduce system dimensionality by identifying high relevant features and its relative grade of importance.

To this end, it is necessary to start from the best model obtained by FIR for the course at hand. As mentioned earlier, FIR selected, from all features of table 1, COEV, FIDP and H1 as the more relevant to predict the final mark. The next step is to study the ranking of influence of this three variables already selected as relevant by FIR. The three selected features have QVAR values of: COEV=0.1384, FIDP=0.1754 and H1=0.1247. To avoid redundant information we only present the QVAR values, however QNOVAR, PVAR and PNOVAR values are also computed (see section 2.2). This means that the most relevant variable is FIDP, then COEV and finally H1. Notice, however, that QVAR values for all the three variables are very similar and, therefore, the prediction improvement using the causal relevance approaches will not be really impressive.

**Table 3.** MSE obtained to Introductory Course when predicting the 5 test data sets using the optimal mask.

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	
MSE classical FIR	5.46%	11.87%	2.60%	13.0%	22.23%	11.03%
MSE best CR method	4.06%	10.66%	2.57%	9.55%	23.51%	10.07%
CR method used	PVAR	PNOVAR	PNOVAR	PNOVAR	QVAR	

The MSEs obtained when using the FIR model identified to predict the 5 test data sets previously mentioned are shown in table 3. The 2<sup>nd</sup> row of the table shows the prediction MSE obtained without causal relevance. All causal relevance methods presented previously have been executed, and the one with lower MSE is presented in the 4<sup>th</sup> row of table 3 together with the error obtained (3<sup>rd</sup> row). If we compare the errors obtained by the FIR inference engine with and without using causal relevance (3<sup>rd</sup> and 2<sup>nd</sup> row, respectively) it can be seen that the CR methods offer an enhancement of the predictions. This enhancement is not spectacular but it is significant if we take into account the reduced amount of data available and the already good results that are obtained with the classical FIR engine.

Once again, the knowledge acquired can be very helpful to educative actors for future courses design and planning.

## 6. CONCLUSIONS

In this paper the authors introduce an e-learning decision support framework developed to improve the e-learning experience. Using this framework teachers and course coordinators can analyze the interaction of the students with the e-learning environment. The soft computing methodologies (FIR, LR-FIR and CR-FIR) that are the data mining core of the framework are able to offer valuable knowledge to both, teachers and students that can be used to enhanced course performance and that opens new possibilities for the pedagogical and instructional designers who create and organize the learning contents. One of the most interesting options is the personalization of the e-learning process. The characterization of the student online behavior would benefit from both a tool capable of determining the relevance of the features involved in the analyzed data set, in terms of the student mark prediction; and a method to extract interpretable rules describing the student learning behavior.

In this research the CECTE *introductory course* is studied on the light of the framework developed. The results obtained using the *analysis of the course evaluation process* functionality can be used by the course advisors to adjust the equation that computes the final mark, i.e. modifying the weights for the most relevant variables and defining a more accurate final mark equation. The logical rules derived from the *understanding student learning behavior* functionality are easily comprehensible by experts in an educative domain, and they may expose problems with the data itself. This knowledge could be used for real time student personalization guidance, and to help teachers in finding patterns of student behavior.

At the moment the e-learning framework presented is functioning only on the CECTE intranet; however we are

implementing several plug-in to allow the connection with the most known e-learning platforms, in such a way that all the educative institutions interested on using this framework can do it.

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