

Prediction of the Network Administration Course Results Based on Fuzzy Inference

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Abstract The prediction of the number of students who will pass or fail the exams in the case of a subject can be very useful information for resource allocation planning purposes. In this chapter, we report on the development of a fuzzy model, that based on the previous performance of currently enrolled students, gives a prediction for the number of students who will fail the exams of the Network Administration course at the end of the autumn semester. These students will usually re-enroll for the course in the spring semester and, conforming to previous experience, will constitute the major part of the enrolling students. The fuzzy model uses a low number of rules and applies a fuzzy rule interpolation based technique (Least Squares based Fuzzy Rule Interpolation) for inference.

1 Introduction

The introduction of the credit system in Hungarian higher education brought several advantages to the students and the institutions as well. However, the increased flexibility and eligibility put also greater responsibility on the shoulders of the students, and as a side effect it contributed to an increase in the average time necessary for the fulfillment of the academic requirements for graduations. It also made resource allocation planning more difficult for the institutional side.

This problem led particularly to a demand for the prediction of the results in the case of the Network Administration course, which is a laboratory-intensive course of the BC program in computer science where students can learn and experience in

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small groups the topics and practical tricks of the configuration and administration of Windows, Linux and hybrid computer networks. In order to ensure a uniform load of the laboratories and teaching staff over two semesters we needed an early estimation of the number of students who will pass or fail the exam at the end of the autumn semester. This is because those students who fail in the autumn semester usually make up the majority of the students who will enrol for this course in the spring semester next year. The prediction is made based on some historical and actual data.

Computational intelligence comprises a wide range of methods (like fuzzy reasoning [2, 8, 18–20], neural networks [22], and evolutionary techniques [13]) that can be easily used for numerical data-based prediction tasks. In this chapter, we report the application of a fuzzy rule interpolation-based inference technique and a rule base optimization method based on the clonal selection principle that ensures the creation of a low complexity fuzzy system with a reduced number of rules.

The rest of this chapter is organized as follows. Section 2 reviews briefly the fuzzy inference technique applied. Section 3 presents the main ideas of the rule base identification method used. Section 4 reports the results of the modeling and conclusions are drawn in Sect. 5.

2 Fuzzy Inference

Fuzzy reasoning systems with multidimensional input spaces can usually ensure full coverage of the input space by rule antecedents with a relatively high number of rules. This number (N_R) depends on two factors, the resolution of the partitions (the number of fuzzy sets in a partition) and the number of input dimensions. It can be calculated by

$$N_R = n_1 \cdot n_2 \cdot \dots \cdot n_k, \quad (1)$$

where n_i is the number of fuzzy sets in the i th input dimension and k is the number of input dimensions.

The high number of rules can increase system complexity, the memory demand of the software, and the inference time as well. Besides, in some cases, due to lack of information not all the rules that describe the exact relation between the input and output of the modeled phenomena can be identified directly by the human experts or by the algorithm which extracts them automatically from experimental data.

Fuzzy rule interpolation (FRI) based inference methods were developed for the above-mentioned cases, aiming at reasoning even from those input values for which a predefined rule does not exist. The research and development of the FRI field was initiated by Kóczy at the beginning of the 1990s (e.g. [24]) and since then several techniques have been developed (e.g. [1, 6, 7, 11, 12, 14–17, 23]). Among these techniques is the Least Squares based Fuzzy Rule Interpolation (LESFRI) method [14], which determines the fuzzy conclusion from the observation (input value) in two steps. First, it generates a new rule for the current input, i.e. the reference points of the rule's antecedent sets will be identical with the reference points of the

observation sets in the corresponding dimensions. Next, it determines the conclusion firing the new rule, i.e. it applies a single rule reasoning approach. We chose to use this method for our experiments owing to its interpolation and extrapolation capabilities and its availability in the free FRI Matlow Toolbox [9], as well as owing to our good experience with its previous applications.

The method LESFRI (Least Squares based Fuzzy Rule Interpolation) [14] determines the fuzzy conclusion from the observation (input value) in two steps. First, it generates a new rule for the current input, i.e. the reference points of the rule's antecedent sets will be identical with the reference points of the observation sets in the corresponding dimensions. Next, it determines the conclusion firing the new rule, i.e. it applies a single rule reasoning approach.

In the first step the antecedent and consequent sets of the new rule are calculated in each dimension by a set interpolation technique called FEATLS (Fuzzy set interpolation Technique based on the method of Least Squares). Its basic idea is that all the sets of the partition are shifted horizontally in order to reach the coincidence between their reference points and the interpolation point (reference point of the fuzzy input/output in the current dimension)(see Figs. 1 and 2).

Next, the shape of the new linguistic term is calculated from the overlapped set shapes preserving the characteristic shape type of the partition (singleton, triangle, trapezoid, polygonal, etc.) applying the method of least squares. For example in case of each breakpoint of the left flank the sum

Fig. 1 Original partition and interpolation point at 0.4

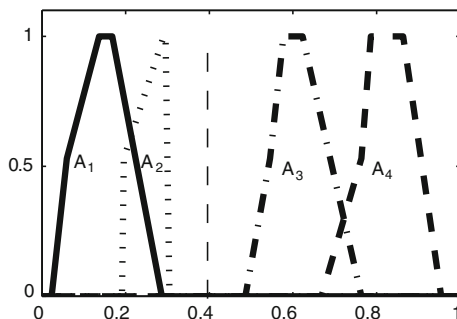
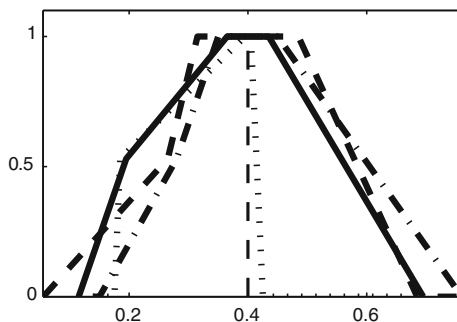


Fig. 2 Virtually shifted sets with their reference points at 0.4



$$Q_j^L = \sum_{l=1}^n w_l \cdot (x_{lj}^L - x_j^L)^2, \quad (2)$$

is minimized, where Q_j^L is the sum corresponding to the j th point of the left flank of the interpolated set, w_l is the weighting factor of the l th linguistic term of the partition, x_{lj}^L is the abscissa of the j th point of the left flank of the l th set and x_j^L is the abscissa of the j th point of the left flank of the interpolated set. The right flank is calculated similarly.

The position of the consequent sets is calculated independently in each output dimension by an adapted version of the crisp Shepard interpolation [21]. Thus the reference point of the conclusion is calculated as a weighted average of the reference points of the consequent sets of the known rules.

$$RP(B^i) = \frac{\sum_{l=1}^N RP(B_l) \cdot s_l}{\sum_{l=1}^N s_l}, \quad (3)$$

where $RP(B^i)$ is the reference point of the interpolated consequent set, N is the number of the rules, $RP(B_l)$ denotes the reference point of the current rule, s_l is the weight attached to the l th rule. The weighting factor is an arbitrary distance function, usually the reciprocal value of the square of the distance.

In the second step of the method the conclusion is determined by the technique SURE-LS (Single RULE REasoning based on the method of Least Squares). The basic idea of the single rule reasoning is that it measures the similarity/dissimilarity between the rule antecedent sets and the corresponding observation sets and it modifies the shape of the conclusion in function of this dissimilarity.

In the case of SURE-LS the dissimilarity on the antecedent side is calculated by the means of weighted averages of the α -cut endpoint distances (ad_α^{aL}), which in case of the left flank is calculated by

$$ad_\alpha^{aL} = \frac{\sum_{j=1}^{n_a} w_{e_j} \cdot (\inf\{A_{\alpha j}^i\} - \inf\{A_{\alpha j}^*\})}{\sum_{j=1}^{n_a} w_{e_j}}, \quad (4)$$

where $A_{\alpha j}^i$ is the α -cut of the antecedent set of the interpolated rule in the j th input dimension, $A_{\alpha j}^*$ is the α -cut of the observation set in the j th input dimension, and w_{e_j} is the weighting factor of the j th antecedent dimension.

Taking into consideration the above calculated differences the characteristic points of the left flank are determined by

$$\inf\{B_\alpha^*\} = \min(\inf\{B_\alpha^i\} - ad_\alpha^{aL}, RP(B^*)), \quad (5)$$

where B_α^i is the α -cut of reinterrogated rule's consequent set and B_α^* is the α -cut of the conclusion.

3 Rule Base Identification

The performance of a fuzzy reasoning system depends strongly on the correctness of the underlying knowledge base. The rule base can be created by human experts based on their experiences, automatically from sample data by an algorithm (e.g. [3, 10, 13, 25]), or using a combination of the two options presented above (a hybrid approach).

In a hybrid approach the human experts create an initial rule base whose parameters will be modified in the course of the optimization process, which usually applies a global and/or a local search technique. Parameters of a fuzzy system can be e.g. those values which describe the fuzzy sets referred to in the antecedent and consequent parts of the rules (such as the reference points of the sets or the abscissa values of the breakpoints).

Another option for the parameter selection represents the identifiers of the language variables used in the rules. Here the task of the optimization procedure is to determine e.g. which fuzzy sets in the consequent parts of the rules ensure the best system performance.

In the course of this project we applied the hybrid approach and the above mentioned last parametrization model. By changing only the fuzzy sets referred in the rule consequents we could ensure semantically good interpretable partitions in the antecedent and consequent dimensions as well. Generally in such cases the search space of the optimal parameter set consists of

$$n_S = (N_R)^{n_o}, \quad (6)$$

discrete points, where N_R is the number of the rules, and n_o is the number of fuzzy sets in the output partition.

The tuning was done by an artificial immune system (AIS) algorithm [13]. The Clonal Selection Algorithm mimics the biological Clonal Selection Principle [4] by implementing mechanisms like clonal selection, clonal expansion, and somatic hypermutation. The first version of the algorithm was suggested by de Castro and von Zuben [5].

The algorithm generates several parameter sets as candidate solutions of the optimization problem. They are called antibodies in the AIS terminology. The initial pool of antibodies is generated as follows. One antibody is created from the initial fuzzy system and contains a description of the system's parameters. From the first instance $N - 1$ copies (clones) are made, where N is the pool size, a parameter of the method. In order to increase the diversity n_R instances are subjected to a hypermutation with a rate of p , where $p \in (0, 1)$ is an arbitrary parameter of the method. The mutation is done by changing the values of some parameters. For each parameter of an antibody a random r ($r \in (0, 1]$) value is generated. If $r < p$ a new value is selected for the parameter randomly from the pool of eligible values.

Next is the calculation of the affinity of each antibody (performance of the fuzzy system represented by the antibody), and the antibodies are sorted in descending

order based on their affinity. The best ones (the first n instances) are selected for cloning. Cloning means that

$$N_c = \text{round}(\beta \cdot N) \quad (7)$$

copies are made from each selected antibody [4], where $\beta \in (0, 1]$ is a user parameter. The clones are subjected to an intensive mutation (hypermutation) which process is also called maturation of the antibodies. It performs a local search in the neighborhood of each instance belonging to the elite group. The neighborhood is closer in the case of antibodies with better performance than in the case of antibodies showing worse affinity. In this case the rate is determined by the formula

$$p = \frac{1}{e^{\rho \cdot PI}}, \quad (8)$$

where PI ($PI \in [0, 1]$) is the performance indicator of the fuzzy system and ρ ($\rho \in (0, 1]$) is a parameter of the method. In case of PI , the lowest possible value corresponds to the worst performance while the highest value indicates the best performance. The affinity of the new antibodies is also measured by means of the fuzzy system's performance.

The resulting pool of antibodies is attached to the original group and the whole repertoire is sorted in descending order based on the affinity values. The first $N - d$ antibodies (where d is parameter of the method) are selected for the next generation and the rest of them are dropped. Then d new instances are created with random bit patterns in order to ensure the diversity of the repertoire. This randomness ensures a global search character to the method.

The algorithm stops when at least one of the following conditions is met.

- n_{af} the number of affinity evaluations exceeds an upper limit—owing to the fact that the calculation of the performance indicator is one of the computationally most expensive steps,
- n_g the number of generations exceeds an upper limit,
- PI_{tr} the affinity of at least one antibody becomes greater than an upper threshold value,
- n_{ni} the number of consecutive generations without any improvement regarding the best affinity value (best antibody) exceeds an upper limit.

Thus the optimization method has at least eight parameters, where the first seven are: N —the number of antibodies in the repertoire (size of the repertoire), n_R —the number of antibodies selected for hypermutation in the first generation, p —the initial hyperlactation rate, n —the number of antibodies selected for cloning, β —the coefficient that determines the number of clones that are created for each selected antibody, ρ —the coefficient which determines to what extent the affinity of an antibody influences the probability of mutation, and d —the number of random antibodies created at the end of each iteration cycle. The rest of the parameter set contains one or more from the above presented stopping criterion.

4 Modeling Results

Our fuzzy modeling project is aimed at the creation of a rule-based system that can predict the number of students who will fail the Network Administration (NA) exam and therefore will enroll in the course again in the subsequent semester.

We chose a two-level solution. At the first level we determined the probability (PS) of passing the Network Administration exam for each student using a fuzzy rule based system and at the second level we calculated an average probability for the whole group of the students who enrolled for the NA course by

$$P_{av} = \frac{\sum_{i=1}^{N_{st}} P_i}{N_{st}}, \quad (9)$$

where N_{st} is the number of students enrolled in the current semester. Next, we calculated the estimated number of students who will pass the exam by

$$N_p = P_{av} \cdot N_{st} = \frac{\sum_{i=1}^{N_{st}} P_i}{N_{st}} \cdot N_{st}. \quad (10)$$

In the course of the generation of the fuzzy model we took into consideration historical data of four past semesters with a total of 122 data records. Thirty records were taken out randomly for test purposes and the remaining 92 data rows were used for the creation and tuning of the rule base.

Based on the available data and previous experiences a rule base containing 21 rules was constructed by human experts. In case of each student we used four input values and one output which are presented below.

Input

- What was the result of the student's last (successful) Computer Networks I (CONI) exam?
Variable: NIR , possible values: 2..5.
- Is this the 1st, 2nd, or 3rd enrollment of the student into the Network Administration course?
Variable: NEN , possible values: 1..3.
- How many credits has the student earned up to now?
Variable: NCr , possible values: SM, AV, BG

Output

- Probability of passing the exam
Variable: PS , possible values: SM, AL, AH, BG

In the first three input dimensions we had crisp values which could be represented by singleton membership functions (see Fig. 3). In case of the fourth input dimension and the output dimension we created partitions with three or four linguistic values (see Figs. 3 and 4).

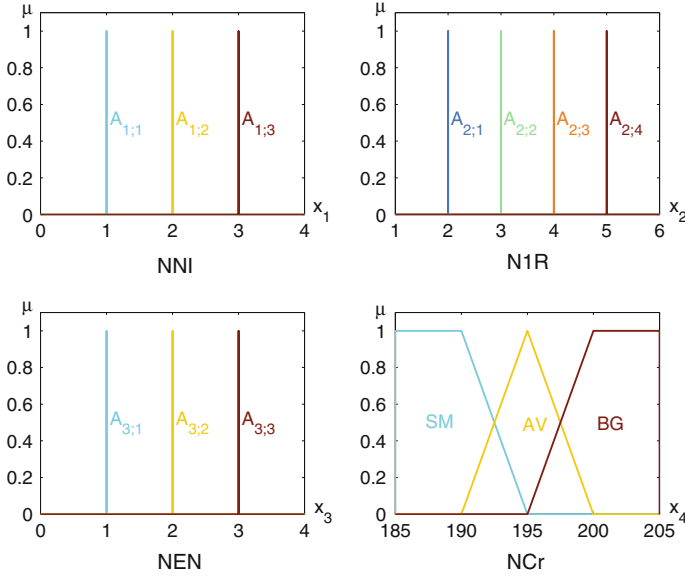
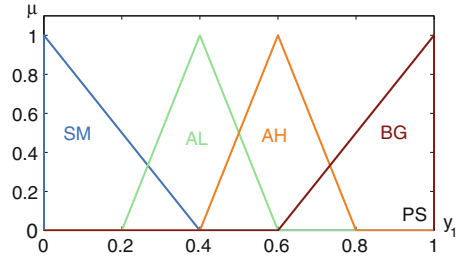


Fig. 3 Input partitions of the fuzzy system

Fig. 4 Output partition of the fuzzy system



We applied the clonal selection based optimization algorithm presented in the previous section for the tuning of the rule base's parameters. The ordinal number of the consequent fuzzy sets in their partition was used as a parameter (values between 1..4) in the case of each rule (*SM*-0, *AL*-1, *AH*-2, *BG*-3).

We chose the following values for the parameters of the algorithm: $N = 30$, $n_R = 15$, $p = 0.5$, $n = 10$, $\beta = 0.4$, $\rho = 0.8$, $d = 10$. We used $n_g = 30$ as stopping criteria. The performance of the fuzzy system was measured by the formula

$$PI = 1 - \sqrt{\frac{\sum_{i=1}^{n_s} (y_i - \hat{y}_i)^2}{n_s}} \cdot \frac{1}{y_{max} - y_{min}}, \quad (11)$$

where n_s is the number of data points involved in the evaluation, y_{min} and y_{max} are the lower and upper bounds for the output values, y_i is the i th output value, and \hat{y}_i is the i th estimated output value (calculated by the fuzzy system).

The initial fuzzy system with the rules created based on our previous experiences provided a performance of $PI = 0.73$ in the case of the training data and $PI = 0.74$ in the case of the test data set. The optimization slightly improved the performance of the system increasing it to $PI = 0.81$ in the case of the training data set and 0.76 in the case of the test data set.

5 Conclusions

In this chapter we reported the results of our efforts regarding the creation of a fuzzy system that can predict the number of students who will fail the Network Administration exam. The main purpose of this work was to support our department's resource allocation activity. Although an exact prediction cannot be made the results can be useful and our further research will concentrate on the improvements by taking into consideration a larger amount of historical data, and increasing the number of parameters included into the tuning process. An examination of other input values is also under consideration.

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