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DECISION-MAKING ALGORITHMS BASED ON DETERMINING THE LEVEL OF STUDENT KNOWLEDGE

Navruza Irmukhamedova
Tashkent University of Information Technologies named after
Muhammad al-Khwarizmi, Tashkent, Uzbekistan

Abstract
In this article, we create decision-making algorithms based on determining the level of student knowledge. The developed system is implemented by means of a non-deterministic logic apparatus in the process of summarizing solutions for evaluating the effectiveness of quality control of students' knowledge. We can express it through practical experiences in creating an expert system that makes firm conclusions based on established criteria for evaluating the effectiveness of education. We will consider the issue of using expert systems in the educational process. The widespread use of Internet technologies ensures the development of new forms of education along with new forms of education, including distance systems or "e-learning systems", In this case, the assessment of the effectiveness of education and the control of the quality of the knowledge received by students has become a rather complex multi-criteria issue. It is required to solve it in modern ways. One of these approaches is the application to the training process of an expert system using a non-deterministic logic device.

Introduction

We will look at the general principles of building a software complex that can comprehensively evaluate the student's learning during the semester, using the principles of rigid logic to classify the level of knowledge of the study group students based on situational analysis. The effectiveness of training can be understood as the level of compliance of the main indicators and values of training with the given criteria. The issue of summarizing the student's mastery is a multi-criteria issue that is difficult to formulate based on the parts of the initial data. If a statistical and mathematical function is used to obtain such an estimate, in the end, it is possible to have a view that is too complex to sufficiently satisfy the necessary requirements.

The application of robust logic allows us to successfully solve the problem with poorly formed initial data. In addition, making and applying rules close to natural language significantly increases the degree of approximation to the required results of inference. In order to separate the factors of mastery grades, in order to evaluate the activity of the learner during the training course, it is necessary to separate such factors in one way or another, so that these values need to be taken into account when forming the final grades. For this, we define the following main categories in the educational process:

- Participation in the lecture.
- Activities in seminars.
- Performance of control works.
- Completion of homework.

The obtained values of the level of performance for each of these categories are used as initial data for summarizing the resulting assessments of mastery.

The categories determined during the conclusion are combined into groups. Because the grades in the categories of the 1st group should ensure the possibility of consideration at a higher level compared to the other group.

Participation in the exhibition and activity in the seminar determines the student's activity, and at the same time, the performance of supervision and homework determines his activity and efficiency during the training course. Determining such intermediate levels provides the necessary work in the formation of the knowledge base.

Let's consider the above category "Participation in the lecture" based on non-deterministic sets, see Equation 1:

$\tilde{x}_1$ = "Participation in the lecture"

$$M(\tilde{x}_1) = < M'_{x1}, M'_{x2}, M'_{x3} > \quad (1)$$

where M'_{x1}=low level;M'_{x2}=middle level;M'_{x3}=high lavel.

Let's look at the category "Activities in seminars" in the same way, see Equation 2:

$\tilde{x}_2$ = "Activities in seminars"

$$M(\tilde{x}) = < M^{"}_{x1}, M^{"}_{x2}, M^{"}_{x3} >$$

(2)

where M''_{x1}=low level; M''_{x2}=middle level; M''_{x3}=high lavel.

We determine the activity of the learner from the above two categories and evaluate it on three levels, see Equation 3.

F - activity

$$M(F) = < M_F^1, M_F^2, M_F^3 >$$

(3)

where M_F^1=low level;M_F^2=middle level;M_F^3=high lavel.

We calculate the values of the elements of the M(F)-set in percentage. Now we express the category "Performance of control works" by non-deterministic variables. It is as follows:

$\tilde{y}_1$=Execution of control works

$$M(\tilde{y}_1) = < M'_{y1}, M'_{y2}, M'_{y3} > \quad (4)$$

where M'_{y1}-low level, M'_{y2}-medium level, M'_{y3}-high level.

Let's look at the "Completion of homework" category in the same way:

$\tilde{y}_2$=Completion of homework

$$M(\tilde{y}_2) = < M''_{y1}, M''_{y2}, M''_{y3} > \quad (5)$$

where M''_{y1}-low level, M''_{y2}-medium level, M''_{y3}-high level.

We determine the effectiveness of the learner's knowledge from the above two categories "Completion of control work", "Completion of homework" and evaluate it on three levels.

B-efficiency

$$M(B) =< M_B^1, M_B^2, M_B^3 > \quad (6)$$

where M_B^1 -low level, M_B^2-middle level, M_B^3-high level.

We calculate the values of the elements of the M(B)-set in percentage.

We determine the student's performance in the semester based on the student's activity and knowledge efficiency.

It requires the development of modeling and assessment (decision-making) with non-deterministic logic methods in assessing students' knowledge through learning outcomes. In this case, it will be possible to construct a relevance function based on the distribution of points for “excellent”, “good”, “average”, “satisfactory”, “unsatisfactory” linguistic variables. Fig. 1. avarege grades above.

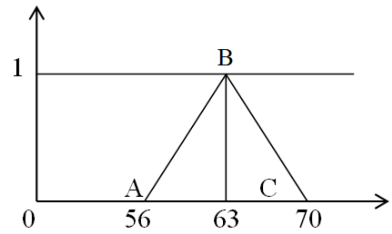

Fig. 1. “Average” grade relevance function.

According to the picture, A(56;0); B(63;1); It can be taken as C(70;0).

$$AB: \frac{x-56}{63-56} = \frac{y-0}{1-0}, \mu_{AB} \frac{x-56}{7} = \mu_{AB}(56) = 0, \mu_{AB}(63) = 1$$

$$CB: \frac{x-70}{63-70} = \frac{y-0}{1-0}, \mu_{CB} = \frac{70-x}{7}, \mu_{CB}(70) = 0, \mu_{CB}(63) = 1$$

$U_1 = \{56,\ 70\}$:

U1: Medium grade={“loosely based”=a1, “moderately based”=a_2, “strongly based”=a_3}. The weighted values of the linguistic variable “loosely based”=a_1 are μ_{AB}={0, 0.1, 0.2, 0.4, 0.5}. “moderately based” = weighted values of a2 linguistic variable μ_{AB}, μ_{CB} ={0.6, 0.7, 0.8, 0.9, 1} “strongly based”=weighted values of a3 linguistic variable μ_{CB}={0, 0.1, 0.2, 0.3, 0.4, 0.5}.

x = 62, $\mu_{AB} = \frac{62-56}{7} = \frac{6}{7} \approx 0.9$ 0.9 we can see that this result holds for a2. x=67, $\mu_{CB} = \frac{70-67}{7} = \frac{3}{7} \approx 0.4$, 0.4 we can see that this result belongs to a_3.

So we cannot go directly from a_1 to a_3. Therefore, we perform the step $a_1 \rightarrow a_2 \rightarrow a_3$ and develop the following solutions:

$a_1 \rightarrow a_2$: {repetition, simple calculations, getting advice, understanding the essence of science, acquiring skills };

$a_2 \rightarrow a_3$: {working on oneself, practical and theoretical training, receiving advice, learning methods available in science, gaining qualifications}.So the result was equal to . Here, “mean-based” is a weighted linguistic variable value.Linguistic variables and solutions for Excellent and Good grades are presented in the same way as the linguistic variables and solutions for medium grades above (Fig. 2. and Fig. 3.).

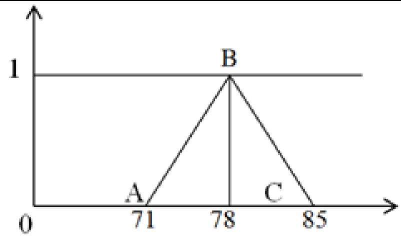

Fig. 2. “Good” grade relevance function.

$$AB: \frac{x-71}{78-71} = \frac{y-0}{1-0}, \mu_{AB} \frac{x-71}{7} = \mu_{AB}(71) = 0, \mu_{AB}(78) = 1$$

$$CB: \frac{x-85}{78-85} = \frac{y-0}{1-0}, \mu_{CB} = \frac{85-x}{7}, \mu_{CB}(85) = 0, \mu_{CB}(78) = 1$$

good grade $U_2 = \{71,\ 85\}$:

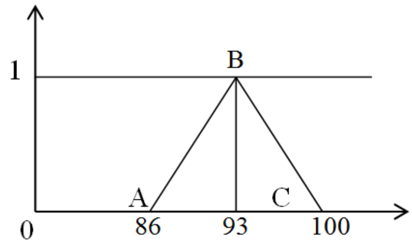

Fig. 3. “Excellent” grade relevance function.

$$AB: \frac{x-86}{93-86} = \frac{y-0}{1-0}, \mu_{AB} \frac{x-86}{7} = \mu_{AB}(86) = 0, \mu_{AB}(93) = 1$$

$$CB: \frac{x-85}{93-100} = \frac{y-0}{1-0}, \mu_{CB} = \frac{100-x}{7}, \mu_{CB}(100) = 0, \mu_{CB}(93) = 1$$

excelent grade $U_3 = \{86{,}100\}$:

When creating decision-making algorithms based on classified data, decision-making algorithms based on classified data are presented in Fig. 4. below, a general scheme of learner’s mastery ratings. In this approach, 3 strict supervisors are used, each of them defines their knowledge system in their work [1].

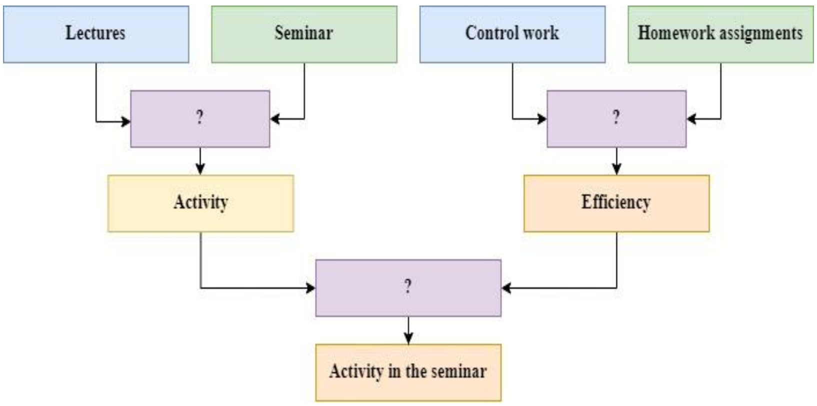

Fig. 4. General rating scheme.

Calculation of statistical estimates. In order to express the idea expressed above in the assessment of mastery, the values given to the input of the inference mechanism, especially the level of performance for each of the specified categories, should be determined in one way or

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another. During the analysis of the subject area, the following principles of obtaining data values were formed.

Attending a lecture. The arithmetic average of all available attendances can be calculated when evaluating attendance at a lecture [2,4]:

$$M = \frac{\sum_{i=1}^{n_m} m_i}{n_m} \qquad (6)$$

Here n_m -is the number of reports; The price of participation in the m_i- i-report.

Activities in seminars. Evaluation of activities in seminars is carried out in an analogous form [3]:

$$M = \frac{\sum_{i=1}^{n_S} s_i}{n_S} \qquad (7)$$

Here n_s-the number of seminars; s_i-i-seminar performance assessment.

Performance of control works. Evaluation of the performance of control works is carried out taking into account the coefficient of complexity determined for each work. These values are significant relative to the weighting factor and are intended to set a higher level when considering the performance of complex tasks than simple ones [4].

$$M = \frac{\sum_{i=1}^{n_t} t_i * c_i^t}{\sum_{i=1}^{n_t} c_i^t} \qquad (8)$$

Here n_t - is the number of control works; t_i - i-job completion price, c_i^t- i - job complexity coefficient.

Completion of homework. Completion of homework assignments will be evaluated in the same way [4].

$$M = \frac{\sum_{i=1}^{n_h} h_i * c_i^j}{\sum_{i=1}^{n_h} c_i^h} \qquad (9)$$

Here n_t - is the number of homework assignments; hi-i-job evaluation, c_i^t - i-task complexity coefficient.

Linguistic variables. To evaluate the learner's learning, we include linguistic variables such as “attended lectures, worked in seminars, completed supervision work, completed homework”. We express the characteristics of variables with concepts such as “activity”, “efficiency” and “grade”.

Programming of classification and decision-making algorithms

In this article, as statistical information, a pilot test is conducted among students of Tashkent University of Information Technologies and Tashkent State Pedagogical University named after Nizami in a multivariate method [5, 6].

We implement programming based on decision-making algorithms based on classified data. Programming is based on the above algorithms. Linguistic variables and variable characteristics can be observed through the Membership Function Editor function in the Fuzzy Logic Toolbox package of the MatLab system. First, we observe the linguistic variable of student exposure in the Membership Function Editor. In this picture, we express the participation of students in the exposure by <occasionally>, <constantly> variables:

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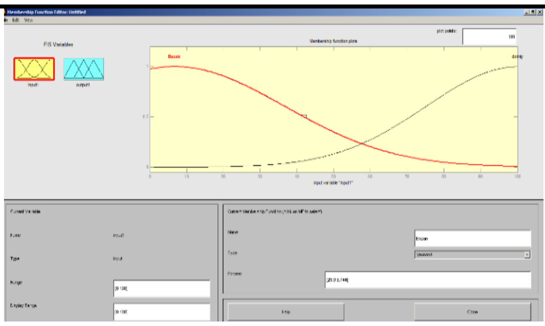

Fig. 5. Representing student exposure in the Membership Function Editor.

Now we monitor the linguistic variable of the students' activity in the seminars in the Membership Function Editor. We express the activity of students in seminars by <very slow>,<periodic>and<very active> variables:

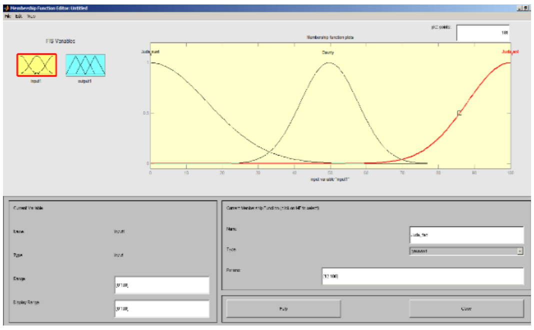

Fig. 6. Representation of students' activities in seminars in the Membership Function Editor.

We monitor the linguistic variable of students' performance of control work in the Membership Function Editor. We express the performance of students in seminars by <bad>, <medium> and <good> variables:

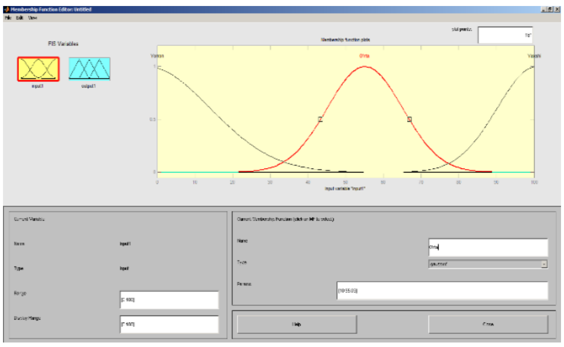

Fig. 7. Representation of students’ control work in the Membership Function Editor.

We track the linguistic variable of students' homework completion in the Membership Function Editor. We can represent the students' homework as well as the students' performance in the seminars by the discrete variables <bad>, <average> and <good>. In this case, the student with the <bad> variable did very poorly on homework. A student with a variable <average> did average homework. A student with a <good> variable is considered to have done homework very well. We express the students' homework by the above function as persistent variables <bad>, <medium> and <good>:

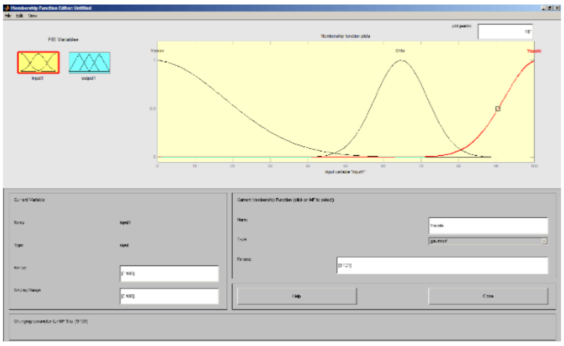

Fig. 8. Representing student homework in the Membership Function Editor.

We observe the characteristics of the linguistic variable of student activity in the Membership Function Editor. We express the activity of students by <low>, <medium> and <high> non-deterministic variables:

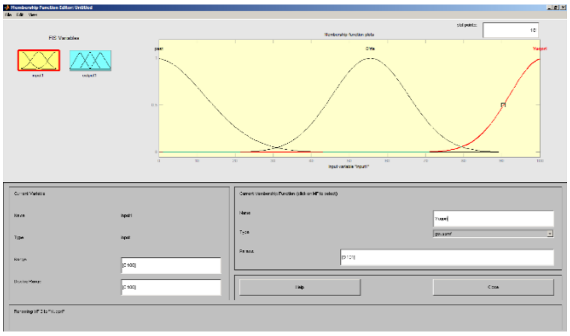

Fig. 9. Representing student activity in the Membership Function Editor.

We observe the characteristics of the linguistic variable of the effectiveness of student knowledge in the Membership Function Editor. We also express the effectiveness of students' knowledge through the variables <bad>, <medium>, <good> and <very good>:

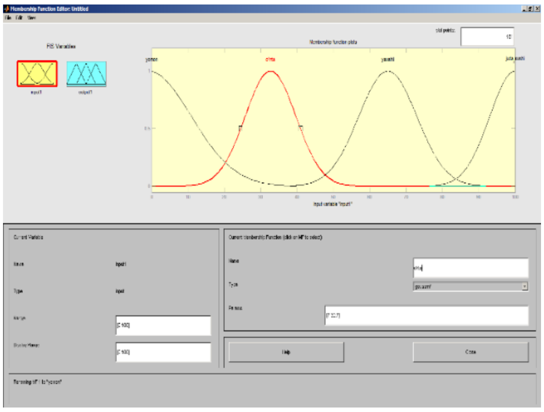

Fig. 10. Expressing the effectiveness of student knowledge in the Membership Function Editor.

We observe the characteristics of the linguistic variable of students' grades in the Membership Function Editor. We also express the grade of students by <bad>, <satisfactory>, <good>, <very good> and <excellent> variables:

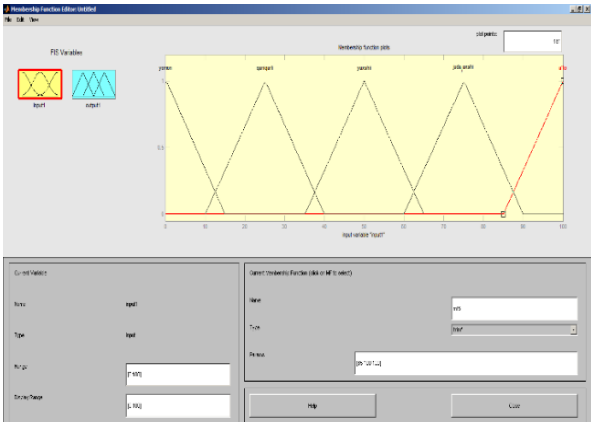

Fig 11. Representing student grades in the Membership Function Editor.

Now we will look at the rules of operation of persistent controllers (controllers) in the form of a table.

Table 1. Determining student engagement through linguistic variables of student exposure and activity in seminars.

Activity		**Participation in the report**	
		sometimes	usually
Activities in seminars	very slow	slow	middle
	periodic	middle	middle
	very active	middle	high

Table 2. Determining the effectiveness of the student's knowledge through the linguistic variables of the student's performance of control work and the completion of homework.

Efficiency		**Performance of control works**		
		bad	middle	good
Completion of homework	bad	bad	bad	middle
	middle	bad	middle	good
	good	bad	middle	very good

Table 3. Determination of the student's assessment by the characteristics of the linguistic variable of the efficiency and activity of the student's knowledge

Grade		Efficiency			
		bad	middle	good	very good
Activity	low	bad	bad	satisfactory	very good
	middle	bad	middle	good	excellent
	middle	bad	middle	very good	excellent

One of the main steps in achieving the goal of decision-making based on the Fuzzy Logic Toolbox model is the correlation between the group's students' mastery indicators and the values of significant linguistic variables. To build the Fuzzy Logic Toolbox model, we first create a .dat file based on the values in the columns of student acquisition scores and weighted linguistic variable values. We upload our created .dat file to the Matlab environment based on the antisemite command. (Fig. 12.)

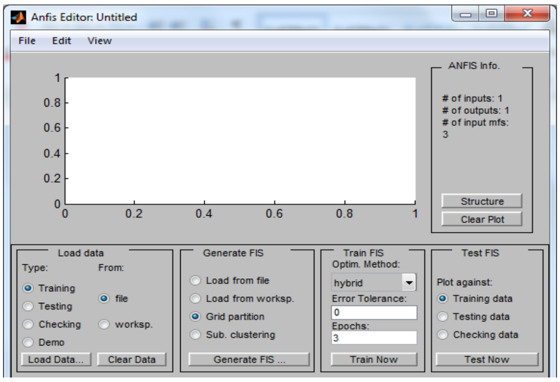

Fig. 12. Representation of students' control work in the Membership Function Editor.

To work in this window, we perform the following steps:

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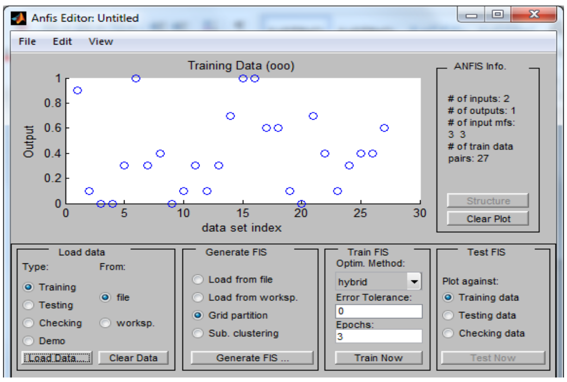

Fig. 13. Representation of students' control work in the Membership Function Editor.

In the image below we can see the rules between incoming and outgoing values.

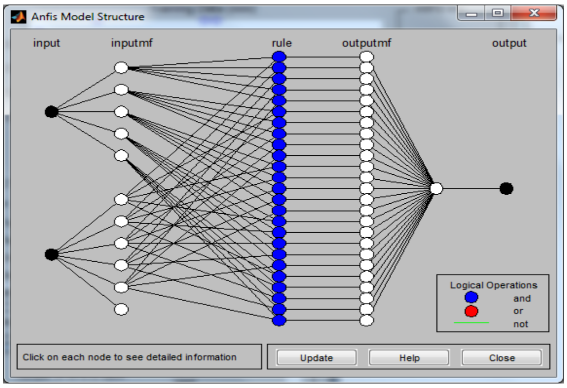

Fig. 14. Representation of students' control work in the Membership Function Editor.

When we give the test now command in the Anfis editor window, we get the following result. (Fig. 3.5) In this picture, the data is represented graphically based on the values in the columns of students' order number, mastery indicators and important linguistic variable values.

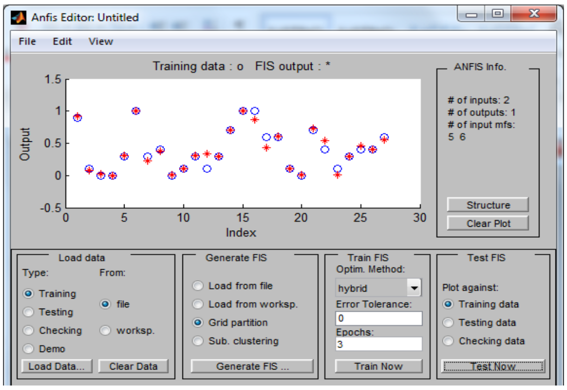

Fig. 15. Representation of students' control work in the Membership Function Editor.

Now, we will model the data using the surface function based on the values in the columns of students' order number, mastery indicators, and weighted linguistic variable values. (Fig. 16.)

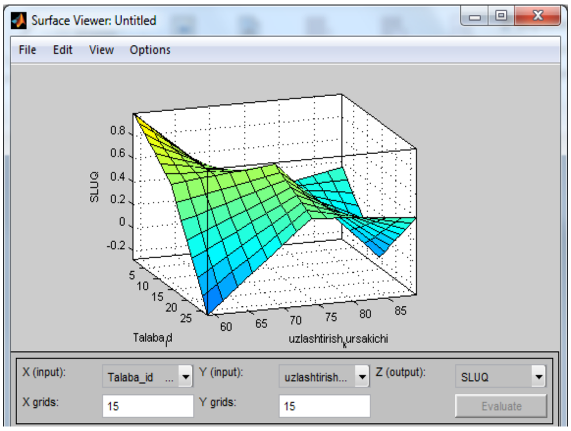

Fig. 16. Representation of students' control work in the Membership Function Editor.

In this model, the number of students, i.e. "Student ID" is 27 students, the learning indicators are min {59 points}, max {89 points} and the weighted linguistic variable values are in the range [0;1] was calculated.

Conclusion

The practical application of the intellectual system for evaluating students' knowledge (as an example of teaching computer architecture) was supported. For this, the goal, content and assessment criteria of computer architecture science were introduced. Statistical information about the marks of the group that mastered this subject, the mastery rate and the rating score in the semester was collected and analyzed. As a statistical reference, the rating record of the students of the Tashkent University of Information Technologies and Tashkent state pedagogical university named after Nizami in the subject "Computer Architecture" for 1 semester was used as a practical application. The values of the linguistic variable were determined based on the student's scores during the semester, and the formula for calculating the weighted linguistic variable value was used. The stages of modeling and conducting experiments on the basis of the Fuzzy Logic Toolbox package of the level of correlation between the mastering indicators of the students of the group and the values of important linguistic variables were considered.

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