Systems for Checking and Testing the Quality of Knowledge Based on Fuzzy Inference

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Abstract

In this article the problems of systems for assessing the quality of knowledge based on test control. The approaches to the development of intelligent systems for testing the quality of knowledge are examined, the functioning of which is based on the apparatus of fuzzy inference. A knowledge assessment model for fuzzy testing systems based on a four-point assessment system is proposed. Also presented are fuzzy systems of testing. In particular, adaptive systems, the advantages of using the fuzzy logic apparatus in building intelligent testing systems designed to improve the accuracy of testing and identifying the quality of knowledge by students. The method of complex assessment of students knowledge based on the Type 2 Tagaki-Sugeno fuzzy model are proposed.

Keywords [1]

Testing systems, fuzzy inference, intelligent teaching systems, fuzzy rule, grading scales

1. Introduction and discussion

In the modern educational industry, automated methods are increasingly being used to identify and test the quality of students' knowledge. In particular, knowledge testing systems are becoming more and more popular, moreover, gradually moving from an auxiliary tool to the main form of knowledge quality control. Knowledge testing systems have several advantages: the speed of knowledge testing, a unified approach to examiners, the ability of a student to take direct part in the examination process, and compare their results with similar results of their colleagues [1, 2].

Considering various grading scales (100-point, 5-point, 7-point, 12-point, etc.), we can note their common feature - not depending on the degree of graduation, most of them have a linguistic scale: “Excellent”, “Good”, “Satisfactory”, “Unsatisfactory”. Moreover, it is not always possible to accurately determine the transition boundary between two neighboring estimates. It can be argued that the process of assessing the quality of knowledge is intellectual in itself, and systems that automate these processes are humanistic systems [3], in which human judgments and the operation of quality indicators play a large role.

Testing systems can have open and closed questions. Open-ended questions suggest an arbitrary answer from the examiner, checking the degree of conformity to the standard, while closed-ended questions have a fixed number of possible answers selected from the available list. Closed questions include: selecting one or more options, drawing up a logical sequence, determining correspondences in response groups, etc.

As a rule, the calculation of the number of points for the completed task is based on the arithmetic calculation of the correct and incorrect selected answer options [4].

There are various approaches to improving the quality of identification and testing of knowledge in the creation of testing systems [5]. We list some of them:

- systems with different levels of task complexity (multisession systems);
- adaptive systems in which the next task (or level) is selected based on previous answers;
- simulation systems for testing knowledge;

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- systems with a combination of open and closed questions.

Classical testing systems, in comparison with full-time examinations, have a number of disadvantages: the examiner's inability to apply an individual approach to each student, a fixed list of questions, difficulties in choosing the next difficulty level and suitable question options, and the main question is how to use the teacher's experience directly during testing.

Considering the fact that in each specific field of knowledge, the teacher's experience and skills can be quite narrow and specialized, we can talk about the need to model their expert reasoning, which, in conditions of incomplete and inaccurate answers to open questions by students, entailed the creation of various intelligent fuzzy systems testing, designed to reproduce the train of thought of the teacher in assessing the knowledge of students [2, 6, 7, 8].

The aim of this work is to consider the principles of building intelligent testing systems using a fuzzy logic apparatus, as well as based on fuzzy logic inference algorithms in order to improve the quality of knowledge identification and assessment.

2. Fuzzy inference systems

Fuzzy inference systems (FS) include the following main stages of their work [9]:

1. Fuzzification of input data.
2. Aggregation of fuzzy rule subcontracts and calculation of their consequents.
3. Accumulation of subcontracts of the entire block of fuzzy rules.
4. Fuzzy inference.
5. Defuzzyfication output values.

2.1. Mamdani Type 1 Fuzzy Inference.

In general, a fuzzy system can be expressed as follows [10]:

$$\bigcup_{j=1}^{k}\left(\left(\bigcap_{i=1}^{n_j} x_i = a_{i,j}\right) \to y = b_j\right), \qquad j = \overline{1, N},$$

where N – number of rules in the IF-THEN fuzzy rule block, b_j – fuzzy rule conclusion, $x_i = a_{i,j}$ – correspondence of a variable x_i to a fuzzy $a_{i,j}$, $\cup\cap$– fuzzy disjunction (conjunction) operations.

Then the conclusion of the fuzzy inference according to the Mamdani algorithm [9, 10] (using the defuzzification procedure by the gravity center method):

$$y = \frac{\int_{Min}^{Max} x \cdot \mu(x) dx}{\int_{Min}^{Max} \mu(x) dx}, \tag{1}$$

where $\mu(x)$ is the membership functions of the fuzzy variables x to the corresponding fuzzy terms, $\mu(x) \to [0,1]$.

2.2. Takagi-Sugeno Type 1 Fuzzy Inference.

The knowledge bases of Takagi-Sugeno fuzzy inference systems contain blocks of fuzzy *if-then* rules [9, 11–12] (Figure 1). Fuzzy zero-order rules of Takagi-Sugeno systems are distinguished by the presence of a zero degree polynomial in the consequent rules:

$$R^m : \ IF\ x_1\ is\ A_1^m\ AND\ x_2\ is\ A_2^m\ AND\ \ldots\ AND\ x_p\ is\ A_p^m\ THEN\ y^m = a_0^m, \tag{2}$$

where $x_1, x_2, \ldots, x_p$ are the fuzzified values of a set of input variables; $A_1^m, A_2^m, \ldots, A_p^m$ are the fuzzy sets of antecedent of each rule m; m – the number of fuzzy rule; a_0^m are the subconclusion of a fuzzy rule, represented as a constant value.

Conventional Takagi-Sugeno fuzzy systems (first order) operate on the basis of *if-then* fuzzy rules of the form:

$$R^m : IF\ x_1\ is\ A_1^m\ AND\ x_2\ is\ A_2^m\ AND\ \dots\ AND\ x_p\ is\ A_p^m$$
$$THEN\ y^m = g^m(x_1, x_2, \dots, x_p),\ \ m = 1,2, \dots, N, \tag{3}$$

where is the function in the consequent fuzzy rule: $g^m(x_1, x_2, \dots, x_p) = a_0 + a_1 x_1 + a_2 x_2 + \dots + a_p x_p$ consists in the form of a linear functional dependence on a set of non-fuzzy values of the input variables, N – the number of fuzzy rules.

The conclusion of the Takagi-Sugeno fuzzy system (which is a numerical value) is calculate (4):

$$y = \frac{\sum_{m=1}^{N} g^m \min_{i=1\dots p^m} \mu_i^m(x_i)}{\sum_{m=1}^{N} \cdot \min_{i=1\dots p^m} \mu_i^m(x_i)}. \tag{4}$$

where $\mu_i^m(x_i)$ – membership functions in the antecedent of a fuzzy rule, where the operation of finding the minimum is used as a conjunction.

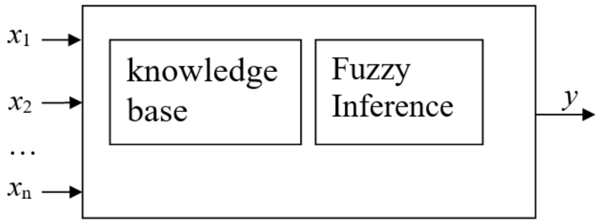

Figure 1: Schema of Type 1 fuzzy inference system

2.3. Takagi-Sugeno Type 2 Fuzzy Inference

Takagi-Sugeno systems of Type 2 (T2) [13] are characterized by the presence in the antecedent of fuzzy rules of fuzzy sets, for which the value of primary belonging is a fuzzy set (fuzzy sets of the second type, invented by L. Zadeh [14]).

The Karnik-Mendel algorithm of fuzzy inference for Takagi-Sugeno T2 systems based on fuzzy sets with interval secondary functions was developed in [15, 16]. This algorithm has a slightly lower computational complexity in comparison with the analogous algorithm for Mamdani Type 2 fuzzy systems [22]. In [12, 17], a parallel algorithm of fuzzy inference for high-order Takagi-Sugeno systems was proposed.

The continuous T2 fuzzy sets have the form:

$$\tilde{A} = \int_X \frac{\mu_{\tilde{A}}(x)}{x} = \int_X \frac{\left[\int_{J_x^u} \frac{f_x(u)}{u}\right]}{x}, \qquad J_x^u = \left\{(x,u) : u \in \left[\overline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)\right]\right\} \subseteq [0,1]. \tag{5}$$

The discrete second type fuzzy sets are presented accordingly:

$$\tilde{A} = \sum_{j=1}^{N} \frac{\mu_{\tilde{A}}(x_j)}{x_j} = \sum_{j=1}^{N} \frac{\left[\sum_{i=1}^{M_j} \frac{f_x(u_i)}{u_i}\right]}{x_j},$$
$$u_i \in J_x^u \subseteq u \in \left[\overline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)\right] \subseteq [0,1], x_j \in X, \tag{6}$$

where f_x – a secondary membership functions, $\overline{\mu}_{\tilde{A}}(x)$ is the upper value of the primary membership functions:

$$\overline{\mu}_{\tilde{A}}(x) = \sup J_x^u, \quad x \in X. \tag{7}$$

$\underline{\mu}_{\tilde{A}}(x)$ is the lower value of the primary membership functions:

$$\underline{\mu}_{\tilde{A}}(x) = \inf J_x^u, \quad x \in X. \tag{8}$$

Takagi-Sugeno T2 FS assumes the use of interval T2 fuzzy sets [22] in the antecedents of fuzzy rules of the following form:

$$\begin{gathered} R^m\colon\ If\ x_1\ is\ \widetilde{A_1^m}\ and\ \dots and\ x_p\ is\ \widetilde{A_p^m} \\ Then\ g(x)^m = w_0^m + w_1^m x_1 + \cdots + w_p^m x_p, \end{gathered} \tag{9}$$

where $\widetilde{A_1^m}$ ... $\widetilde{A_p^m}$ – interval T2 fuzzy sets, m is the number of the rule. Interval T2 fuzzy sets have the form:

$$\tilde{A} = \int_X \frac{\mu_{\tilde{A}}(x)}{x} = \int_X \frac{\left[\int_{J_x^u} \frac{1}{u}\right]}{x}, \qquad J_x^u = \left\{(x,u)\colon u \in \left[\overline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)\right]\right\} \subseteq [0,1]. \tag{10}$$

2.4. Iterative Karnik-Mendel algorithm for Takagi-Sugeno Type 2 fuzzy inference system

The Karnik-Mendel algorithm [15, 16] assumes the use of constant secondary membership functions. The initial step of this algorithm is to execute the activation of Type 2 consequents of a fuzzy rule base $(g(x)^m, m = 1 \dots N)$ and finding for each rule the intervals $[\underline{f}^m(x), \overline{f}^m(x)]$.

The next steps of the algorithm are the operation of lowering the type and finding the interval output of the fuzzy system according to formulas (11–13). In [18], a study of interval output values in fuzzy systems of the second type is given.

$$G(\mathrm{x}) = [g_l(\mathrm{x}), g_r(\mathrm{x})], \tag{11}$$

$$g_l(\mathrm{x}) = \min_{\substack{f_j^m(x) \in \left[\underline{f}^m(x), \overline{f}^m(x)\right] \\ m=1,\dots,N}} \frac{\sum_{m=1}^N f_j^m(\mathrm{x}) g^m(\mathrm{x})}{\sum_{m=1}^N f_j^m(\mathrm{x})}, \tag{12}$$

$$g_r(\mathrm{x}) = \max_{\substack{f_j^m(x) \in \left[\underline{f}^m(x), \overline{f}^m(x)\right] \\ m=1,\dots,N}} \frac{\sum_{m=1}^N f_j^m(\mathrm{x}) g^m(\mathrm{x})}{\sum_{m=1}^N f_j^m(\mathrm{x})}. \tag{13}$$

Thus, multiple calculation of fuzzy rule consequents on the interval $[\underline{f}^m(x), \overline{f}^m(x)]$ is performed, since the obtained values may differ. The final output value of the Takagi-Sugeno FS T2 is calculated according to (14):

$$g(\mathrm{x}) = 1/2\left(g_l(\mathrm{x}) + g_r(\mathrm{x})\right). \tag{14}$$

Figure 2 shows the structure of a Type 2 fuzzy system model, where $\mathrm{x} = (x_1, x_2, \dots, x_p)$ – vector of crisp input values, $\tilde{\mathrm{x}} = (\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_p)$ – a set of fuzzy input variables obtained as a fuzzyfication result.

3. Adaptive fuzzy inference systems for testing students based on fuzzy selection of the next level of complexity

One of the problems associated with the development of testing systems is the intellectualization of the algorithm for choosing the next level of difficulty when passing a multi-level test by a student.

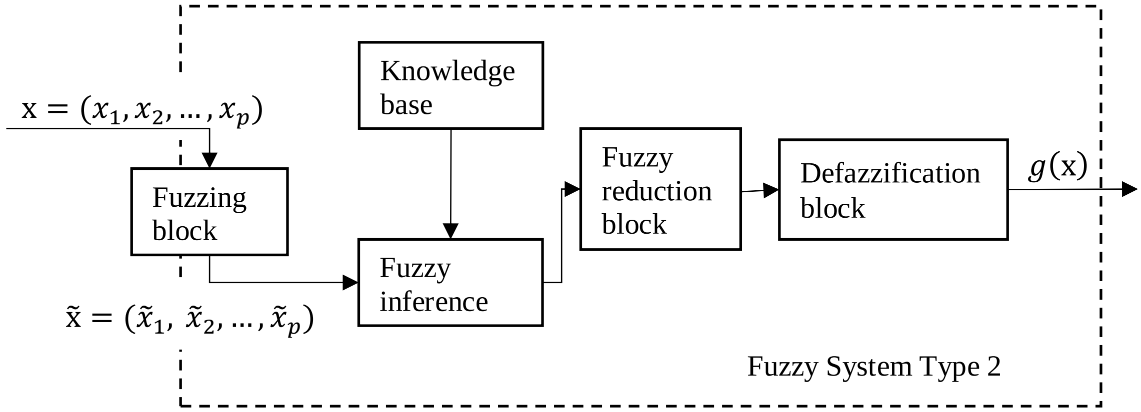

Figure 2: Fuzzy inference system Type 2

The approach proposed in [4] involves the use of the methodology of a specific teacher or expert in the automation of multilevel testing systems. Thus, the fuzzy system is not directly involved in passing the test, however, as an intermediate link between the levels.

The input data vector is information about the last level of difficulty of the test task passed by the student, the success of his passage, and the average assessment of passing all the tests at the previous stages can also be taken into account.

The output is the value of the selected difficulty level at the next stage of testing. Figure 3, 4 show the linguistic variables "complexity" and "correctness" (relative to the last test performed) by type 2 triangular membership functions with interval secondary membership functions (the numerical scale of difficulty levels depends on the specific system and is not given here):

The knowledge base can be represented by the following block of fuzzy rules (fragment):

$$R_1: IF x_1 = High\ AND x_2 = Good$$
$$THEN\ y_1 = High;$$
$$R_2: IF x_1 = Low\ AND x_2 = Excellent$$
$$THEN\ y_2 = Average;$$
$$\dots$$
$$R_n: IF x_1 = Average\ AND x_2 = Satisfactory$$
$$THEN\ y_n = Low;$$

Thus, this approach can be applied to multilevel testing systems for which a set of difficulty levels of tasks passed by a student is a non-trivial component of identifying the level of knowledge.

4. Adaptive fuzzy testing systems based on fuzzy processing of student's answers

Another approach to creating adaptive testing systems is the intellectualization of the process of evaluating results [19–21].

Figure 5 shows a diagram of an adaptive knowledge testing system based on the use of fuzzy inference algorithms when processing student test answers and deriving the final knowledge score. Methods for constructing hierarchical fuzzy systems are given in [22–24].

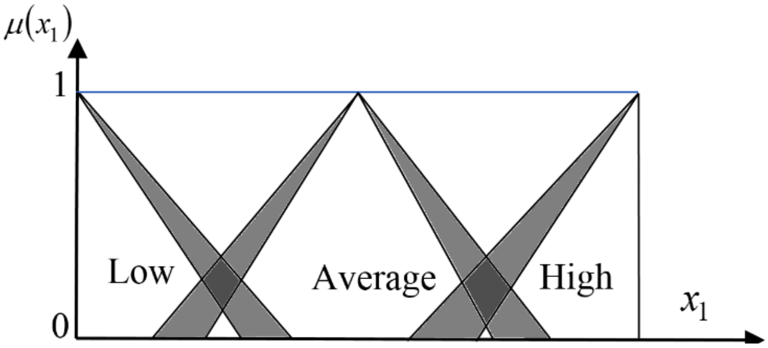

Figure 3: Linguistic variable «complexity of the last completed task

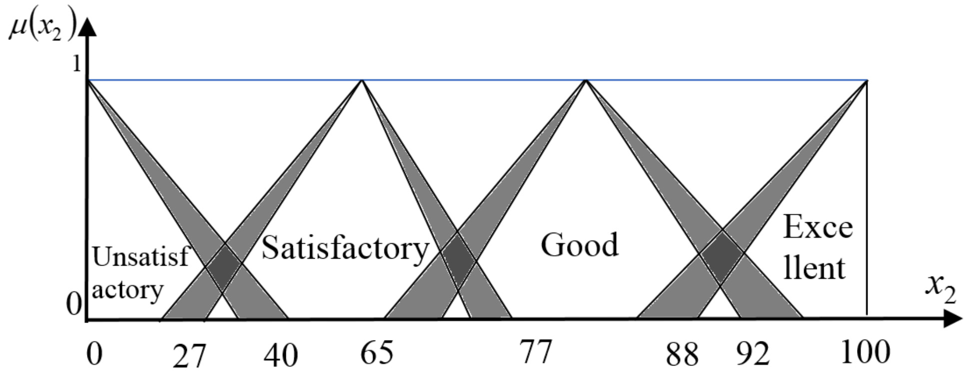

Figure 4: Linguistic variable «correctness of the last completed task» on a 100-point scale

A model of fuzzy assessment on a 4-point scale is proposed due to its versatility and implicit presence in most modern scales. In this diagram (Figure 5) there are n inputs and N = 4 the number of options for sub-connections. Where the number n corresponds to the number of test tasks, N – to the set of possible options for evaluating the completed task:

N = {“Unsatisfactory”, “Satisfactory”, “Good”, “Excellent”}.

The input vector $X = \{x_1, x_2, ..., x_n\}$ is the set of results of answers to many test questions. The membership functions of the input data to a particular fuzzy term for a 100-point scale can be similar to the membership functions shown in Figure 4.

The conclusion of the fuzzy system is a qualitative indicator of a student’s knowledge of the set of N linguistic terms (which, however, can, if necessary, be reduced to a quantitative form). The fuzzy inference algorithm can be selected depending on the way the fuzzy rules consequents are presented.

The knowledge base of the intellectual testing system is presented in the form of fuzzy predicate rules IF-THEN, in which such assessment rules can be displayed that are inherent to a particular teacher, taking into account the field of knowledge.

The fragment of a block of fuzzy rules is presented below:

$$R_1: IF x_1 = Good\ AND x_2 = Good$$

$$THEN\ y_1 = Good;$$

$$R_2: IF x_3 = Satisfactory\ AND x_3 = Good$$

$$THEN\ y_2 = Satisfactory;$$

$$\dots$$

$$R_n: IF x_1 = Excellent\ AND x_2 = Satisfactory$$

$$THEN\ y_n = Excellent.$$

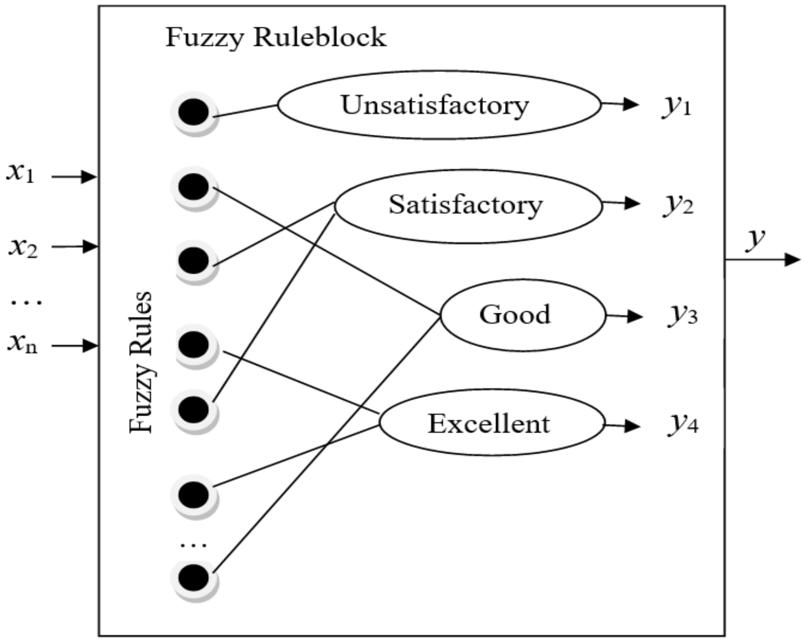

Figure 5: The scheme of a fuzzy system for testing the quality of knowledge

It is worth noting that in this model the consequents of fuzzy rules are also fuzzy values.

The output value of the fuzzy Mamdani system for estimates on a four-point scale is written as follows:

$$Y = \{y_1, y_2, y_3, y_4\};$$

$$y_1 = \bigcup_{Unsatisfactory} \mu(x);$$

$$y_2 = \bigcup_{Satisfactory} \mu(x);$$

$$y_3 = \bigcup_{Good} \mu(x);$$

$$y_4 = \bigcup_{Excelllent} \mu(x).$$

There $\bigcup$ are determines the fuzzy conjunction operation when performing the accumulation operation of the subclauses of fuzzy Mamdani rules. Conclusion of the fuzzy system will be produced by defuzzing the output variable Y according to (1).

In the case of using the fuzzy Takagi-Sugeno knowledge base, the $\bigcup$ operation is accordingly replaced by the summation operation

$$y_i = \sum_{N_i} x\mu(x),$$

and the output value is calculated according to (4).

The output linguistic variable is shown in Figure 6. We can observe a rather high degree of vagueness of the “Good” and “Excellent” ratings in order to increase the objectivity of knowledge control.

Figure 6 shows the result of the accumulation of the three fuzzy rules presented above and finding the final student grade by the center of gravity method.

This approach to building knowledge quality control systems helps to a large extent to bring the process of evaluating test results closer to that in which pedagogical experience and the methodology for testing the quality of knowledge by an expert teacher are involved.

5. The method of complex assessment of students' knowledge based on the Type 2 Tagaki-Sugeno fuzzy model

A method of fuzzy assessment of the quality of knowledge has been developed to obtain a comprehensive characteristic of a student for a training course (module). The Takagi-Sugeno fuzzy inference model with interval fuzzy membership functions of type 2 was taken as a basis. This model allows one to take into account the vague nature of the boundaries of linguistic estimates. Thus, giving at the output a more objective characteristic of knowledge (using the Karnik-Mendel fuzzy inference algorithm according to formulas (11-14).

The Takagi-Sugeno fuzzy model, the fuzzy rule consequents of which are presented in the form of functional dependencies, was not chosen by chance. Since this model allows you to form an expert opinion based on the numerical rating points given to the student during the course.

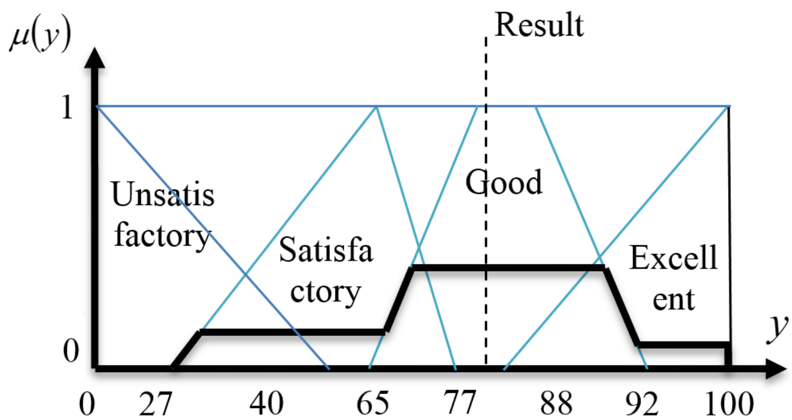

Figure 6: Accumulation of fuzzy rule subclauses and application of the center of gravity defuzzification procedure

Figure 7 schematically shows the organization of the fuzzy rule calculations when using the proposed method. Every fuzzy rule R^k of rule block $R = \{R^1, R^2, \dots, R^n\}$ as input parameters $X = \{x_1, x_2, \dots, x_m\}$ in the antecedent are accepts the evaluation x_i for each lesson (topic), where m is number of lessons.

The block of rules for fuzzy inference is drawn up by an expert teacher and can take into account the nonlinear dependencies of a student's knowledge for individual lessons (topics). This may take into account the incompleteness of the student's knowledge, as well as the subjective methodology of teaching and assessing certain academic disciplines.

6. Final reasoning

The linguistic nature of fuzzy mathematics, which makes it possible to operate with qualitative quantities, makes it possible to introduce fuzzy characteristics into the system. This helps the teacher to more accurately formulate and evaluate the requirements regarding the complexity of the tasks, as well as improve the interaction of the system with students during the tests.

The introduction of a 100-point rating scale did not solve the problem of the accuracy and objectivity of the knowledge assessment system, but rather made it more fragile and vulnerable. Indeed, the verge of transition of the Satisfactory score (74 points) to the Good score (75 points) is 1 point.

Fuzzy systems can eliminate this drawback by establishing a varying degree of fuzzy transitions from one estimate to another. And also introducing additional quality indicators, such as “pretty good”, “almost satisfactory”, “not very good”, “brilliant” and others.

Sometimes a useful feature of fuzzy testing systems is the adjustment of the severity of evaluating the results, with the ability for students to give fuzzy-logical answers when passing through the testing procedure used in [2].

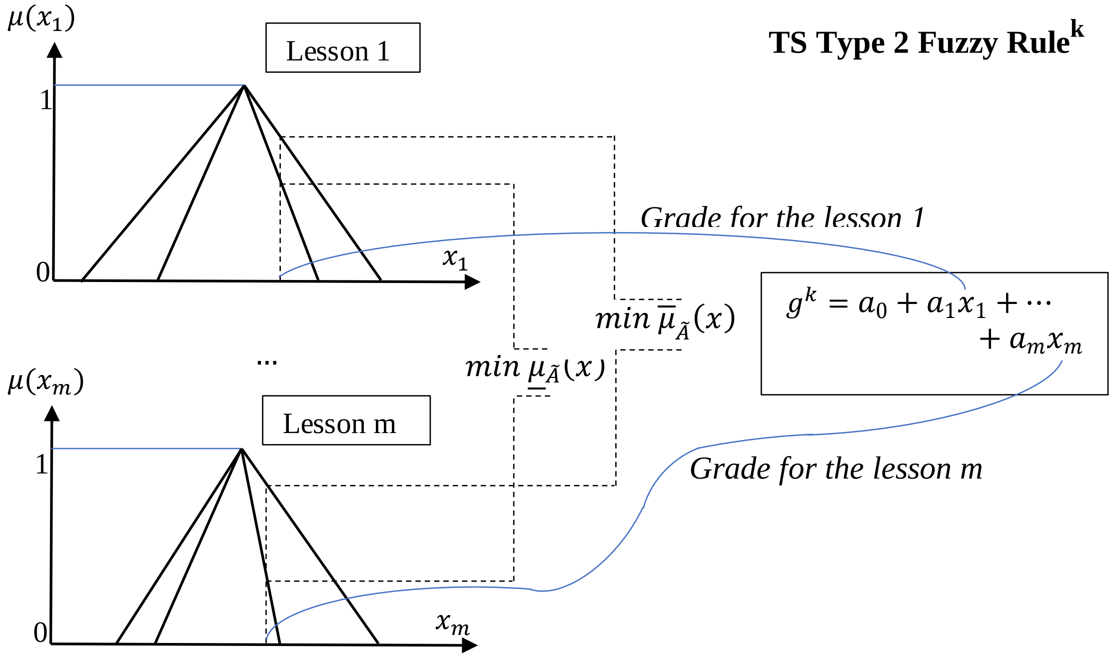

Figure 7: Organization scheme of the Takagi-Sugeno Type 2 fuzzy rule in the complex assessment of student knowledge

7. Conclusions

The apparatus of fuzzy logic in the design of testing systems allows you to more accurately identify gaps in student knowledge. And at the same time, given the incompleteness of answers during the tests, to identify quantitative and qualitative indicators of existing knowledge, without requiring the student to give knowingly false answers in the absence of them.

The paper considers testing systems for identifying and checking the quality of students' knowledge, operating on the basis of the fuzzy inference methods. The method of complex assessment of students' knowledge based on the Type 2 Takagi-Sugeno fuzzy model are proposed. A knowledge assessment model for fuzzy testing systems based on a four-point assessment system are proposed.

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