# INTELLIGENT SYSTEMS BASED ON FUZZY DECISION MAKING IN EDUCATION

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## Abstract

The development and implementation of software and hardware platforms that support and reinforce students' involvement in the educational process via information technology is an urgent task. Intellectual systems and learning environments are a promising direction of research and application, improving the quality and efficiency of the educational process. Adaptive learning and expert-training systems are related to intelligent environments and can be developed via the following technologies, platforms and solutions:

- technologies based on Computer-Based Training (CBT), Internet-Based Training (IBT) or Web-Based Training (WBT);
- platforms and tools that support Virtual Learning Environment (VLE), Mobile Learning (M-learning) based on industrial standards such as SCORM;
- analytical solutions' development for monitoring the educational process and choosing an individual learning path;
- development of cross-platform, multi-browser systems for organizing and supporting the learning process, including eLearning and collaborative learning systems, that use a wide range of mobile equipment (tablet computers, e-books, and etc.);
- digital laboratories and interactive learning environments.

Such solutions can be realized on the basis of software products or "cloud" services, modeled on SaaS.

The goal of this research work is to improve the efficiency and quality of the educational process by analyzing, developing and implementing the intellectual learning environment.

In order to achieve these goals, we need to complete the following tasks:

1. To analyze existing training systems;
2. To develop own mathematical models and methods that support and reinforce students' involvement in the educational process;
3. To develop an architecture of intellectual learning environment (ILE);
4. To implement this learning environment into the educational process.

In order to perform the second task, we proposed a fuzzy mathematical model that includes an ontological model of a subject domain, a model of a learner's profile, a model of dynamic scenarios, and a procedure for diagnosing a learner's competency. The effectiveness of the developed mathematical model and its program implementation was confirmed by pedagogical experiments (more than 300 students on the Bachelor's program), during which the quality and students' motivation to learn increased by an average of 20%.

In order to complete the third task, we used the IEEE P1484.1 standard concerned with the implementation of a component-based architecture of an intelligent learning environment. Software interfaces such as a "bridge", client-server architecture, databases and environments are intensively used.

The above-said products are developed by the Institute of Distance and Further Education of the Ulyanovsk State Technical University on basis of the Moodle platform and are implemented at the rank of industrial enterprises of the Ulyanovsk region. The experience of the intellectual learning environments' use was summarized- their implementation had increased the quality education.

Keywords: Method, learning, trajectory, prediction, fuzzy, diagnostic.

# 1 INTRODUCTION

Among all the simulation systems, tools, educational platforms, and computer-based learning complexes, LMS (Canvas, Blackboard, Moodle, OpenEdX, Edmodo, Desire2Learn, and Sakai) is most widely used.

The LMS architecture is represented by the core of the system and different plug-ins to it. The principle of the system is education using distance learning technologies (it means study any time and at any place), while it is possible to monitor the educational process and report on the learning processes. LMS is a central place for the accumulation, storage and processing of information, presented as a student’s experience. It should be noted that similar systems have long been used by colleges and universities all over the world to manage and administer online and blended learning. As a rule, LMSs perform usual tasks for students that are: provide an access to curricula, lectures, tasks, and grades, and also maintain communication between peers as well as between students and educators through their institution’s LMS. The university faculty can also monitor the students’ participation and learning process effectiveness at the individual (personalized) level and in the first, second, third and fourth courses of Bachelor's degree as well as Master's degree. Nevertheless, some experts in intelligent training systems’ development and application believe that current LMSs have limited capabilities, focus primarily on the processes related to learning management, and not on learning itself. Next generation LMS or next generation digital learning environment (NGDLE) refers to the development of more flexible spaces that support personalization, meet universal design standards, and play an important role in formative learning assessment. Instead of existing as a single application, they are a set of plug-ins, each and which has its own purpose.

We offer our own mathematical support in practice for implementing a set of plug-ins to Moodle LMS in order to enhance the educational process effectiveness.

The paper has the following structure. The abstract describes a general idea of the paper. The introduction focuses on LMS. The Related work section presents the related research works. The Problem section describes the research and practical significance of the problem. The Mathematical models with fuzzy logics section contains the mathematical formulas of subject domain models, learners, classification and decision-making procedures. The section called Computer components to build fuzzy computer-based learning has architectural solutions in the form of plug-ins with SaaS technology. The Experiment section contains computational experiment’s results. The conclusion summarizes the scientific and practical significance of author's developments.

# 2 RELATED WORK

Significant theoretical and practical successes in solving the tasks of the problem under consideration have been achieved by the research schools of the Institute of Physics of the Academy of Sciences of the USSR, the Academy of Sciences of Ukraine, the Moscow State University, the Research Institute of the Higher School of Economics, the Moscow Power Engineering Institute, the Moscow Engineering Physics Institute, the Moscow Institute of Physics and Technology, etc. [1]. Russian scientists Rybina G.V. [2], Stefanyuk V.L. [3], Tarasov V.B. [4], Brusilovsky P.L. [5], Bashmakov A.I. and I.A. [6], Kureichik V.N. [7], Kamayev V.A. [8] and others, as well as Kabassi K. [9], Dorca F.A. 10, Bergasa-Suso, Garcia, Graf, Ozpolat and Akbar, Chang, Simsek, Darwesh, Montazer and Ghorbani, Deborah [19], Dung and Florea [20], Jyothi [21], and others have also made the contribution to the theory of intelligent automated learning systems.

In 2009, there were research works about smart-learning tools, for example, in Tikhomirov V.P. and Patterson S.’s works.

Since 2013, massive open online courses (MOOC) have been widely adopted, the research of which was carried out by Barker R., Kozlov A. N., Kukharenko V.N., and etc.

There are paradigms of computer-based learning tools’ organization and implementation, classified according to the curriculum structure (linear, branched and combined):

1 Based on the concept of specialized expert systems (combined structure) [2].

2 Based on hypertext and hypermedia (linear structure) [6].

3 Based on the integration of expert systems and hypertext / hypermedia (combined structure) [5].

4 Based on the concept of using artificial intelligence methods (multi-agent systems, neural networks, etc.) (combined structure) [7, 22].

5 Based on the active use of social networks - smart-environments (branched structure).

6 Based on the concept of massive application – MOOC (massive open online courses) (linear structure).

## 3 PROBLEM

At the World Innovation Summit for Education, leading educators, policy makers and government organizations from different countries have repeatedly identified the need for radical change: today's learning process is failing to adequately prepare young people for the future world. The growing gap between existing education systems and systems required to meet the future generations' needs and the computer-based training's effectiveness increase are fundamental scientific and technical challenges. Although computer-based training has only been used since the 60s of the 20th century, significant progress has been made: it has been developed training systems, systems and complexes (environments) allowing the learning process to be automated, object-oriented and individual. However, the main problem of optimal subsystems' interaction within a single system when computer-based learning systems' design and organization has not been solved. The learning management systems' prospective direction is the use of intelligent tools. The goal of this research work is the development of the theory of intelligent learning tools' design, including a complex of computer models and methods that are the basis of the mathematical, software and information support of training systems, systems and complexes (environments), networks.

## 4 MATHEMATICAL MODELS WITH FUZZY LOGICS

Mathematical models contain a domain model, a fuzzy model of student, a scenario and the fuzzy diagnostic procedure.

The domain model is represented by authors as a tree of ontologies, which uses hierarchical, associative, and ordinal links between objects ontologies and subject processes dynamically. Each ontology corresponds to a learning element. Hierarchical links are used to describe the object and the subject process at different degrees of detail. Ordinal links put description in order on one hierarchical level and determine the ontologies chains. Associative links connect hierarchical ontologies and ordinal ontologies of different levels.

The domain model is the knowledge base including learning programs, techniques, methods, models and practices, that allows to adequately representing learning material. The domain model is given as:

$$\begin{gathered}\text{DomainModel} = \{\text{ObjectName}, \text{Functions}, \text{Processes}, \text{Data}, \\ \text{Patterns}, \text{MetaData} \mid \text{ortree}, \mathrm{p}, \text{view}\}\end{gathered},$$

where $\text{ObjectName} = \{\text{ObjectName}_i,\ i = 1...E\}$ is a set of subject objects names; $\text{Functions} = \{\text{function}_i,\ i = 1...Z\}$ is a set of subject functions; $\text{Processes} = \{\text{process}_i,\ i = 1...P\}$ is a set of subject processes; $\text{Data} = \{\text{data}_i,\ i = 1...D\}$ is a set of subject data; $\text{Patterns} = \{\text{Operation}_i,\ \text{Command}_i,\ \text{Method}_i,\ i = 1...T\}$ is a set of subject templates, $\text{Operation} = \{\text{operation}_i,\ i = 1...O\}$ is a set of subject operations, $\text{Command} = \{\text{command}_i,\ i = 1...C\}$ is a set of subject commands, $\text{Method} = \{\text{method}_i,\ i = 1...S\}$ is a set of subject methods to run a command, $\text{Atom} = \{\text{notion}_i,\ \text{action}_i,\ i = 1...A\}$ is a set of knowledge «toms», consisting of elementary concepts and the simplest actions, $\text{Atom} \in \text{Stage}, \text{Atom} \in \text{Procedure}$, $\text{Atom} \in \text{Operation}$, $\text{Atom} \in \text{Command}$, $\text{Atom} \in \text{Method}$; $\text{MetaData} = \{\text{key}_i,\ \text{hash-function},\ i = 1...H\}$ is model metadata, where $\langle \text{key}_i \rangle$ is a tuple of associative keys, $\text{hash} - \text{function}$ is a hash function for element searching; $\text{ortree}$ is an hierarchical relation; $\mathrm{p}$ is a relation of the order; $\text{view}$ is an associative relation.

The pattern structure of $\text{PatternOperation}$ (subject operations), $\text{PatternComand}$ (subject commands), $\text{PatternSposob}$ (subject methods) is one and the same. For example, the structure of $\text{PatternOperation}$ is:

$$\begin{gathered}\text{PatternOperation} = \{\text{name, purpose, motivation, applicability, structure, participants, relations, results,} \\ \text{implementation, example, applications, related patterns}\}.\end{gathered}$$

A fuzzy model of the student is developed by authors, which reflects the dynamic level of his/her ability to solve problems. The level is determined by fuzzy linguistic criteria parameters (knowledge, abilities, skills and competence).

Description of the student model is given as:

$$\text{StudentModel} = \{\text{Knowledge}_i, \text{Ability}_i, \text{Skill}_i,\ \text{Competency}_i,\ \text{profile} \mid \text{calcK}, \text{calcA}, \text{calcS}, \text{calcC},\ i = 1..N\},$$

where $\text{Knowledge}_i$, $\text{Ability}_i$, $\text{Skill}_i$, $\text{Competency}_i$ are arrays of grades for knowledge, abilities, skills and competence respectively, $N$ is the number of scenario control points $K_i$. The range of values of the grade calculation functions is given in pairs $(D,\ \mu)$: $\text{calcK}, \text{calcA}, \text{calcS}, \text{calcC} \in (D,\ \mu)$, where $D$ is a value of Euclidean distance function, $\mu$ is a value of the class characteristic membership function [23], [24], [25], $\text{profile} = \{\text{grade}_1, \text{grade}_2, \text{grade}_3, ..., \text{grade}_s\}$ is a set of linguistic characteristics.

$$\text{calcK}:\ \text{markTeor}_i \to \text{grade}_i,\ \text{calcA}:\ \text{mark}_i \to \text{grade}_i,\ \text{calcS}:\ t_i \to \text{grade}_i,$$
$$\text{calcC}:\ \text{calcK}, \text{calcA}, \text{calcS} \to \text{grade}_i$$

where $\text{markTeor}_i$ is a set of grades for the solution of theoretical problems, $\text{mark}_i$ is a set of grades for the operations completed, $t_i$ is a set of the timeframes which were taken to solve problems. $\text{calcK}, \text{calcA}, \text{calcS}, \text{calcC}$ functions are implemented with fuzzy Kohonen maps and the custom developed rating scale (Table 1) in interval and linguistic forms.

***Table 1.*** *The rating scale on the range of values of $\mu$ function.*

| Linguistic characteristic | Distance interval (deviation interval) |
|---|---|
| $grade_s$ | $\left[\mu_{2s-1} \times \sum_{e=1}^{card(X)} w_{ije}; \mu_{2s} \times \sum_{e=1}^{card(X)} w_{ije}\right]$ |

The block diagram of the fuzzy map is shown in Fig. 1. The dots in Fig. 1 mean the scalability potential of fuzzy maps architecture.

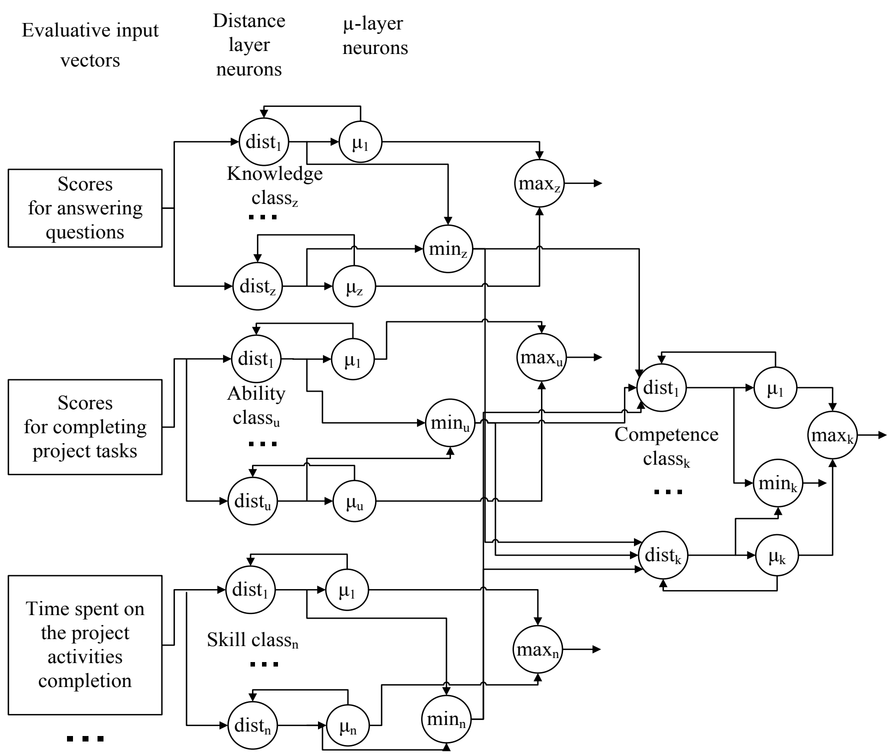


*Figure 1. Block diagram of Kohonen map representing student characteristics evaluation.*

$\mu$ membership function is given as:

$$\mu_{ij} = e^{-0.5\times dist_{ij}^{2}},\ i = 1\ldots C,\ j = \{1,2,3,4\},$$

where C is a number of class subclasses; j has a value from 1 to 4 because there are four classes: knowledge, ability, skill and competence.

Activity of distance layer neurons is calculated as the Euclidean distance (deviation) of the desired activity:

$$dist_{ij} = \sqrt{\sum_{e=1}^{T}\left(x_e - w_{ije}\right)^2},$$

where $T$ is a number of criteria parameters of the input grade vector $X$, $x_e$ is an element of the vector $X$, $w_{ije}$ is weight of the edge connecting element $x_e$ and $ij$ class neuron.

When fuzzy map usage is repeated the feedback allows you to update the weight coefficients at each $t$ step

$$W_{ij}(t+1) = W_{ij}(t) + \mu_{ij}(t)\cdot dist_{ij}\left(X,\ W_{ij}(t)\right),$$

which improves the grading accuracy.

Four output fuzzy map tuples are given as $\langle dist_j,\ \mu_j\rangle, j=1\ldots4$, where $dist_j$ is a value of the neuron $j$ class activity, $\mu$ is a value of the input vector to a particular class $j$ membership function.

A model of learning scenario is developed by authors. The model is based on a system, consisting of a directed graph, vertex maps and alternative choice of the learning trajectory. The model is given as:

$$Scenariy = \{G(vertex, edge), Reflaction, Alternativ\},$$

where $G(vertex,\ edge)$ is a scenario directed graph, $vertex = \{v_i,\ i = 1\ldots V\}$ is a set of attribute vertices, $edge = \{e_i,\ i = 1\ldots E\}$ is a set of edges; $Reflaction = \{Rf_1,\ Rf_2,\ Rf_3,\ Rf_4\}$ is a set of heterogeneous vertex mappings into the subject objects ($Rf_1$ is the names of subject objects, function objects, processes, data, patterns (see the DomainModel model), $Rf_2$ is the test questions, $Rf_3$ is the practical subject tasks, $Rf_4$ is the $K_i$ control points, containing the required (target) linguistic criteria characteristics values of the student); $Alternativ = \{v_j,\ \text{if } v_i \text{ is incidential to } v_j \text{ and } v_i \neq K_i,\ v_i \text{ p } v_j\}$ is the student's choice of learning trajectory from $v_i$ noncontrol vertex.

The diagnostic procedure of the student's knowledge, abilities, skills and competence is based on classification with fuzzy Kohonen maps, which are proven to be the universal classifiers.

Student model parameters change by event at the $K_i$ scenario control points. Evaluative input vectors go to the input of the fuzzy map, which classifies the input data and generates the fuzzy characteristics of the student's progress. The number of the knowledge class neuron inputs equals the number of input vector elements scores for answering questions. The number of the ability class neuron inputs equals the number of input vector elements scores for completing project tasks. The number of the skill class neuron inputs equals the number of input vector elements of time spent on the project activities completion. The number of the competence class neuron inputs equals 3 (knowledge, abilities, skills) (see Fig. 1).

The classification is performed by using fuzzy maps and the custom developed rating scale in interval and linguistic forms (see Table 1).

The decision of choosing learning scenario trajectory is made depending on the student's progress: should he/she continue learning using the static scenario (learning trajectory defined by scenario model) or develop a dynamic scenario which is based on student and domain models automatically (the structure scenario synthesis is carried out). Scenario reconstruction changes the static scenario by adding scenario constructed using domain model elements. The need to reconstruct the scenario arises when a diagnostic procedure shows the result ($\mu_t$), which unsatisfies the target project characteristics of the student ($\mu_c$) defined at $K_i$ point: $\mu_t < \mu_c$ (for knowledge, abilities, skills and competence). The $h$ function is defined to organize the stages of knowledge, abilities, skills and competence progress, which has a minimum value of $\mu$ relating to one of the classes of knowledge, abilities, skills and competence:

$$h = \min\left(\mu_{knowledge}, \mu_{abilities}, \mu_{skills}, \mu_{competence}\right).$$

The usage of $h$ function allows to distributing the learning material evenly to obtain well-balanced individual characteristics for the entire trajectory.

All the characteristics control values in the control points $K_i$ for $Knowledge_i$, $Ability_i$, $Skill_i$, $Competency_i$ are determined by the “AND” operator:

$\wedge\mu_i$, $i = 1 \ldots N$, where $N$ is the number of $K_i$ control points to register the learning process prehistory (his/her characteristics in student model) in the trajectory planning procedure.

The function output value is a common subset for all the $\mu_i$ functions on the set of values.

Prediction algorithm of the dynamic scenario is as follows.

Learning elements of the domain model which are associated with the control element $K_i$ are selected. It is marked as $E$.

One student criteria parameter (knowledge, ability, skill or competence) is selected which has a minimum value of $\mu$. It is marked as $P$.

Learning elements are selected from the $E$ set, which are associated with $P$ (forming $DE$ – tuple).

Control theoretical and practical learning material is added to $DE$ – tuple, which is related to $P$.

Control element $K_i$ is added.

The trajectory composed of the $DE$ – tuple elements determines the student’s set of learning elements. The number of selected learning elements may be regulated by hierarchical, ordinal and associative connectivity of elements in the domain model.

## 5 COMPUTER COMPONENTS TO BUILD FUZZY COMPUTER-BASED TRAINING

The generalized component-service organization of computer-based training in accordance with standard IEEE P1484.1 is the basis of the software implementation of the method (Fig. 2).

Subject environment is represented by objects and learning processes, the interaction of which is organized with the help of the «Bridge» software interface that is linked with the «Program core» and is working to provide the information exchange.

The «Program core» is the manager that encapsulates system services and system components.

The «Program area» component implements the domain model and interacts with the «Program core» and educational content database.

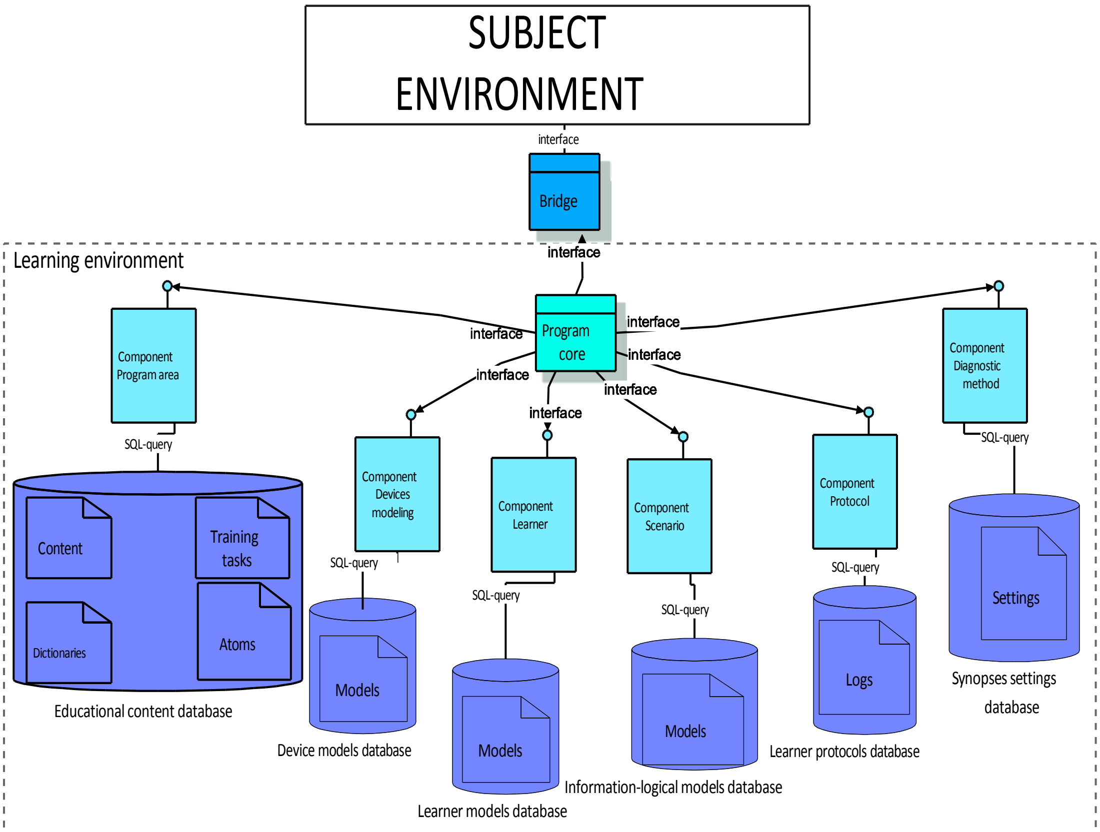


*Figure 2. Software implementation of method for individual student trajectory prediction. The «Devices modelling» component implements the devices model, interacts with the «Program core» and the devices models database.*

The «Learner» component implements student model, interacts with the «Program core» and the learner models database. The «Scenario» component implements learning scenario, interacts with the «Program core» and the information-logical models database. The «Protocol» component implements the information flow protocol, interacts with the «Program core» and the learner protocols database. The «Diagnostic method» component implements the individualization method, interacts with the «Program core» and the synopses settings database.

## 6 EXPERIMENT

Traditional adaptive learning methods are based on a modular principle. Each module contains a certain number of elements that have a learning element adapted to the specific level of the trained engineer's knowledge. Formula for efficiency evaluation is given as:

$$\frac{L_S}{L_p} = \frac{element_{modul} \times element_{submodul}}{element_{scenariy} + element_{cadmodel}},$$

where $element_{modul}$ is the number of modules, $element_{submodul}$ is the number of learning elements in a module, $element_{scenariy}$ is the number of scenario's learning elements, $element_{cadmodel}$ is the number of learning elements of a subject domain model.

There is a graph of the application efficiency of a new adaptive planning and control method of a learning path in Fig. 3. The author's method gain, lettered P, is 2 times compared to S.

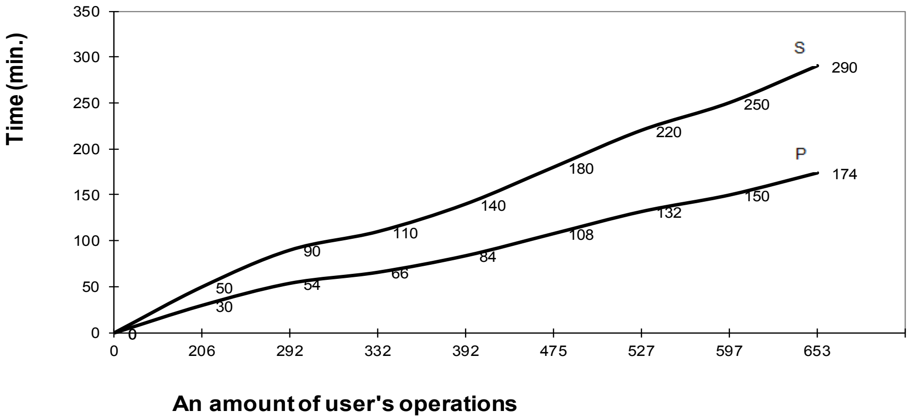


*Figure 3. Dependence training time on the number of concepts and operations:*
*S – known adaptative methods, P – author's adaptative method.*

## 7 CONCLUSIONS

A new method for individual learning trajectory prediction which is based on fuzzy student model and fuzzy diagnostic procedures, planning in computer-based training that enhances the quality and reduces the learning process timeframe is developed by authors. Program implementation of the component-oriented network computer-based training is developed by authors. The systems are based on the proposed method, which provides system functionality interoperability without recompiling the source code.

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