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SECTION 4. Computer science, computer engineering and automation.

THE ALGORITHM OF INDIVIDUAL LEARNING PATH CORRECTION IN INTELLIGENT MULTI-AGENT LEARNING SYSTEM

Abstract: It was developed the algorithm of individual learning path correction. The algorithm of individual learning path correction involving Takagi-Sugeno-Kang fuzzy neural network includes the following operations: the determination of in-out variables; the choice of model out and rule base formation; the choice of fuzzification function and determination of learning curve parameters; the identification of learning curve elements to the fuzzy rules; fuzzification layer parameter setting; conclusion layer parameter setting. The algorithm allowed correct individual learning path at every step of work with the intelligent learning system in terms of learners' special characteristics. The developed algorithm is software-based and successfully tested.

Key words: intelligent learning system, individual learning path, fuzzy neural network, multi-agent system.

Language: English

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Introduction

Currently the most important problems determining the level of acceleration of society technical progress are workforce productivity increase and the improvement of final product quality. Therefore it's necessary to prepare skilled workforce that possess abilities in different disciplines received by intelligent learning systems (ILS) [1].

The progress in ILS development is contingent on high level of hardware and software of modern information and communication technologies. At the same time the main scope of work in creating automated teaching systems do the programmers without teacher's training. Experts in didactics and methodology can't use potential didactic possibilities of computing technologies in full. One of the main possibilities is adaptable control on learning process. Under adaptable control by ILS is meant management providing the formation of an individual learning path the correction of which is made taking into account the following factors [2]: the student's beginner level for discipline study (section, topic); current education analysis; student's psychological makers; the results in current and final check.

At the moment by ILS developing are used different conceptual approaches: objective oriented, event-oriented, automated and others. It's noted that the realization of adaptable control on learning process in ILS intends: on the one hand the student's wide discretion and on the other hand permanent correction of individual learning path from ILS. As the result of which the situation can occur that were not foreseen by the ILS operation algorithm. The pointed antilogy can be settled by agent-oriented approach [3, 4, 5].

Materials and Methods

To develop the algorithm of individual learning path correction was offered to use Takagi-Sugeno-Kang fuzzy neural network. The teaching is made by genetic algorithm. The choice of Takagi-Sugeno-Kang output model is contingent on the possibility to present the conclusion function as polynom parameters of which can be set automatically with the use of different algorithms including the genetic one. Mathematical model includes the following operations: the determination of inputs and outputs; the choice of output model and rule base formation; the choice of fuzzification model and determination of learning curve parameters; the determination of



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belonging of learning curve elements to fuzzy rules; fuzzification layer parameter setting; conclusion layer parameter setting.

In the function of input linguistic variables were suggested the following ones: “the quantity of prompting given while problems solving”, “the task complexity”, “the current control result” and “degree of freedom of choice”.

In the capacity of input variable “degree of freedom of choice” – x_4 was used the value of degree of freedom of choice received at the stage of defuzzification of output variable of individual learning path formation algorithm or the value received in output of neural network at previous stage of learning.

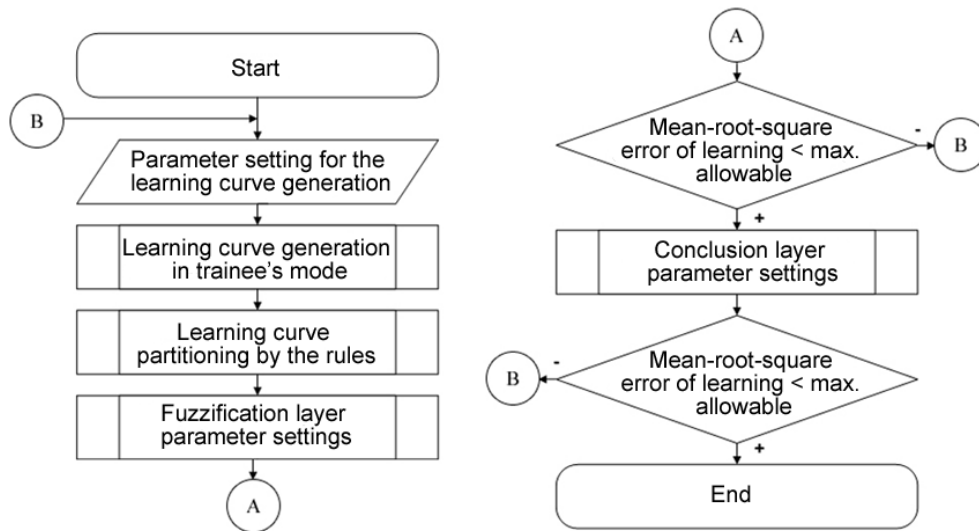
For practical realization of individual learning path formation algorithm was designed an intelligent database of agent [6] intelligent performance including $M \times N \times K \times P$ of fuzzy rules where M, N, K, P - the quantity of term sets in each of four input fuzzy variables [7, 8]. As fuzzification functions determining the belonging of input value to

the corresponding fuzzy set for all the rules was chosen Gauss aggregate function:

$$\mu_{A_i}^k(x_i) = \frac{1}{1 + \left(\frac{x_i - c_k^i}{\sigma_k^i} \right)^{2b_k^i}},$$

where c_k^i, σ_k^i, b_k^i – learning parameters of Gauss aggregate function, $i = \overline{1,4}, k = \overline{1,144}$.

For teaching of the first and the third layer of fuzzy neural network was applied the continual genetic algorithm. The fuzzification layer teaching (the first layer) was done independently in every rule. Learning parameters $c_k^0, \sigma_k^0, b_k^0, \dots, c_k^3, \sigma_k^3, b_k^3$ were coded in chromosome with 12 genes. By learning of parameters $p_0^k, p_1^k, p_2^k, p_3^k$ of conclusion layer (the third one) was used the generalized learning curve. The standard form of chromosome while learning of fuzzification layer for the first rule is presented on picture 1.



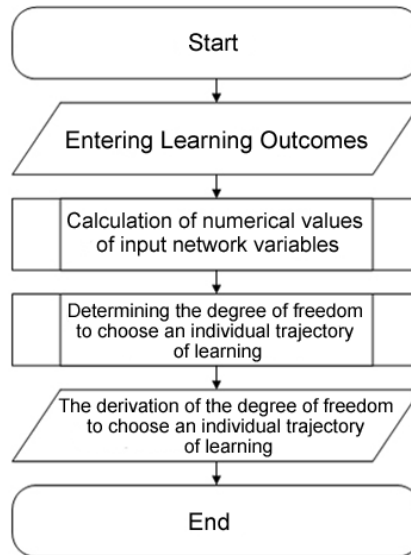
Picture 1 – The standard form of chromosome while learning of fuzzification layer for the first rule.

The developed model of the trainee allows generate data for fuzzification and conclusion layers learning. The teacher plays an expert role in that case that sets model parameters relying on experience and knowledge.

The individual learning path correction algorithm is the work in two modes: agent learning; the determination of freedom choice degree of individual learning path on the base of experience. The individual learning path correction algorithm in agent learning mode is presented on picture 3.

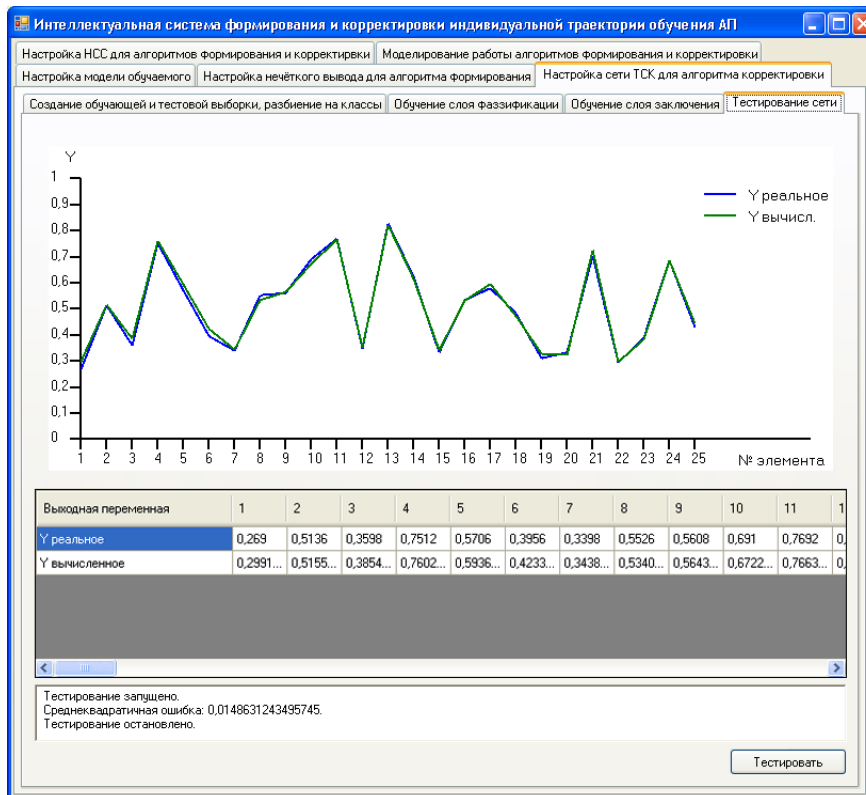
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Picture 2 – The individual learning path correction algorithm in the learning mode.

The test results of developed algorithm are presented on picture 3.



Picture 3 – Program screenshot at the stage of network testing.

Conclusion

The test results of skilled fuzzy neural network are presented on the diagram. The received mean-root-square error value determined from evaluated

and real values of output variable testify that the learning of the network is successful [9, 10]. It allows take decision on individual learning path properly.

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