Fuzzy Logic-Based Evaluation of IoT Training Simulators

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Abstract: Developers offer various options for virtual simulators that allow training in diagnosing Internet of Things (IoT) systems. To select devices with the best characteristics, as well as to identify shortcomings and improve virtual simulators, tools for assessing their characteristics are in demand. An adequate selection of virtual simulators with the best characteristics, as well as the identification of their shortcomings for subsequent improvement, are urgent research problems. The presented research is aimed at solving these problems. A system has been developed for assessing the characteristics of virtual simulators intended for IoT systems training in diagnosis. It is based on the use of fuzzy logical inference. As indicators for assessing the characteristics of virtual simulators used for training IoT systems in diagnosis, it is proposed to use indicators of image realism, sound realism and diversity of training scenarios sets, as well as a general indicator of virtual simulator functioning. The parameters of the membership functions of fuzzy sets and individual outputs of fuzzy rules were automatically selected using a neural network setup. In order to study the proposed fuzzy logical inference system, a model of the process of assessing the virtual simulators characteristics intended for IoT systems training in diagnosis has been developed in the MATLAB software environment using the libraries of the Simulink package. Numerous computational experiments have been carried out using this software model. A comparison of their results with the results of real IoT systems diagnosing showed that the higher the values of the generalized indicator of the virtual simulator functioning, the greater the probability of correct diagnosis of IoT systems by the specialists who trained on it. Thus, the proposed fuzzy inference system can be recommended for evaluating the characteristics of virtual simulators designed to teach diagnostics of Internet of Things systems.

1 INTRODUCTION

A promising scientific and technological direction is the creation of virtual simulators that help to learn the skills of diagnosing and monitoring the correct operation of various technical systems. The object of our research was virtual simulators used to acquire skills in diagnosing the operation of Internet of Things (IoT) systems. The scope of Internet of Things systems application includes applications for smart home [1], industry [2], healthcare [3], [4], ecology [5], energy [6], construction [7] and others [8].Currently, manufacturers offer various options for virtual simulators, specializing in smart city systems [9], smart agriculture [10], smart manufacturing [11] and other IoT applications [12]. Such software facilitates the process of Mastering the specifics of IoT devices setting up and operating, building wireless Internet of Things networks and detecting their incorrect operation. An urgent task is to develop tools for evaluating such virtual simulators. Such evaluation tools are necessary to select devices with the best.

Mastering the specifics of IoT devices setting up and operating, building wireless Internet of Things networks and detecting their incorrect operation. An urgent task is to develop tools for evaluating such virtual simulators. Such evaluation tools are necessary to select devices with the best characteristics, as well as to identify shortcomings to improve.

The relevant research problems are the adequate selection of virtual simulators with the best characteristics, as well as the identification of their shortcomings for subsequent improvement. Adequate assessment tools for such virtual simulators are needed to solve these problems.

Many studies have been devoted to evaluating the effectiveness of virtual simulators. In particular, an assessment of the effects resulting from the use of VR games for teaching engineering sciences is presented [13]. Work [14] It is devoted to evaluating the usefulness of a hysteroscopic surgery simulator. The study of students' perception of a virtual simulator designed to acquire fire extinguishing skills is presented [15]. The assessment of the success of mastering the necessary skills using a dental simulator was performed [16]. A method for evaluating the performance of helicopter rescue crews trained using virtual reality scenarios is proposed [17]. The advantages of the above studies are that they provide an opportunity to show that the use of virtual simulators can improve the effectiveness of training. The disadvantages of the available means of evaluating the effectiveness of the use of virtual simulators in various fields include the fact that they are based mainly on the use of subjectively compiled questionnaires and do not have the necessary theoretical justification. In addition, an analysis of publications has shown that insufficient attention is paid to evaluating the characteristics of virtual simulators used for training in the diagnosis of Internet of Things networks.

The significance of this study is to improve the process of evaluating the characteristics of virtual simulators used for training in the diagnosis of Internet of Things networks. This improvement is proposed based on the development of a new evaluation system for virtual simulators, which is based on the use of mathematical fuzzy inference.

2 CREATION AND CONFIGURATION OF A FUZZY LOGICAL INFERENCE SYSTEM

In order to evaluate the characteristics of virtual simulators, it is proposed to create a system based on fuzzy logical inference. The scientific reasoning behind this proposal is that the mathematical apparatus of fuzzy logical inference is successfully used to solve many applied problems [18] - [22], including tasks related to estimating various quantities [23] - [26]. A neural network was used to adjust the parameters of the fuzzy inference system. For this purpose, neural network tools were used, which are created in the MATLAB-Simulink software environment and are used to solve many problems [27] - [30].

In the process of forming a training sample for neural network setup, it is necessary to make some surveys. Each test person should learn how to diagnose IoT systems using one virtual simulator. The person then has the opportunity to evaluate the performance of the virtual simulator according to three criteria: image realism (IR), sound realism (SR), and variety of training scenario sets (VAR). Scores for these criteria are given on a scale from 1 (lowest score) to 10 (highest score).

After training, the person tests the functioning of real IoT systems and diagnoses their malfunctions. The diagnosis accuracy is assessed by the value DR=0 if the person incorrectly diagnoses the technical condition of the IoT system, and by the value DR=1 in the case of an error-free diagnosis. The assessments of the virtual simulator characteristics and the values of the correct diagnosis of the technical condition of the IoT system received from the test person are entered into a special relational database, a fragment of which is presented in Table 1.

Table 1: Fragment of the training sample.

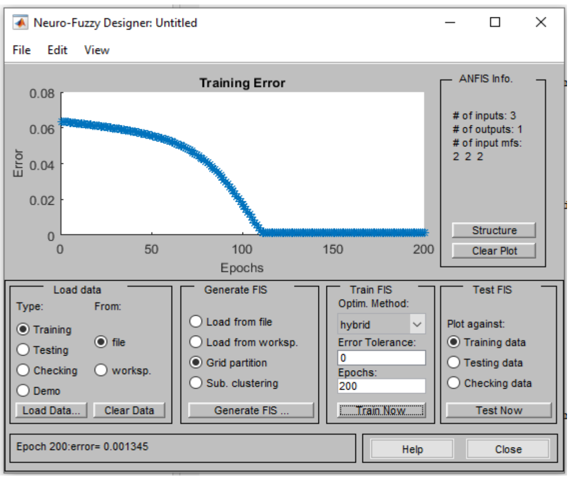
Training sample line number	IR	SR	VAR	DR
1	9	9	8	1
2	8	7	6	1
3	4	5	3	0
…	…	…	…	…
800	5	7	9	1

The training sample presented in Table 1 contains 800 rows. To form it, it is necessary to involve 200 persons, each of whom evaluates the virtual simulator characteristics, and then diagnoses the operation of 4 real IoT systems. The training data obtained in this way is used to configure the neural network for the fuzzy inference system.

The created fuzzy inference system uses three input variables that characterize the image realism, the sound realism and the variety of training scenarios provided by the virtual simulator. At the output, the system produces the VSI value of a generalized indicator of the virtual simulator functioning.

The creation and configuration of the fuzzy logical inference system was carried out in the MATLAB software environment using the anfisedit command. Two triangular membership functions were used to fuzzily each input variable. The zero-order Sugeno algorithm was chosen as a fuzzy inference algorithm, which has been successfully used to create various fuzzy control systems [31] - [33].

The system was configured over 200 training cycles. For training, a hybrid algorithm was used that implements a combination of the least squares method and the inverse gradient descending method [34] - [36]. In Figure 1, you can observe how the training error gradually decreases and reaches values close to zero after the 110th cycle of the system configuration.



# of inputs: 3
# of outputs: 1
# of input mfs:
2 2 2

Optim. Method: hybrid
Error Tolerance: 0
Epochs: 200

Epoch 200:error= 0.001345

Figure 1: Setting up a fuzzy logical inference system.

The setup of the created fuzzy logical inference system is carried out using the generated neural network structure presented in Figure 2. This structure is a multilayer fuzzy neural network (Adaptive Neuro-Fuzzy Inference System, ANFIS), each layer of which serves to perform one or another fuzzy logical inference procedure in accordance with the zero-order Sugeno algorithm.

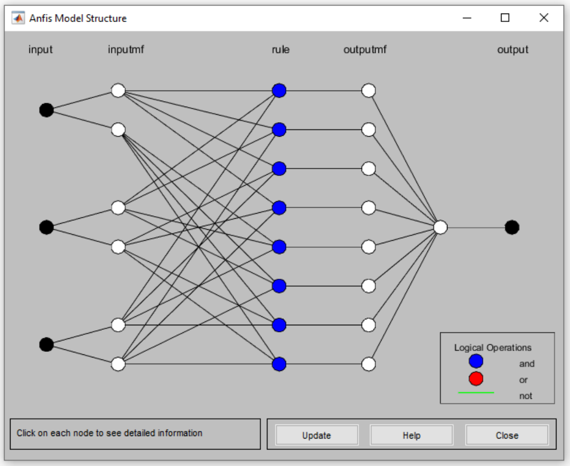
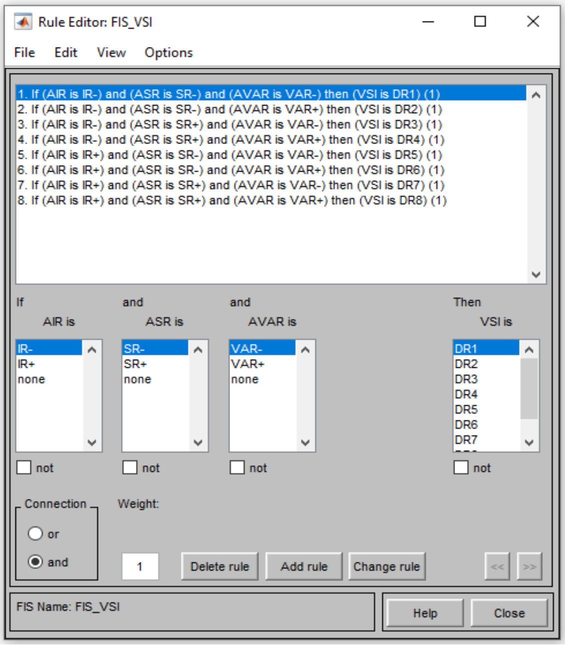


Figure 2: Structure of the ANFIS system.

Values of the membership functions parameters of input variables and individual outputs of fuzzy rules are automatically selected as a result of the execution of ANFIS training cycles. These values make the training errors minimal.

The fuzzy inference system configured in this way can be used to evaluate the characteristics of virtual simulators intended for t training in diagnostics of Internet of Things devices. As a result of system creating and configuration, 8 fuzzy rules were formed, the appearance of which is presented in Figure 3.



1. If (AIR is IR-) and (ASR is SR-) and (AVAR is VAR-) then (VSI is DR1) (1)
2. If (AIR is IR-) and (ASR is SR-) and (AVAR is VAR+) then (VSI is DR2) (1)
3. If (AIR is IR-) and (ASR is SR+) and (AVAR is VAR-) then (VSI is DR3) (1)
4. If (AIR is IR-) and (ASR is SR+) and (AVAR is VAR+) then (VSI is DR4) (1)
5. If (AIR is IR+) and (ASR is SR-) and (AVAR is VAR-) then (VSI is DR5) (1)
6. If (AIR is IR+) and (ASR is SR-) and (AVAR is VAR+) then (VSI is DR6) (1)
7. If (AIR is IR+) and (ASR is SR+) and (AVAR is VAR-) then (VSI is DR7) (1)
8. If (AIR is IR+) and (ASR is SR+) and (AVAR is VAR+) then (VSI is DR8) (1)

Weight: 1

FIS Name: FIS_VSI

Figure 3: Basis of fuzzy rules.

The fuzzy rules include the following values: AIR is the average value for assessing the image realism; IR^{+} is the fuzzy set “high value assessment of image realism”; IR^{-} is the fuzzy set “small value assessment of image realism”; ASR is the average value of sound realism assessment; SR^{+} is the fuzzy set “high value of sound realism assessment”; SR^{-} is the fuzzy set “small value of sound realism assessment”; $AVAR$ is the average value of training scenarios diversity assessment. VAR^{+} is the fuzzy set “high value of training scenarios diversity assessment”; VAR^{-} is the fuzzy set “small value of training scenarios diversity assessment”; DR_1, DR_2, …, DR_8 is the values of individual outputs of fuzzy rules.

In accordance with zero-order Sugeno algorithm, the following procedures are performed in the fuzzy inference process:

- Fuzzification;
- Aggregation;
- Activation;
- Defuzzification.

When performing the fuzzification procedure, the following values of the membership functions of the input variables to the fuzzy sets $IR^+(AIR)$, $IR^-(AIR)$, $SR^+(ASR)$, $SR^-(ASR)$, $VAR^+(AVAR)$ and $VAR^-(AVAR)$ are calculated in accordance with the expressions:

$$IR^-(AIR) = \begin{cases} 1, \ AIR \le IR_1^-; \\ \dfrac{IR_0^- - AIR}{IR_0^- - IR_1^-}, \ IR_1^- < AIR < IR_0^-; \\ 0, \ AIR \ge IR_0^-; \end{cases} \quad (1)$$

$$IR^+(AIR) = \begin{cases} 0, \ AIR \le IR_0^+; \\ \dfrac{AIR - IR_0^+}{IR_1^+ - IR_0^+}, \ IR_0^+ < AIR < IR_1^+; \\ 1, \ AIR \ge IR_1^+; \end{cases} \quad (2)$$

$$SR^-(ASR) = \begin{cases} 1, \ ASR \le SR_1^-; \\ \dfrac{SR_0^- - ASR}{SR_0^- - SR_1^-}, \ SR_1^- < ASR < SR_0^-; \\ 0, \ ASR \ge SR_0^-; \end{cases} \quad (3)$$

$$SR^+(ASR) = \begin{cases} 0, \ ASR \le SR_0^+; \\ \dfrac{ASR - SR_0^+}{SR_1^+ - SR_0^+}, \ SR_0^+ < ASR < SR_1^+; \\ 1, \ ASR \ge SR_1^+; \end{cases} \quad (4)$$

$$VAR^-(AVAR) = \begin{cases} 1, \ AVAR \le VAR_1^-; \\ \dfrac{VAR_0^- - AVAR}{VAR_0^- - VAR_1^-}, \ VAR_1^- < AVAR < VAR_0^-; \\ 0, \ AVAR \ge VAR_0^-; \end{cases} \quad (5)$$

$$VAR^+(AVAR) = \begin{cases} 0, \ AVAR \le VAR_0^+; \\ \dfrac{AVAR - VAR_0^+}{VAR_1^+ - VAR_0^+}, \ VAR_0^+ < AVAR < VAR_1^+; \\ 1, \ AVAR \ge VAR_1^+; \end{cases} \quad (6)$$

where IR_0^- and IR_1^- is the fuzzy set IR^- membership function parameters; IR_0^+ and IR_1^+ is the fuzzy set IR^+ membership function parameters; SR_0^- and SR_1^- is the fuzzy set SR^- membership function parameters; SR_0^+ and SR_1^+ – fuzzy set SR^+ membership function parameters; VAR_0^- and VAR_1^- is the fuzzy set VAR^- membership function parameters; VAR_0^+ and VAR_1^+ is the fuzzy set VAR^+ membership function parameters.

The aggregation procedure consists of estimating the degree of truth values $G_1, G_2 \dots G_8$ of fuzzy rules:

$$G_1 = IR^+(AIR) \wedge SR^+(ASR) \wedge VAR^+(AVAR), \quad (7)$$

$$G_2 = IR^+(AIR) \wedge SR^+(ASR) \wedge VAR^-(AVAR), \quad (8)$$

$$G_3 = IR^+(AIR) \wedge SR^-(ASR) \wedge VAR^+(AVAR), \quad (9)$$

$$G_4 = IR^+(AIR) \wedge SR^-(ASR) \wedge VAR^-(AVAR), \quad (10)$$

$$G_5 = IR^-(AIR) \wedge SR^+(ASR) \wedge VAR^+(AVAR), \quad (11)$$

$$G_6 = IR^-(AIR) \wedge SR^+(ASR) \wedge VAR^-(AVAR), \quad (12)$$

$$G_7 = IR^-(AIR) \wedge SR^-(ASR) \wedge VAR^+(AVAR), \quad (13)$$

$$G_8 = IR^-(AIR) \wedge SR^-(ASR) \wedge VAR^-(AVAR). \quad (14)$$

The activation procedure consists of calculating the numerator and denominator of the following expression:

$$VSI = \frac{\sum_{k=1}^{8} G_k DR_k}{\sum_{k=1}^{8} G_k}. \quad (10)$$

The defuzzification result is calculated by dividing the numerator by the denominator in expression (15).

As a result, the output of the created system receives the calculated value of the generalized indicator of the virtual simulator functioning.

So, in order to evaluate the performance of virtual simulators used for training in the diagnosis of Internet of Things networks, the following procedures are proposed:

1) The virtual simulator being evaluated is being studied by experts;
2) Each expert evaluates the image realism, sound realism, and variety of scenarios provided by the virtual simulator;
3) the grading results are fed to the input of the fuzzy inference system;
4) Fuzzification, aggregation, activation and defuzzification are performed during fuzzy inference, as a result of which the value of the generalized indicator of the functioning of the virtual simulator is evaluated.

The higher the value of the generalized indicator, the higher the resulting score of the virtual simulator.

3 EXPERIMENTAL STUDIES

Let's consider how a fuzzy inference system can be used to evaluate virtual simulators designed for diagnosis training of Internet of Things devices. The evaluated virtual simulator is studied by experts. Each expert then rates the visual realism, sound realism, and variety of scenarios provided by the virtual simulator. Scores for each parameter are averaged:

$$AIR = \frac{\sum_{j=1}^{J} IR_j}{J}, \tag{16}$$

$$ASR = \frac{\sum_{j=1}^{J} SR_j}{J}, \tag{17}$$

$$AVAR = \frac{\sum_{j=1}^{J} VAR_j}{J}, \tag{18}$$

where:

- J is the number of experts involved;
- IR_j is the assessment of the image realism given by an expert j;
- SR_j is the sound realism assessment given by an expert j;
- VAR_j is the scenarios diversity assessment given by expert j.

To conduct computational experiments to evaluate the characteristics of virtual simulators used in the field of IoT, a process model of estimating the characteristics of virtual simulators has been developed in the MATLAB software environment using the libraries of the Simulink package. The functional diagram of the model is presented in Figure 4.

The values AIR, ASR and $AVAR$ are calculated using the AIR_subsystem, ASR_subsystem and AVAR_subsystem, respectively, and are displayed by the virtual recorder Display_AIR_ASR_AVAR. Then the obtained values become the input of the Fuzzy Logic System.

The evaluation result is the value of the output VSI is a general indicator of the virtual simulator functioning. The value of the resulting indicator is displayed by the virtual recorder Display VSI.

Numerous computational experiments and real tests have shown that the estimated value of the virtual simulator VSI indicator correlates well with the PCD value is the probability of correctly diagnosing real IoT systems by those specialists who were trained on this virtual simulator.

Table 2 presents data that show how characteristics of 4 virtual simulators were assessed by 10 experts.

Using these data, the values AIR, ASR and $AVAR$ were calculated using formulas (16) – (18) applying AIR_ subsystem, ASR_ subsystem and AVAR_ subsystem. These values were entered to fuzzy inference system as input variables. Then, at the output of this system, the values of the generalized indicator of each virtual simulator functioning were obtained.

Then the probability of correct diagnosis of real IoT systems was assessed by experts who were trained on the studied virtual simulators. Data for probability estimation are presented in Table 3.

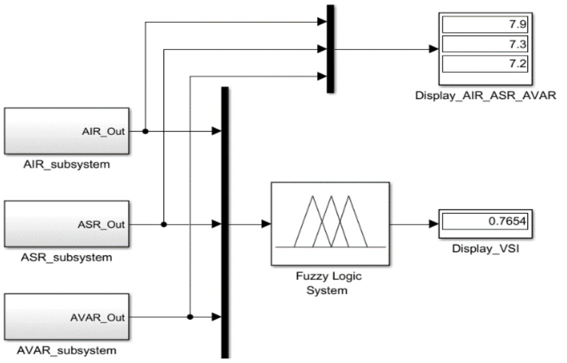


Figure 4: Functional diagram of the process software model of assessing the characteristics of virtual simulators used in the field of IoT.

The Table 3 contains values DR_{ix} that are the diagnosis results of IoT-system x by expert i, trained on a specific virtual simulator was calculated using the (19):

$$PCD = \frac{\sum_{i=1}^{I} \sum_{x=1}^{X} DR_{ix}}{I \cdot X}. \tag{19}$$

Diagrams were constructed based on the results of experiments and calculations. Figure 5 shows the VSI and PCD values obtained from a study of four different virtual simulators used for training in Internet of Things systems diagnosis.

Table 2: Experts' assessment of the virtual simulators' characteristics.

j	Evaluated virtual simulator											
	1			2			3			4		
	IR_j	SR_j	VAR_j	IR_j	SR_j	VAR_j	IR_j	SR_j	VAR_j	IR_j	SR_j	VAR_j
1	7	8	7	8	8	8	9	8	9	9	8	9
2	8	6	8	8	7	8	8	8	8	8	9	8
3	9	6	6	9	6	7	9	7	7	9	7	8
4	7	7	8	7	7	8	8	7	8	9	8	8
5	8	7	7	9	7	8	9	7	8	9	7	8
6	8	7	6	8	8	6	8	8	7	8	8	7
7	7	8	7	8	9	7	8	9	7	9	9	8
8	6	8	6	7	8	6	7	8	7	7	8	7
9	7	7	8	7	7	8	8	7	8	8	7	8
10	8	6	7	8	6	6	8	7	7	8	8	8

Table 3: Results of IoT systems diagnosis by experts trained on virtual simulators.

i	Virtual simulator used for training											
	1			2			3			4		
	The diagnosed IoT system, x			The diagnosed IoT system, x			The diagnosed IoT system, x			The diagnosed IoT system, x		
	1	2	3	1	2	3	1	2	3	1	2	3
1	1	1	0	1	1	1	0	1	1	1	1	1
2	0	1	1	1	1	0	1	1	1	1	1	0
3	1	0	0	1	1	1	1	1	0	1	1	1
4	1	0	1	1	0	0	1	1	1	1	0	1
5	1	1	1	0	1	1	1	1	0	1	1	1
6	0	1	1	1	1	0	1	0	1	1	0	1
7	1	0	1	1	1	1	1	1	0	1	1	1
8	1	1	0	1	0	1	1	1	1	1	1	0
9	1	0	1	1	1	1	1	0	1	0	1	1
10	1	1	0	1	0	1	1	1	1	1	1	1

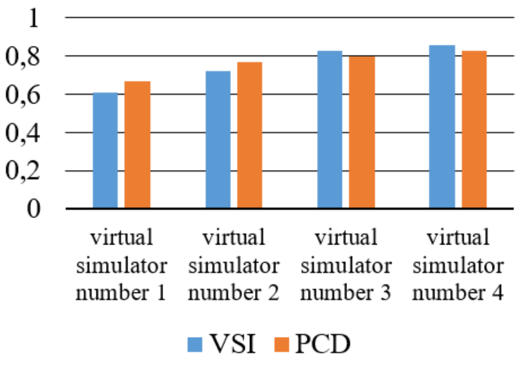


Figure 5: Diagrams of VSI and PCD values obtained from the study of four different virtual simulators.

Figure 5 shows that the higher the generalized indicator values of the virtual simulator, the greater the probability of correct IoT systems diagnosis by those experts who trained on it. Thus, the proposed fuzzy inference system can be recommended for on one of the simulators. The probability of correct diagnosis of real IoT systems by experts who were assessing the virtual simulators characteristics that are intended for training in Internet of Things systems diagnosis.

The value of the results obtained in comparison with the results of other modern studies lies in the fact that the proposed system makes it possible to evaluate the value of a generalized indicator that takes into account the most important criteria for the functioning of virtual simulators. It should also be noted that the quality of the fuzzy inference system settings depends on the number of experts involved. This can be attributed to the limitations of the proposed development.

3 CONCLUSIONS

The goal of the study was achieved, namely, a fuzzy logical inference system was developed that allows for improving the process of assessing the virtual simulators characteristics used for training in Internet of Things systems diagnosis.

The following results were obtained in the work:

1) An analysis of capabilities and specifics of the virtual simulators functioning used for training in Internet of Things systems diagnosis was carried out. The analysis showed that developers offer various options for virtual simulators that allow to train the diagnosing of IoT systems. To select devices with the best characteristics, as well as to identify shortcomings and improve virtual simulators, tools for assessing characteristics are used.
2) As indicators for assessing the characteristics of virtual simulators used for training in IoT systems diagnosis, it is proposed to use indicators of image realism, sound realism and training scenarios sets diversity, as well as a general indicator of the virtual simulator functioning. Scores for the first three indicators are given by experts in points from 1 (lowest score) to 10 (highest score). The values of the general indicator of the virtual simulator functioning should adequately take into account the values of the particular indicators of image realism, sound realism and the training scenarios sets diversity provided by the virtual simulator.
3) An assessment system has been developed for the characteristics of virtual simulators intended for training in IoT systems diagnosis. It is based on the use of fuzzy logical inference. The parameters of the membership functions of fuzzy sets and individual outputs of fuzzy rules were automatically selected using a neural network setup. The average values of assessments of image realism, sound realism, and the variety of training scenarios are fed to the input of the fuzzy logical inference system. Fuzzy inference procedures (fuzzification, aggregation, activation, and defuzzification) are then performed using these values. As a result, the desired value of the generalized indicator of the virtual simulator functioning is recorded at the output of the fuzzy logical inference system.
4) In order to study the proposed fuzzy logical inference system in the MATLAB software environment using the libraries of the Simulink package, a model of the process of assessing the characteristics of virtual simulators intended for training in diagnosing IoT systems has been developed. Numerous computational experiments have been carried out using this software model. A comparison of their results with the results of real IoT systems diagnosing showed that the higher the values of the generalized indicator of the virtual simulator functioning, the greater the probability of correct IoT systems diagnosis by the experts who trained on it. This confirms the feasibility of using the developed fuzzy logical inference system to evaluate the characteristics of virtual simulators used to IoT systems diagnosis.

The results obtained can be recommended for use in companies that develop and improve virtual simulators designed for educational purposes. The proposed development can be used as the basis for creating software for evaluating the usefulness of virtual simulators created for training in the correct diagnosis of the technical condition of Internet of Things systems.

Future work will focus on developing tools for evaluating the performance of virtual simulators used to teach IoT network management.

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