Method of operational monitoring of technical condition of multiservice communication network on the basis of hierarchical fuzzy inference

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Abstract. The paper proposes a method of operational monitoring of the technical condition of network elements of a multiservice communication network, based on the use of hierarchical fuzzy inference. The proposed method can be implemented in the creation of operational decision support systems for the management of multiservice communication networks. The analysis of the results of numerical simulation of the proposed method, which showed its high efficiency. The necessity of implementation of the proposed method based on the application of the concept of intelligent agents is substantiated. The functional structure of the intelligent agent for the implementation of operational functional monitoring of the technical condition of network elements of a multiservice communication network is developed. On the basis of the results of the assessment of the required performance, the possibility of hardware and software implementation of the proposed method and algorithm, which allows to monitor the technical condition in a time close to real time, is shown.

1. Introduction

Any multiservice communication network (MCN) is a large, complex, heterogeneous, hierarchical and geographically distributed system. The property of reliability for MCN is one of the main characteristics providing effective application of MCN on purpose [1].

With the increase in the size of the MCN, the increasing complexity of the telecommunications equipment used and the expansion of the list of communication services provided, the task of effective management of the MCN becomes much more difficult. Network administrators, which depend on the quality and reliability of the MCN, as a rule, have a fairly small time resource to analyze the current situation and develop control solutions to eliminate failures or failures in the network equipment. In addition, they have to make decisions in conditions of incomplete information about the technical condition of the network elements.

All this leads to a discrepancy between the physical and functional capabilities of the operator or decision-maker (DM), the increasing complexity of the tasks that need to be solved to maintain the network in working condition. Thus, the development and implementation of elements of the intelligent system of operational decision support (SODS) for the operational monitoring of the technical condition of the elements of the MCN is an urgent scientific and technical problem.

The variety of the main parameters and characteristics of the MCN, the high dynamics of their changes, their different physical nature, determines the complexity of solving the problem of operational monitoring of the state of network elements (NE) in the MCN by traditional methods, for example, statistical [5, 6, 16].

This article proposes a method of operational monitoring of the technical condition of the NE in MCN, based on the use of the mechanism of hierarchical fuzzy inference. In the proposed approach, the use of methods and algorithms for intelligent data processing is due to the following circumstances: (1) uncertainty of the reasons that may be caused by failures and changes in the technical condition of nodes and communication channels; (2) incomplete information on the state of the NE and the MCN as a whole, which is subject to processing; (3) the time delay of transmission of data on the functional state of the NE to the processing units.

As it is known [9, 10], operational support of decision-making under uncertainty is the solution of a set of semi-structured or unstructured problems in terms of time constraints on their solution. The characteristic features of such problems are the lack of methods for solving them on the basis of direct data transformation. Thus, decisions must be made in the absence of complete information about the process, phenomenon, event, etc.

The main way to resolve the contradictions is to abandon the traditional requirements for the accuracy of the input data, on the basis of which further analysis is carried out. Such requirements are an essential attribute of rigorous mathematical analysis and solving well-defined problems. However, the application of fuzzy set theory methods, fuzzy inference methods in conjunction with the methods of logical analysis in the aggregate allows to implement adequate methods of operational decision support under uncertainty.

The novelty and theoretical contribution of the work are as follows: (1) a method of hierarchical fuzzy inference for the identification of the functional and technical state of the NE MCN; (2) a modification of the method of subtractive (mountain) clustering for the analysis of the technical state of the processor module NE MCN; (3) the implementation of the developed methods of operational decision support regarding the technical state of the NE, proposed on the basis of the concept of intelligent agents (IA). Suggested approach allows to identify maintenance factors NE which have no property of statistical stability.

2. Statement of the problem research

The process of functioning of the restored NE MCN can be represented as a sequence of time intervals of working States and downtime, including failures and recovery of elements. The length of these intervals is determined by various factors. In the first approximation, the intervals can be considered mutually independent random variables having a certain distribution with average times. The mean time between failures T_0 is calculated as

$$T_0 = \sum_{i=1}^{n} t_i / n. \tag{1}$$

The average recovery time T_1 is calculated according to the expression:

$$T_1 = \sum_{i=1}^{n} \tau_i / n. \tag{2}$$

The reliability of the NE MCN is defined as the probability of finding NE in working condition. It is equal to the mathematical expectation of the fraction of time during which the NE is in good condition. This definition is equivalent to the concept of availability factor K_Γ. In this case, the following expression is true:

$$K_\Gamma = T_0 / (T_0 + T_1), \tag{3}$$

or (for a communication line):

$$K_\Gamma = \mu / (\mu + \lambda), \tag{4}$$

where: $\lambda = 1 / T_0$ – is the failure rate of the equipment; $\mu = 1 / T_1$ – is the recovery rate of the equipment.

Analysis of expressions (3) and (4) shows that the increase in the value of $K_Г$ corresponds to a decrease in the recovery time of the object of control T_1, which, in turn, can be represented as follows:

$$T_1 = t_{det} + t_{ev} + t_{des} + t_{ex} \rightarrow min, \tag{5}$$

where: t_{det} – is time of detection of deviation from the normative mode of functioning; t_{ev} – is time of an assessment of a new situation concerning a condition of the controlled NE; t_{des} – is time of development and decision – making; t_{ex} – is time of implementation of the decision.

Thus, the formulation of the problem for the SODS is to develop a solution for the management of the state of the NE MCN, which fulfilled the condition (5). The solution implementation time is determined by the technical characteristics of the operations support subsystem (OSS).

3. The analysis of the problem

Currently, the solution of the tasks of monitoring the technical condition of the NE is implemented in the MCN on the basis of the concept "agent – manager", which is discussed in detail in [2-4]. According to this concept, the *agent* previously accumulates information about the current state of the NE, and then transmits it to the *manager*. The Manager, in turn, provides it in a convenient form to the network administrator. This approach implements the "discovery – information" paradigm. Management of NE is implemented by the network administrator. Statistical methods are used in the basis of known and implemented in practice approaches to monitoring the state of NE [5].

In some works, to reduce a priori uncertainty and reduce the reaction time to changes in the state of NE, it is proposed to use intelligent methods [7-10]. In this case, the discovery – solution paradigm is implemented. In a number of works it is proposed to use neural network methods to monitor the state of the network [11, 12]. In work [13] the dynamic evolutionary system with fuzzy logic realizing adaptive training in the mode of time close to real is considered. However, taking into account the variety of the estimated parameters, in the known works on monitoring the state of NE, the elements of SODS that implement the methods of making optimal and rational decisions are given insufficient attention. At the same time, the experience of application of fuzzy inference mechanisms for decision-making on detection of abnormal behavior and safety risk management in the MSS, given in [14, 15], suggests the legitimacy of the idea of its use for operational monitoring of the state of the NE in the MCN.

The theoretical basis of hierarchical fuzzy situational networks can be the basis for the practical implementation of methods of operational control of the technical condition of the NE MCN [7 – 10, 14 - 16]. However, such categories as reference fuzzy situations are used for decision-making in known methods. With the growth of the network size and, accordingly, with the growth of its dimension, the application of this approach becomes extremely difficult, and often impossible. To solve the problem, it is proposed to combine hierarchical methods for assessing the fuzzy situation of the technical state of the network element of fuzzy mathematical programming methods. Using the methods of fuzzy mathematical programming it is proposed to search for a rational management decision.

4. Method of evaluating the condition of the ne in the mcn

Let the input variables characterizing the state of NE in MCN take the form of linguistic input variables after the fuzzification unit of the Mamdani fuzzy inference machine and are given in the following form:

$$\langle x, T, U, G, M \rangle \tag{6}$$

where: x is the variable name; T – term set, each element of which specifies a fuzzy set to the universal set U; G – syntactic rules that generate the membership functions of the names of terms; M is the semantic rule that defines the membership function of the fuzzy terms generated by the syntax rules of

G. Fuzzy inference for the formation of estimates of the state of NE in MCN based on the method of fuzzy inference Mamdani has the following form [8, 9]:

$$(x_1 = a_{1j}\theta_j \ldots \theta_j x_n = a_{nj}) \times w_j \Rightarrow y_j = d_j,\ j = 1,\ldots,m \qquad (7)$$

where: a_{ij} – fuzzy term, which evaluates the variable x_i in the j-th rule of the knowledge base; d_j – conclusion of the j-th rule; m – the number of rules in the knowledge base; w_j – weights for each j – th rule of the knowledge base ($w_j \leq 1$); θ_j – logical operation, linking parcels in the j-th rule of the knowledge base. As a result of the operation of defuzzification of the fuzzy set Y, which can be carried out, for example, using the method of determining the center of gravity, a clear value of the output y is obtained.

Summarizing the above results, it is proposed to assess the current situation of the state of the control object to implement the mechanism of fuzzy inference, which has a hierarchical structure. An example of implementing such a structure as an IA is shown in figure 1. The same figure shows a variant of IA interaction with a NE. In the presented structure, the number of hierarchical levels is conditional and can be changed in accordance with the solution of a specific problem. Each hierarchical level in its composition contains fuzzy inference machines. NE, for example, a router, in figure 1 is represented as a set of hardware, operating system, application software and network element management system. NE operates as part of the MCN and communicates with IA regarding procedures for operational decision support.

IA functionally consists of a situation assessment module, a decision-making module, a module for solving information and computational problems. The peculiarity of the structure of IA is the absence of intermediate operations of defuzzification and fuzzification. These operations are performed at the input and output of the SODS.

The inputs of fuzzy logic output machines of the first level of the hierarchy receive feature vectors $\{Xi\}$ of each controlled functional group of parameters that determine the technical condition of the NE.

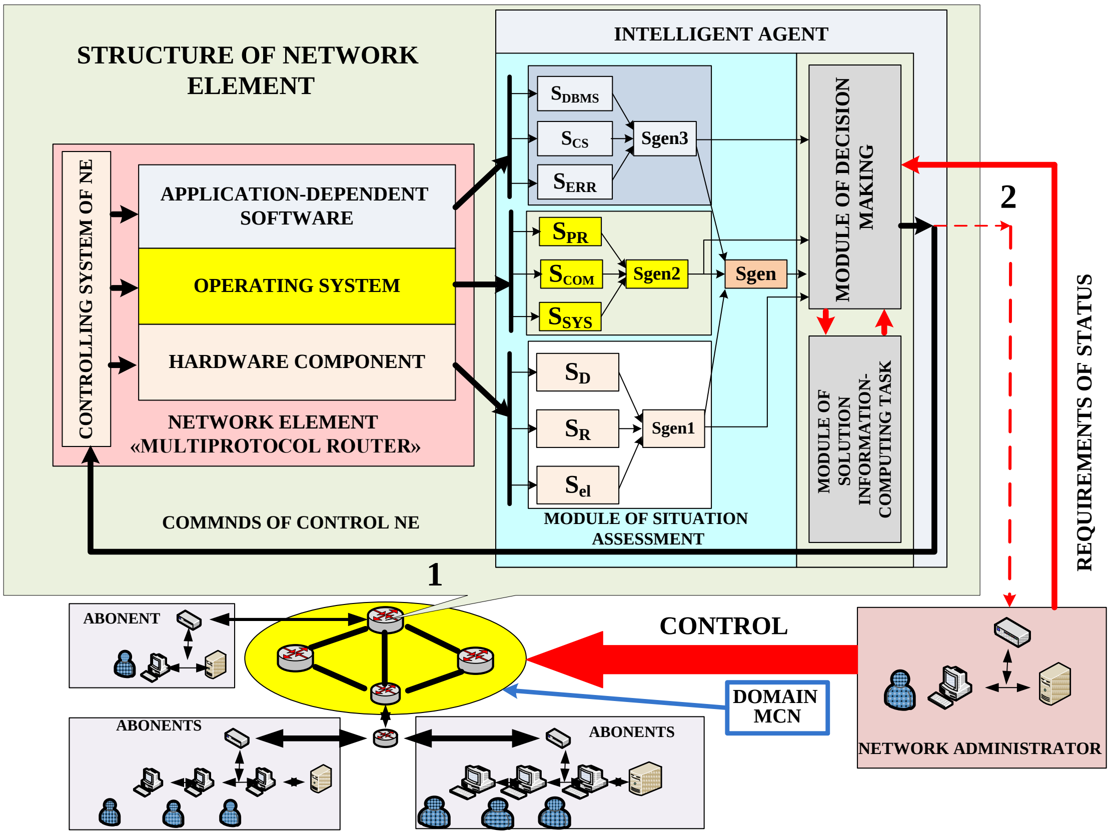


Figure 1. The structure of IA and its interaction with NE.

At the output of the hierarchical layer, a set of estimates of the fuzzy situation {Si} of the SE state with respect to each functional group of parameters is formed. The next level of the hierarchy aggregates these estimates.

It should be noted that it is possible to use a variant of the hierarchical structure of the NE state assessment process based on cluster analysis methods [14, 16]. This structure can be used for a large number of input variables characterizing the technical condition of the NE. Such an approach can be used, for example, to control the performance of the solution of a set of application tasks by the processor module of a network element. As the main clustering methods, it is advisable to choose the method of subtractive clustering, if a priori the number of possible clusters is unknown [14].

The fuzzy situation of the state of NE is formed in the following form:

$$S^i_{NE} = F_1 (\{S^i_{fg}\}, \{X^i_{fg}\}, R^i_{fg}), . \quad (8)$$

Where S^i_{NE} – fuzzy situation of NE state; F_1 – aggregation operator; $\{S^i_{fg}\}$ – set of fuzzy situations of states of controlled functional groups of NE; $\{X^i_{fg}\}$ – set of fuzzy parameters of states of controlled functional groups of NE; R^i_{fg} – set of functional and technological resources of NE.

Then the solution for the management of the NE would be:

$$R_{sl}{}^i_{NE} = F^i_{sl\ NE} (S^i_{NE}, \{X^i_{fg}\}, R^i_{fg}), \quad (9)$$

where: $R_{sl}{}^i_{NE}$ – the decision for management of NE; $F^i_{sl\ NE}$ – the statement of decision on management of the NE.

On the basis of the proposed approach, the method of monitoring of the technical condition of the NE model can be represented in the form of the generalized algorithm having the following form:

STEP 1. «BEGINNING»;

STEP 2."Monitoring of the technical condition of NE»;

STEP 3."Formation of values of fuzzy situations for each controlled functional group of NE»;

STEP 4."If $\mu(S^i_{fg}) \geq \mu(S^i_{fg0}) \forall i,$ the functioning of the NE staff»;

STEP 5."If $\exists i, \mu(S^i_{fg\,\partial on}) \leq \mu(S^i_{fg}) < \mu(S^i_{fg0})$,the technical condition of the SE has deteriorated, but is acceptable»:

ACTION: "Preparing a solution for the case of further deterioration of the situation, the request for additional resources from a higher level of management»;

STEP 6."If $\exists i, \mu(S^i_{fg\,\partial on}) > \mu(S^i_{fg})$, the technical condition of the SE has deteriorated, operation is impossible."

ACTION: "Solution for the case of NE failure, request an additional resource from a higher level of management, redistribution of resources between other NE, if the resource is received, the restoration of NE, if not, the output of NE from the network. NE restored ? YES – continue monitoring. Go to step 2. NO – go to step 7»;

STEP 7. «END».

There are two options for making a decision:

1. The decision is made by the IA directly on the NE itself, and the higher level of management, for example, the network administrator, is only notified of the decision. This is possible if the authority of the SODS is delegated to a higher level.
2. The decision, as in the first case, is made by the IA, but is verified and can be adjusted by a higher level of management, taking into account its preferences.

The proposed SODS inherit the features of multi-agent systems. These include the following properties:

1. System agents adapt to the network architecture and adequately respond to changes in the configuration of network equipment.
2. IA is distributed evenly across all of the NE in MCN, which allows to rationally (optimally) allocate computing resources.
3. Failure of one IA part of its functions themselves can take other IA.
4. The high degree of information security. The security subsystem does not have a dedicated control center, since the agents are distributed evenly throughout the system; therefore, it is more difficult to attack the MCN than the network with a centralized security server. Distributed information and distributed protection require an attacker to attack many nodes at the same time.
5. Possibility of centralized management. Changes in agents can be produced centrally and interaction protocols of agents be transferred to any point of safety.

Figure 2 shows the proposed modified algorithm of subtractive (mining) clustering of the evaluation of the technical condition of the processor module NE.

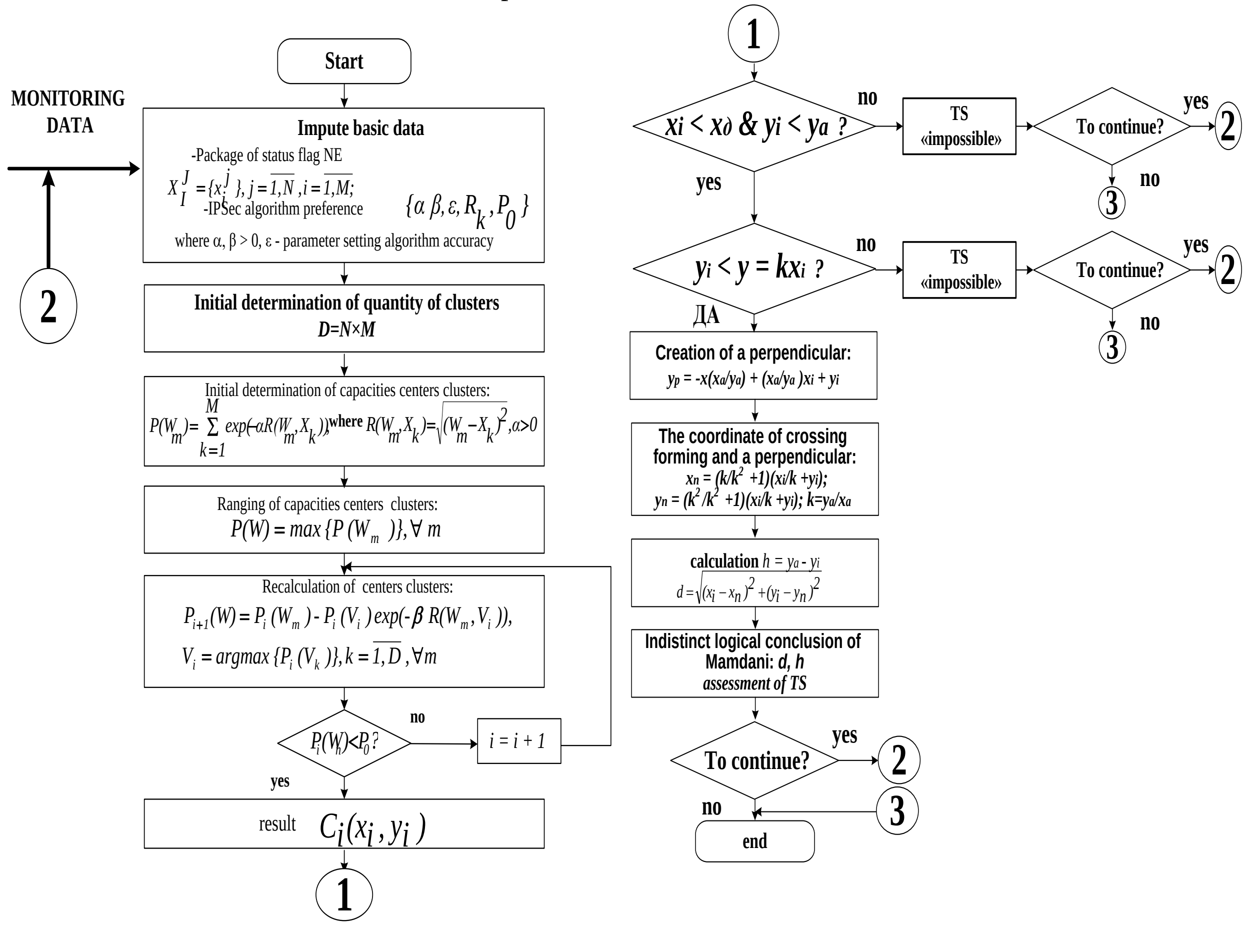


Figure 2. Generalized modified algorithm of subtractive clustering.

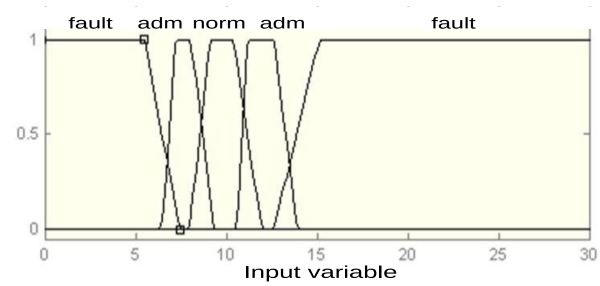
Features of functioning of the modified algorithm of subtractive (mountain) clustering of an assessment of a technical condition of the processor module of NE are explained in figure 5 and consist in the following. After clustering and obtaining the coordinate values of the cluster centers *Ci* (x_i, y_i), the distances from these centers to the corresponding permissible and unacceptable zones of the phase plane are estimated, on the basis of which, using the fuzzy inference method of Mamdani, a decision is made about the current technical condition of the processor module NE.

5. Analysis of the results of numerical simulation

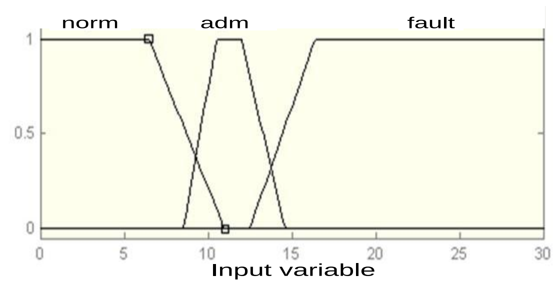
For numerical simulation as an example was chosen SE "ROUTER" (figure 1). n the numerical experiment, the state of SE was estimated by the following functional parameters (FP):

1. Electrical parameter;
2. Performance of application tasks;
3. The status of the software.

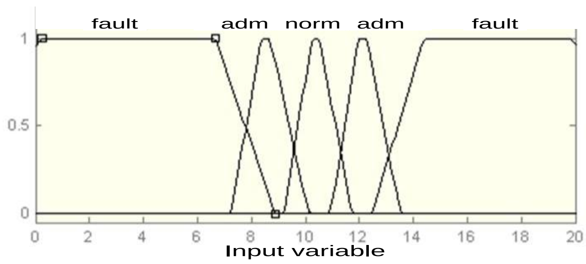
As an example, figures 3 and 4 present the characteristics of the fuzzy inference system to assess the fuzzy situation on the electrical parameters of the NE.



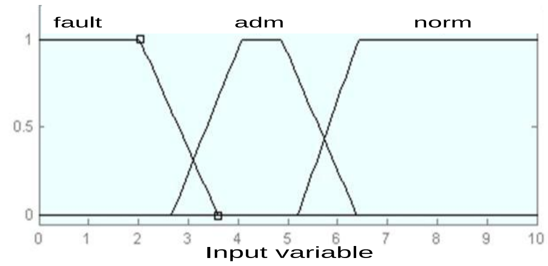
a) FP «power supply» parameter



b) FP of the «attenuation» parameter

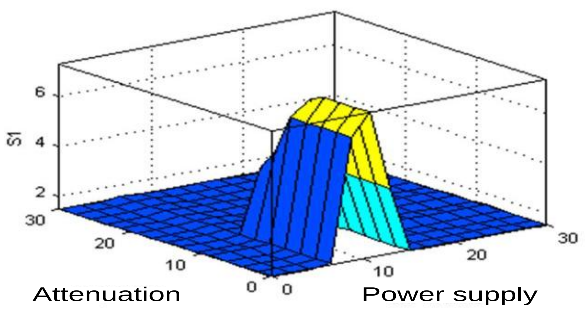


c) FP parameter «interface resistance»

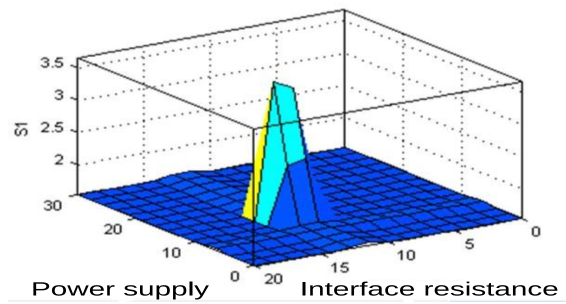


d) FP values of fuzzy situation S_{num}

Figure 3. Input and output function accessories (FP) IA electrical parameters.



a) FP «power supply – attenuation »



b) FP «power supply – interface resistance»
c)

Figure 4. Example of two-dimensional membership functions (FP).

Without loss of generality, in this computational experiment all membership functions are represented by trapezoidal functions. This is due to the simplicity of their practical implementation. Conducted various studies confirm their acceptable approximation properties [15, 17].

Figure 5 shows examples of joint operation of the functional modules "Attenuation", "Processor Temperature" and "Power Supply voltage" in the time domain.

On the upper and middle graph the digits " 1 "denote the permissible level of the controlled parameter value, and the digits" 2 " denote their critical values. These levels are determined by α - sections of the corresponding membership functions.

The lower figure shows a graph of the value of the FLAG parameter. If the situation is normal, the value "FLAG" is 0. If the situation worsens but is acceptable, the value of the FLAG parameter is 1. If the situation is invalid, the " FLAG " is 2.

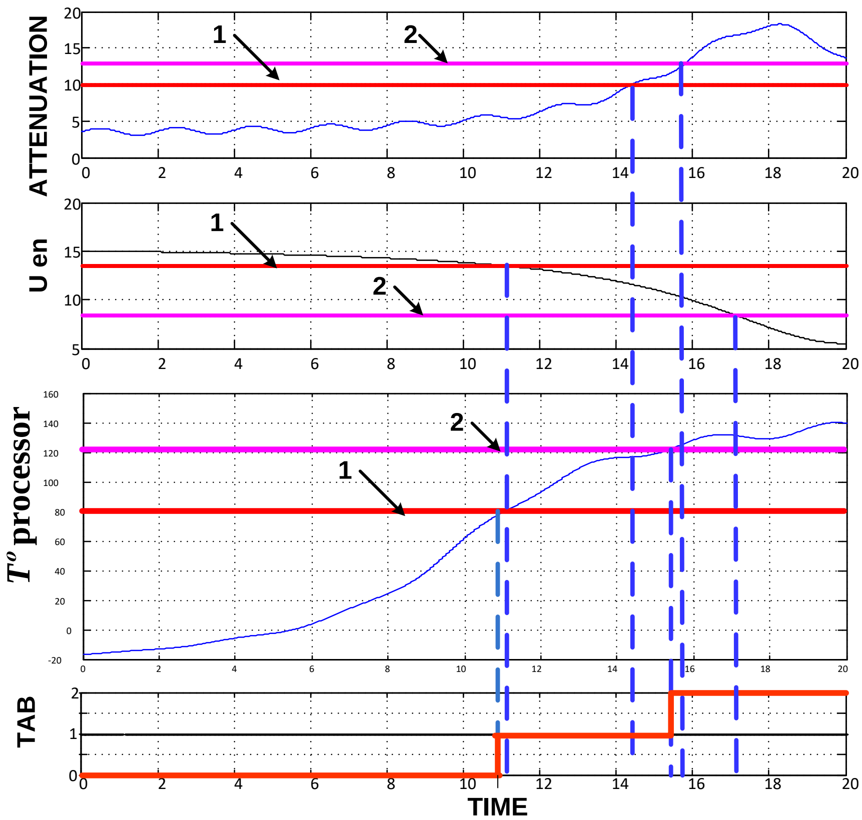


Figure 5. Joint operation of the modules "Attenuation", "Processor Temperature" and "Supply Voltage" in the time domain.

A modified method of subtractive clustering is used to evaluate the performance of solving applied problems (figure 2). The properties of this method in solving applied problems have been studied in detail in [16]. Here we note only its features when it is used to assess the technical condition of the processor module SE.

Time for solving applied problems in the time slot allocated by the task Manager can be represented as:

$$T_N = \sum_{i=1}^{N} (T_{\text{ож}\,i} + T_{\text{дост}\,i} + T_{\text{реш}\,i}), \tag{10}$$

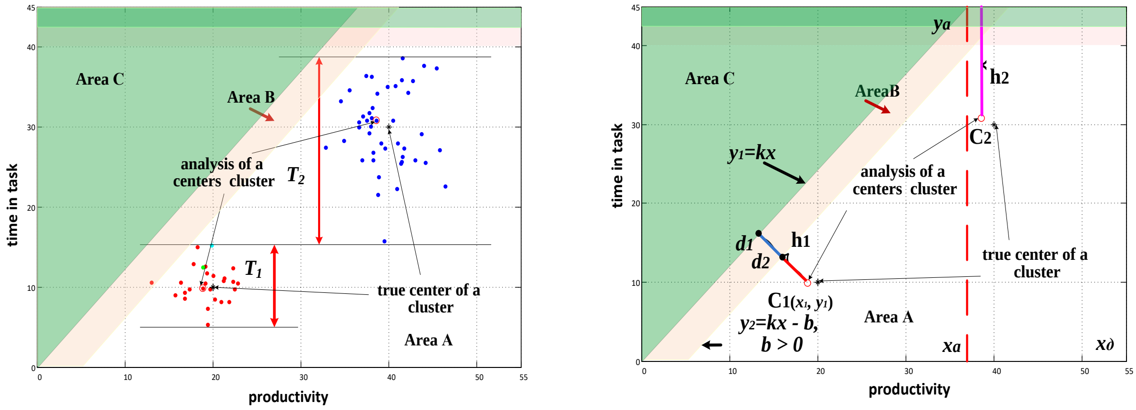
where: $T_{\text{ож}\,i}$ – the time of loading the parameters of the i - th task in the cache memory of the processor; $T_{\text{дост}\,i}$ – processor access time to the cache memory; $T_{\text{реш}\,i}$ – the time of the i-th task.

The number of operations performed by the processor is:

$$M = \sum_{i=1}^{N} (V_i \cdot T_{\text{реш}\,i}), \tag{11}$$

where V_i – the speed of the processor. Then the performance is equal to M/T_N . How can we see that the performance of the problem is a random variable.

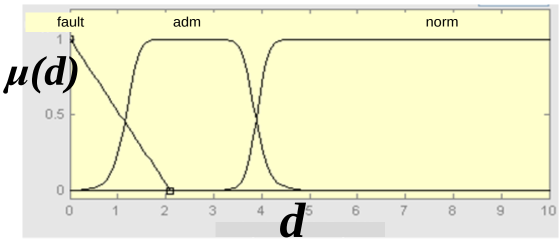
Figure 6 shows the results of numerical simulation of the subtractive clustering method to assess the performance of the processor module. Figure 6 (a) shows the analyzed clustering characteristics for the two cases. The first case-during T1 25 applied problems are solved, in the second case, during T2 35 problems are solved. Figure 6 (b) shows the results of an assessment of cluster centre positions for different time intervals. Area C in both figures is an invalid area. It is characterized by the fact that the time to solve the problems of SE given their numbers and processor performance is unacceptably large. Area B is the acceptable state of the processor module, and area A corresponds to its normal state.

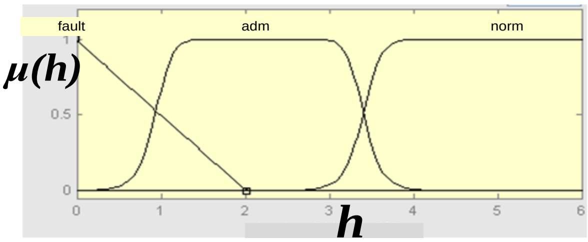


a) b)

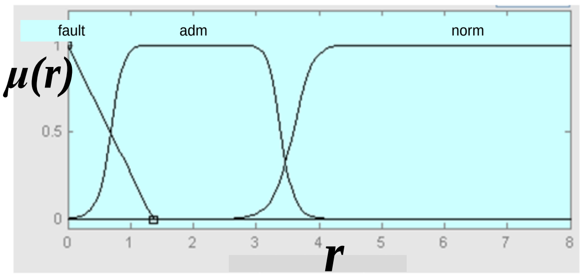
Figure 6. The simulation results evaluate the performance of the processor module.

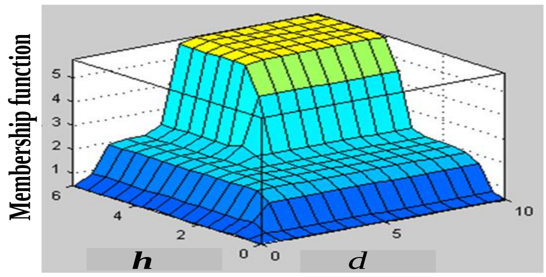
During the computational experiment the average relative error of cluster centers estimation δ≤ 7% was obtained. Figure 7 shows examples of membership functions of the fuzzy inference algorithm Mamdani to assess the technical condition of the processor module.





a) The FP parameter ***d*** b) The FP parameter ***h***





c) The output FP d) The joint distribution FP parameters ***d*** и ***h***

Figure 7. FP algorithm, fuzzy inference Mamdani assessment of the technical condition of the processor module.

Table 1 shows the results of a computational experiment to assess the technical condition of the processor module. The analysis showed that at the time of obtaining the solution no more than 1 MS (10-3 seconds) when implementing the IA on FPGA, taking into account the possible parallelization of the computational procedures, the computational performance of 0.18 Mgfl/s is required. When implemented on a unified processor - 0.6 Mgfl/s. These results allow us to conclude about the possibility of implementing the proposed methods and algorithms both on universal processors and on the basis of FPGA technology.

Table 1. Results of functioning of the modified algorithm of subtractive clustering.

№/№	d	h	The value of the output Terme
1	1.5	0.5	«unacceptably»
3	1	1	«unacceptably»
4	1	1.5	«unacceptably»
5	1	2	«unacceptably»
6	1.5	2	«acceptably»
7	2	2	«acceptably»
8	3	2	«acceptably»
9	5	6	«norm»
10	10	5	«norm»

The data obtained in the numerical experiment indicate the high efficiency of the proposed methods for assessing the state of SE based on the model of a typical functional element. The proposed algorithms operate in the time mode, close to real.

6. Conclusion

On the basis of the analysis of methods to ensure the reliability of the MSS formulated the task of operational monitoring of the NE.

On the basis of the proposed mechanism of fuzzy hierarchical inference, an algorithm for operational monitoring of the state of NE was developed.

The analysis of the results of the experimental evaluation of the developed algorithm showed its high efficiency. The accuracy and reliability of the algorithm for assessing the state of NE is determined by the characteristics of the primary sources of the analyzed information.

The developed hardware and software for a research of the offered methods and algorithms allows to carry out the analysis of experimental results for the wide range change parameters of functioning technical condition for NE MCN.

The direction of further research is associated with the use of fuzzy inference for decision-making on the management of MCN.

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