Monitoring the State of Elements of Multi-service Communication Networks on the Basis of Fuzzy Logical Inference

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Abstract—**The paper considers an approach for monitoring the state of elements of multi-service communication networks, based on application of fuzzy logical inference. The proposed approach can be implemented to design the systems for operative support of decision making in multi-service communication networks. The results of numerical simulation of the proposed method are analyzed, which showed that the method has high efficiency.**

Keywords- network monitoring; multi-service communication networks; fuzzy logical inference.

I. INTRODUCTION

Multi-service network (MSN) belongs to the class of big complex heterogeneous hierarchical geographically distributed systems. For such systems, the functional characteristics defining the reliability are some of the main characteristics [1]. With the growing size of networks, complexity of equipment and the extension of their functionality, the responsibilities of network administrators for the correctness and validity of decisions made for network effective management significantly increased. Network administrators, which determine the quality and reliability of MSN, as a rule, have sufficiently small time resource to make analysis of the current situation and develop management solutions to minimize the number of errors when making decisions on elimination of arising faults or failures in the network equipment. In addition, they have to make decisions in conditions of incomplete information about the technical state of the network elements. All this leads to discrepancy between physical and functional possibilities of the operator, and to the increasing complexity of the tasks that need to be solved to maintain the network in workable state. In this regard, the development and implementation of an intelligent operational decision-making system (ODMS) for monitoring and diagnostics of technical state of MSN elements is an actual scientific problem.

As an example, Table 1 shows the main managed parameters, which determine the quality of MSN services. Table I shows the diversity of the basic MSN parameters to be managed, their different physical nature, as well as different scales of their measurement. All this determines the complexity of solving the problem of monitoring the state of network elements (NEs) using traditional methods.

TABLE I. PARAMETERS OF MSN SERVICES

#	MSN Element	Parameter
1	Multiplexor, demultiplexor	Efficiency, Electric parameters, Interface
2	Communication lines	Bandwidth, Impedance, Attenuation, Noise Level, Resistance
3	Router	Performance, DBMS, OS, Applied Software, Electrical parameters, Interface, Protocols
4	Commutator	Bandwidth, Electrical parameters, Buffers, Interface, OS
5	Server	Functions, DBMS, OS, Applied Software, Performance, Electrical parameters
6	Gate	Performance, Capacity, Electrical parameters, Protocols, Interface

In this paper, we propose a new approach for the monitoring of the NE state in MSN, based on application of the fuzzy logical inference. The necessity of usage of fuzzy data processing methods in the proposed approach is caused by the following factors: (1) uncertainty of the reasons that can result in failures of nodes and communication channels; (2) incomplete information about the NE state and MSN as a whole, which is subject to processing; (3) delay for transmission of the NE state data to the processing nodes. Theoretical contributions and novelties of the paper are as follows: (1) the mechanism of fuzzy logical inference on NE states with hierarchical structure is proposed; (2) an approach based on the use of intelligent agents for decision making is suggested; (3) an algorithm for fuzzy models training that does not require significant computing resources is offered.

Further structure of the paper is as follows. Section 2 specifies the problem of the operational monitoring of the NE state in MSN. Section 3 discusses the results of relevant works. Section 4 considers the method for assessment of NE states in MSN. Section 5 shows and analyzes the results of experimental evaluation of the proposed approach. Section 6 contains the main conclusions and directions for further research.

II. PROBLEM STATEMENT

The process of functioning of NEs of MSN can be represented as a sequence of time intervals of workable states and outages, including failures and recovery (Figure 1). The duration of these intervals is determined by various factors. The following notations are used in Figure 1: t_i – NE's workability interval; τ_i – NE's outage interval.

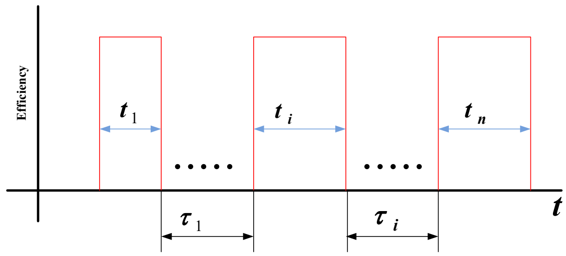


Figure 1. Intervals of workability and outages.

In the first approximation, the intervals can be considered mutually independent random variables, having certain distribution with the average times. The mean time between failures (MTBF) T_0 is calculated as

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

Mean recovery time T_1 is calculated as follows:

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

Reliability of NE of MSN is defined as the probability of existing of NE in a workable state in the conditions of failures. It is equal to the mathematical expectation of time during which the NE is in workable state. This definition is equivalent to the concept of the coefficient of availability K_a. In this case, the following expression is true:

$$K_a = \frac{T_0}{T_0 + T_1}, \tag{3}$$

or (for communication line):

$$K_a = \frac{\mu}{\mu + \lambda}, \tag{4}$$

where $\lambda = 1 / T_0$ is the rate of equipment failures; $\mu = 1 / T_1$ is the rate of equipment recovery. The probability of NE failure is determined as follows:

$$K_0 = 1 - K_1. \tag{5}$$

Analysis of expressions (3) and (4) shows that increasing of K_1 value corresponds to reduction of the recovery time of the controlled object T_1, which, in its turn, can be represented as follows and should be minimized:

$$T_1 = t_{\text{det}} + t_{\text{ev}} + t_{\text{des}} + t_{\text{ex}} \rightarrow \min, \tag{6}$$

where t_{det} is the time of detection of deviation from normative functioning mode; t_{ev} is the time of estimation of the new situation relatively to the state of the controlled NE; t_{des} is the time of elaboration and making decision; t_{ex} is the time of decision realization.

Thus, the task of the decision-making support (DMS) system is in production of such decision, in which the condition (6) is met. The time of decision realization is determined by the technical characteristics of the operations support subsystem (OSS). This time does not depend on DMS characteristics.

III. Related Work

Currently, the NE state monitoring is based on the concept of "agent – manager", which is described in details in [2]-[6]. According to this concept, the *agent* pre-accumulates information about the current NE state, and then sends it to the *manager*. The manager, in its turn, provides it in a convenient form to the network administrator. This approach implements the paradigm of "detection – informing". The MSN is controlled by the network administrator. Known and practically implemented approaches to the NE state monitoring are based on the statistical methods [7].

In some papers to reduce the a priori uncertainty and decrease the reaction time to change the NE state, it is proposed to use intelligent techniques [8]-[12]. On their basis it is possible to realize the paradigm of "from the state detection to decision". In a number of papers, it is proposed to use neural networks for network state monitoring [13][14]. Kasabov et al. [15] suggest a dynamic evolutionary fuzzy logic system that implements adaptive training in a near real time. However, it should be noted that, given the diversity of estimated parameters, in the known papers on the NE state monitoring insufficient attention is paid to the DMS elements that are implementing the methods for making optimal and rational decisions. At the same time, the experience of using the mechanisms of fuzzy inference for making decisions to identify anomalous behavior and manage the security risks in the MSN, given in [16][17], allows to assert about appropriateness of its use for the NE state monitoring.

IV. Assessment of the Network Element State

Let us assume that after the block of fuzzification of the Mamdani fuzzy inference machine the input variables, characterizing the NE state in MSN, take the form of linguistic input variables and are defined as follows:

$$\langle x, T, U, G, M \rangle, \tag{7}$$

 ISBN: 978-1-61208-596-8

where x is variable's name; T is term-set, each element of which is determined by the fuzzy set on universal set U; G is syntactic rules, generating the membership functions of terms' names; M is semantic rules, determining the membership rules on fuzzy terms, generated by the syntactic rules from G.

Fuzzy logical inference for generation of estimations of situations of the NE state in MSN based on the Mamdani fuzzy inference has the following form [9][10]:

$$(x_1 = a_{1j}\theta_j ... \theta_j x_n = a_{nj}) \times w_j \Rightarrow y_j = d_j,\ j = 1,...,m\ , \quad (8)$$

where a_{ij} is a fuzzy term, by which the variable x_i in j-th rule of the knowledge base is estimated; d_j is conclusion of j-th rule; m is number of rules in the knowledge base; w_j are weight coefficients for each j-th rule of the knowledge base ($w_j \leq 1$); θ_j is logical operation, connecting premises in j-th rule of the knowledge base.

In the expression (8), all values of input and output variables are represented by fuzzy sets. We introduce the following membership functions:

– $\mu_j(x_j)$ – membership function for input x_i, corresponding to fuzzy term a_{ij}, i.e.:

$$a_{ij} = \int \mu(x_i)/x_i, \quad (9)$$

– $\mu(y_i)$ – membership function for output y_i, corresponding to fuzzy term d_{ij}, i.e.:

$$d_{ij} = \int \mu(y_i)/y_i, \quad (10)$$

Then the degree of execution of j-th rule for current input vector $X^* = (x_1^*, x_2^*, ..., x_n^*)$ is determined as

$$\mu_j(X^*) = (\mu_j(x_1^*)\ ...\ \chi_j\ \mu_j(x_n^*)) \times w_j,\ \ j = \overline{1, m}, \quad (11)$$

where operator χ_j is determined as

$$\chi_j = \begin{cases} t\text{ - norm when } \chi_j =< \text{AND} >, \\ s\text{ - norm when } \chi_j =< \text{OR} > . \end{cases} \quad (12)$$

Then the result of fuzzy inference may be represented as

$$y^* = \{\frac{\mu_1(x^*)}{d_1}, \frac{\mu_2(x^*)}{d_2}, ..., \frac{\mu_m(x^*)}{d_m}\}. \quad (13)$$

The carrier of the fuzzy set, determined by the expression (13) is the set of fuzzy terms $\{d_1, d_2, ..., d_m\}$. For transition to the fuzzy set, determined on the carrier y, the operations of implications like

$$d_j^* = \int \min \frac{(\mu_j(X^*), \mu(y_j))}{y},\ \ j = \overline{1, m}\ , \quad (14)$$

as well as the operations of aggregation like

$$y^* = \int \max \frac{(\mu_j(X^*), \mu(y_j))}{y},\ \ j = \overline{1, m}\ , \quad (15)$$

are done.

As the result of the defuzzification of the fuzzy set Y (which can be done, for example, using the method of determining the gravity center), the exact value of output y is turned out. Summarizing the above results, to assess the current state of the NE it is proposed to implement in DMS the mechanism of fuzzy inference with two-level hierarchical structure that is represented in Figure 2. In the given structure, the number of levels is conditional and can be modified when solving a specific task. Each hierarchical level comprises the machines of fuzzy inference. The particularity of this structure is the lack of intermediate operations of defuzzification and fuzzification. These operations are fulfilled on the DMS input and output. For each group of controlled functional parameters, defining the NE state, the features vectors $\{X_i\}$ arrive on the inputs of the fuzzy logical inference machines of the first level of the hierarchy.

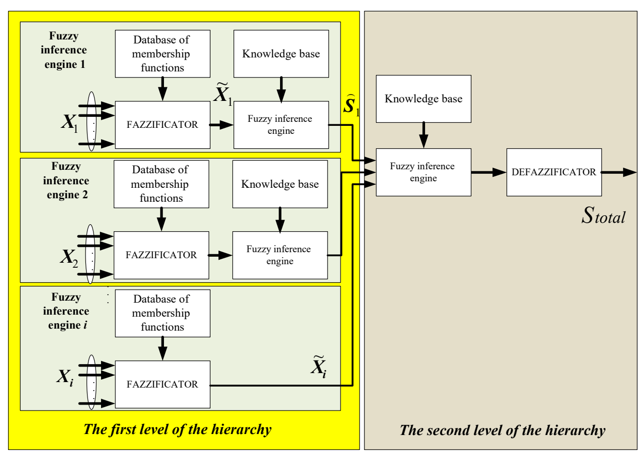


Figure 2. The structure of the mechanism of fuzzy logical inference.

At the output of the hierarchical layer a set of fuzzy assessments of the situation $\{S_i\}$ of the NE state for each functional group of parameters is formed. These estimates are aggregated on the second level of the hierarchy.

Figure 3 shows a variant of the hierarchical structure of the process of the NE state assessment based on cluster analysis. This structure can be used for a large number of input variables, characterizing the NE technical state, and implements a hierarchy of methods of fuzzy cluster analysis with subsequent classification of the obtained results.

The structure of the classifier corresponds to the considered structure of the fuzzy logical inference system.

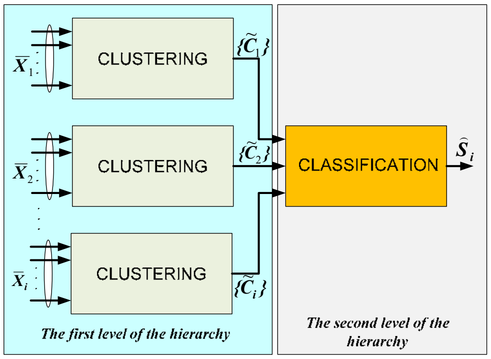


Figure 3. The structure of the NE assessment process.

It is advisable to choose as the main clustering techniques: (1) the method of fuzzy *k*–means if the number of clusters is known a priori; (2) subtractive clustering methods, if a priori the number of clusters is unknown.

A fuzzy situation of the NE state is formed as follows:

$$S^i_{NE} = F_1\left(\{S^i_{fg}\},\{X^i_{fg}\},R^i_{fg}\right), \qquad (16)$$

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

Then the solution on NE control will be as follows:

$$R^i_{sl,NE} = F^i_{sl,NE}\left(S^i_{NE},\{X^i_{fg}\},R^i_{fg}\right) \qquad (17)$$

where $R^i_{sl,NE}$ is a solution for NE control; $F^i_{sl,NE}$ is an operator of decision making on NE control.

On the basis of the proposed approach, the generalized algorithm for monitoring of technical state of typical NE can be represented as shown in Figure 4. In this figure, $\{X_i\}$ is a set of input features of the functional groups' state; $\{S_i\}$, $i=\overline{1,N}$, is a set of fuzzy situations, characterizing the state of each functional NE group. These include, for example, the NE performance, electromechanical characteristics (containing the value of the active and wave resistances of interfaces), the current operating temperature of the processor module, the number of software faults per time unit, etc.

There are two variants of decision-making:

1. The decision is made by the intelligent agent (IA) exactly at NE itself, and the higher control level, such as network administrator, is only notified about the decision made. This is possible if such rights are delegated to by the higher level.

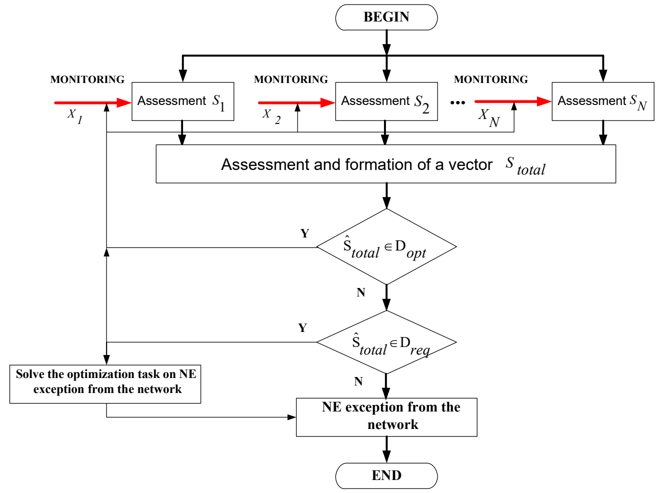


Figure 4. Generalized algorithm of NE monitoring.

2. The solution, as in the first case, made by IA itself, but is acknowledged and can be corrected by a higher control level taking into account its preferences.

It should be noted that the proposed DMS inherits the features of multi-agent systems. These include the following properties:

1. Adaptation. The agents adapt to the network architecture and adequately respond to changes in the network equipment configuration.

2. Rationality of resource allocation. IAs are evenly distributed across all the NEs in the MSN that allows to rationally (optimally) allocate computing resources.

3. Fault tolerance. At failure of one IA a part of its functions can be taken by other IAs.

4. Ensuring a high degree of information security. The security subsystem does not have the dedicated control center (decision-making center), as the agents are evenly distributed throughout the system, therefore it is more difficult to attack the MSN than a network with a centralized security server. Distributed over the network information and distributed protection require the attacker to attack many sites at the same time.

5. The possibility of centralized control. Introducing changes into agents' work can be performed centrally and by agent interaction protocols be transferred to any point.

V. EXPERIMENTAL RESULTS

For numerical simulation, an NE "router" was chosen as an example. The structure of the intelligent agent for NE "router" state assessment is outlined in Figure 5. In the numerical experiment, the NE state was estimated according to the following functional parameters:

1. Electrical parameters: power; active resistance of interfaces; attenuation of communication lines to which the interfaces are connected.

2. Performance: processor unit performance; switching module performance; state of memory buffers.

3. State of software: state of the database management system; software state; number of failures of the software and the operating system.

We denote the estimates for each such group of parameters as S_1, S_2, and S_3, respectively. Numerical simulation was carried out in MATLAB R 2014b.

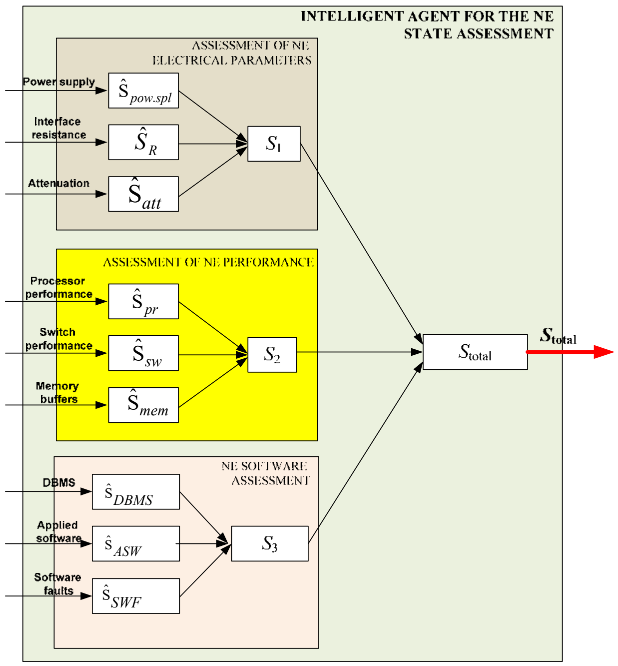
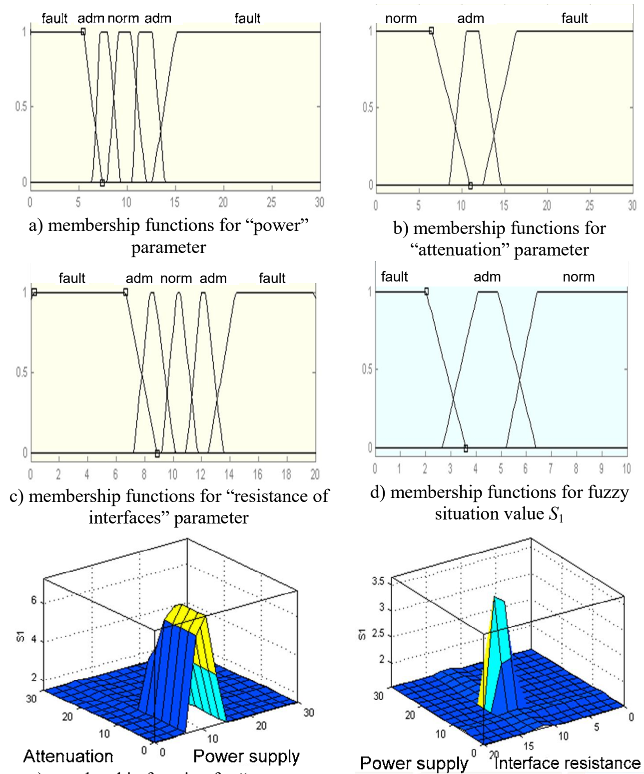


Figure 5. The structure of the intelligent agent.

Figure 6 represents the characteristics of the fuzzy inference system for evaluation of the fuzzy situation using the NE electrical parameters. Figure 6-a shows the membership functions for the "power" parameter. When forming this function, it was assumed that a supply voltage equal to 10 V 5% is considered normal. Deviations of +10% and -15% are considered as the maximum permissible. Values exceeding these values are considered as failures. Similarly, the membership functions for "attenuation" parameter, shown in Figure 6-b, are constructed. It was believed that the signal attenuation corresponds to the norm, if it does not exceed 5-6 dB. Attenuation equal to 8-11 dB is considered acceptable. If the attenuation exceeds 12 dB, then a failure is fixed, since the router will not perform its functions. The approach to building the membership functions for "resistance of interfaces" parameter (Figure 6-c) is similar to the approach discussed above. The membership functions for the fuzzy situation value S_1 are shown in Figure 6-d. These functions perform the aggregation of the membership functions of the individual parameters belonging to group 1, and characterize three states – "normal", "acceptable" and "failure". Figure 6-e and Figure 6-f show sections of the multidimensional function S_1 for possible pairs of separate parameters: "power-attenuation" and "power-resistance of interfaces", respectively.



a) membership functions for "power" parameter

b) membership functions for "attenuation" parameter

c) membership functions for "resistance of interfaces" parameter

d) membership functions for fuzzy situation value S_1

e) membership function for "power – attenuation"

f) membership function for "power – resistance of interfaces"

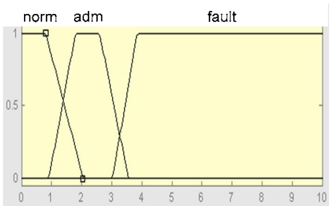
Figure 6. Evaluation of fuzzy situation using the NE electrical parameters.

Figure 7 depicts the characteristics of the fuzzy inference system to evaluate the fuzzy situation using the NE software, and Figure 8 shows the characteristics of the fuzzy inference system to evaluate the fuzzy situation.

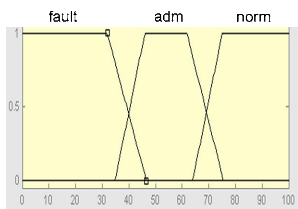
The construction of membership functions for these functional groups is similar to the first functional group. Without loss of generality, in this computational experiment all the membership functions are represented by trapezoidal functions. This is due to the simplicity of their practical implementation. The conducted studies confirm their acceptable approximation properties [16][17]. Numerical modeling of the functioning of the intelligent agent was carried out by the Monte Carlo method with a given probability and methods of generating random processes with given statistical characteristics. These events and random processes simulated the numerical, functional, logical and linguistic data of the sensors arriving at the input of the intelligent agent for each monitored functional group of the router. The results of computational evaluation for common fuzzy situation S_{total} concerning the NE state are represented in table II. The rows of the table correspond to possible combinations of estimates of fuzzy situations for individual groups of functional elements.

One of the problems, solved by development and implementation of this class DMS, is the task of preliminary training.

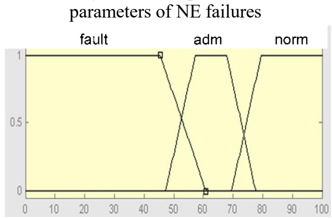
 ISBN: 978-1-61208-596-8



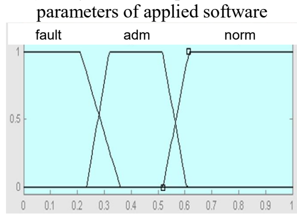
a) fuzzy membership function for parameters of NE failures



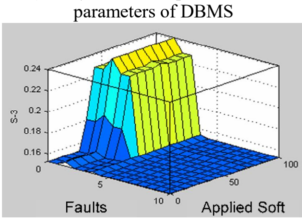
b) fuzzy membership function for parameters of applied software



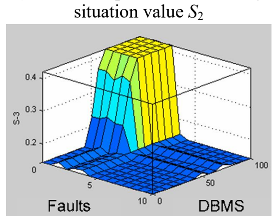
c) fuzzy membership function for parameters of DBMS



d) membership functions of fuzzy situation value S_2

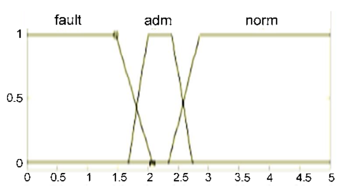


e) common membership function for «faults – applied soft»

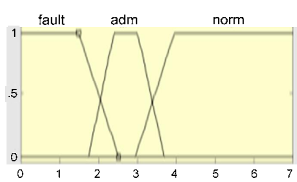


f) common membership function for «faults – DBMS»

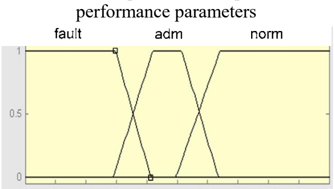
Figure 7. Evaluation of the fuzzy situation using the NE software.



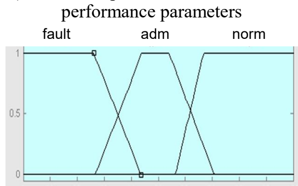
a) membership function for processor performance parameters



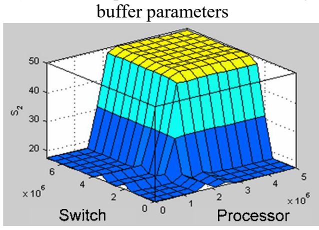
b) membership function for NE switch performance parameters



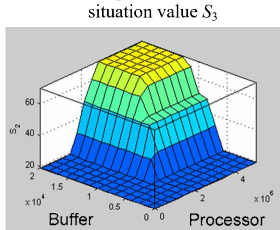
c) membership function for NE memory buffer parameters



d) membership function for the fuzzy situation value S_3



e) membership function for "states of switching matrix – processor"



f) membership function for "states of buffer – processor"

Figure 8. Evaluation of the fuzzy situation using the NE performance.

In [16][17], they tested the training algorithm of fuzzy model using a set of test input data. The proposed modification of the algorithm is presented in Figure 9. In the first step of the algorithm, a set of test training data samples is generated for each monitored functional group.

TABLE II. RESULTS OF EVALUATION OF NE STATE FUZZY SITUATIONS

##	S_1	S_2	S_3	S_{total}
1	norm	norm	norm	norm
2	admissible	admissible	admissible	admissible
3	admissible	norm	norm	admissible
4	fault	admissible	norm	fault
5	norm	fault	admissible	fault
6	admissible	admissible	fault	fault
7	norm	norm	fault	fault

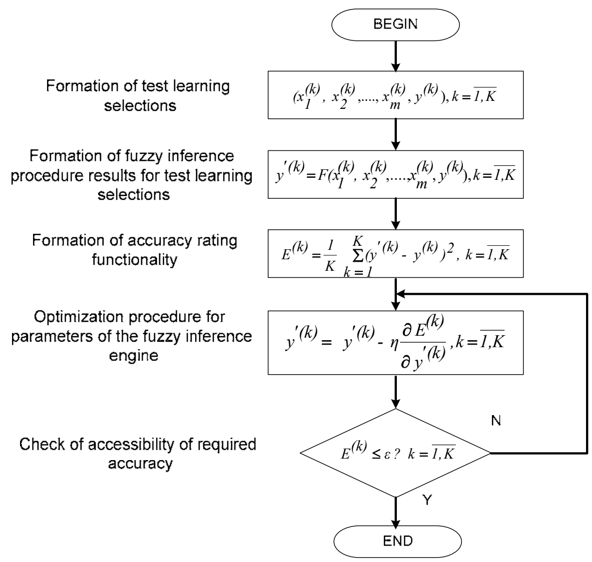


Figure 9. Training algorithm of fuzzy model.

In the second step, the results of fuzzy inference procedures are formed on the basis of training samples of the source data. In this case, the input training samples can be either numerical or linguistic variables. In the third step, the functional of the degree of accuracy is formed. In the overwhelming majority of cases, this functional belongs to the class of quadratic functionals. In the fourth step, an iterative gradient procedure is performed, which allows to optimize the membership functions for the corresponding parameters of the fuzzy inference mechanism. In the final fifth stage, the accuracy of the fuzzy inference system is checked. If this accuracy is acceptable, then the algorithm is completed. If not, it returns to step 4.

The main characteristics and properties of the training algorithm of fuzzy model are as follows: the amount of training samples is much less than the amount of data to compute the sufficient statistics used in statistical methods to ensure the same given accuracy; easy implementation of the algorithm; implementation of this algorithm does not require significant computing resources; the convergence of this algorithm is provided in approximately 5-17 iterations; despite the fact that this algorithm belongs to the class of algorithms of preliminary training, it can be applied also for training of fuzzy inference systems and their operation. The data, obtained in the numerical experiments, indicate high efficiency of the proposed methods of the NE state assessment based on the model of the intelligent agent and the mechanism of logical inference. The *duration of the final NE status assessment* in all cases was in the range from 100 to 150 msec. The *duration of the final NE status assessment* in all cases was in the range from 100 to 150 msec. The calculations were performed on a personal computer of a typical configuration (Intel Xeon 4x2 GHz CPU Cores, 2 GByte). In traditional statistical approaches (considered in [2]-[7]) this duration is related with calculation of correlation dependences. Its value lies between 5 to 30 seconds depending on the composition of the initial data used. Comparison of the obtained duration estimate with the estimate performed according to the traditional approaches shows a gain of 50 to 180 times. Proceeding from expressions (3) and (6), the decrease of the duration of the final NE status assessment leads to decrease the NE recovery time and increase the coefficient of availability respectively from 0.9-0.95 to 0.95-0.99. Thus, the method proposed allows to increase the MSN reliability significantly. *The accuracy of the final NE status assessment* for numerical parameters was not less than 0.95. For symbolic parameters, in all cases, the accuracy was 1.0. For comparison, with the statistical approach, the accuracy for numerical parameters lies in the range from 0.9 to 0.97, and for symbolic values the statistical estimate generally loses its meaning. Thus, this conclusion is justified by the following factors: the high completeness of the representation of heterogeneous primary information about the NE state, which is then analyzed and aggregated; the possibility of learning and self-learning of intelligent agents; the possibility of organizing parallel computational procedures for evaluating the state of NE, which provides the possibility of its operation in real time; high accuracy of NE state estimation; the ability to quickly track various failures and short-term violations in the operation of NE hardware and software; the absence of the need to collect and process various statistical data on the functioning of the NEs. In addition, the use of intelligent agents in conjunction with the developed methods and algorithms ensures to implement the principle of self-organization when providing and restoring the specified state of MSN as a whole.

VI. CONCLUSION

On the basis of the analysis of the methods for ensuring the MSN reliability, the task of the operational monitoring of the NE state was formulated. Using the proposed mechanism for fuzzy hierarchical inference the algorithm for operational monitoring of the NE state was developed. Analysis of the results of the experimental evaluation of the developed algorithm in comparison with the statistical approach has shown its higher speed and accuracy for NE state estimation, as well as the possibility of predicting its further state. All this allows us to speak about the high efficiency of the proposed approach for monitoring of the NE state in MSN. The future research is associated with the use of fuzzy inference for making decisions on MSN control.

ACKNOWLEDGMENT

This research is being supported by the grants of the Russian Foundation of Basic Research (15-07-07451, 16-37-00338, 16-29-09482), partial support of budgetary subjects 0073-2015-0004 and 0073-2015-0007, and Grant 074-U01.

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