Intellectual method of operational evaluation of the network element state to ensure the quality of services in corporate multiservice communications networks

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Abstract. The work proposes and investigates an intelligent method and algorithms for on-line assessment of the state of network elements to ensure the required quality indicators of provided communication services in corporate high-speed multiservice communication networks. The developed method and algorithms operate in a mode close to real time. One of the features of corporate multiservice communication networks is the high dynamics of changes in their state. The main task of the automated control system, which is an integral part of the corporate multiservice communication network, is to ensure the specified quality of the provided communication services to the consumer. Thus, the relevance of the research presented in the work is due to the fact that most of the management processes in corporate high-speed multiservice communication networks must be implemented in a mode close to real time with a given quality. The basis of the method for operational assessment of the state of network elements is the concept of creating and using intelligent agents. In the proposed approach, intelligent agents are created as hierarchical fuzzy situational networks, in which control solutions, in contrast to known methods based on the use of reference situations, are applied based on solving a hierarchical set of optimization problems using fuzzy mathematical programming methods. The main paradigm of their functioning is "situation - action".

1 Introduction

The intensive development of transport and logistics systems, industry, as well as business is characterized by the successful use of corporate multiservice communication networks (CMCN), which provide users with the provision of various infocommunication services. As a rule, CMCN consist of local computer networks and global telecommunication networks that unite them. Thus, the technical platform of CMCN is a logically structured set of high-speed communication channels, routers (packet switching nodes), service servers and communication services provided to users of CMCN, as well as a hierarchical

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automated communication control system (ACCS). The functional basis of CMCN is the technology of telecommunications and new generation networks (NGN), the core of which is packet networks based on the TCP/IP/MPLS protocol stack, which integrate various communication services [1-4].

It is known that in CMCN the traffic of various applications is very diverse [5 -7]. It has a complex statistical structure. Its parameters, as a rule, are the values of non-stationary nonlinear random processes, while the specified requirements for the quality of services and provided communication services (Quality of Service - QoS) must be fully met.

To complement the functionality of the TCP/IP/MPLS protocol stack in terms of ensuring the quality of communication services (QoS) when transmitting heterogeneous network traffic, two mutually complementary traffic management models have been developed and applied – the Integrated Service model and the Differentiated Service model [8]. In addition, packet networks use RSVP (Resource Reservation Protocol) and RTP (Real – time Transport Protocol) protocols, which allow to control end-to-end delays in packet transmission [9, 10].

However, there are objective difficulties in the construction and implementation of methods and algorithms for the operational assessment of parameters and characteristics that determine the quality of communication services in CMCN. They are due to the complexity and large spatial scope of CMCN network infrastructure, its heterogeneity, the need for a quick and high-quality analysis of a large number of various dynamically changing network and information parameters and characteristics for making management decisions, which, in turn, have inaccuracy, uncertainty and fuzziness. The noted features of the CMCN functioning and the process of its management determine the need for the development and application of intelligent methods for the operational development and implementation of managerial decisions on managing the quality of communication services of CMCN. This determines the need to develop such methods, which is an urgent scientific problem.

2 Analysis of the problem and statement of the research task

The network characteristics that most significantly affect the quality of service are defined by the ITU – T Y.1540 and Y.1541 recommendations [11, 12]. These include:
- reliability of the network / network elements;
- probability of loss of transmitted packets;
- throughput of the network / communication channel, which is measured in bits per second;
- packet transmission delay;
- packet transmission delay variation.

The parameters related to the required throughput for different applications can be defined according to the ITU – T Y.1221 recommendations [13].

The main mechanisms for ensuring QoS in CMCN, as well as in NGN networks, include [14]:

1. Mechanisms in the control plane, including:
- access control when connecting;
- QoS – routing;
- resource reservation based on the RSVP protocol.

2. Mechanisms in the data plane, which include:
- management of buffers of switching nodes (for example, management of router buffers);
- prevention and management of traffic congestion;
- package marking mechanisms;
- organization and planning of queues;

- traffic classification;
- traffic characteristics management.
3. Mechanisms in the management plane, consisting of methods and procedures:
- network measurements;
- ensuring the implementation of agreements on the service level agreement of SLA (Service Level Agreement).

QoS control mechanisms in the CMCN should be implemented using ACCS. ACCS of networks of the NGN class is developed and created on the basis of the concept of the hierarchical network management model TMN (Telecommunication Management Network) [15 - 17]. The ACCS of CMCN of the levels of control of service (CS), network (CN), technological control (TC) and management of network elements (NE) should manage QoS in a mode close to real time. This is due to the fact that these levels of control must ensure effective network management, including QoS management, when the needs of users for the provided communication services change, or when the state of CMCN changes due to various destructive external influences. Such impacts include threats to network and computer security or internal technical network failures of various software and hardware, NE, communication service servers, and so on.

The peculiarities of the QoS control problems solved by the ACCS make it extremely difficult to apply approaches to the control of the CMCN based on the construction of models of the control object, as well as on the use of well-known statistical methods, since CMCN is a large, distributed and complex system. Its characteristic features are a large spatial range, high dynamics of state change, stochasticity, multidimensionality and nonlinearity of the processes taking place in it [7 - 8].

The most promising approach to the synthesis of ACCS of CMCN is an approach based on the use of the concept of distributed intelligent agents (IA) and the use for their implementation of fuzzy methods and models that implement the principle of "situation - action" [18 - 20]. The main advantages of this approach are the focus on the analysis and modeling of processes, which can be represented in the form of logical-temporal sequences, in the form of a spatial interconnected distributed system of control objects, as well as in the form of an interconnected set of processes occurring in them. The main algorithms and models of this class include fuzzy automata, fuzzy hierarchical networks, fuzzy Petri nets, fuzzy situational networks, fuzzy cognitive maps, fuzzy semantic networks [21].

The works [19, 20] substantiate the prospect of synthesizing automated control systems in complex systems of organizational and technical type based on the situational approach. In this case, the principle of constructing an ACCS on the basis of a situational approach is not the construction and analysis of the CMCN model as a control object, but the analysis and regulation of the CMCN management process model.

Let us note the main methods that implement the concept of situational control [18 - 21]:

- methods based on the formation of a detailed list of descriptions of possible (reference) situations. For large complex systems, this is not entirely justified due to its complexity and cumbersomeness. Sometimes this approach cannot be implemented in principle due to the possible exponential growth of the number of reference situations;
- the most acceptable are approaches based on combining the principles of situational management and methods of fuzzy logic and fuzzy inference, which are called methods of fuzzy situational approach.

A feature of automated control systems designed to support the management process of complex organizational and technical systems is that they must not only identify the current situation, but also determine the rational modes of functioning of controlled systems.

Thus, the task of the presented study is to develop a method for a distributed hierarchical fuzzy situational network for assessing the parameters of the state of network elements in the CMCN in order to ensure a given quality of the provided communication services, based on the concept of creating and using intelligent agents.

3 Method of operational evaluation of the network element state based on hierarchical fuzzy situational networks

The proposed functional structure of an intelligent agent (IA) for managing the quality of communication services is shown in Figure 1. The same figure shows the scheme of interaction of the IA with the NE.

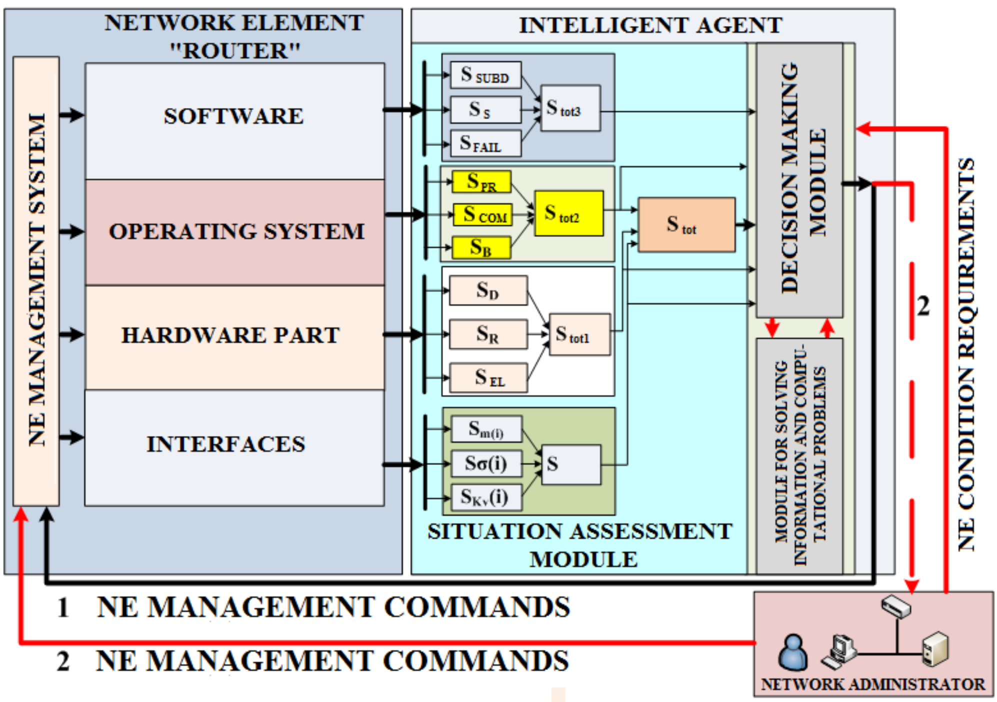


Fig. 1. The functional structure of the IA for managing the quality of communication services.

IA consists of a module for assessing the situation of the state of the NE, a module for solving information and computational problems and a module for making decisions. If the network administrator (decision maker, DM) delegates to the IA the ability to implement the decision made through the automated NE system, then the management will be implemented in an automatic mode (Fig. 1, arrow 1). In this case, the IA only informs the decision maker about the adopted and implemented decisions on the control of the NE [22].

Let us consider briefly the principle of functioning of the IA. Let $P_{fg}= \left\{p_{fg1}, p_{fg2}, \ldots p_{fgm}\right\}$ be a set of features that describe the state of some functional group of NE, for example, the state of the operating system (OS), which are fed to the input of the IA during monitoring. Features p_{fgi} ; $i=\overline{1,m}$ are described by their linguistic variables:

$$\langle p_{fgi}, T_i , U_i \rangle, \tag{1}$$

where $T_i=\{T^i_1, T^i_2,\ldots, T^i_m\}$ - term is a set of linguistic variable; m is the number of fuzzy values of the p_{fgi} attribute; U_i is base set of the p_{fgi} feature. The terms T^i_j ($i=\overline{1,m}$, $j=\overline{1,k}$)

are described using the corresponding fuzzy sets A_{ij} determined using the values of the membership functions $\mu_{A_{ij}}(p_{fgi})$ in the corresponding base sets $p_{fgi} \in U_i$:

$$A_{ij}=\left\{\left(\mu_{A_{ij}}\left(p_{fgi}\right)\Big/_{p_{fgi}}\right)\right\}, p_{fgi} \in U_i. \quad (2)$$

Then the assessment of the fuzzy situation of the state of the NE of IA is formed on the basis of the hierarchical construction of Mamdani fuzzy logical inference machines, as a fuzzy set of the second level in the form [21, 23, 24]:

$$S_{fg}=\left\{S_{fg}(p_{fgi})\Big/_{p_{fgi}}\right\}, i=\overline{1,m} \quad (3)$$

where:

$$S_{fg}(p_{fgi})=\left\{\left(\mu_{A_{ij}}\left(p_{fgi}\right)\Big/_{T_j^i}\right)\right\}, j=\overline{1,k}. \quad (4)$$

For example, the state of the IA, shown in Fig. 1, with the given values of the functional attributes 〈"Software state (SS)", "OS state", "Hardware state (HS)", "Traffic state (TS)"〉 can be described by the following fuzzy situation:

$$S_{fg\,1}=\left\{\frac{0.9}{\text{SS:"normal"}}, \frac{0.95}{\text{OS:"normal"}}, \frac{0.8}{\text{HS:"permissible"}}, \frac{0.75}{\text{TS:"permissible"}}\right\} \quad (5)$$

The value of the general situation of the state of the NE will have the form $S_{fg\ \text{total}}$ = 〈"permissible"〉 .

In the presented structure of the IA, the number of hierarchical levels is conditional and can be changed in accordance with the solution of a specific problem in the design of the IA.

At the inputs of fuzzy inference machines of the first level of the hierarchy, vectors of signs $\{p_{fgi}\}$ of each controlled functional group of parameters that determine the functional and technical state of the NE are received. At the output of the hierarchical layer, a set of estimates of the fuzzy situation $\{S_{fg}(i)\}$ of the state of the NE with respect to each functional group of parameters is formed. The next level of the hierarchy aggregates these estimates.

The hierarchical fuzzy situational control network of the NE can be represented as:

$$S_l= \langle F_l(\{S_{fg}^l\}, \{p_{fgi}\}, R_{fg}^l)\rangle, \quad (6)$$

where S_l is fuzzy situation of the NE state; F_l is aggregation operator; $\{S_{fg}^l\}$ is a set of fuzzy situations of states of controlled functional groups of NE; $\{p_{fgi}\}$ is a set of fuzzy parameters of states of controlled functional groups of NE; R_{fg}^l is the solution for the control of the NE, resulting from the solution of optimization information – computational problems using methods of fuzzy mathematical programming [25].

The generalized algorithm for the operational estimation of the NE state based on the proposed method has the form [22]:

STEP 1. "BEGINNING";

STEP 2. "Evaluation of the technical condition of the NE";

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

STEP 4. "If $\mu(S^l_{fg}) \geq \mu(S^l_{fg0})$ $\forall$ l, the NE functioning is normal";

STEP 5. "If $\exists$ l, $\mu(S^l_{fg\ ADD}) \leq \mu(S^l_{fg}) \leq \mu(S^l_{fg0})$, then the technical condition of the NE has worsened, but it is acceptable":

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

STEP 6. "If $\exists$ l, $\mu(S^l_{fg\ ADD}) \geq \mu(S^l_{fg})$, then the technical condition of the NE has worsened, operation is not possible."

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

STEP 7. "END".

The method and algorithm for estimating traffic parameters is based on the concept of conditional nonlinear Pareto – optimal filtering by V.S.Pugachev. Its essence is as follows [26, 27].

Traffic observations have the form of a random sequence (RS) *x(i)* specified at discrete times *t = i ={1, 2, ..., n,..}*, with finite values of the mathematical expectation and variance and are described by a nonlinear additive – multiplicative model:

$$x(i)= \theta(i)\cdot\omega(i-1)+\xi(i),$$

where $\cdot\,\omega(*)$ is an unknown random function of observations, $\theta(i)$ is a random variable, and $\xi(i)$ is a disturbance of observations with zero mathematical expectation and finite variance. The vector criterion for evaluating the mathematical expectation of RS $x(i)$ and its standard deviation (SD) has the form:

$$J(i) = M\{\bar{\varepsilon}\} = \{M\,(m(i) - \hat{m}(i))^2 \to \min,\ M(\sigma(i) - \hat{\sigma}(i))^2 \to \min\},$$

where $\hat{m}(i)$, $\hat{\sigma}(i)$ are the estimates of the mathematical expectation and the standard deviation of the RS *x(i)* at step *i*, and $m(i)$, $\sigma(i)$ are their true values at this step.

The forecast function of the current value of the mathematical expectation of the RS is defined as:

$$\hat{m}(i)=\frac{1}{N}\sum_{k=1}^{N} x(i-k), \quad i = 1, 2, .., n,..,$$

where *N* is the size of the sliding window, which is chosen to be relatively small. The forecast of the standard deviation estimate of the RS at step *i* is made in the same sliding window:

$$\hat{\sigma}(i)=\sqrt{\frac{1}{N-1}\sum_{k=1}^{N} x^2(i-k)-(\frac{1}{N}\sum_{k=1}^{N} x(i-k))^2}$$

We construct the correcting procedure for the component of the estimate of the mathematical expectation of the functional (8), with further generalization to the vector case.

As a rule, the value of the functional $J(\hat{m}(i))$ is not observable, but only the implementation of its gradient with a random error is available:

$$\nabla Q(\xi, \hat{m}(i)) = \nabla J(\hat{m}(i)) + \xi,\ \xi \in R^n$$

where ξ is the gradient observation error. Let us assume that ξ are centered, uncorrelated errors in estimating the gradient of the quality functional. Functional (11) will be minimized using a recurrent pseudo-gradient algorithm (PGA) of the form [28 - 30]:

$$\hat{\hat{m}}\ (i+1) = \hat{\hat{m}}\ (i) - \lambda_m(i+1)\nabla Q(\xi, \hat{m}(i+1)),$$

where $\nabla Q(\xi, \hat{m}(i+1))$ is some random direction of motion in the phase space at the point $\hat{m}(i+1)$, $\hat{\hat{m}}\ (i)$ is the corrected estimate of the mathematical expectation at the previous step. Note that $\{\lambda_m(i)\}$ is a sequence of positive numbers, which for a stationary RS must satisfy the Dvoretsky conditions [28 - 30]:

$$\sum_{i=1}^{\infty} \lambda_m(i) = \infty, \quad \sum_{i=1}^{\infty} \lambda_m^2(i) < \infty \tag{13}$$

The implementation of the quality functional at the point $\hat{m}(i+1)$ has the form:

$$\nabla Q(\xi, \hat{m}(i+1)) = (\hat{m}(i+1) - \hat{\hat{m}}\ (i))^2$$

After transformations, the recurrent PGA for estimating the value of the mathematical expectation will have the form:

$$\hat{\hat{m}}\ (i+1) = \hat{\hat{m}}\ (i) + \lambda_m(i+1)\left(\hat{m}(i+1) - \hat{\hat{m}}\ (i)\right)$$

Note that for a symmetric distribution density of RS values $\hat{m}(i)$, it is possible to use PGA of the form:

$$\hat{\hat{m}}\ (i+1) = \hat{\hat{m}}\ (i) + \lambda_m(i+1)\varphi\left(\hat{m}(i+1) - \hat{\hat{m}}\ (i)\right)$$

where a non-decreasing monotone function can be used as the function $\varphi(*)$, for example, the sign function $\varphi(*) = sign\ (*)$. As noted in [28–30], its application makes it possible to increase the PGA resistance to random errors in the estimation of the gradient of the quality functional.

A generalization of algorithm (15) is the vector PGA for estimating the RS parameters, which has the form [7]

$$\hat{\hat{H}}\ (i+1) = \hat{\hat{H}}\ (i) + Z(i+1) \times \nabla Q(i+1),$$

where $\hat{\hat{H}}\ (i+1)$ is the vector of estimates of the RS parameters at step $i+1$:

$$\hat{\hat{H}}\ (i+1) = \left[\hat{\hat{m}}\ (i+1), \hat{\sigma}(i+1)\ \right]^T.$$

The matrix $Z(i+1)$ is the diagonal matrix of the step coefficients of the estimated parameters.

The structure of algorithms (15) and (16) is invariant with respect to the statistical characteristics of the RS $x(i)$, with an accuracy determined by the accuracy of identifying its parameters. This statement is based on the application of the central limit theorem [7]. Its consequence is that for any probabilistic properties of traffic, the structure of the algorithm for estimating its parameters is constant, only its parameters can change.

For the estimation of the parameters of non-stationary RS, condition (13) restricts the use of the PGA, since the PGA must track changes in the value of the traffic parameters, and not converge to their certain values. Therefore, it is proposed to restrict the sequence $Z(i)$ from below to a constant value. In this case, the standard deviation of the estimate will also be bounded from below. Therefore, it is necessary to find a compromise between the speed and accuracy of estimating the parameters of the RS [7].

Modules of gradients of the components of the vector quality functional are proportional to the rate of change of the parameters of the RS. As noted in [7, 29, 30], such dependencies are in the nature of problems that are difficult to formalize. It is proposed to automate the adjustment of the PGA step coefficients based on the Takagi - Sugeno fuzzy inference method or on the basis of its particular form - the singleton method [25, 31], in the form:

$$\textbf{IF}<\hat{\hat{H}}(i)\in D1>\textbf{OR}<\nabla Q(i)\in D2>\textbf{OR}<\hat{\sigma}(i)\in D2>\textbf{TO}\ Z(i+1)=Z(l)\ \textbf{AND}\ N=Nk \quad (19)$$

To implement these rules, the system of fuzzy inference is preliminarily trained using experimental data obtained at the stage of its design [7].

There are several variants of analytical approximation of the average time delay dependence on the flow parameters and the characteristics of the serving device for queuing systems of the *G/G/1* class [32]. One of the most frequently used functional representations is the dependence obtained in [33, 34], in which the upper bound on the total delay time for servicing a claim and its transmission to the communication line has the form:

$$t_{k,l} \le \frac{\rho_{k,l}}{\lambda_{k,l}} + \frac{K_{a\,k,l}^2 + \rho_{k,l}^2 \cdot K_{b\,k,l}^2}{2 \cdot \lambda_{k,l}(1-\rho_{k,l})}, \quad (20)$$

where $t_{k,l}$ is the service delay time and its transmission to the communication line; $\lambda_{k,l}$ is value of the intensity of the input flow; $\rho_{k,l}$ is the utilization factor of the communication line; $K_{a\,k,l}^2$ is the squared coefficient of variation of the input flow; $K_{b\,k,l}^2$ is the squared coefficient of variation of the process of servicing the request in the line *(k, l)*. In expression (20), all input quantities can be estimated using PGA (15) - (17).

The probability of packet loss P_{loss} for CMCN with a limited buffer is determined for a system of the *G/G/1/N* type, which is the most general model, in accordance with the expression [33, 34]:

$$P_{loss} \approx \frac{1-\rho}{1-\rho^{\frac{2}{K_a^2+K_b^2}N+1}} \rho^{\frac{2}{K_a^2+K_b^2}N} \quad (21)$$

where ρ is the utilization factor of the communication line, *N* is the buffer capacity, K_a^2 is the value of the squared coefficient of variation of the input traffic, K_b^2 is the value of the squared coefficient of variation of the traffic processing process at the switching node. These values, as well as the current values of traffic intensities, are proposed to be estimated using the PGA (15) - (17). For the standard deviation of the *M/M/1/N* type, expression (21) is simplified and can have the following form:

$$P_{loss} \approx \frac{1-\rho}{1-\rho^{N+1}}\rho^N, \text{ or, if } \rho^N \ll 1,\ P_{loss} \approx \rho^N. \quad (22)$$

For a data transmission network, in which *M* are packet switching nodes, the total probability of packet loss is calculated in accordance with the rule [32]:

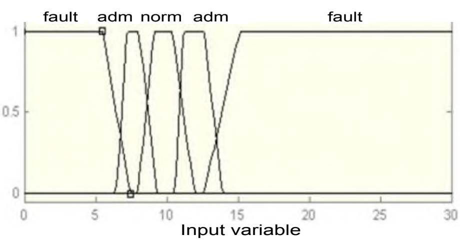
$$P_{loss\ Total} \approx 1 - \prod_{i=1}^{M}(1-P_{loss\ i}) \quad (23)$$

The developed approaches to assessing the current fuzzy situation of the NE state allow to implement almost all QoS mechanisms in the CMCN.

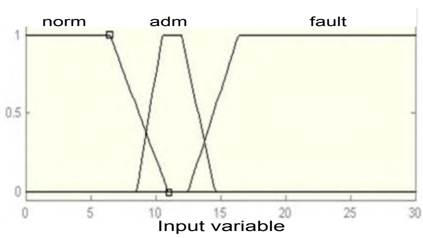
4 Analysis of the results of numerical simulation

In the numerical experiment, the general state of the NE was estimated by functional groups, the performance of the processor module, the state of the software, the electrical parameters of the processor module and the interfaces of the NE.

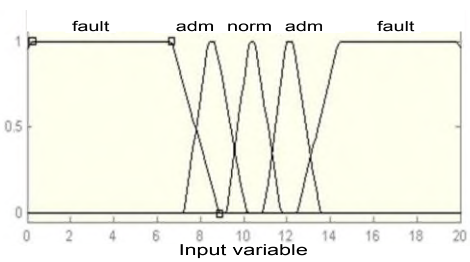
As an example, Fig.s 2 and 3 show the characteristics of the fuzzy inference system for assessing the fuzzy situation of the state of the electrical parameters of the NE of the "HARDWARE PART" functional group. These Fig.s show one-dimensional and two-dimensional membership functions (MF) of possible values of these parameters.



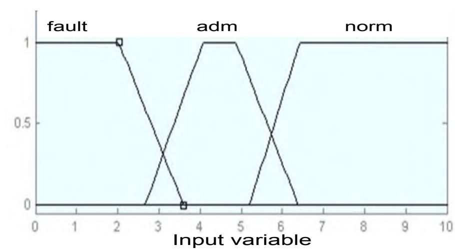
a) MF of the "power supply" parameter



b) MF of the "attenuation" parameter



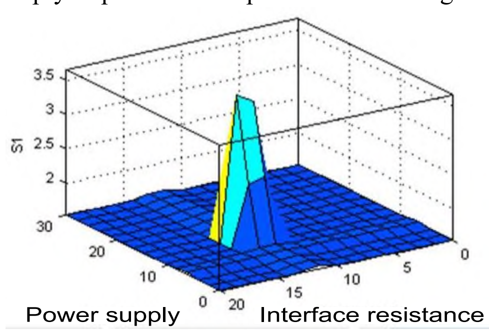
c) MF of the "interface resistance" parameter



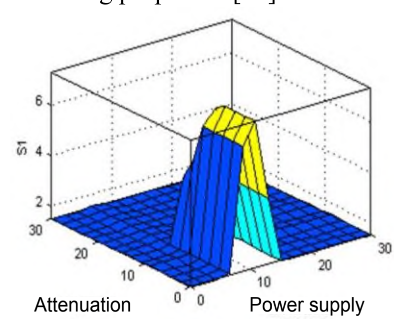
d) MF values of the fuzzy situation S_{tot1}

Fig. 2. Input and output membership functions of the IA electrical parameters.

In this computational experiment, all MF have a trapezoidal form, which are quite simply implemented in practice and have good approximating properties [25].



a) membership functions "el. power supply-interface resistance"



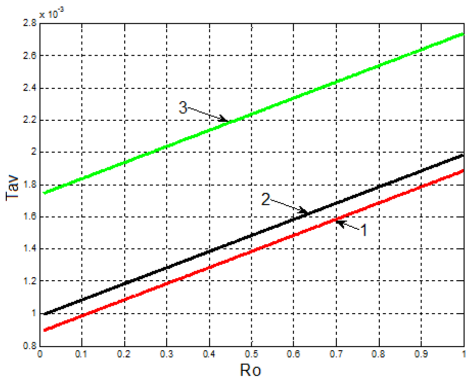
b) membership functions "el. power supply - attenuation"

Fig. 3. An example of two-dimensional MF.

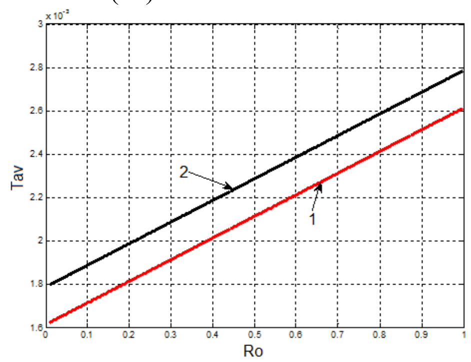
The analysis of the required performance of the processor module of the IA showed that to implement the assessment of the technical condition of the NE, it is enough to have its performance at the level of 1.8 – 1.9 Gfl. In this case, the cycle time for making a management decision will be approximately 15 – 70 $\times 10^{-6}$ s (15 – 70 μs). The accuracy of the NE state assessment algorithm is largely determined by the characteristics of the primary sensors of the analyzed information. All the experiments performed showed high stability of the functioning of the hierarchical fuzzy situational network. No unreliable output linguistic variables were recorded during the experiment.

The accuracy characteristics of algorithms (15) – (17) were studied in sufficient detail in [7]. It is shown that the average relative error in estimating the traffic parameters of CMCN for the Pareto distribution does not exceed 10%. In other cases, this error does not exceed 5 – 7%.

Fig. 4 shows the dependences of the total delay time for servicing a claim and its transmission to the communication line in accordance with (20).



a) 1 – Poisson flow with known characteristics; 2 – Poisson flow, relative estimation error $K_{a\ k,l}$ ^ 5%; 3 – lognormal flow with $K_{a\ k,l}$ = 1.4

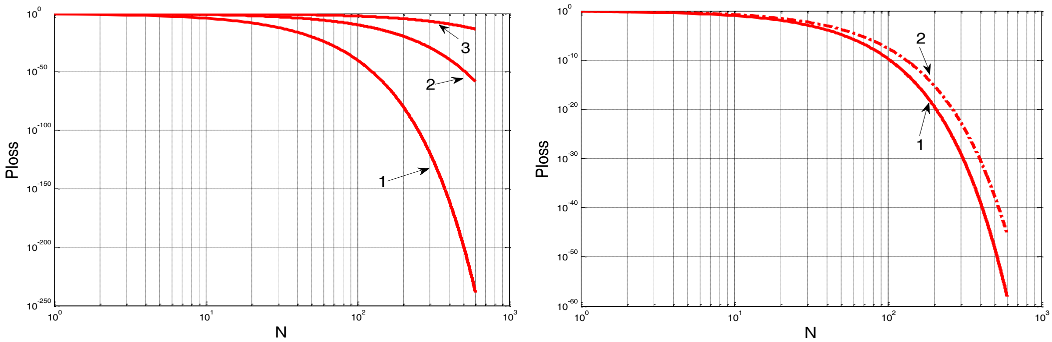


b) 1 – lognormal flow with $K_{a\ k,l}$ = 1.4; 2 – lognormal flow with $K_{a\ k,l}$ = 1.4, the relative estimation error $K_{a\ k,l}$ 5%.

Fig. 4. Average delay time for traffic processing on the NE.

The studies carried out have shown that the estimation of the average delay in servicing a claim and its transmission to the communication line is made with an average relative error of less than 10%. It should be noted that the proposed method for estimating traffic parameters allows one to estimate the current forecast of the service delay time of the claim, which is important for the implementation of mechanisms for the operational management of QoS indicators of the CMCN.

The dependences of the probabilities of packet loss on the values of the sizes of the NE buffers $P_{loss} = \vartheta(N)$, for the given values of ρ, are shown in Fig. 5. From the given dependences it follows that with the current estimate of the traffic parameters, it is possible to estimate the size of the NE buffers for ensuring the required QoS indicators. The average relative error in predicting the buffer size, at high values of the channel utilization coefficient ρ, does not exceed 6 – 8%, which is a sufficient value for the operational control of the NE.



a) 1 – ρ=0.4; 2 - ρ=0.8; 3 - ρ=0.9 b) 1 – ρ=0.8; 2 - ρ=0.85.

Fig. 5. - Dependences of the probabilities of packet loss on the values of the sizes of the NE buffers.

5 Conclusions

Analysis of the results of modeling the intelligent method and algorithms for the operational assessment of the state of the NE to ensure QoS in the CMCN showed the possibility of its operation in a mode close to real time. The delay in making a management decision is no more than a few tens of microseconds. At the same time, the average relative error in assessing the main technical characteristics of the NE and the parameters of network traffic does not exceed 10%, which is a sufficient value for the implementation of the tasks of the operational management of the NE and the network domain as a whole.

The proposed method can function both in the model of integrated and in the model of differentiated services providing QoS of communication services in the CMCN.

The advantages of the proposed method include the fact that the IA systems adapt to the network architecture and adequately respond to changes in the configuration of network equipment, they are distributed across all NE in the CMCN, which makes it possible to rationally distribute computing resources.

Analysis of the results obtained allows us to assert the flexible possibility of implementing this method both on universal processors and based on FPGA technology.

References

1. ITU-T: General overview of NGN. Recommendation Y.2001 (2004)
2. ITU-T: General principles and general reference model for Next Generation Networks. Recommendation Y.2011 (2004)
3. ITU-T: General overview of the Global Information Infrastructure standards development. Recommendation Y.100 (1998)
4. ITU-T Recommendation G.1000, Communications quality of service: A framework and definitions (2001)
5. O.A. Simonina Models for calculating QoS indicators in next generation networks: Dissertation for the degree of candidate of technical sciences, 129 (2005)
6. O.I. Shelukhin, A.V. Osin, S.M. Smolsky Self-similarity and fractals. Telecommunication applications, 368 (2008)
7. S. A. Ageev, I. B. Saenko, I. V. Kotenko Method and Algorithms of Anomaly Detection in Multiservice Network Traffic based on Fuzzy Logical Inference.

Informatsionno - upravliaiushchiesystemy Information and Control systems,**3**, 61 – 68 (2008)
8. A.N. Nazarov, K.I. Sychev Models and methods for calculating performance indicators of nodal equipment and structural and network parameters of next generation communication networks, 389 (2010)
9. RFC 2205: Resourse ReSerVation Protocol (RSVP) – Version 1 Functional Specification
10. RFC 3550: RTP: A Transport Protocol for real – Time Applications
11. Recommendation ITU – T Y.1540. Internet protocol data communication service – IP packet transfer and availability performance parameters, 2011. (Recommendation ITU-T Y.1540 defines parameters that may be used in specifying and assessing the performance of speed, accuracy).
12. Recommendation ITU – T Y.1541. Network performance objectives for IP – based services
13. Recommendation ITU – T Y.1221. Traffic control and congestion control in IP – based networks
14. Sefz N. QoS Standarts for IP – Based Networks. *IEEE Communication Magazine*, 82 – 89 (2003)
15. ITU-T: Recommendation M.3010. Principles for a telecommunications management network (2000)
16. ITU-T: Recommendation M.3020.TMN interface specification methodology (2000)
17. ITU-T: Recommendation M.3400. TMN management functions. (2000)
18. A.N. Melikhov, L.S. Bernstein, S.N. Korovin Situational-advising systems with fuzzy logic, 272 (1990
19. Pospelov D.A. Situational management: theory and practice. / D.A. Pospelov - M: Nauka, 1986. – 288 p.: ill.
20. V.V. Borisov, M.M. Zernov Implementation of a situational approach based on a fuzzy hierarchical situational-event network, *Artificial intelligence and decision making*,**1**, 17-30 (2009)
21. V. V. Borisov, V. V. Kruglov, A. S. Fedulov *Fuzzy models and networks*, 284 (2012)
22. S. A. Ageev, A. A. Gladkikh, D. V. Mishin, A. A. Privalov, Method of monitoring of technical condition of multiservice communication network on the basis of hierarchical fuzzy inference, *Fuzzy Technologies in the Indasry*, 211 – 221 (2018)
23. E. Mamdani and H. Efstathion. Higher-order logics for handling uncertainty in expert systems,.**3**, 243-259 (1985)
24. E. Mamdani and S. Assilian. "An Experiment in Linguiste Syntheses with Fuzzy Logic Controller", *Int. Man-Machine Studies*, **7**, 1, 1-13, (1975)
25. A. Pegat Fuzzy modeling and control: trans. from English. M.: BINOM Laboratory of Knowledge, 798, (2013)
26. V.S. Pugachev, Generalization of the theory of conditionally optimal estimation and extrapolation, *Reports of Academy of Sciences of the USSR*. , **262**, 3, 535 – 538 (1982)
27. V.S. Pugachev Conditionally optimal filtration and extrapolation of continuous processes, *Automation and telemechanics*, **2**, 82-89 (1984)
28. B.T. Polyak, Ya.Z. Tsypkin. *Pseudo-gradient adaptation and learning algorithms Automation and telemechanics,* **3**. 45-63 (1972)

29. B.T. Polyak, Ya.Z. Tsypkin Optimal pseudo-gradient adaptation algorithms. *Automation and telemechanics*, **8**. Pp. 74-84 (1980)
30. Granichin O.N. Randomized optimization and estimation algorithms for almost arbitrary noise, 291 (2003)
31. T. Takagi, M. Sugeno, Fuzzy Identification of Systems and Its Applications to Modeling and Control. In: IEEE Trans. on System, Man and Cybernetics, **15**,1, 11-132. (1985)
32. B.S. Goldstein Communication networks: Textbook for universities, 400 (2011)
33. L. Kleinrock, Queueing Systems, **1** (1975).
34. L. Kleinrock, Queueing Systems, Volume II: Computer Application. (1976).
35. S. Ageev, V. Karetnikov, Adaptive method of detecting traffic anomalies in high-speed multi-service communication networks, *E3S Web of Conferences*, **157**, 04027 (2020). doi:10.1051/e3sconf/202015704027
36. V. Karetnikov, G. Chistyakov, Tasks of developing the aquatory for testing autonomus ships in inland waterways, *E3S Web of Conferences*, **157**, 02010. (2020). doi:10.1051/e3sconf/202015702010