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Assessment the Quality of Telecommunication Services by Fuzzy Inferences System

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***Abstract*—**Fuzzy inference method based approach to the forming of modular intellectual system of assessment the quality of communication services is proposed. Developed under this approach the basic fuzzy estimation model takes into account the recommendations of the International Telecommunication Union in respect of the operation of packet switching networks based on IP-protocol. To implement the main features and functions of the fuzzy control system of quality telecommunication services it is used multilayer feedforward neural network.

***Keywords*—**Quality of communication, IP-telephony, Fuzzy set, Fuzzy implication, Neural network.

I. Introduction

AT the present stage of development of telecommunications and wireless communications technologies improving the quality of telecom services is most nagging problem. Telecom services is constantly being improved by increasing the speed of data transmission, greater mobility of users, expanding the range of services, improving the utilization of radio frequency spectrum and the degree of network equipment intellectuality and subscriber gadgets. At the same time, improving the telecommunication occurs at the junction of contradiction between the ever-growing consumer demand for subscription services and the limited number of frequencies that is completely objective. In turn, this causes a significant expansion of the range of services provided by the Capcom, increasing consumer demands for services quality and, as a result, improvement of existing control technologies.

The fact of the matter is that during operation the objective technical characteristics of communication networks are inherited by systems of telecommunication services, thereby transforming into the characteristics of the provided services. But also communication services have their characteristic features, among which quality is the dominant. Moreover, if at the initial operation and advance communication networks the service quality characterized by a set of objective technical characteristics, then at the stage of operation it is already occur the transformation of these characteristics, as under competitive market for telecommunications services the quality of networks becomes the subject of discussion and subjective assessments of their users. As a result, the category of quality of telecommunication services is increasingly shifting towards nonmetrizable characteristics reflecting a common measure of subjective satisfaction of consumers [8].

As any consumer product telecommunication service complies with the market laws. Therefore, increasing the customer base providing competitive position and, consequently, profit markup turning into the main prerogative of telecommunications companies. The requirements of communication subscribers, which evaluate communication service through their subjective judgments, such as "the presence (or absence) of communication interruptions", "it is not enough (or enough) good audibility", "acceptable (or unacceptable) speech intelligibility" etc., become the dominant factors for the management of telecommunications companies. Actually, subscriber choice for benefit of one or another telecommunication service is realized by the set of listed subjective requirements to communication quality.

The main goal is the creation of the intelligent assessment system of telecommunication services quality on the base of fuzzy inference system implemented in the neural network logical basis.

A fuzzy logic system quality assessment and management of telecommunication services is developed in the neural network logical basis. Due to itself ability to structural and parametric learning it is able to control the communications network through subjective consolidated customer satisfaction of telecom services level. The structure of the proposed system is formed on the base of available training examples by neural learning technology with regard to adaptation of fuzzy logic (implicative) rules and to finding the optimal input and output membership functions.

Developed system of quality assessment of telecommunication services is able to control and as appropriate to adjust the network parameters and, thus, to ensure operative decision making to increase the customer base. In the future, this system is able to operate in off-line mode, as during its development and adaptation it is not necessary to use heuristic knowledge and involve an expensive expert knowledge. The proposed approach to create a system of quality assessment of communication services allows quickly and relatively easily diversifying results to other types of services in telecommunications. It is enough to collect sufficient statistics of consolidated user ratings for different scenarios of functioning of the selected network connection.

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II. Problem Definition

It is obvious that subjective estimations of users to a communication quality are derivative of objective (technical) characteristics of the telecommunications network and result of their interaction with characteristics of traffic load. In a highly competitive market place this nonmetrizable subjective estimations of users are becoming objective functions through which management of the company can estimate subjective satisfaction of the client. Subject to a multiservice of modern telecommunications networks, it is necessary to solve this problem for all range of communication services within the creation of uniform system of assessment of the quality processing both objective (structured) and subjective (semi-structured or unstructured) quality indicators.

III. Communication Services Quality Control System under Fuzzy Environment

Today one of effective methods of managerial technologies is elements of artificial intelligence including fuzzy logic and fuzzy processors, which well proved in telecommunication administration [2], [8]. In particular, application of methods of fuzzy logic in the cognitive networks management allows considering easily a set of parameters for decision-making and does not demand difficult mathematical calculations [6], [7], [10]. Moreover, the mathematical apparatus of the fuzzy sets theory allows to operate equally easily both metrizable and nonmetrizable data [7], [8], [10].

Let us consider a standard functional diagram of the communication services quality control system [5] on the base of fuzzy inferences mechanism allowing quickly to obtain a multi-objective estimation of provided telecommunication service under fuzzy information (see Fig. 1).

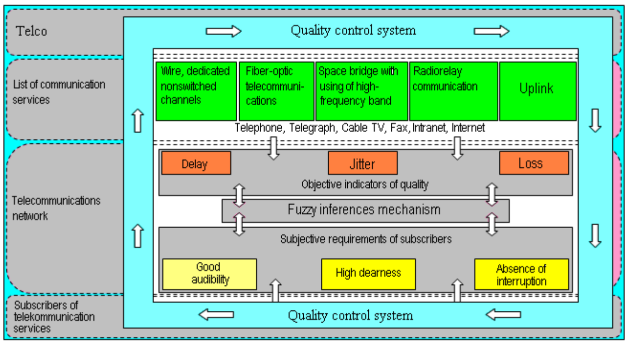


Fig. 1 Functional diagram of the communication services quality control system

As objective quality indicators, we will choose those that can control at determination the quality levels of communication services. Moreover, these indicators should be well known, uniquely interpreted and, most importantly, reflected the quality of services adequately. In a number of recommendations of the International Telecommunication Union (ITU) for prevalent packet networks on the base protocols IPv4 and IPv6 it is proposed to control the specific objective quality indicators to determine the level of services [1]. In particular, the recommendation ITU Y.1541 provides network service classes (Network QoS Classes) formed by objective criteria (quality) of user communication services and applications. As such indicators, in given recommendations are numerical values of network performance parameters, which are presented in Table I.

TABLE I
CLASSIFICATION OF SERVICE BY NETWORK PERFORMANCE PARAMETERS

Network performance parameter	Nature of network performance objective	QoS Classes					
		0	1	2	3	4	5 (U*)
IPTD: IP-packet Transfer Delay	Upper bound on the mean IPTD	100 ms	400 ms	100 ms	400 ms	1 s	U
IPDV (Jitter): IP-packet Delay Variation	Upper bound on the $1 - 10^{-3}$ quintile of IPTD minus the minimum IPTD	50 ms	50 ms	U	U	U	U
IPLR: IP-packet Loss Ratio	Upper bound on the packet loss probability	1×10^{-3}	1×10^{-3}	1×10^{-3}	1×10^{-3}	1×10^{-3}	U
IPER: IP-packet Error Ratio	Upper bound	1×10^{-4}					U

* Unspecified class

As an example, consider the telephone communications by IP-protocol (IP-telephony), which is an application of a more general technology VoIP (Voice over IP) to transmit voice. Choosing this service is justified by the fact that IP-telephony is very sensitive to jitter.

According to the recommendation Y.1541 IP-telephony can function under performance parameters corresponding to classes 0 and/or 1 [1]. Herewith providing services in Class 0 guarantees high quality and hence satisfaction of network users. At the same time, the quality of IP-telephony services in class 1 will be a little worse and it would have to be offset by the implementation of additional options to continue to expand its customer base. In other cases, the communication quality will be too low.

In [5] it was proposed a very interesting approach for generating fuzzy quality evaluation system of communication services. By means of generated consistent linguistic rules author analysis the quality of services on the basis of available information about the network performance parameters (see Table I), i.e. judges their quality on the basis of objective characteristics interpreted by adequate fuzzy sets. However, in the presented approach is not quite clearly showed: how these objective qualities of network services are transformed into subjective judgments of consumers, in their subjective criteria of estimation. In other words, forming the cause-effect relations between these characteristics could be classified qualities of provided services by the network user satisfaction, actually, what we are going to do.

IV. Classification of Satisfaction Degrees of Communication Service Users (by Example of IP-Telephony)

Obviously, the evaluation of the communication services quality is a multi-objective procedure meaning application of compositional rule of aggregation of estimation for each concrete case. To evaluate the quality of IP-telephony service we choose five estimated concepts for network performance parameters: u_1 – "TOO LOW"; u_2 – "LOW"; u_3 – "LOW ENOUGH"; u_4 – "SIGNIFICANT"; u_5 – "HIGH". Simpler words, in the capacity of $C=(u_1, u_2, u_3, u_4, u_5)$ we will mean a set of characters classifying the communication services quality. Then, assuming that the technical characteristics of the network (assessment criterions of quality) are the fuzzy sets, assessment of provided IP-telephony services one can realize with using sufficient set of fuzzy implicative rules of the form "*If*…, *then*…", and on their basis we will determine the appropriate scale of satisfaction gradation of client base.

So, we formulate our opinions as follows [4]:

e1. if on transmission of IP-packet transfer delays are not observed and delay variation is low, then the quality of the network is satisfactory;

e2. if in addition to the above requirements there are no losses of IP-packet, then the quality of the network is more than satisfactory;

e3. if in addition to the conditions specified in the e_2 errors on transmission of IP-packet are not occur, then the quality of the network is perfect;

e4. if on transmission of IP-packet delay variation is low and there are no losses and errors, then the quality of the network is very satisfactory;

e5. if on transmission of IP-packet there are no transfer delays and losses, though errors are observed, then the quality of the network is just the same satisfactory;

e6. if on transmission of IP-packet there are losses and errors, then the quality of the network is unsatisfactory.

In these statements, which are essentially cause-effect relations, the following features are input characteristics:

- X_1 – availability of IP-packet Transfer Delay;
- X_2 – availability of IP-packet Delay Variation;
- X_3 – IP-packet Loss Ratio;
- X_4 – IP-packet Error Ratio,

and as the output characteristic Y actually we will be assume the quality assessment of communication services – the level of consumer satisfaction. Then, defining appropriate values (terms) of the linguistic variables X_i (i=1÷4) and Y, on the basis of the above statements let's construct the following implicative rules:

e1. if X_1=NOT OBSERVED and X_2=LOW, then Y=SATISFACTORY;

e2. if X_1=NOT OBSERVED and X_2=LOW and X_3=NOT OBSERVED, then Y=MORE THAN SATISFACTORY;

e3. if X_1=NOT OBSERVED and X_2=LOW and X_3=NOT OBSERVED and X_4=NOT OBSERVED, then Y=PERFECT;

e4. if X_2=LOW and X_3=NOT OBSERVED and X_4=NOT OBSERVED, TO Y=VERY SATISFACTORY;

e5. if X_1=NOT OBSERVED and X_3=NOT OBSERVED and X_4=OBSERVED, then Y=SATISFACTORY;

e6. if X_3=OBSERVED and X_4=OBSERVED, then Y=UNSATISFACTORY.

Linguistic variable Y is defined on a discrete set J={0;0.1;0.2;…;1}. Then its terms used in implicative rules one can describe by fuzzy sets with appropriate membership functions [3]:

- $\tilde{S}$=SATISFACTORY, $\mu_{\tilde{S}}(x)=x$, $x\in J$;
- $\widetilde{MS}$=MORE THAN SATISFACTORY, $\mu_{\widetilde{MS}}(x)=\sqrt{x}$, $x\in J$;
- $\tilde{P}$=PERFECT, $\mu_{\tilde{P}}(x)=\begin{cases}1, & x=1,\\ 0, & x<1,\end{cases}$ $x\in J$;
- $\widetilde{VS}$=VERY SATISFACTORY, $\mu_{\widetilde{VS}}(x)=x^2$, $x\in J$;
- $\widetilde{US}$=UNSATISFACTORY, $\mu_{\widetilde{US}}(x)=1-x$, $x\in J$.

Fuzzification of terms in the left-hand sides of the accepted rules one can exercise by using of Gaussian membership functions:

$$\mu(u)=\exp\left(-\frac{u^2}{\sigma_k^2}\right)\ (k=1\div 4), \tag{1}$$

restoring the fuzzy sets on the support vector (u_1, u_2, u_3, u_4, u_5), where $u_i=\frac{d_{i-1}+d_i}{2}$ (i=1÷5) (see Fig. 2). The values for σ_k are selected on the basis of the degree of importance of features that classify the quality of communication services.

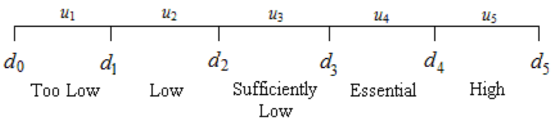


Fig. 2 Uniform gradation of network performance parameters according to their levels

In Fig. 2 the gradation of network performance levels is presented in a general form. However, it is obvious that interval [d_0, d_5] can be easily reduce to the unit interval [0, 1] by the simple transformation $x=d_0+t(d_5-d_0)$, where $t\in[0,1]$. Therefore, evaluating the quality of telecommunication service in terms of its technical characteristics graded on the scale of unit interval (see Fig. 3), where $d_i=0.2\cdot i$ (i=0÷5), let us describe the terms from the left-hand sides of implicative rules as follows:

- NOT OBSERVED (IP-packet Transfer Delay):

$$\tilde{A}=\frac{0.9394}{u_1}+\frac{0.5698}{u_2}+\frac{0.2096}{u_3}+\frac{0.0468}{u_4}+\frac{0.0063}{u_5};$$

- LOW (IP-packet Delay Variation):

$$\tilde{B}=\frac{0.9518}{u_1}+\frac{0.6412}{u_2}+\frac{0.2910}{u_3}+\frac{0.0889}{u_4}+\frac{0.0183}{u_5};$$

- NOT OBSERVED (IP-packet Losses):

$$\widetilde{C}=\frac{0.9216}{u_1}+\frac{0.4797}{u_2}+\frac{0.1299}{u_3}+\frac{0.0183}{u_4}+\frac{0.0013}{u_5};$$

- NOT OBSERVED (IP-packet Errors):

$$\widetilde{D}=\frac{0.8948}{u_1}+\frac{0.3679}{u_2}+\frac{0.0622}{u_3}+\frac{0.0043}{u_4}+\frac{0.0001}{u_5}.$$

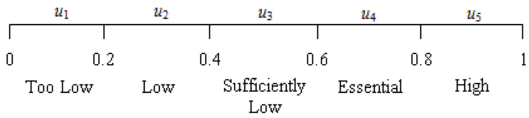


Fig. 3 The levels of network performance parameters on the scale of the unit interval

Then, subject to these formalisms, the fuzzy rules are formulated as:

e1. if $X_1=\widetilde{A}$ and $X_2=\widetilde{B}$, then $Y=\widetilde{S}$;

e2. if $X_1=\widetilde{A}$ and $X_2=\widetilde{B}$ and $X_3=\widetilde{C}$, then $Y=\widetilde{MS}$;

e3. if $X_1=\widetilde{A}$ and $X_2=\widetilde{B}$ and $X_3=\widetilde{C}$ and $X_4=\widetilde{D}$, then $Y=\widetilde{P}$;

e4. if $X_2=\widetilde{B}$ and $X_3=\widetilde{C}$ and $X_4=\widetilde{D}$, then $Y=\widetilde{VS}$;

e5. if $X_1=\widetilde{A}$ and $X_3=\widetilde{C}$ and $X_4=\neg\widetilde{D}$, then $Y=\widetilde{S}$;

e6. if $X_3=\neg\widetilde{C}$ and $X_4=\neg\widetilde{D}$, then $Y=\widetilde{US}$.

Further, for the left-hand sides of these rules let us compute the membership function $\mu_{\widetilde{M}_i}(u)$ (i=1÷6). In particular, we have [9]:

$$e_1:\mu_{\widetilde{M}_1}(u)=\min\{\mu_{\widetilde{A}}(u),\mu_{\widetilde{B}}(u)\},$$

$$\widetilde{M}_1=\frac{0.9394}{u_1}+\frac{0.5698}{u_2}+\frac{0.2096}{u_3}+\frac{0.0468}{u_4}+\frac{0.0063}{u_5};$$

$$e_2:\mu_{\widetilde{M}_2}(u)=\min\{\mu_{\widetilde{A}}(u),\mu_{\widetilde{B}}(u),\mu_{\widetilde{C}}(u)\},$$

$$\widetilde{M}_2=\frac{0.9216}{u_1}+\frac{0.4797}{u_2}+\frac{0.1299}{u_3}+\frac{0.0183}{u_4}+\frac{0.0013}{u_5};$$

$$e_3:\mu_{\widetilde{M}_3}(u)=\min\{\mu_{\widetilde{A}}(u),\mu_{\widetilde{B}}(u),\mu_{\widetilde{C}}(u),\mu_{\widetilde{D}}(u)\},$$

$$\widetilde{M}_3=\frac{0.895}{u_1}+\frac{0.368}{u_2}+\frac{0.062}{u_3}+\frac{0.004}{u_4}+\frac{0.0001}{u_5};$$

$$e_4:\mu_{\widetilde{M}_4}(u)=\min\{\mu_{\widetilde{B}}(u),\mu_{\widetilde{C}}(u),\mu_{\widetilde{D}}(u)\},$$

$$\widetilde{M}_4=\frac{0.8948}{u_1}+\frac{0.3679}{u_2}+\frac{0.0622}{u_3}+\frac{0.0043}{u_4}+\frac{0.0001}{u_5};$$

$$e_5:\mu_{\widetilde{M}_5}(u)=\min\{\mu_{\widetilde{A}}(u),\mu_{\widetilde{C}}(u),1-\mu_{\widetilde{D}}(u)\},$$

$$\widetilde{M}_5=\frac{0.1052}{u_1}+\frac{0.4797}{u_2}+\frac{0.1299}{u_3}+\frac{0.0183}{u_4}+\frac{0.0013}{u_5};$$

$$e_6:\mu_{\widetilde{M}_6}(u)=\min\{1-\mu_{\widetilde{C}}(u),1-\mu_{\widetilde{D}}(u)\},$$

$$\widetilde{M}_6=\frac{0.0784}{u_1}+\frac{0.5203}{u_2}+\frac{0.8701}{u_3}+\frac{0.9817}{u_4}+\frac{0.9987}{u_5}.$$

As a result, the rules are interpreted in a more compact form:

e1. if $X=\widetilde{M}_1$, then $Y=\widetilde{S}$;

e2. if $X=\widetilde{M}_2$, then $Y=\widetilde{MS}$;

e3. if $X=\widetilde{M}_3$, then $Y=\widetilde{P}$;

e4. if $X=\widetilde{M}_4$, then $Y=\widetilde{VS}$;

e5. if $X=\widetilde{M}_5$, then $Y=\widetilde{S}$;

e6. if $X=\widetilde{M}_6$, then $Y=\widetilde{US}$.

To convert these implicative rules as per usual let us use Lukasiewicz's implication [4]:

$$\mu_{\widetilde{H}}(u,j)=\min(1,1-\mu_{\widetilde{M}}(w)+\mu_{\widetilde{Y}}(j)). \tag{2}$$

In this case for each pair $(u,j)\in U\times Y$ we obtain the following fuzzy relations on $U\times Y$:

$$R_1=\begin{Vmatrix}0.0606 & 0.1606 & 0.2606 & 0.3606 & 0.4606 & 0.5606 & 0.6606 & 0.7606 & 0.8606 & 0.9606 & 1.0000\\ 0.4302 & 0.5302 & 0.6302 & 0.7302 & 0.8302 & 0.9302 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.7904 & 0.8904 & 0.9904 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9532 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9937 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\end{Vmatrix}$$

$$R_2=\begin{Vmatrix}0.0074 & 0.3946 & 0.5256 & 0.6261 & 0.7108 & 0.7855 & 0.8530 & 0.9150 & 0.9728 & 1.0000 & 1.0000\\ 0.5203 & 0.8366 & 0.9676 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.8701 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9817 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9987 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\end{Vmatrix}$$

$$R_3=\begin{Vmatrix}0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052\\ 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321\\ 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378 & 0.9378\\ 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957 & 0.9957\\ 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999 & 0.9999\end{Vmatrix}$$

$$R_4=\begin{Vmatrix}0.1052 & 0.1152 & 0.1452 & 0.1952 & 0.2652 & 0.3552 & 0.4652 & 0.6952 & 0.7452 & 0.9152 & 1.0000\\ 0.6321 & 0.6421 & 0.6721 & 0.7221 & 0.7921 & 0.8821 & 0.9921 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9378 & 0.9478 & 0.9778 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9957 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9999 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\end{Vmatrix}$$

$$R_5=\begin{Vmatrix}0.9848 & 0.9948 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.5203 & 0.6203 & 0.7203 & 0.8203 & 0.9203 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.8701 & 0.9701 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9817 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\\ 0.9987 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000\end{Vmatrix}$$

$$R_6=\begin{Vmatrix}1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 0.9216\\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 0.9797 & 0.8797 & 0.7797 & 0.6797 & 0.5797 & 0.4797\\ 1.0000 & 1.0000 & 0.9299 & 0.8299 & 0.7299 & 0.6299 & 0.5299 & 0.4299 & 0.3299 & 0.2299 & 0.1299\\ 1.0000 & 0.9183 & 0.8183 & 0.7183 & 0.6183 & 0.5183 & 0.4183 & 0.3183 & 0.2183 & 0.1183 & 0.0183\\ 1.0000 & 0.9013 & 0.8013 & 0.7013 & 0.6013 & 0.5013 & 0.4013 & 0.3013 & 0.2013 & 0.1013 & 0.0013\end{Vmatrix}$$

At the intersection of fuzzy relations R_1, R_2, …, R_6 finally we obtain the following general functional solution that reflects a cause-effect relation between the network performance parameters and quality of communication services:

$$R_3=\begin{Vmatrix}0.0606 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.1052 & 0.9216\\ 0.4302 & 0.5302 & 0.6302 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.6321 & 0.5797 & 0.4797\\ 0.7904 & 0.8904 & 0.9299 & 0.8299 & 0.7299 & 0.6299 & 0.5299 & 0.4299 & 0.3299 & 0.2299 & 0.1299\\ 0.9532 & 0.9183 & 0.8183 & 0.7183 & 0.6183 & 0.5183 & 0.4183 & 0.3183 & 0.2183 & 0.1183 & 0.0183\\ 0.9937 & 0.9013 & 0.8013 & 0.7013 & 0.6013 & 0.5013 & 0.4013 & 0.3013 & 0.2013 & 0.1013 & 0.0013\end{Vmatrix}$$

To determine the level of quality of telecommunications services one can apply the composition rule of conclusion under fuzziness [6], [10]:

$$\widetilde{E}_k=\widetilde{G}_k\circ R, \tag{3}$$

where $\widetilde{E}_k$ is k-th level quality of communication services, the $\widetilde{G}_k$ is k-level mapping of network performance parameters in the form of fuzzy subsets. Then, choosing the composition rule as

$$\mu_{\widetilde{E}_k}(j) = \max_u \{\min(\mu_{\widetilde{G}_k}(u), \mu_R(u))\}; \tag{4}$$

and assuming that $\mu_{\widetilde{G}_k}(u) = \begin{cases} 0, u \neq u_k; \\ 1, u = u_k, \end{cases}$ finally we have: $\mu_{\widetilde{E}_k}(j) = \mu_R(u_k, j),$ i.e. $\widetilde{E}_k$ is k-th row of matrix R.

Now for the classification of telecommunication services quality we use defuzzification procedure for fuzzy outputs of applied model. Therefore, for the assessed concept of network performance u_1 fuzzy interpretation of the corresponding level of quality communication services will be a fuzzy set:

$$\widetilde{E}_1 = \frac{0.0606}{0} + \frac{0.1052}{0.1} + \frac{0.1052}{0.2} + \frac{0.1052}{0.3} + \frac{0.1052}{0.4} + \frac{0.1052}{0.5} + \frac{0.1052}{0.6} + \frac{0.1052}{0.7} + \frac{0.1052}{0.8} + \frac{0.1052}{0.9} + \frac{0.9216}{1.0}.$$

Determining the level sets $E_{1\alpha}$ and calculating their respective cardinal numbers $M(E_{1\alpha})$ by formula $M(E_{1\alpha}) = \sum_{j=1}^{n} \frac{x_j}{n}$, we have:

- for $0<\alpha<0.0606$: $\Delta\alpha=0.0606$, $E_{1\alpha}=\{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha})=0.5$;
- for $0.0606<\alpha<0.1052$: $\Delta\alpha=0.0446$, $E_{1\alpha}=\{0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha})=0.55$;
- for $0.1052<\alpha<0.9216$: $\Delta\alpha=0.8164$, $E_{1\alpha}=\{1\}$, $M(E_{1\alpha})=1$.

To find the point estimates of the fuzzy outputs $\widetilde{E}_k$ let us use the following equation [3]:

$$F(\widetilde{C}) = \frac{1}{\alpha_{\max}} \int_0^{\alpha_{\max}} M(E_{k\alpha}) d\alpha,$$

where $\alpha_{\max}$ is a maximal value on $\widetilde{E}_k$. In this case, we have:

$$F(\widetilde{E}_1) = \frac{1}{0.9987} \int_0^{0.9987} M(E_{1\alpha}) d\alpha = (0.5 \cdot 0.0606 + 0.55 \cdot 0.0446 + 1 \cdot 0.8164) = 0.9454.$$

For assessed concept of network performance u_2

$$\widetilde{E}_2 = \frac{0.4302}{0} + \frac{0.5302}{0.1} + \frac{0.6302}{0.2} + \frac{0.6321}{0.3} + \frac{0.6321}{0.4} + \frac{0.6321}{0.5} + \frac{0.6321}{0.6} + \frac{0.6321}{0.7} + \frac{0.6321}{0.8} + \frac{0.5797}{0.9} + \frac{0.4797}{1.0}$$

respectively we have:

- for $0<\alpha<0.4302$: $\Delta\alpha=0.4302$, $E_{1\alpha}=\{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha})=0.50$;
- for $0.4302<\alpha<0.4797$: $\Delta\alpha=0.0494$, $E_{1\alpha}=\{0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 1\}$, $M(E_{1\alpha})=0.55$;
- for $0.4797<\alpha<0.5302$: $\Delta\alpha=0.0506$, $E_{1\alpha}=\{0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9\}$, $M(E_{1\alpha})=0.50$;
- for $0.5302<\alpha<0.5797$: $\Delta\alpha=0.0494$, $E_{1\alpha}=\{0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9\}$, $M(E_{1\alpha})=0.55$;
- for $0.5797<\alpha<0.6302$: $\Delta\alpha=0.0506$, $E_{1\alpha}=\{0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8\}$, $M(E_{1\alpha})=0.50$;
- for $0.6302<\alpha<0.6321$: $\Delta\alpha=0.0019$, $E_{1\alpha}=\{0.3; 0.4; 0.5; 0.6; 0.7; 0.8\}$, $M(E_{1\alpha})=0.55$.

The point estimate of the fuzzy outputs $\widetilde{E}_2$ will be:

$$F(\widetilde{E}_2) = \frac{1}{0.6321} \int_0^{0.6321} M(E_{2\alpha}) d\alpha = (0.5 \cdot 0.4302 + 0.55 \cdot 0.0494 + 0.5 \cdot 0.0506 + 0.55 \cdot 0.0494 + 0.5 \cdot 0.0506 + 0.55 \cdot 0.0019) = 0.5080.$$

Similarly, one can determine point estimates for all other outputs:

- at the level of network performance $u_3 - F(\widetilde{E}_3) = 0.3161$;
- at the level of network performance $u_4 - F(\widetilde{E}_4) = 0.2456$;
- at the level of network performance $u_5 - F(\widetilde{E}_5) = 0.2271$.

Thus, in the accepted assumptions the total scale for the estimation of IP-telephony quality can look as shown in Fig. 4.

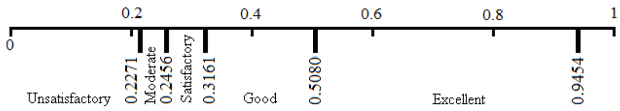


Fig. 4 Scale of gradation of quality of IP-telephony services

In essence, the value 0.2271, which is the smallest defuzzified output of fuzzy model for the multi-criteria assessment of IP-telephony quality, corresponds to the consolidated unsatisfactory assessment of network users as the upper bound. Similarly, we mean that from the point of view of consumers of the IP-telephony services the defuzzified output:

- 0.2456 is the upper bound of estimation “Moderate”;
- 0.3161 is the upper bound of estimation “Satisfactory”;
- 0.5080 is the upper bound of estimation “Good”;
- 0.9454 is the upper bound of estimation “Excellent”.

V. Communication Services Quality Scoring System and its Analysis

Now, after we have established the reasonable scale for the classification of the services quality, let us consider a fuzzy model to evaluate the quality of communication services. For this purpose, let us use the following rather trivial implicative rules [4]:

1. if Transfer Delay is TOO LOW and Jitter is TOO LOW and Loss Ratio is TOO LOW and Error Ratio is TOO LOW, then IP-telephony quality is EXCELLENT;
2. if Transfer Delay is LOW and Jitter is LOW and Loss Ratio is LOW and Error Ratio is LOW, then IP-telephony quality is GOOD;

3. if Transfer Delay is SUFFICIENTLY LOW and Jitter is SUFFICIENTLY LOW and Loss Ratio is SUFFICIENTLY LOW and Error Ratio is SUFFICIENTLY LOW, then IP-telephony quality is SATISFACTORY;
4. if Transfer Delay is ESSENTIAL and Jitter is ESSENTIAL and Loss Ratio is ESSENTIAL and Error Ratio is ESSENTIAL, then IP-telephony quality is MODERATE;
5. if Transfer Delay is HIGH and Jitter is HIGH and Loss Ratio is HIGH and Error Ratio is HIGH, then IP-telephony quality is UNSATISFACTORY;

As input characteristics there are used five assessed concepts, which are terms of linguistic variables – network performance parameters. Using ranges of numerical values of the network performance parameters (see Table I), let us realize given rules in the notation of MATLAB/Fuzzy Sets Toolbox. Linguistic variable "quality of communication services", which assigns five fuzzy values (terms), formalized by Gaussian membership functions with vertices at the points: 0.2271, 0.2456, 0.3161, 0.5080 and 0.9454 is the output characteristic.

Therefore, after setting the input and output characteristics of the fuzzy model in the form of Gaussian membership functions and fuzzy implicative rules let us proceed to analyze the work of the scoring system. Realization of rules in the notation of MATLAB/Fuzzy Sets Toolbox demonstrates that the consolidated level of network quality at best hypothetical values of its performance parameters does not exceed 0.837 (see Fig. 5).

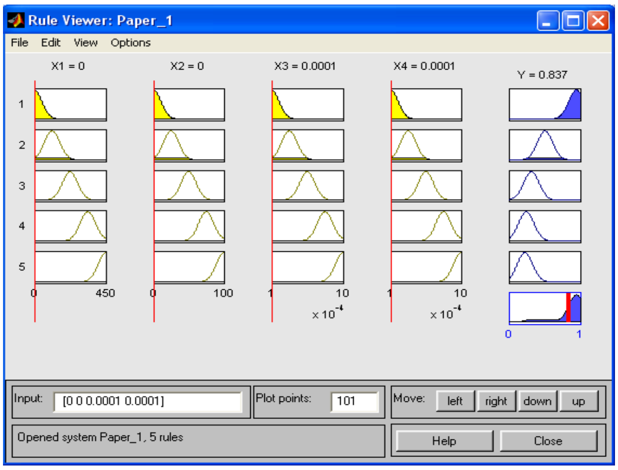
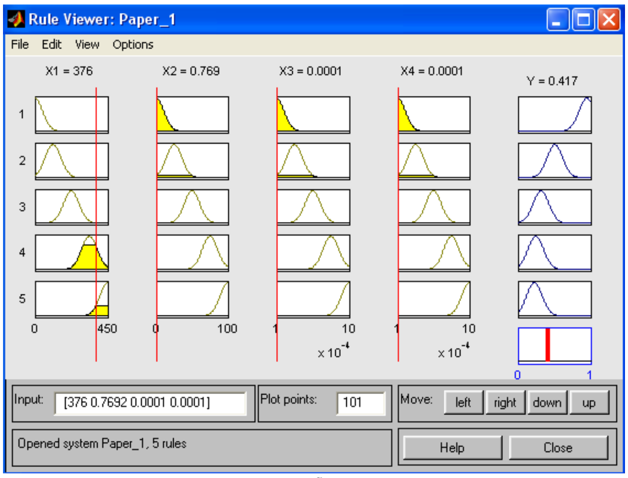
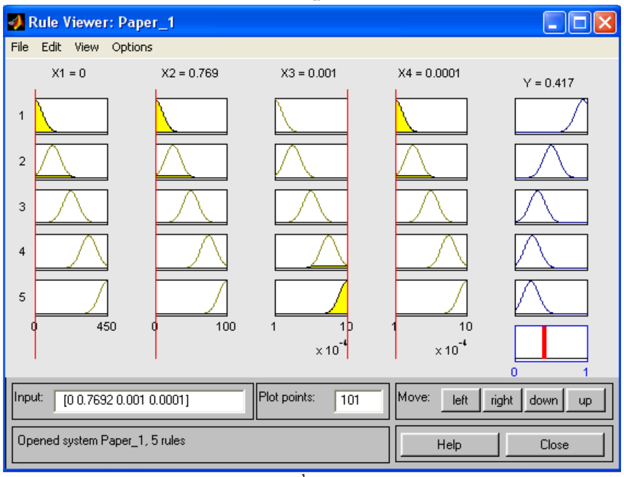


Fig. 5 Assessment of quality of IP-telephony services with the best values of the performance parameters

With increasing of IP-packet transfer delay to 376 ms the level of services falls to 0.417 (according to the obtained scale this value corresponds to a good quality of network) and remains invariable for its further growth (see Fig. 6 (a)). With the loss of IP-packet share to 10-3 the quality of network services slumps to value 0.417 (see Fig. 6 (b)). It is necessary to note that under given scenarios the quality of communication services remains invariable with increasing levels of jitter.



a



b

Fig. 6 Quality of IP-telephony services at two extreme values of the network parameters

As is known fuzzy logic allows modeling uncertainty of human language and allows the involvement in the computational process nonmetrizable subjective categories, which, in particular, used by consumers for evaluating of provided services [2], [8], and [9]. Application of fuzzy logic allows taking into account a set of heterogeneous parameters for decision-making and does not demand difficult mathematical calculations.

In this section, comparatively reasonable scale for gradation of the consolidated estimates of IP-telephony users was obtained by limited set of consistent implicative rules. On this base offered IP-telephony services quality scoring system does not differ by itself parametrical and structural optimization. Possible inaccuracies can be eliminated due to implementation of a self-training element of system on the basis of the historical data [7]. Nevertheless, even in the rough the offered system can be diversified on any other communication services and, thereby, becomes a basis for creation of the modular intellectual scoring system for telecommunication services.

Thus, the fuzzy scoring system for communication services is capable to control communication network functioning through the subjective consolidated satisfaction of clients with level of services provided to them. This system is simple with a view to design and can be easily adapted to various conditions.

VI. Fuzzy Inferences System in the Logic Basis of Neural Network

Neural networks and fuzzy logic systems are universal methods of cause-effect relationship modeling. As a rule, their union allows to create fundamentally new software, which can significantly extend the class of problems of control and decision-making under uncertainty, inaccuracies and noise. Although neural networks and fuzzy logic systems have formal similarities, but between them there are significant differences. By its nature, a Fuzzy Logic System (FLS) is a structured numerically appraisal mechanism built in the form of fuzzy implicative rules of the type "*If* ..., *then* ...". To represent composition rule of conclusion output of each rule is weighted in accordance with the degree of membership of its inputs and for all outputs of rules a centroid providing generation of suitable output of FLS is calculated.

Most often, the FLS design is carried out by trail-and-error method [11], [18]. In this case, the majority approach means a subjective choice of membership functions and linguistic rules on the base of heuristic knowledge in the field of human-operating systems or existing controllers with subsequent testing of designed FLS for generating a suitable output. Otherwise, the membership functions and/or logic rules must be adjusted.

Research in this area provided the self-training procedure of FLS, which includes:

- modification of the rules based on the concept of "linguistic phase plane" [12];
- "logic examination" method for conversion process of input-output data in the fuzzy control rules based on the "fuzzy identification" concept [20].

Significant development the technology of FLS optimization was reflected in the works [16], [19]. However, quite successful active researches in the field of FLS design have been carried out still.

The neural networks as train able dynamic systems are stable under noise and able to generalize their acquired properties. The neural network consists of a large number of interconnected processing elements (neurons), which differ in their ability to learn and are generated by training examples or data. The main applied functions of neural networks are pattern recognition, function approximation, optimization, classification and clustering.

Currently, due to the fact that the internal (or hidden) layers of neural networks are in some sense "non-transparent" for users, most studies concentrates around the forming of optimal structures and sizes of networks. However, neural networks have largely used from mid-80 years of XX century, when American mathematician D. Rumelhart proposed a learning algorithm "error back-propagation" [17]. Just hence, the neural networks introducing their train ability into automatic control theory have been the object of active research of FLS designers [13], [14].

This section discusses the mode of realization of Fuzzy Logic System of Quality Assessment (FLSQA) of Telecommunications Services (TS) on the base of generalized neural network model. This model presented in the form of a multilayer feedforward neural network supports the ideology of fuzzy control in the neural network logical basis. Thus, FLSQA is automatically generated by training and testing on the base of relevant sets of the input-output training data.

In the neural network model input and output neurons represent the input states and output control signals/scores, respectively, and the neurons of hidden layers represent the membership functions and fuzzy implicative rules. All this allows to simulate human reasoning processes within the neural network structure, as well as to keep the agreed rules of inference engine as in the case of traditional inference systems. Moreover, the proposed architecture of FLSQA in the framework of optimization of a single objective function allows simply formulating both parametric training (i.e. training of membership functions) and structural learning (the choice of the optimal set of fuzzy implicative rules). Such approach provides an original solution of the problem of multicriteria optimization under design of FLSQA.

In [15] it is described the traditional (generalized) model of fuzzy logic control and decision-making, which was implemented on a feedforward neural network with multi-layer topological structure. It is necessary to adapt the structure and functions of this system for solving the task of evaluating the quality of services of the telecommunications network, i.e. using this approach to create a system FLSQA, which would be able to control the operation of the network connection through subjective consolidated customer satisfaction by TS level.

VII. Realization of FLSQA in the Neural Network Logical Basis

In the context of discussed arguments in [4] it is presented the generalized scheme of FLSQA (see Fig. 7). This scheme incorporates three main components: fuzzifier, inference engine and fuzzy rule base, and defuzzifier [15].

Fuzzifier performs the procedure of fuzzification by predefined membership functions describing the input data in the form of fuzzy sets as values (terms) of the input linguistic variables. The basic rules are fuzzy implicative rules of the form "*If* ..., *then* ...", which will initially describe the expert (heuristic) knowledge in the subject field of quality assessment of TS.

Inference engine implementing these rules composition induces a fuzzy conclusion about the TS quality to develop an adequate managerial decision.

Defuzzifier performs defuzzification procedure for fuzzy outputs, i.e. representation of fuzzy conclusions about the quality of the TS quality in the form of crisp numbers by, for example, centroid method. In this case, the main problem of

FLSQA design is to establish appropriate input-output membership functions and fuzzy logic rules.

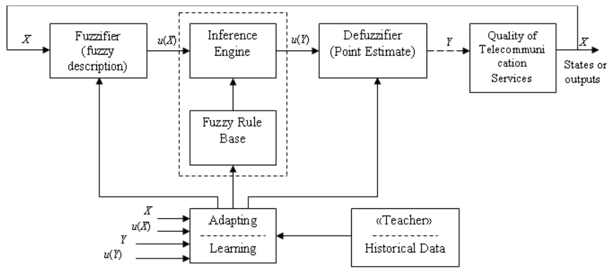


Fig. 7 Conceptual scheme of FLSQA

Based on the basic structure and concept of the FLS, FLSQA in the neural network logical basis with connectional topological structure and training ability is designed to overcome this problem. Fig. 8 shows the structure of such system, which consists of five layers.

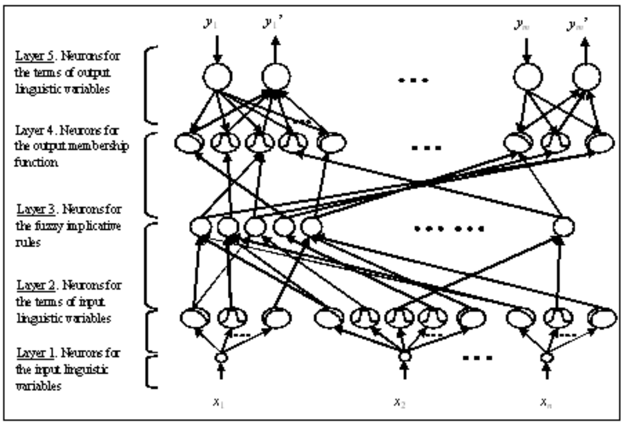


Fig. 8 FLSQA in notation of feedforward 5-layer neural network

Neurons of first (input) layer represent the input linguistic variables and, therefore, they can be interpreted as receptors. Fifth layer is the output and, therefore, all its neurons essentially act as effectors. Neurons in the second and fourth layers are activated as membership functions[1] (triangular, trapezoidal, Gaussian, bell-shaped, etc.) to represent terms (values) of the corresponding linguistic variables. Each neuron of the third layer imitates one fuzzy logic rule, and a set of such neurons are included in this layer forms a basic set of fuzzy logic rules. Relationships between the third and fourth layers in the aggregate function as connection (associative) inference engine. Input connection to the third layer determine the causes (preconditions) for fuzzy logic rules, and the input connection to the fourth layer predetermine the consequences, i.e., in other words, in the aggregate these relationships form a cause-and-effect relations in the framework of fuzzy inference engine. Thus, each neuron-rule has at most one input connection from the some neuron – term of input linguistic variable.

In general, the input for each neuron of the given connection neural network is formulated as:

$$\text{Input} = f(u_1^k, u_2^k, ..., u_p^k;\ w_1^k, w_2^k, ..., w_p^k), \tag{5}$$

where k denotes the number of layer; p denotes the number of input connection; u_i^k (i=1÷p) denotes the i-th signal from the k-th layer; w_i^k (i=1÷p) denotes the weight of the i-th connection from the k-th layer. In the framework of the adopted notations outputs of neurons as a result of their activation is denoted as:

$$\text{Output} = o_i^k = a(f)\ \ (i=1\div p), \tag{6}$$

where $a(\cdot)$ is the activation function. In particular, as the activation function one can select the following sigmoid function:

$$a = \frac{1}{1+e^{-f}},\ f = \sum_{i=1}^{p} w_i^k u_i^k. \tag{7}$$

Let us describe the functions of the neurons of each of the five layers of proposed neural network [15].

First layer neurons are usually chosen as linear. They transmit input signals to the next layer neurons directly by connection with unit weight ($w_i^1 = 1$), so that:

$$f = u_i^1 \text{ and } a=f. \tag{8}$$

Each neuron from second layer represents a membership function, i.e. its output will be induced by one type of membership function. For example, in case of the bell-shaped function, we have:

$$f = -\frac{(u_i^2 - m_{ij})^2}{\sigma_{ij}^2} \text{ and } a=e^f, \tag{9}$$

where m_{ij} and σ_{ij} are, respectively, the center (or middle) and width (or variance) of the bell-shaped membership function of the fuzzy set describing the j-th term of the i-th input linguistic variable x_i. Here the weight of connection to the second layer (w_{ij}^2) are interpreted as m_{ij}.

Connections to third layer are used for representation of preconditions (predicate) in the cause-and-effect relations, which are reflected by fuzzy implicative rules. Then each neuron of this layer will be imitate the action of a fuzzy logic operator "AND" in the form of:

$$f = \min\left(u_1^3, u_2^3, ..., u_p^3\right) \text{ and } a=f. \tag{10}$$

In this case, the weights of all connections to 3rd layer will be unit ($w_{ij}^3 = 1$).

[1] In some cases, the membership functions can be realized by neural subnets, which naturally enhance the total number of FLSQA layers.

For further training the neurons from fourth layer operate in two modes: the transmission of signals from the bottom to the top, and the transmission of signals from top to bottom. In transmit mode from the bottom to the top connections to the fourth layer must reproduce the fuzzy logic operation "OR" to integrate the initiated rule, which realizes a consequence in the form of:

$$f = \sum_{i=1}^{p} u_i^4 \text{ and } a = \min(1, f). \tag{11}$$

Here we assume that $w_{ij}^4 = 1$. When transmitting signals in a mode from top to bottom the neurons of this layer and connections to the fifth layer function similarly to neurons of second layer except that there is only one neuron is used to represent the membership function, reflecting the term of output linguistic variable. In the case of using of on-line learning algorithm the neurons of this layer function such as shown in Fig. 8, i.e. only in transmit mode from the bottom to the top.

In the case of applying the hybrid learning algorithm in fifth layer also provides the presence of two types of neurons. Neurons of the first type provide signal transmission from the top to the bottom for supply the neural network by training data. Here we have:

$$f = y_i \text{ and } a = f. \tag{12}$$

The neurons of the second type provide signal transmission from the bottom to the top for realization of the system output. These nodes are attached to them connections imitate the work of defazzifier. If we assume that m_{ij}^5 and σ_{ij}^5 are, respectively, the centers and widths of output membership functions, then for simulation the centroid method of defuzzification the following expressions can be used:

$$f = \sum w_{ij}^5 u_i^5 = \sum (m_{ij}\sigma_{ij}) u_i^5 \text{ and } a = \frac{f}{\sum \sigma_{ij} u_i^5}. \tag{13}$$

Here, it is not difficult to notice, the weights of connections to the fifth layer (w_{ij}^5) are represented as $m_{ij}\sigma_{ij}$. In the case of applying the on-line learning algorithm the neurons of this layer function in the transmit mode from the bottom to the top, thereby provide the resultant output.

VIII. Simulation of FLSQA in Notation of MATLAB (by Example of VoIP)

The main objective of the simulator is to conduct of simulation, demonstration of building (including training) and functioning of the target system. In our case, the simulator simulates the creation of FLSQA in notation of five-layer feedforward neural network with help of which the estimation of TS quality is realized. FLSQA having the train ability by training examples is designed to operate automatically. The main purpose is to demonstrate the ability of FLSQA to estimate the work of communication network (for example, IP-telephony) on the base of existing statistics of subjective data about customer satisfaction by provided TS levels.

As assessment criterion the performance parameters of IP-telephony network are chosen: IP-packet Transfer Delay (IPTD), IP-packet Delay Variation (IPDV – Jitter), IP-packet Loss Ratio (IPLR), IP-packet Error Ratio (IPER), with help of which the objective scoring of TS quality are control. In Section IV there are established the cause-and-effect relations that show how these parameters are transformed into subjective judgments of consumers, into their subjective assessment criteria:

- availability (or absence) of communication interruption;
- inadequate (or enough) good audibility;
- acceptable (or unacceptable) speech intelligibility, etc., and, thus, the TS qualities are classified by the network user satisfaction degrees.

The proposed simulation has two objectives. The first is to show that the proposed FLSQA can simulate FLS of estimation only on the base of using the set of historical input-output data obtained from the study of satisfaction degrees of IP-telephony customers. The second goal is to show the advantage of the proposed FLSQA over traditional FLS of estimation in terms of its inherent train ability (i.e. the possibility of optimizing of the input-output membership functions and implicative rules).

So as input linguistic variables let us select the following: x_1– IPTD; x_2 – jitter; x_3 – IPLR; x_4 – IPER. According to the classification of ITU constraints for these variables are intervals: $0 \le x_1 \le 1000$ ms; $0 \le x_2 \le 50$ ms; $0 \le x_3 \le 10^{-3}$; $0 \le x_4 \le 10^{-4}$ [1]. As output we will assume the linguistic variable y is the quality IP-telephony, values of which form classes 0, 1, 2, 3, 4 and 5 (see Table I).

Thus, as an example of TS let us consider the IP-telephony, i.e. telephone communication by IP-protocol, which is an application of a more general VoIP technology for voice transmission (Voice over IP). Choosing this service is justified by the fact that IP-telephony is very sensitive to jitter.

According to recommendation Y.1541 of ITU IP-telephony can function in the presence of performance parameters corresponding to classes 0 and/or 1 [1]. In this case, providing of services in Class 0 guarantees high quality and, hence, satisfaction of network users. At the same time, the quality of IP-telephony services in Class 1 will be a little worse and it would have to compensate by the introduction of additional options to continue to expand its customer base. In other cases, the communication quality is too low.

Table II shows that for providing the highest class of service (0) it is necessary to provide low levels of IP packet Transfer Delay, jitter, IP packet Loss Ratio and IP packet Error Ratio. To provide the service in class 1 allowable range of delay can be increased to average values. In the context of these arguments is not difficult to form a basic set of linguistic variables and rules for design the Fuzzy Inference System (FIS). For convenience, all variables are arranged in Table II.

TABLE II
VARIABLES OF FUZZY INFERENCE SYSTEM IN THE FRAMEWORK OF FLSQA

	Input linguistic variables	
x_1	Variable name	IPTD – IP packet Transfer Delay
	Term-set	LOW, AVERAGE, HIGH
	Range	[0, 450]
x_2	Variable name	Jitter
	Term-set	LOW, HIGH
	Range	[0, 90]
x_3	Variable name	IPLR – IP packet Loss Ratio
	Term-set	LOW, HIGH
	Range	[0, 0.0015]
x_4	Variable name	IPER – IP packet Error Ratio
	Term-set	LOW, HIGH
	Range	[0, 0.00015]
	Output linguistic variable	
y	Variable name	Service quality of IP-telephony
	Term-set	LOW, AVERAGE, HIGH
	Range	[0, 1]

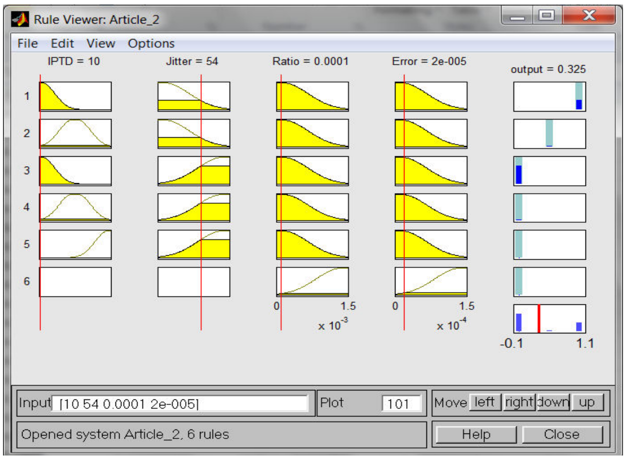


Fig. 9 Realization of rules by MATLAB FIS-editor

Based on recent discussions, the cause-and-effect relation between input and output characteristics is constructed in the form of following implicative rules [9], [10]:

d1. if IP packet Transfer Delay is LOW and Jitter is LOW and IP packet Loss Ratio and Error Ratio is LOW, then service quality of IP-telephony is HIGH;

d2. if IP packet Transfer Delay is AVERAGE and Jitter is LOW and IP packet Loss Ratio and Error Ratio is LOW, then service quality of IP-telephony is AVERAGE;

d3. if IP packet Transfer Delay is LOW and Jitter is HIGH and IP packet Loss Ratio and Error Ratio is LOW, then service quality of IP-telephony is LOW;

d4. if IP packet Transfer Delay is AVERAGE and Jitter is HIGH and IP packet Loss Ratio and Error Ratio is LOW, then service quality of IP-telephony is LOW;

d5. if IP packet Transfer Delay is HIGH and Jitter is HIGH and IP packet Loss Ratio and Error Ratio is LOW, then service quality of IP-telephony is LOW;

d6. if IP packet Loss Ratio is HIGH and IP packet Error Ratio is HIGH, then service quality of IP-telephony is LOW.

Realizing these rules in MATLAB notation by Sugeno type FIS-editor (see Fig. 9), finally let us form the training sample pairs (Table III).

TABLE III
INPUT-OUTPUT DATA SET FOR TRAINING OF FLSQA

Inputs				Output
IPTD (x_1)	Jitter (x_2)	IPLR (x_3)	IPER (x_4)	Service quality
406	39	0.0015	0.00006	0.00209
100	59	0.0002	0.00004	0.19900
10	54	0.0001	0.00002	0.32500
90	51	0.0015	0.00002	0.09020
207	18	0.0012	0.00013	0.00516
439	33	0.0007	0.00002	0.04000
141	69	0.0010	0.00011	0.00564
372	49	0.0006	0.00005	0.06500
135	83	0.0004	0.00001	0.03350
129	74	0.0001	0.00001	0.06630
36	21	0.0000	0.00005	0.82000
22	77	0.0003	0.00010	0.05640
178	25	0.0005	0.00002	0.45000
360	73	0.0002	0.00012	0.01150
103	44	0.0010	0.00014	0.00626
50	21	0.0008	0.00011	0.12400
416	5	0.0014	0.00011	0.00043
100	84	0.0010	0.00001	0.03260
17	55	0.0003	0.00011	0.19400
46	60	0.0003	0.00005	0.21800
409	73	0.0009	0.00005	0.00356
368	17	0.0001	0.00004	0.34600
26	74	0.0009	0.00013	0.00406
65	6	0.0012	0.00011	0.02310
102	41	0.0005	0.00004	0.42900
87	68	0.0003	0.00007	0.11200
312	37	0.0011	0.00006	0.06900
4	53	0.0001	0.00004	0.34200
290	48	0.0004	0.00011	0.09680
281	3	0.0012	0.00007	0.06270
102	42	0.0012	0.00008	0.04000
163	50	0.0000	0.00008	0.22900
314	22	0.0002	0.00001	0.39800
180	3	0.0002	0.00006	0.51700
227	67	0.0003	0.00002	0.07690
368	34	0.0001	0.00013	0.08990
143	13	0.0009	0.00006	0.31000
391	44	0.0010	0.00006	0.02040
64	53	0.0007	0.00010	0.09490
93	30	0.0002	0.00000	0.62400
281	25	0.0004	0.00003	0.39100
113	38	0.0008	0.00011	0.06480
361	71	0.0012	0.00001	0.01520
363	26	0.0015	0.00000	0.09280
147	39	0.0004	0.00002	0.38000
53	3	0.0001	0.00013	0.57300
29	79	0.0014	0.00004	0.01460
411	84	0.0010	0.00013	0.00006
178	64	0.0001	0.00008	0.09920
105	16	0.0009	0.00000	0.66700

Therefore, forming a training set, it is feasible to download Sugeno type ANFIS-editor whose appearance with loaded training data is shown in Fig. 10.

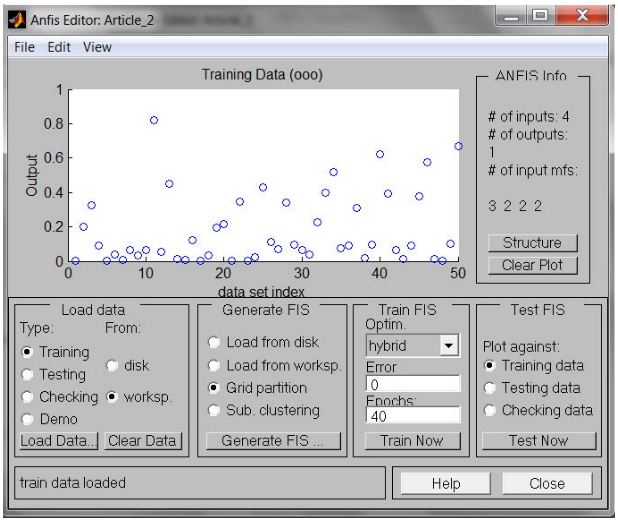


Fig. 10 Graphic interface of ANFIS-editor after loading data

Further, let us generate the structure of Sugeno type FIS, which is a model of the hybrid network in the MATLAB package. For this purpose via a dialog box let us activate the Gaussian membership functions to describe the selected terms of the input and output variables (see Table III). After generation of the hybrid network structure one can visualize the structure of FLSQA in notation of five-layer neural network (Fig. 11).

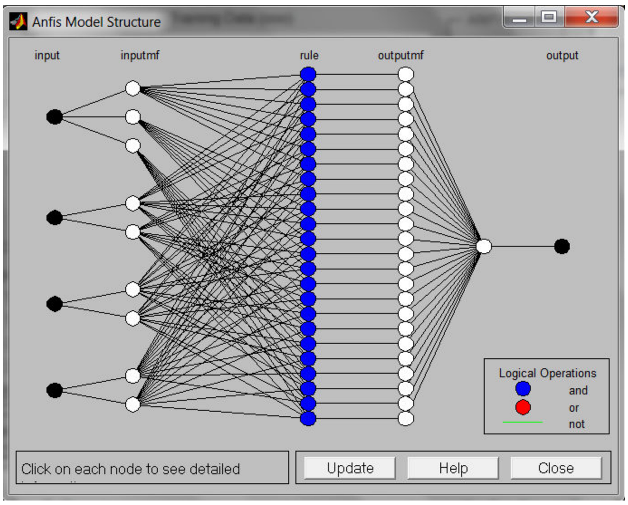


Fig. 11 The structure of FLSQA in notation of five-layer neural network

For considered example, the FIS in the neural network logic basis contains 4 input variables with 3 terms for x_1, with 2 terms for the rest, 24 implicative rules, one output variable with 24 terms. As supervise training method we have chosen a hybrid method, which is a combination of the least square method and the method of decreasing the reverse gradient. The process of learning is illustrated in the window of visualization in the form of an error – training cycles number diagram (Fig. 12).

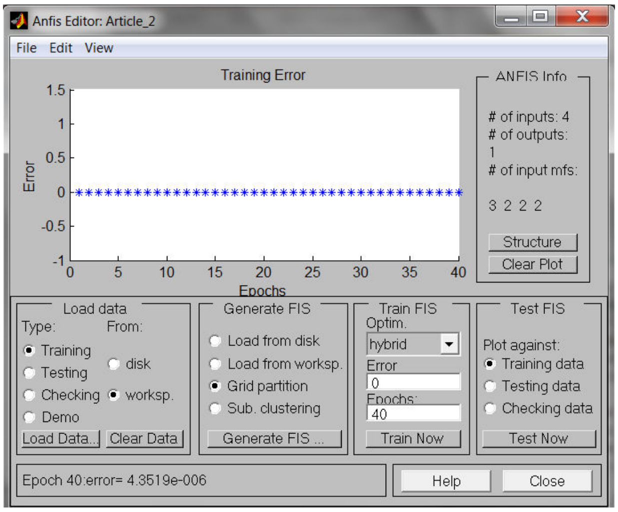


Fig. 12 Error – training cycles number diagram

Further parameters adjustment of designed and trained FLSQA can be carried out by standard graphics tools of MATLAB\FIS option. Thus, Fig. 13 shows the optimized membership functions describing the terms of the input linguistic variables.

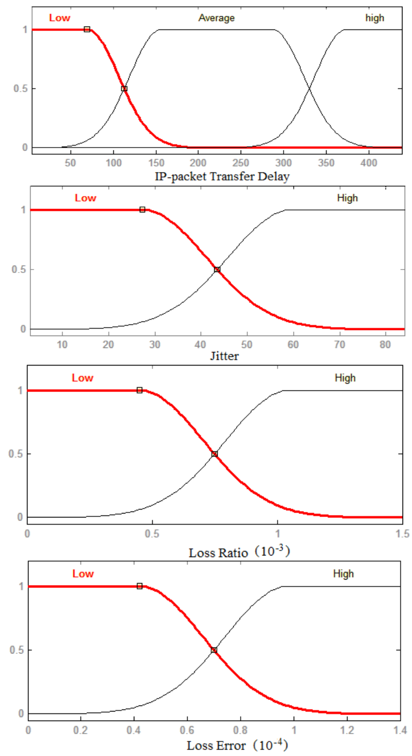


Fig. 13 Optimized input membership functions

Following Fig. 14 presents a graphical interface for viewing the rules of generated fuzzy inference system and a fragment of an optimal set of basis implication rules.

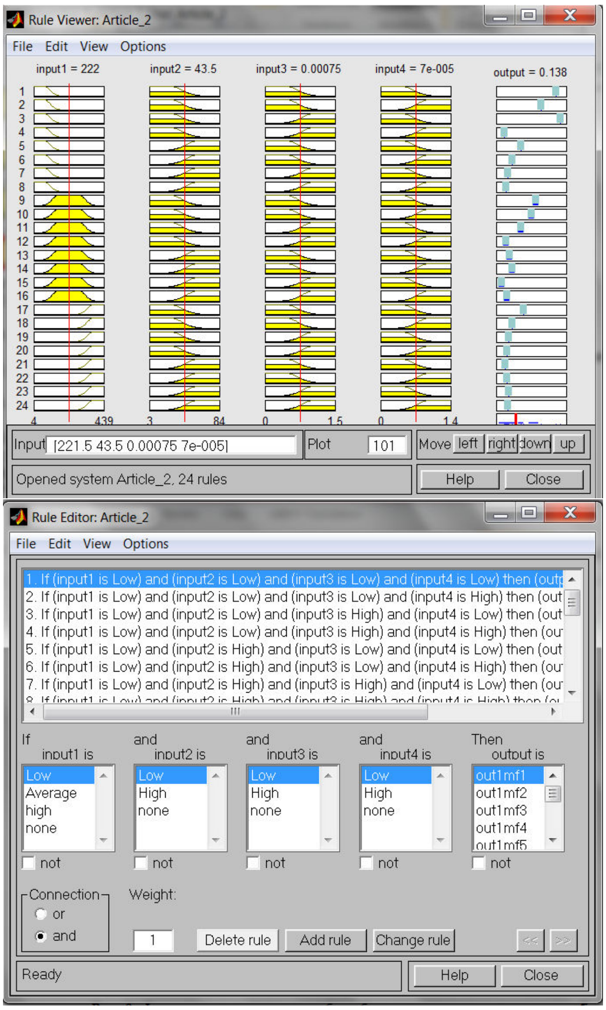


Fig. 14 Graphical interface for viewing the rules of generated fuzzy inference system and fragment of an optimal set of basis implication rules

Table IV lists the "trained" fuzzy implicative rules in a simplified form. For example, rule 1 marked in Fig. 14 is interpreted as:

IF x_1 is LOW (i.e. the term 1) and x_2 is LOW (i.e. the term 1) and x_3 is LOW (i.e. the term 1) and x_4 is LOW (i.e. the term 1), **THEN** y is VERY HIGH (i.e. the term 5).

Fig. 15 shows the distribution of parameters of adapted FIS outputs, in fact, on the basis of which were installed 5 clusters – terms for the output variable y.

TABLE IV
LOGIC RULES ARE TRAINED BY HYBRID ALGORITHM

Rule number	Cause				Effect
	x_1	x_2	x_3	x_4	y
1	1	1	1	1	5 (VERY HIGH)
2	1	1	1	2	4 (HIGH)
3	1	1	2	1	5 (VERY HIGH)
4	1	1	2	2	1 (VERY HIGH)
5	1	2	1	1	3 (ACCEPTABLE)
6	1	2	1	2	2 (LOW)
7	1	2	2	1	2 (LOW)
8	1	2	2	2	1 (VERY LOW)
9	2	1	1	1	4 (HIGH)
10	2	1	1	2	4 (HIGH)
11	2	1	2	1	3 (ACCEPTABLE)
12	2	1	2	2	1 (VERY LOW)
13	2	2	1	1	2 (LOW)
14	2	2	1	2	2 (LOW)
15	2	2	2	1	1 (VERY LOW)
16	2	2	2	2	1 (VERY LOW)
17	3	1	1	1	3 (ACCEPTABLE)
18	3	1	1	2	2 (LOW)
19	3	1	2	1	2 (LOW)
20	3	1	2	2	1 (VERY LOW)
21	3	2	1	1	1 (VERY LOW)
22	3	2	1	2	1 (VERY LOW)
23	3	2	2	1	2 (LOW)
24	3	2	2	2	1 (VERY LOW)

Trained fuzzy implicative rules

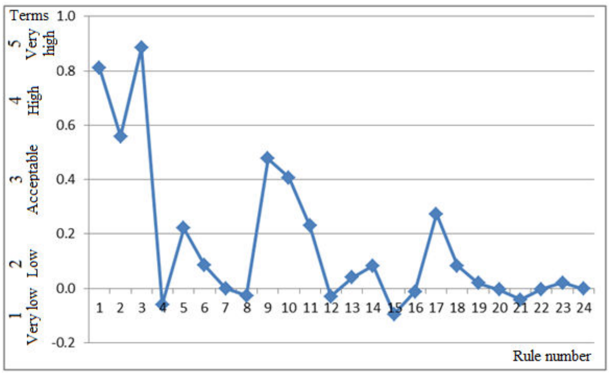


Fig. 15 Aggregate output of adapted FIS parameters

IX. INSTEAD CONCLUSION

In the process of simulation it has been used 4 objective criteria of the telecommunications network quality. On the base of these criteria by application of the adapted type Sugeno FIS it was able to obtain the adequate cause-and-effect relation between the objective parameters of performance networks, on the one hand, and subjective consolidated estimates of users, on the other (see Fig. 16).

The overall quality of IP-telephony does not exceed the value of 0.55 at the maximum 1, relatively moderately decreases with increasing delays of IP-packets and falls sharply by passing the portion of lost packets of value 10^{-3} and by passing the portion of errors during IP-packets transmission of value 10^{-4}. IP packet Transfer Delay in more than 400 ms reduces to degradation of quality even at the level of jitter 50 ms, which corresponds to practical observations for IP-telephony services.

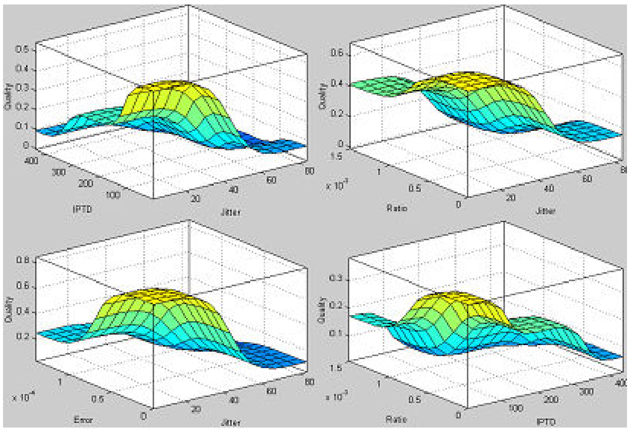


Fig. 16 Dependences between network quality assessment and objective indicators

Further Fig. 17 shows curves illustrating dependences between the quality of IP-telephony and each parameter separately. In turn, they confirm the above conclusion about the changes in the overall quality of IP-telephony network.

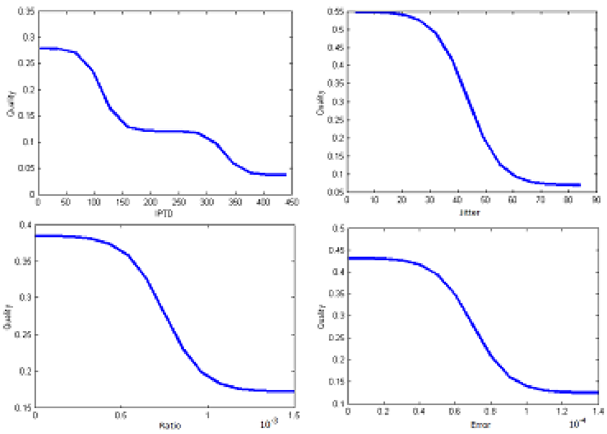


Fig. 17 Dependences between the quality of IP-telephony and each parameter of IP-telephony network

The proposed system FLSQA allows rather quickly and relatively easily diversifies their functions to other services of the telecommunications network. It is necessary to collect sufficient statistics of consolidated user ratings on different scenarios of functioning of the selected network connection.

Thus, by FLSQA one can control and adjust the network parameters in order to ensure the operating decision-making to increase the customer base. In the future, such system will be able to operate in stand-alone mode, as in its development and adaptation is not necessary to involve the heuristic knowledge and costly expert services.

REFERENCES

[1] International Telecommunication Union Recommendation. http://www.itu.int/rec/recommendation.asptype=series&lang=e&parent=T-REC (2012). Accessed 1 July 2014.

[2] J. Kacprzyk, R.R. Yager, *Management Decision Support Systems Using Fuzzy Sets and Possibility Theory*. Cologne: Verlag TUV Rheinland, 1985.

[3] R.R. Rzaev, *Intellektualniy Analiz Dannykh v Sistemakh Podderzhki Priniatiia Reshenii* (Data Mining in Decision Support Systems). Moscow: Lambert Academic Publishing, 2013 (in Russian).

[4] R.R. Rzaev, A.I. Goyushov, “Mnogokriterialnaia otsenka kachestva telekommunikatsionnykh uslug na osnove primeneniia mekhanizma nechetkogo vyvoda” (“Multi-criteria estimation of the quality of communication services on the base of using of fuzzy inference mechanism”), *AMEA Xabarlary*, vol. 33, no. 6, 2014, pp. 56–66 (in Russian).

[5] D. Sokolov, “Nechetkaia sistema otsenki kachestva” (“Fuzzy system of quality estimation”), *Technology and communication facilities*, no. 4, 2009, pp. 26–28 (in Russian).

[6] R.R. Yager, L.A. Zadeh, *An Introduction to Fuzzy Logic Applications in Intelligent Systems*. Norwell: Kluwer Academic Publisher, 1992

[7] R.R. Yager, L.A. Zadeh, *Fuzzy Sets, Neural Networks and Soft Computing*. New York: Van Nostrand Reinhold, 1994.

[8] L.A. Zadeh, “Rol miagkikh vychislenii i nechetkoi logiki v ponimanii, konstruirovanii i razvitii informatsionnykh/intellektualnykh sistem” (“The role of Soft Computing and Fuzzy Logic in understanding, design and development of information/intelligent systems”), *Novosti iskusstvennogo intellekta*, no. 2-3, 2001, pp. 7–11.

[9] L.A. Zadeh, *The Concept of a Linguistic Variable and its Application to Approximate Reasoning*. New York: American Elsevier Publishing Company, 1974.

[10] H. Zimmerman, *Fuzzy Sets Theory and Its Applications*. New York: Kluwer Academic Publishers, 2001.

[11] J.A. Bernard, “Use of rule-based system for process control”, *Control System Magazine*, vol. 8, no. 5, 1988, pp. 3–13.

[12] M.Braae, D.A. Rutherford, “Selection of parameters for a fuzzy logic controller”, *Fuzzy Sets Systems*, vol. 2, no. 3, 1979, pp. 185–199.

[13] B. Kosko, *Neural Networks and Fuzzy Systems*. New York: Englewood Cliffs, 1992.

[14] C.T. Lin, C.S. George Lee, “Neural network-based fuzzy logic control and decision system”, *Transactions on Computers*, vol. 40, no. 12, 1991, pp. 1320–1336.

[15] C.T. Lin, C.S. George Lee, “Supervised and unsupervised learning with fuzzy similarity for neural network-based fuzzy logic control systems”. In: Yager, R.R., Zadeh, L.A. (ed) *Fuzzy Sets, Neural Networks, and Soft Computing*, New York: Van Nostrand Reinhold, 1994, pp. 85–125.

[16] T.J. Procyk, E.H. Mamdani, “A linguistic self-organizing process controller”, *Automatica*, vol. 15, no. 1, 1979, pp. 15–30.

[17] D.E. Rumelhart, G.E. Hinton, and R.J. Williams, “Learning internal representations by error propagation”, *Parallel Distributed Processing*, no. 1, 1986, pp. 318–362.

[18] M. Sugeno (ed.), *Industrial Applications of Fuzzy Control*. Amsterdam: Elsevier Science Publishers, 1985, pp. 231–239.

[19] T. Takagi, M. Sygeno, “Derivation of fuzzy control rules from human operator’s actions”, in *Proc. IFAC Symposium. Fuzzy Information Knowledge Representation Decision Analysis*, Marseilles, 1983, pp. 55–60.

[20] R.M. Tong, “Synthesis of fuzzy models for industrial processes”, *Int. Gen Systems*, no. 4, 1978, pp. 143–162.