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Monitoring and Security Assessment of Traffic in Communication Channels of Technological Corporate Computer Networks

F. H. Pashayev[1], J. I. Zeynalov[2], H. T. Najafov[2]

[1]Ministry of Science and Education of the Republic of Azerbaijan, Institute of Control Systems, Baku, Azerbaijan
[2]Department of Electrical and Electronics Engineering, Nakhchivan State University, Nakhchivan, Azerbaijan

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *It is mentioned in the article that in recent times the technical aspects of computer networks assessment of the situation, various threats, especially the Internet many theoretical and practical works on solving the issues of protection from attacks dedicated (see 11-16).*
- *What constitutes cyber security in many cases, cyber attacks means and goals were investigated (17).*
- *It was noted that the technical condition of computer networks Neural networks are active for assessment and defense purposes applied (18-20).*

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *Architecture of technological corporate computer networks and information by analyzing the conceptual model of information flows flow monitoring points are defined.*
- *The volume of traffic on network channels is determined.*
- *Informative for evaluating the technical capacity of the network signs, indicators are defined.*
- *The impressions of the operating staff as the main indicators evaluated.*
- *The technical condition of the network from the created indicators A three-layer neural network applied to evaluate the input and Algorithm for training a neural network with fixed outputs given.*

Corresponding author:
H. T. Najafov

E-mail:
hasan.nacafov@ndu.edu.az

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ABSTRACT

The article proposes a four-level generalized architecture of technological corporate computer networks (TCCNs) and assesses the elements of this architecture and information exchange via communication channels between their levels. The volume of information that is generated at the levels of sensors and technologicalprocesses, which carry out most of their activities and functions without human participationand are transmitted to higher levels, is estimated, the functions of traffic monitoring in channels are investigated, and the functions of the distribution of the information volume over time are considered. It is noted that in channels associated with sensors and technological processes, the distribution function mainly behaves as a constant function. However, traffic in communication channels associated with human activity at the upper levels of the network has a certain daily periodicity. Both cases can be used when monitoring specific channels. Formulas are given in the form of integral and discrete sum functions for determining the volume of information passing through a channel in a given time interval. Here, the average volume of information passing through a selected channel per unit of time and the peak factor of the information volume are determined. Various methods and tools are used to assess the technical condition of the TCCNs channels and their resistance to Internet threats. To address this, the article proposes a three-level backpropagation neural network. Indicators with informative features are created to determine the inputs and outputs of the neural network. Among these indicators, there is an important indicator that is formed based on the experience of the operating personnel. Five different values are formed from the impressions of the operating personnel as indicator estimates. The inputs of the neural network are mainly formed from these generated indicators. The outputs of the neural network are also determined on the basis of the impressions of the operating personnel. A network training data set is formed from the inputs and outputs of neural networks. The final result of the article is the learning algorithms based on backpropagation algorithms.
Index Terms—Average information volume, information indicators, operating personnel impressions, technological corporate computer networks (TCCNs) channels, technical condition of channels, peak factor

I. INTRODUCTION

It is known that various variants and designs of technological corporate computer networks (TCCNs) have been created. Examples include monitoring, diagnostics, and control systems created for technical objects; these systems are mainly created as three-level systems [1, 2]. In the corporate environment, networks and systems are created in accordance with the enterprise architecture [3, 4]. The lower level of TCCNs usually contains primary transducers converting various physical parameters into analog signals. As a rule, the outputs of these transducers are analog signals that are converted into binary codes using analog-to-digital converters (ADCs) of object controllers. These object controllers group primary transducers and ensure that unique numbers are assigned to the signals received from these converters [5].

Some intelligent primary transducers have built-in ADCs that convert analog signals into digital ones and transmit a signal consisting of a sequence of digits (codes) to mid-level elements via the exchange channel. The assignment of unique numbers is carried out through the converter itself,

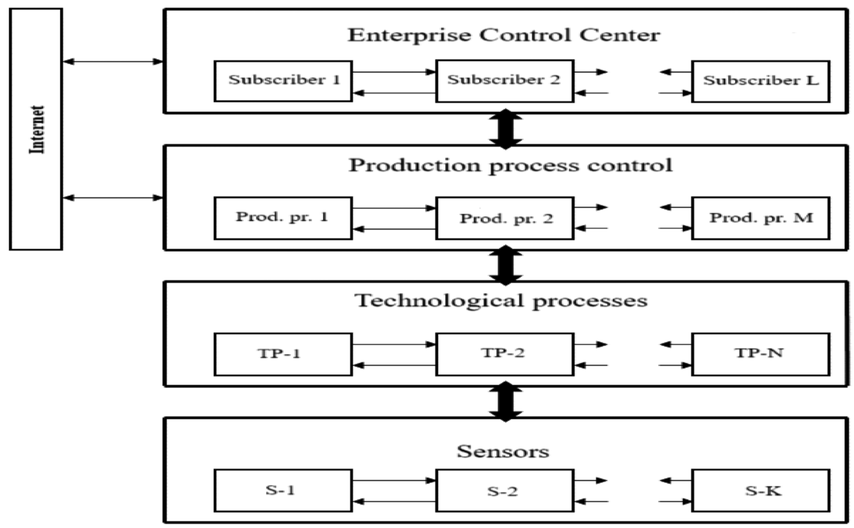

Fig. 1. Generalized architecture of the enterprise's distributed information system.

and grouping operations take place on elements at the level above the primary transducer.

An automated system for monitoring and controlling any technological process or technical object can, in general, be in general represented as a four-level distributed information system (DIS) as follows (Fig. 1). Here, the first level is the technological equipment control level. Primary transducers (sensors) of various types are located at this level. The choice of primary transducers depends on the technological equipment and the physical processes taking place here.

The second level in this architecture is the technological process control level. This level is built on technological process controllers (TPC). It can be seen as from the architecture, the primary transducers are connected to the controllers in groups, and data in the form of analog signals coming from the technological equipment are converted into codes and digitized in the controllers.

Therefore, process controllers are placed as close as possible to the primary transducers. Here, the distance is determined by the output signals of the primary transducers. Primary transducers are the main sources of information in the system. Theoretically, these two levels can be considered one level. The elements of these levels are the most numerous elements of the system, and the reliable operation of the system depends on them. When creating technological process control systems, high requirements are imposed on the selection of numerous low-level elements. The second level of the system shown in Fig. 1 is the production process control level. This level of the system is built on computers using various communication tools and software and hardware suites. Technically, the connection of this level with the first level is mainly ensured via RS 232, RS 485, RS 422 type interfaces connecting Com ports. It is known that RS 232 protocols allow for one-to-one connection of computers at a distance of 5–8 m, and up to 15 m when using shielded cables. In some computers, up to eight such communication channels can be created using special means. When using RS 485, RS 422 protocols, controllers and computers can be connected at a distance of up to 1200 m, and several computers or controllers can be on one cable.

Some modern systems use radio communications to provide long-distance connectivity between first- and second-level elements.

In Fig. 1, the third level of the system is the enterprise control level. It is called the Enterprise Control Center. Since it is connected to the second level mainly via a local area network or the Internet, the elements of this level can cover a large territory and be located in different parts of the country. From the point of view of ensuring the efficiency and effectiveness of enterprise management, various workplaces and centers are set up at this level. Workplaces of executives such as the director (CEO), chief engineer, chief technologist, production manager, etc. are usually created here. Servers and databases are created at this level to ensure the control of technological processes at the enterprise.

To monitor the information exchange (traffic) in the enterprise's DIS, it is necessary to measure traffic in some communication channels. Measurement points can be created in communication channels between sensors and technological processes (SS point); technological processes and production processes (TP point); and production processes and the control point (MM point). Measurement points can also be on other channels if necessary. Possibilities for improving the network for monitoring traffic in communication channels and determining the volume of information at various network levels must be created and assessed [6].

The article presents a method for determining the volume of traffic in TCCNs, creating indicators for assessing the quality of information exchange, assessing the state of information exchange channels, and monitoring it using neural networks.

II. PROBLEM STATEMENT

The architecture shown in Fig. 1 can also be considered a conceptual model of TCCN information flows [7-10]. Work should be carried out to monitor and assess traffic in the network communication channels in order to ensure the reliable operation of the TCCN, assess its technical condition, and protect against various Internet attacks.

The need to ensure control over the movement of transport is inherent in almost every enterprise. One of the main tasks that falls on specialists is the selection and introduction of suitable software and hardware tools capable of performing these functions [11-13].

It should be noted that there are numerous recent studies on the protection of computer networks and industrial facilities from Internet attacks [14, 15]. One of the main methods used in practice is setting up a firewall and ensuring constant control over it [16]. Many studies examine the concept of cybersecurity in general, and the goals and means of cyber attacks [17].

Numerous theoretical and practical studies are being conducted on the use of neural networks with the purpose of assessing the technical condition of computer networks and protecting them from Internet attacks [18-20].

This article differs from the abovementioned works in that the main information flows in the network are determined as a result of studying the architecture of the TCCN and the conceptual model of information flows in the TCCN. The main problems set here are as follows:

- determining the loading of network channels and traffic load and
- determining informative features for assessing the state of channels and determining the input and output data of a three-layer backpropagation neural network for assessing the state of channels and the probability of external interference in the channels, providing training algorithms. Here, the impressions of the network operating personnel are presented as one of the main informative features. The outputs of the neural network are also formed based on the impressions of the operating personnel.

A. Determining the Loading of Technological Corporate Computer Networks Channels

To create a model for controlling the TCCN channel load, it is necessary to register computers and controllers used in the network as network users. Practically, every physical user also accesses the network through a computer and receives information from it. Thus, each of the network users can create a connection with other users. A communication channel can consist of one or more parts. Routes on individual channels can be implemented in different ways depending on the technical condition of the network. For simplicity, we can assume that there are

N users in the network, between whom a total of

$$1+2+\ldots+(N-1)=\frac{N(N-1)}{2}$$

communication channels can be created.

It should be noted that the need for channel monitoring exists at every enterprise. In our case, the organization of traffic monitoring at the SS and TP points is of great importance. To organize monitoring on the channels of these points and on any other channel, it is necessary to select software and hardware tools [7, 8].

Channels may be loaded differently throughout the day. For instance, in channels related to parts closely associated with technological processes, exchanges may be carried out sporadically, even in an approximately uniformly distributed manner (Fig. 2). Such channels can be called technological. The figure shows a graph of the distribution of the exchange volume in a technological channel over time over several hours [21].

In the figure, the X-axis shows time, and the Y-axis shows requests to the selected channel in different units of time. However, requests to channels related to people's daily activities have a certain periodicity and are tied to working hours. This is evidenced by data taken from the AzScienceNet network of the Azerbaijan National Academy of Sciences [22] (Fig. 3). According to the data in Fig. 4, a smoothed graph of the average day by minute is shown together with the channel capacity (Fig. 4). The channel capacity is indicated by a green line.

If we assume that the volume of information passing through the channel in time Δt is $\Delta v = v(t)\Delta t$, then the volume of information passing through the channel in the time interval $t \in [T_1, T_2]$ can be calculated as

$$V_{1,2}=\int_{T_1}^{T_2} v(t)\,dt. \tag{1}$$

Since the volume of information passing through the channel is known in the form of discrete quantities measured over units of time, then to estimate the volume of information passing through the selected channel in individual time intervals, the above integral must be replaced with the sum.

$$V_{1,2}=\sum_{T_1}^{T_2} v(t) \tag{2}$$

The average volume of information passing through a selected channel over a unit of time in this time interval or any other time interval can be found as follows:

$$V_{av\,1,2}=\frac{\sum_{T_1}^{T_2} v(t)}{T_2-T_1}. \tag{3}$$

The peak factor of the volume of information passing through the channel can be calculated as:

$$P_v=\frac{\max(v(t))}{V_{av\,1,2}}. \tag{4}$$

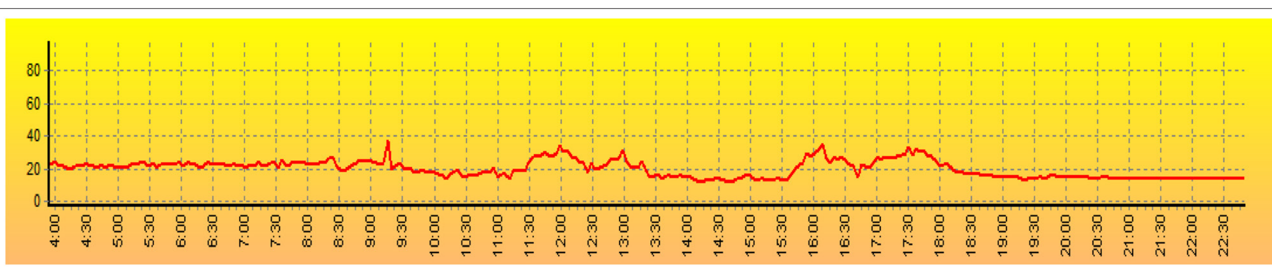

Fig. 2. Distribution of requests in technological channels over time.

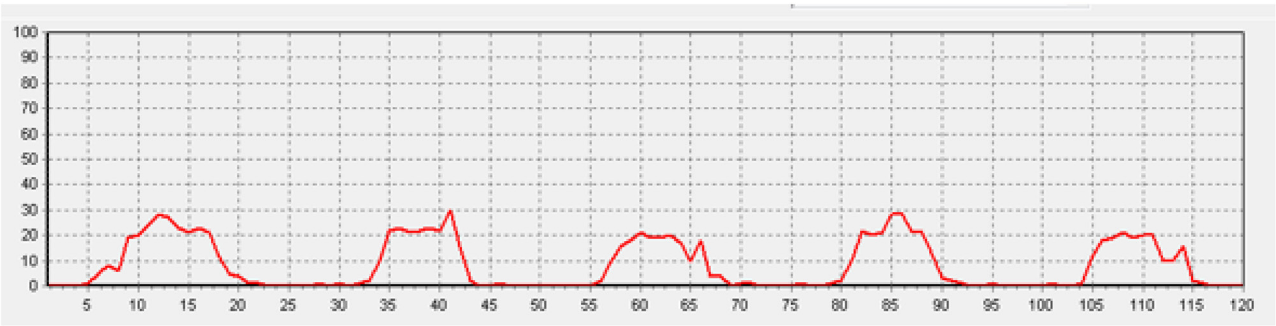

Fig. 3. Graph of the time dependence of network requests over the working days of a selected week.

The following characteristics, calculated for time intervals when the volume of information passing through the selected channel exceeds the channel capacity, may be important in solving the problems of monitoring the loading of channels, assessing their quality, and determining the presence of outside interference in these channels. For this purpose, we denote by $T1_i$ the left part of each interval where the volume of information exceeds the capacity, and by $T2_i$ the right part. Suppose that the number of cases of exceeding the limit of the volume of information transmitted through the channel over the monitoring period is *M*. The duration of such cases over the monitoring period can be found from the following sum:

$$\bar{T} = \sum_{i=1}^{M} (T2_i - T1_i) \tag{5}$$

This parameter can play a role of a serious indicator in determining the presence of outside interference in the channels.

$$I_1 = \bar{T}$$

The ratio of the volume of information transmitted in cases of exceeding the limit to the total volume of information transmitted over the monitoring period can be the second indicator. If we denote the volume of information transmitted in cases of exceeding the limit by $\bar{V}$, then we can write

$$\bar{V} = \sum_{t \in \bar{T}} v(t). \tag{6}$$

Then the second indicator will be

$$I_2 = \frac{\bar{V}}{V_{1,2}}. \tag{7}$$

In addition to this parameter, the number of cases of exceeding the limit over the monitoring period *M* can also be used as an indicator.

B. Determining the Traffic Load

To solve the traffic load problem, it is necessary to estimate the volume of information coming from sensors, which are primary data transmitters in various network nodes, especially at the technical equipment control level and at the technological process control level. It is known that sensors, whose outputs are analog signals, and smart sensors, whose outputs are binary codes, are used in practice. Analog-to-digital converters and controllers are selected depending on the frequency characteristics and sensitivity of the sensors used. Reading information transmitted by sensors with frequencies exceeding their frequency range can lead to repeated reading of the same information. Therefore, the maximum reading frequency can be determined as

$$w = min \left\{ \begin{array}{l} upper\ limit\ of\ the\ sensor\ frequency\ range, \\ maximum\ conversion\ frequency\ of\ ADC \end{array} \right\}.$$

However, the actual sensor reading frequencies are selected in accordance with the strategy of process monitoring and control, taking into account the information needs of corporate network users and adjusted for network capacity.

Time of information delivery to users

Determining the volume of information I3

Determining the volume of information coming from sensors: by the frequency of requests, and information coming in each request

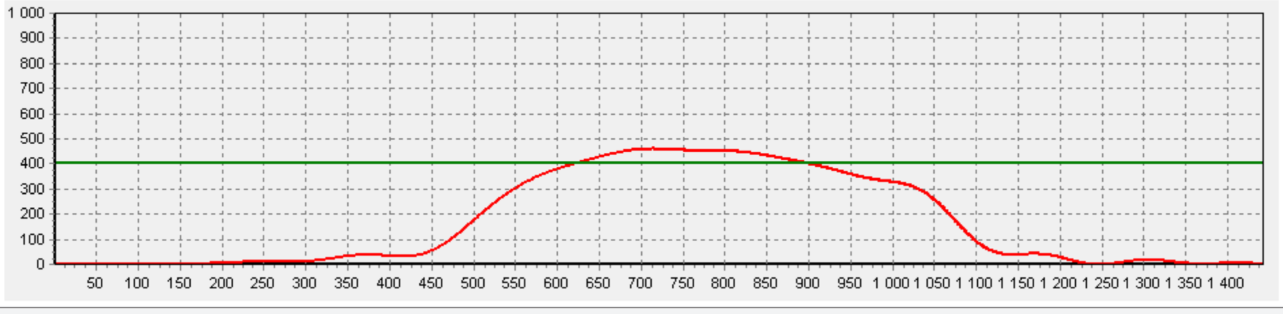

Fig. 4. Graph of distribution of requests for an average day, in minutes.

It is known that when converting analog sensor signals into binary codes by means of ADCs, one, two, or even four bytes can be converted depending on the sensitivity of the converter. This information can be stored as bytes, which are converted to occupy less space in controllers. Considering Fig. 1, it can be assumed that there are L sensors in the system. The type of sensors, the sensitivity of ADCs, and other characteristics are determined at the stage of network design. It can be assumed that the number of ADCs is also L. $B_l = w_l k_l$ bytes can be received from the l-th sensor per unit of time, where B_l is the number of bytes received per unit of time from the l-th sensor, w_l is the reading frequency of the l-th sensor, and k_l is the number of bytes received in each reading. Under these conditions, the number of bytes received per unit of time from the sensors connected to the system will be $V_s = \sum_{l=1}^{L} B_l$. The number of bytes received over a certain period of time T will be $V_T = T * V_s$. These bytes constitute the information base of the distributed memory in the memory of the various controllers connected to the network. Here, the distribution of the database is naturally carried out automatically between the controllers.

Volumes of information as a result of converting information received from analog inputs, converting to natural units, and scaling

It is known that it is impossible to store the memory information base for a long time. Therefore, in order for users of this network to be able to use this information, it must be sent to computers, converted into decimal numbers, the corresponding units of physical quantities to which they belong, stored in databases, and used.

Conversion to a decimal number when the length of the positive code is two bytes:

Decimal number = high byte * 256 + low byte If a positive code is given by four bytes, it can be converted as follows:

Decimal number = [(4th byte * 256 + 3rd byte) * (256 + 2nd byte) * (256 + 1st byte)]

However, the received codes do not always correspond to positive values of the measured parameters. The last left bit (high-order bit) of the codes corresponding to positive values is 0, and the last right bit (low-order bit) of the codes corresponding to negative values is 1. Therefore, after the two-byte code corresponding to the negative value of the measured parameter has been converted in the manner described earlier, the following operation must be performed:

If the resulting decimal number is greater than exp(15*ln(2)) = 32768

Decimal number = must be decimal number − 65536, which will be a negative number.

In the case of a four-byte code, if the resulting decimal number is greater than exp (31*ln 2) = 2147483648

Decimal number = must be a decimal number − 4294967295 which will be a negative number.

To convert the obtained decimal numbers to natural units of the measured parameters, we will adopt the following:

If the smallest possible value of the decimal number obtained as a result of code conversion is x_1, the largest possible value is x_2, and the current value is x, the smallest possible value of the measured parameter is y_1, the largest possible value is y_2, and the unknown current value is y, then this value can be found as follows:

$$y = y_1 + \frac{y_2 - y_1}{x_2 - x_1}\left(x - x_1\right) \tag{8}$$

Such conversions are mainly carried out at the third level of the system level, the level of production process control. Therefore, the main control function can be placed at the TP point between technological processes and production processes. The indicators can be the volume of information passing through the

$$I_3 = V_{1,2} = \sum_{T_1}^{T_2} v\left(t\right)$$

channel, the volume of information coming from the $I_4 = V_T = T * V_s$ sensors, and the relative value of the difference between these two $I_5 = abs\left(I_3 - I_4\right)$ parameters.

Thus, the obtained results can not only be stored in binary and decimal form but also, if necessary, converted into text form and stored in various databases.

Depending on the technological process and the nature of the technical device, the measured parameters may be temperature, pressure, flow rate, and other parameters. In equipment with rotating parts, such parameters as vibration acceleration or vibration speed, the number of cycles per unit of time can be measured. Depending on the problems being solved, various requirements may be imposed on the measurements. For example, when solving vibration diagnostics problems, requirements are imposed on the fast measurement of vibration parameters. Processing of received signals using spectral, correlation, or wavelet transforms imposes various requirements on the volume of stored information. In many cases, various parameters are measured from points close to each other in certain nodes of the technological process or technical device. In this case, the node and the part are combined in the project under one name, and the values of the autocorrelation and cross-correlation functions of the information obtained here, the configuration of peaks in their wavelength divisions, and the values obtained during wavelet transforms can be used as special diagnostic features.

1) Auxiliary Information from External Sources of Information

The solution to the problem of receiving and processing information from external sources of information must be analyzed when designing a specific TCCN and included in the algorithms and software of the network. This information can be divided into two main groups:

1. Information pertaining to the network itself may include details about maintenance work being carried out on individual network nodes, maintenance work being carried out at a user's workstation, notification that the user will not request information for a certain period of time, and other information of this kind. This information may result in temporary adjustments to the directions and modes of information exchange in the computer network.
2. Information comes from outside the network. This may include mainly information received from the weather bureau and other sources that may affect the operation of technological processes.

2) Information Obtained as a Result of the Software Suite Operation
As can be seen from Fig. 1, numerous computers and controllers are used at the enterprise control level, production control level, and technological process control level of the TCCN. These computers and controllers use various software tools. As a result of the operation of these software tools, new information is created, which is transmitted in different directions via network communication channels.

Taking into account the above, the database of technological information of the TCCN may have the following approximate structure:

- Name of the unit or part.
- Time of measurement or calculation.
- Name of the measured parameter.
- Threshold values of the measured parameter.
- Current value of the measured parameter.
- Name of the calculated parameter.
- Threshold values of the calculated parameter.
- Current value of the calculated parameter.
- Information received from external sources of information.
- Threshold values of information obtained from external sources of information.
- Current value of information received from an external information source.
- Diagnostic information about the state of a process or technical equipment.

As can be seen, other details can be included in this structure, and the structure can be adjusted. Finally, the structure is created and verified during the network design. Development of a model of computer resources of the TCCN and dynamic distribution of these resources among users.

Computer resources refer to the following computer parameters.

C. Impressions of the Operating Personnel
The impressions of the operating personnel play a major role in monitoring communication channels and assessing the security of the channels. These impressions are formed by the difficulties that arise during operation, the increase or decrease in the number of failures, the time spent on troubleshooting, and other factors. The repetition of malfunctions and the causes discovered during their elimination also play an important role here. If these causes are related to the state of technical equipment or the age of the software, such causes are considered natural and are not recorded as external interference in the network. Events whose cause cannot be clearly determined, and malfunctions that are eliminated by restarting the system, are considered alarming malfunctions and can be attributed to external interference. Thus, the following subjective assessments can be obtained from the impressions of the operating personnel:

- TCCN works reliably.
- There are software and technical issues in the operation of TCCN.
- The probability of external interference in the operation of the TCCN is low.
- There is a possibility of external interference in the work of the TCCN.
- The probability of external interference in the operation of the TCCN is high.

These assessments, along with other indicators, can form part of the neural network input data. To do this, these assessments need to be converted into numerical values. Values such as 01, 02, 03, 04, and 05 can be used here. These values can play the role of both the sixth indicator and the output data.

A three-layer backpropagation neural network [23, 24] can be chosen as the neural network (Fig. 5).

As an activation function for this neural network, we use the following sigmoid function:

$$f(x)=\frac{1}{1+e^{-x}} \tag{9}$$

e of the main distinguishing features of this function is that its derivative can be calculated in a simple way.

$$f(x)'=f(x)*(1-f(x) \tag{10}$$

The following tasks related to the neural network need to be solved:

- Determining the structural elements of the neural network.
- Determining the inputs of the neural network.
- Determining the outputs of the neural network.
- Providing a learning algorithm.

- Let us determine the structural elements of the neural network as follows:
- The weight vectors of layers *I, II,* and *III* are denoted by $w_1[i, j]$, $w_2[i, j]$, $w_3[i, j]$, respectively;
- *N1* is the number of input data.
- N_1, N_2, and N_3 are the number of neurons in layers *I, II* and *III*, respectively. As can be seen from the figure, N_3=1
- $s_1[j]$, $s_2[j]$, $s_3[j]$ are the parameters characterizing the state of neurons in layers *I, II* and *III*, respectively;
- $y_1[i]$, $y_2[i]$, $y_3[i]$ are the output functions of neurons in layers *I, II* and *III*, respectively.

Denote the values of the input data as the abovementioned indicators by x_i and take them as $N_3 = 1$.The input data are taken from the correspondence table t_{ki}, n_{ki}, and the output data from the correspondence table *REZ [k, i]* (Table I).

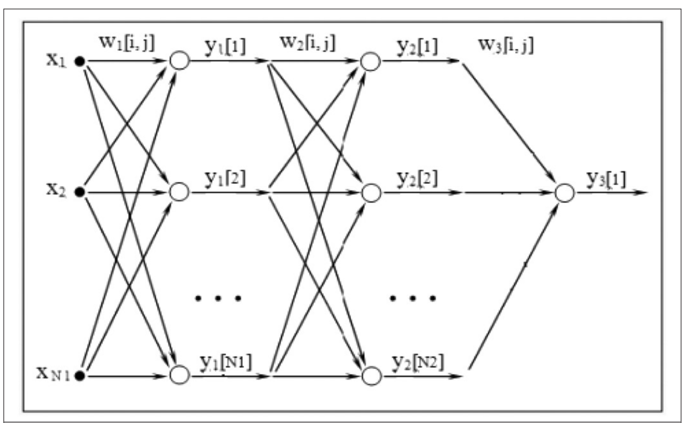

Fig. 5. Three-layer backpropagation neural network.

TABLE I. TABLE OF INPUTS AND OUTPUTS OF THE NEURAL NETWORK

I1	I2	I3	I4	I5	I6	Output
I_{111}	I_{211}	I_{311}	I_{411}	I_{511}	1	1
I_{112}	I_{212}	I_{312}	I_{412}	I_{512}	1	1
…	…	…	…	…	…	…
I_{11J}	I_{21J}	I_{31J}	I_{41J}	I_{51J}	1	1
I_{121}	I_{221}	I_{321}	I_{421}	I_{521}	2	2
I_{122}	I_{222}	I_{322}	I_{422}	I_{522}	2	2
…	…	…	…	…	…	…
I_{12J}	I_{2J}	I_{32J}	I_{42J}	I_{52J}	2	2
…	…	…	…	…	…	…
I_{151}	I_{251}	I_{351}	I_{451}	I_{551}	5	5
I_{152}	I_{252}	I_{352}	I_{452}	I_{552}	5	5
					…	…
I_{15J}	I_{25J}	I_{35J}	I_{45J}	I_{55J}	5	5

Input and output data set.

The set of input and output data can be defined as shown in the following table for the TP point between the technological processes and the production processes. Here, we can set the output data values according to the operating personnel impression values given above. The input data can be different corresponding values of the six indicators mentioned earlier. These values can be formed as a result of operation and monitoring over a certain period of time.

The input values I_{Kmn} in this table have the following meaning:

k is the input serial number, *m* is the value of the output and the sixth indicator, respectively, and *n* is the ordinal number of the input value.

The state and output function of neurons in layer I are calculated using the formulas:

$$S1[j]=\sum_{i=1}^{N1} x_i * W1[i,j], j=1,\dots,N1$$

$$Y1[i]=\frac{1}{1+e^{-S1[i]}} \tag{3.3}$$

The state and output function of neurons in layer II are calculated using the formulas:

$$S2[j]=\sum_{i=1}^{N2} x_i * W2[i,j], j=1,\dots,N2$$

$$Y2[i]=\frac{1}{1+e^{-S2[i]}}$$

The state and output function of neurons in layer III are calculated using the formulas:

$$S3[j]=\sum_{i=1}^{N2} x_i * W3[i,j], j=1,\dots,N3$$

$$Y3[i]=\frac{1}{1+e^{-S3[i]}}$$

The neural network associated with each communication channel is trained as independent subnetworks of the general neural network, having the same structure but different coefficients. These subnetworks form a set of networks equal to the number of channels in the maximum case, and the sets created on the basis of input and output values according to the table constitute the data set of the neural network.

Training is carried out according to the following algorithm:

If we take *Rez [k, i]* as the predicted data, the correction parameters for layers III, II, and I are calculated as follows:

$$\cdot\ 3[\mathrm{i}]=(\mathrm{REZ}[\mathrm{k,i}]-\mathrm{Y3}[\mathrm{i}])*\mathrm{f3}(\mathrm{S3}[\mathrm{i}],\ \mathrm{i}=1,\dots,\mathrm{N3}$$

$$\cdot\ 2[\mathrm{i}]=\mathrm{f2}'(\mathrm{S2}[\mathrm{i}]*\sum_{j=1}^{N3} w3[i,j]\delta 3[j], i=1,\dots,N2$$

$$\cdot\ 1[\mathrm{i}]=\mathrm{f1}'(\mathrm{S1}[\mathrm{i}]*\sum_{j=1}^{N2} w2[i,j]\delta 2[j], i=1,\dots,N1$$

The weights of the network layers are corrected using the following algorithms.

For layer I of the network:

$$WS1[i,j]=W1[i,j]+\vartheta * \cdot\ 1[\mathrm{j}]*\mathrm{x}[\mathrm{i}], \mathrm{j}=1,\dots,\mathrm{N1}$$

$$W1[i,j]=WS1[i,j]$$

For the II layer of the network:

$$WS2[i,j]=W2[i,j]+\vartheta * \cdot\ 2[\mathrm{j}]*\mathrm{Y1}[\mathrm{i}], \mathrm{i}=1,\dots,\mathrm{N1}, \mathrm{j}=1,\dots,\mathrm{N2}$$

$$W2[i,j]=WS2[i,j]$$

For network layer III:

$$WS3[i,j]=W3[i,j]+\vartheta * \cdot\ 3[\mathrm{j}]*\mathrm{Y2}[\mathrm{i}], \mathrm{i}=1,\dots,\mathrm{N2}, \mathrm{j}=1,\dots,\mathrm{N3}$$

$$W3[i,j]=WS3[i,j]$$

where ϑ is the speed of the learning process.

The training error for all layers is calculated using the formula:

$$\mathrm{E}=\frac{1}{2}\sum_{i=1}^{N3}(\mathrm{REZ}[\mathrm{k,i}]-\mathrm{Y3}[\mathrm{i}])^2$$

The training continues until the required error threshold is attained. As can be seen from Table I, the training process can take quite a long time. The final result is taken as the value *REZ [k, i]* for the interval under consideration. The network coefficients (weight vectors) obtained after the training process are stored in the database separately for each channel for subsequent use.

III. CONCLUSION

In the article, the main information channels in the network are determined as a result of studying the architecture of the TCCN and the conceptual model of information flows in the TCCN. The article is aimed at solving the following main problems:

- 0 determining the loading of network channels and traffic load,
- 1 determining the informative features for assessing the state of channels and determining the input and output data of a three-layer backpropagation neural network for assessing the state of channels and the probability of external interference in the channels, providing training algorithms. Here, the impressions of the network operating personnel are presented as one of the main informative features that can be calculated and measured. The outputs of the neural network are also formed based on the impressions of the operating personnel. To implement the training process of the neural network, a training schedule is created, on the basis of which the operation and training of the neural network are carried out.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

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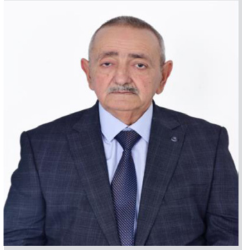
REFERENCES

1. A. G. Goryunov, *Telecontrol and Teleoperation*. Tomsk, 2013, 23p (in Russian). Retrieved from https://portal.tpu.ru/SHARED/a/ALEX1479/study/dis2_TKiTU/Tab2/Uchebnoe_posobie_TK_TU.pdf
2. A. A. Abdullayev, A. A. Javadov, A. A. Levin, and I. A. Nabiyev, *Telemechanical Complexes for Oil Industry*. Moscow: Nedra, 1982, 200p (in Russian).
3. I. Y. Kulikova, and Y. A. Ulanov, *Enterprise Architecture: Textbook; Vladimir State University Named after A.G. and Stoletov N.G. Vladimir*. Publishing House of VlSU, 2020, 124p (in Russian). Retrieved from https://dspace.www1.vlsu.ru/bitstream/123456789/8289/1/01925.pdf
4. V. A. Astapchuk, and P. V. Tereshchenko, *Architecture of Corporate Information Systems: Textbook*. Novosibirsk: Publishing House of NSTU, 2015, 75p (in Russian). Retrieved from https://urait.ru/bcode/531569
5. T. A. Aliev, G. A. Guluyev, A. H. Rzayev, N. E. Rzayeva, F. H. Pashayev, and R. M. Gadimov, "Correlation extremal system for controlling the onset of malfunctions of oil field equipment by analyzing their wattmeter and dynamometer charts" *Mekhatronika, Avtomatizatsiya, Kontrol*, vol. 24, pp. 249–259, 2023. [CrossRef] (in Russian).
6. D. P. Zegzhda, A. F. Suprun, and Y. G. Anisimov. "Assessment of the possibility of upgrading information security systems in the planned time frame, Information security problems," *Computer Systems*, 2024, vol. 4, pp. 80–87 (in Russian).
7. A. Y. Fridman, and V. G. Kurbanov, "Formal conceptual model of industrial-natural complex as a means of controlling computational experiment," *Proc. of SPIIRAS*, vol. 37, pp. 37–60, 2014. [CrossRef] (in Russian).
8. S. Yu. Mirskaya, "Development of a conceptual and logical model of information system of intern training," *Vestn. Severo-Kavkazskogo Federalnogo Univ.*, vol. 6, pp. 107–118, 2018. (in Russian).
9. A. Olivé, "Introduction" in Conceptual Modeling of Information Systems. Springer, 2007, pp. 1-36.
10. V. N. Dubinin, "Conceptual modeling of control systems based on Iec 61499 functional blocks", *Tstu bulletin*, vol. 15, No. 3, 2009, pp. 467–477 (in Russian).
11. Available: https://smoff.ru/howitworks/monitoring-trafika-lokalnoy-seti.
12. F. H. Pashayev, J. I. Zeynalov, and H. T. Najafov, "Development of software and hardware to protect technological processes from cyber threats. Information security problems, " *Comput. Syst.*, vol. 2, pp. 104–116, 2024. Available: https://jisp.ru/o-zhurnale/tekushhij-nomer/ (in Russian).
13. L. Bekteshi, "Implementation of the intelligent traffic monitoring system," *IJETT*, vol. 71, no. 7, pp. 383–393, 2023. [CrossRef]
14. A. Vasilyev, "A brief history of the evolution of cyberattacks," *Int. Res. J.*, vol. 11, no. 137, 2023[CrossRef]8p. (https://doi.org/10.23670/IRJ.2023.137.39) (in Russian).
15. A. Chertkov, "Cybersecurity of industrial automation, " *Control. Eng. Russ.*, vol. 2, no. 68, pp. 22–25, 2017. (in Russian).
16. O. R. Laponina, "Fundamentals of network security. Part1," *Firewalls: Textbook*. Moscow: INTUIT National Open University, 2014, 378 p. (in Russian).
17. Available: https://www.kaspersky.ru/resource-center/definitions/what-is-cyber-security.
18. . M. Pawlicki, R. Kozika, and M. Choras, "A survey on neural networks for (cyber-) security and (cyber-) security of neural networks," *Neurocomputing*, vol. 500, pp. 1075–1087, 2022.[CrossRef].
19. . M. Gallo, G. De Luca, L. D'Acierno, and M. Bott, "Artificial neural networks for forecasting passenger flows on metro lines," *Sensors (Basel)*, vol. 19, no. 15, 3424, 2019, . [CrossRef].
20. . S. Gumaste, D. G. Narayan, S. Shinde, and A. K. Amit, "Detection of DDoS Attacks in OpenStack-based Private Cloud Using Apache Spark", *JTIT*, vol. 82, no. 4, pp. 62–71, 2020. [CrossRef]
21. . R. K. Alekperov, and A. A. Huseynova, "Development of an adaptive model for optimal load distribution in corporate networks," *Telekommunikatsii*, , vol. 9, pp. 17–21, 2012. (in Russian).
22. . , , R. G. Alakbarov, F. H. Pashaev, and O. R. Alakbarov, "Forecasting cloudlet development on mobile computing clouds," *IJITCS*, vol.9, No.11, pp.23–34, 2017. [CrossRef]
23. . *Fundamentals of Neural Networks: Architectures, Algorithms, and Applications* (L. Fausett, Ed.). Englewood Cliffs, United States of America: Prentice-Hall, Incorporated, 1994, 461p, pp. 289–300.
24. R. Rojas. Neural Networks. Berlin: Springer-Verlaq, 1996, pp. 151-184 https://link.springer.com/book/10.1007/978-3-642-61068-4



Fahrad Heydar Pashayev is the author of 175 scientific works. He is a Doctor of Sciences in Engineering and an Associate Professor. He works at the Ministry of Science and Education of the Republic of Azerbaijan, Institute of Control Systems, as the Head of laboratory. His areas of scientific interest include identification methods and control systems, mathematical modeling of technological processes, technical and ecological systems, methods of signal recognition and technical diagnostic systems, decision-making methods in systems of different purposes, and software development.

Javanshir Ibrahim Zeynalov In 1989, Javanshir Ibrahim oglu Zeynalov graduated from the Faculty of "Automation of Production Processes" of the Azerbaijan Oil and Chemical Institute. In 1996, he defended his Ph.D. dissertation in Technology. Since 2000, he has been an associate professor at the "Communication and Information Technologies" department. In 2013, he defended his doctoral dissertation in Computer Science in Mathematics. He is a professor of the Department of Electronics and Information Technologies. Currently, he works as a dean at the Faculty of "Architecture and Engineering" at Nakhchivan State University. He is the author of 95 scientific articles, 2 teaching aids, 4 methodical aids, and one monograph. His scientific work is mainly related to the optimal management of problems related to distance measurements and uncertainties and the application of neural networks to their solution. He is an honored teacher of Nakhchivan Autonomous Republic.

Hasan Taghi Najafov Hasan Taghi oglu Najafov graduated with a bachelor's degree from Nakhchivan University in 2011 in Azerbaijan. He graduated with a master's degree from Nakhchivan State University in 2016 in Azerbaijan. He works as a teacher at Nakhchivan State University. He is PhD student at Nakhchivan State University. His research interests are data processing, computer sciences, and computer and corporate networks. He is the author of 10 scientific papers in different journals and 16 proceedings.