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SECURITY OF COMPUTER NETWORK FUNCTIONING BASED ON A NEURON MODEL OF OVERLOAD CONTROL

The method of ensuring the operation security of computer network based on the proposed overload prediction and detection scheme is considered. Congestion management is performed by adjusting the incoming data flow and analyzing the network performance sensitivity function. The gradient of the sensitivity function characterizes the rate of change of this function and provides the optimal direction for adjusting the speed of the data source.

The results of a comparative analysis of congestion control methods based on the analysis of the queue length and the sensitivity indicator with 1- and 3-step horizons by predicting the state of the network are presented.

Key words: telecommunication network, safety of operation congestion prediction, sensitivity function, gradient, neural system, queue management, prediction horizon

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БЕЗПЕКА ФУНКЦІОНУВАННЯ КОМП'ЮТЕРНОЇ МЕРЕЖІ НА ОСНОВІ НЕЙРОННОЇ МОДЕЛІ КОНТРОЛЮ ПЕРЕВАНТАЖЕННЯ

Запропонований спосіб забезпечення безпеки функціонування комп'ютерної мережі на основі схеми прогнозування і виявлення перевантажень. Керування перевантаженням здійснюється шляхом регулювання вхідного потоку даних і аналізу функції чутливості продуктивності мережі. Градієнт функції чутливості характеризує швидкість зміни даної функції і надає оптимальний напрям для налаштування швидкості джерела даних. Для визначення функції чутливості запропоновано використання простої нейронної мережної моделі динамічної системи. Визначення градієнту за поточним значенням знаку функції чутливості показника продуктивності здійснюється на основі алгоритму адитивного збільшення / множинного зменшення. Даний алгоритм є альтернативою системи прогнозування перевантаження і керування потоком, заснованої на контролі поточного значення величини вхідної черги у порівнянні з заданим порогом. Розглянута нейронна модель для багатокрокового передбачення стану черги на стороні приймача телекомунікаційної мережі.

Представлені результати порівняльного аналізу способів контролю перевантаження на основі аналізу довжини черги і на основі аналізу показника чутливості з 1-кроковим та 3-кроковим горизонтами передбаченням стану мережі. Дослідження проведене для синусоїдальної та випадкової функцій вузького місця черги. Показано, що ключові показники ефективності мережі для схеми на основі функції чутливості кращі, ніж для схеми на основі аналізу довжини вхідної черги. Для систем на основі аналізу функції чутливості схема з трикроковим горизонтом передбаченням стану забезпечує кращу продуктивність і меншу величину черги на обслуговування ніж схема з однокроковим горизонтом.

Ключові слова: *комп'ютерна мережа, безпека функціонування, прогнозування перевантаження, функція чутливості, градієнт, нейронна система, управління чергою, горизонт передбачення.*

Introduction

Efficiency and safety of functioning of a computer (telecommunications) network are largely determined by the methods used to manage data flows and routing. The key task of ensuring the necessary quality of information system functioning is forecasting and prevention of overloads. Data traffic management should ensure the avoidance or minimization of the appearance of congestion [1-3], which contributes to reducing the risk of data loss, safe operation and minimization of data delay - key indicators of network efficiency. Note that a computer network is a complex system used by competing users [3-6].

Devices and network resources (processor time, bandwidth, name space, logical channels) have limited (finite) capabilities, which leads to conflicts between users. This can cause a significant decrease in system performance and data loss. Bandwidth decreases and can lead to network collapse, i.e. bandwidth drops to zero and a complete loss of data occurs. This is typical behavior of "competing" systems.

In scientific literature by definition [7-9]: congestion is defined as "user data loss caused by increased network load". There are also other definitions of overload, but they do not contradict each other.

Congestion has the most significant effect on the key performance indicators of the computer network and the quality of user service. The above determines the relevance and necessity of conducting research in this direction.

Statement of the ensuring security problem of information exchange
Based on overload management systems

A fairly detailed classification of congestion forecasting methods is proposed in the works [10-11], in which the RED, TSR Veno, Tail Drop, WRED, etc. algorithms were analyzed. It is shown that the task of data flow and overload management is one of the areas of ensuring cyber security of information exchange in the telecommunications network. These works are more of a review nature, quantitative evaluations of the effectiveness of the considered methods are not provided. The reason for this, obviously, is the lack of statistical data of a sufficiently large volume.

In [12], the methods of overload forecasting based on the analysis of the sensitivity indicators of the initial characteristics of the computer network as a mass service system are considered. However, the asymptotic characteristics of the sensitivity functions have not been definitively determined in the work, and the analytical expressions for the functional relationship between the parameters of the sensitivity functions and the corresponding parameters of the queue management system have not been obtained.

The aim of this research is the improvement and development of a method of overload control and forecasting using feedback on the sign of the sensitivity function of computer network performance, as well as modeling and conducting a comparative analysis of known and proposed solutions for various functions of maintaining the incoming data flow.

Adjustment of the input flow of data based on the neural network model

In [13], the use of a simple neural network model of a dynamic system with the use of feedback on the sign of the sensitivity function of network performance is proposed for congestion prediction. The proposed algorithm of additive increase / multiple decrease determines the change in the speed of the data source depending on the sign of the sensitivity function of the performance indicator. This algorithm is an alternative to the system based on threshold filling of the queue, i.e. congestion control based on the queue length indicator.

The algorithm and regulation rule of additive increase / multiple decrease of source speed is defined in the form of an analytical expression

$$\Delta J(t) = \partial J / \partial R(t) = -E(t+i\tau) \, \partial \hat{G}(t+i\tau) / \partial R(t), \quad i = 1, 2, \ldots L,, \tag{1}$$

where $J(t)$ – estimated data on the presence or threat of overloading;

$\Delta J(t)$ – the gradient of the congestion assessment system at a moment in time t;

$G(t)$ – the length of the queue or service delay at a point in time t;

$\hat{G}(t+i\tau)$ – the predicted length of the queue or service delay at a point in time $t+i\tau$, neural network output;

$R(t)$ – the instantaneous rate of the queue at the entrance at the instant of time t;

$E(t)$ –monitored parameter deviation function (error);

τ – timing period, system clock frequency period;

L – prediction horizon.

Note that the derivative $\partial \hat{G}(t+i\tau) / \partial R(t)$ in our case, it represents the network sensitivity parameter - the gradient of the system efficiency indicator [7].

Based on the expression (1), the parameter is determined R_{qs} – speed of queue service.

Cost function), as the objective function of the presence of congestion is defined as follows:

$$J = \frac{1}{2} e^2 (t+i\tau) = \frac{1}{2} \left[Q - \hat{G}(t+i\tau) \right]^2, \quad i=1,2,\ldots L$$

Here Q is the maximum permissible value $G(t)$.

Control signal in (1) for $R(t)$ must provide the minimum value of the quantity J. The control variable is determined according to the gradient descent rule [14]:

$$R(t+\tau) = R(t) + \Delta R(t) = R(t) - \eta \, \partial J / \partial R(t)$$

Overload indicator $B(t)$ is formed depending on the gradient of the system $\Delta J(t)$ at a moment in time t [13]:

$$\begin{Bmatrix} B(t) = 0 \ \ if \ \ J(t) < 0 \\ \\ B(t) = 1 \ \ if \ \ J(t) \ge 0 \end{Bmatrix}. \tag{2}$$

In work [13], the scheme of regulation of the input flow based on the analysis of the sensitivity indicator is presented. However, it does not provide a complete picture of the guaranteed overload prediction based on the analysis of the sensitivity index.

It should be noted that the tasks of flow control and congestion prevention have certain differences. Congestion prevention ensures that the network can handle the proposed traffic. To do this, it is necessary to analyze the behavior of all routers, data forwarding and storage processes, as well as take into account many other factors that reduce the bandwidth of the network [15, 16].

Flow control, on the contrary, refers to the traffic between two specific stations - the sender and the receiver. The task of flow control is to match the transmission speed of the sender with the speed at which the receiver is able to receive the flow of packets. Flow control is usually implemented using feedback between the receiver and the sender.

It should be noted that congestion control algorithms also use feedback in the form of special messages regarding slowing down of data transmission rates by various senders. Thus, a host can receive a slow transmission message in two cases: when the stream being transmitted cannot be handled by the receiver, or when the entire network cannot handle it.

In fig. 1 shows the overload detection scheme based on the analysis of the sensitivity indicator and the regulation of the incoming data flow (RIDF) from data sources $D_1 \ldots D_s$. based on sensitivity index analysis.

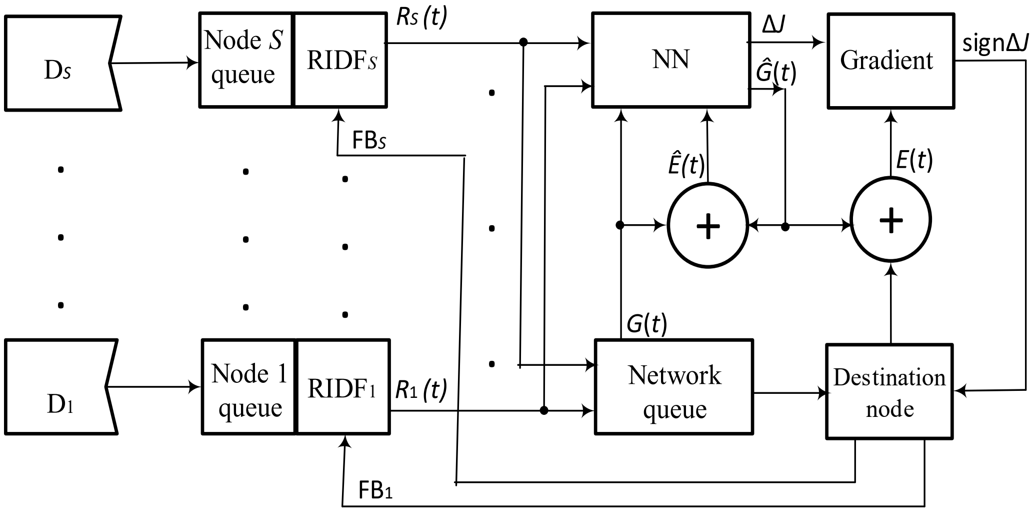


Fig. 1. Overload detection scheme based on the analysis of the sensitivity indicator

Note that at the points of formation of deviations is real $G(t)$ and the predicted parameter $\hat{G}(t)$ calculated by the neural network NN is counted with different signs.

The analytical presentation of the control algorithm for additive increase / multiple decrease of source speed is as follows [13]:

$$R(t+\tau)=\begin{Bmatrix} R(t)+F^{+},\ \Delta J(t-\tau)<0 \\ \\ R(t)-F^{-},\ \Delta J(t-\tau)\geq 0 \end{Bmatrix}.$$

The value of quantities $R_1(t) \ldots R_S(t)$ (rates of regulated input streams from data sources $D_1 \ldots D_S$) enter the input layer of the neural network NN, and incoming streams from sources to the network queue. Based on the analysis of the received data and the current value of the network queue length $G(t)$ the output layer of the neural network tracks the value of the function J (presence or threat of overloading) and its deviation. The sign of the magnitude of the deviation sgnΔJ is taken into account by the destination node when forming the feedback signal and the threat of overload.

The considered overload detection circuit can also be built using parameters feedback $FB_1 \ldots FB_s$ and adjusting the input flow based on the analysis of the sensitivity indicator [13].

4. Comparative analysis of the efficiency of overload detection schemes

In work [17], a connection was considered in which the numerical value of the bottleneck is determined by a sinusoidal function integer[35(1+sin(2πτ/T))+10] packets/unit of time (integer - whole part of a number). The connection is characterized by the following set of parameters:

– peak velocity of the source $R_{\max}$=100 packets/unit of time;
– minimum speed $R_{\min}$ =0 packets/unit of time;
– unit of time τ =0,25 мс;
– the overload threshold is set at Q = 500 packets;
– coefficient of additive increase $F^{+}=R_{\max}/16$;
– coefficient of multiplicative reduction $F^{-}=15/16$;

For comparative analysis, we will choose a connection in which the bottleneck of the queue is characterized by a "random" service speed. The set of connection parameters is the same as for the sinusoidal function.

As in work [17], we will present the simulation results based on the following overload control methods:

a) analysis of queue length (Fig. 2);

b) analysis of the sensitivity indicator with 1-step prediction of the network state (Fig. 3);

c) analysis of the sensitivity indicator with a 3-step prediction of the network state (Fig. 4).

The graphs have the following designations:

– real values of the parameters are given by the dashed line, predicted by the solid line;

– G – queue size (number of requests);

– R_{qs} – speed of queue service, (requests/sec);

– R_{ds} – speed of the data source, (requests/sec).

Let's determine the following performance indicators for modeling:

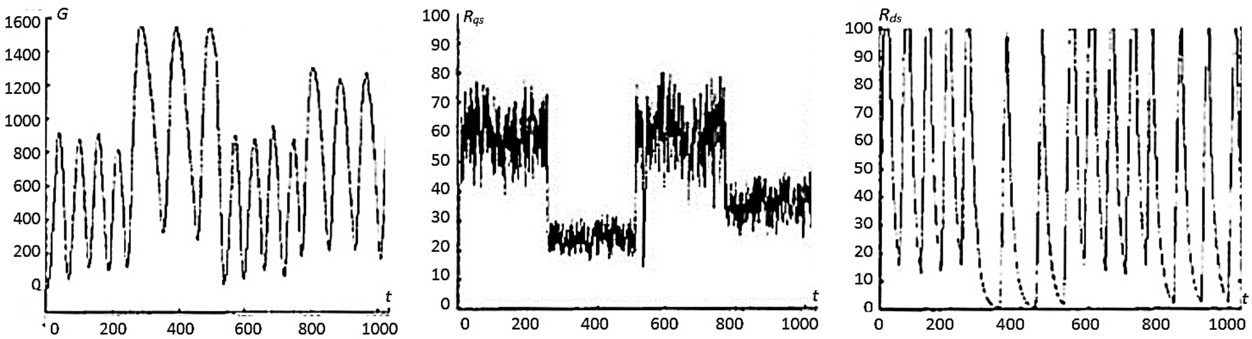
– $G_{\max} = \max\{G(t),\ 0 \le t \le T\}$: – maximum value G(t) represents the buffer size required by the bottleneck to avoid packet loss, T – simulation execution time;

– average queue size and source speed, defined as $\hat{f} = \frac{1}{T}\int_{0}^{T} f(t)\,dt$;

– the variance of the queue size and the source speed, defined as $\sigma^2 = \frac{1}{T}\int_{0}^{T} [f(t) - \hat{f}]^2\,dt$.

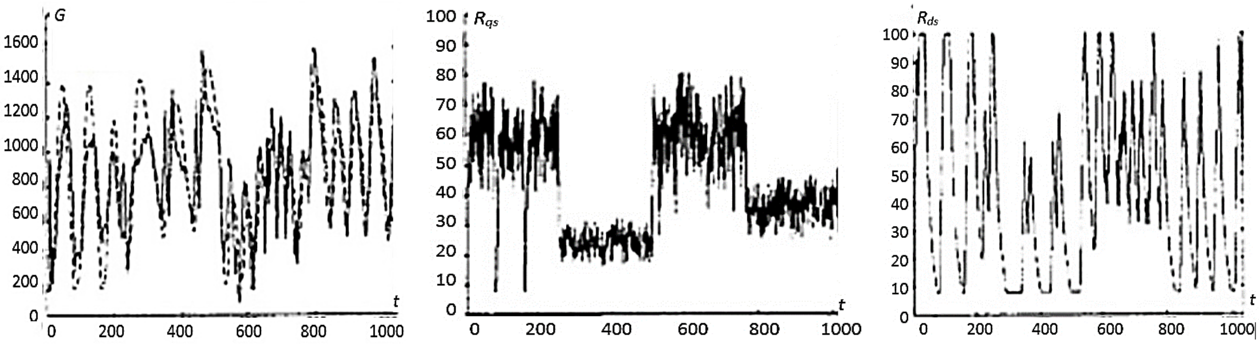
As mentioned above, the overload indicator $B(t)$ according to (2) is formed depending on the gradient of the system $\Delta J(t)$. Therefore, for the completeness of the comparative analysis of the systems, it is advisable to consider the graphs of the gradients $\Delta J(t)$ systems for connections with sinusoidal and random service functions.

Such graphs for systems based on the analysis of the sensitivity indicator are shown in fig. 5 with 1-step and in fig. 6 with 3-step network status prediction.



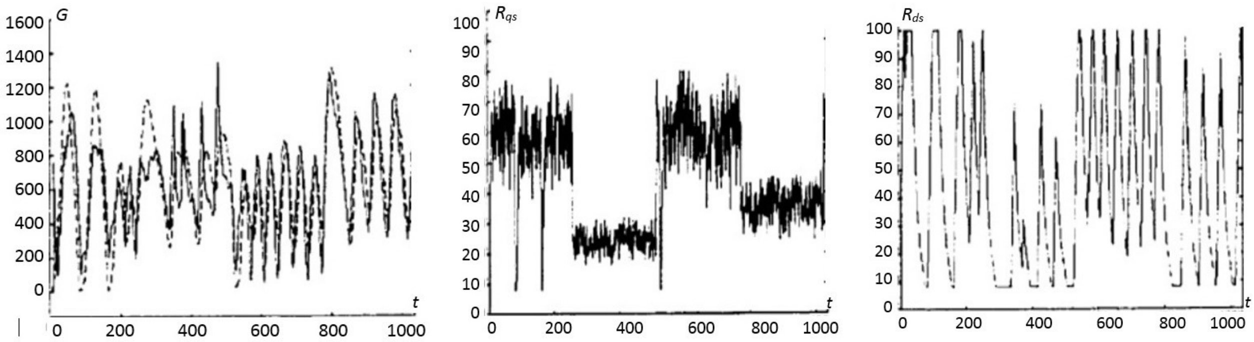
a)* queue size *G ***b*) speed of queue service R_{qs}** ***c)* source speed R_{ds}**

Fig. 2. Congestion control based on queue length analysis



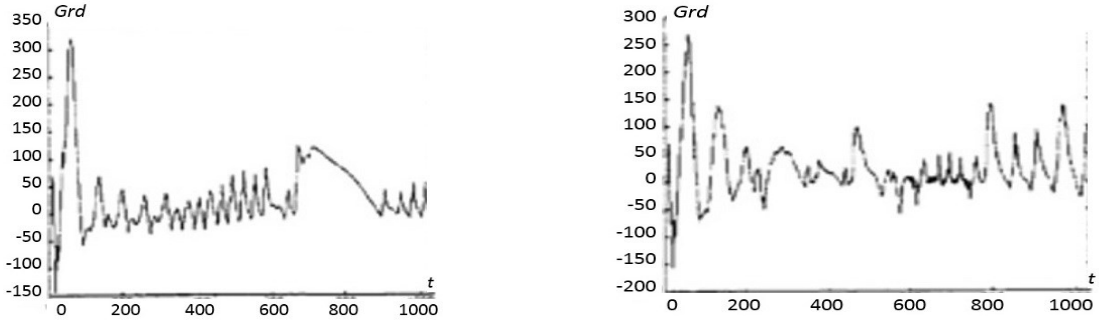
a)* queue size *G ***b*) speed of queue service R_{qs}** ***c)* source speed R_{ds}**

Fig. 3. Circuit-based overload control with 1-step prediction



a) **queue size** ***G*** *b)* **speed of queue service** R_{qs} *c)* **source speed** R_{ds}

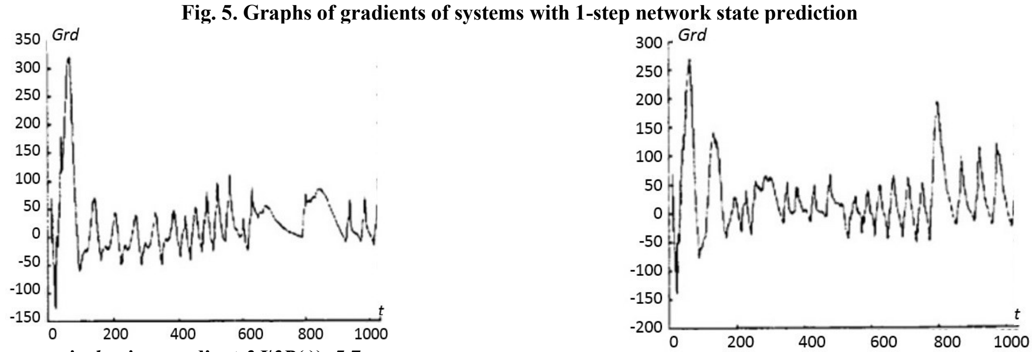
Fig. 4. Circuit-based overload control with 3-step prediction



vertical axis **– gradient ∂J/∂R(*t*))** ***vertical axis*** **– gradient ∂J/∂R(*t*))**

a) **Bottleneck queue: "sinusoidal" service rate** *b)* **Bottleneck queue: "random" service rate**

Fig. 5. Graphs of gradients of systems with 1-step network state prediction



vertical axis **– gradient ∂J/∂R(*t*)) 5.7** ***vertical axis*** **– gradient ∂J/∂R(*t*) 5.8**

a) **Bottleneck queue: "sinusoidal" service rate** *b)* **Bottleneck queue: "random" service rate**

Fig. 6. Graphs of gradients of systems with 3-step network state prediction

A short list of simulation results is given in Table 1, where G_{av} and R_{av} denote the time-averaged queue size and source speed.

Table 1

List of simulation results

Approach	Type of service	$G_{\max}$	G_{av}	$\sigma^2(G)$	Index $G_{\max}$	R_{av}	$\sigma^2(R)$
On a queue basis	Random	1560	724.5	187569.3	757	45.1	1370.1
	Sinusoidal	1556	713.8	179305.5	281	45.7	1211.4
Gradient: 1-Step	Random	1293	666.2	108986.4	481	44.4	878.3
	Sinusoidal	1428	653.3	86115.5	48	44.4	1066.9
Gradient: 3-Step	Random	1307	622.9	88526.7	800	44.2	929.9
	Sinusoidal	1443	628.7	89936.5	49	44.5	1139.7

Analysis of the given graphs shows the following:

1) Key indicators of network efficiency and the quality of congestion prediction are practically independent of the functions of servicing the incoming data flow (requests).

2) Queue size G is smaller for the sensitivity-based scheme than for the queue-based scheme. However, the sensitivity-based scheme with 3-step state prediction provides better performance, i.e., lower service queue size, than the corresponding 1-step prediction scheme.

3) A scheme based on queue size analysis is more sensitive to changes in the queue service rate than sensitivity-based schemes. It should be noted that in the scheme based on the queue, with a significant decrease in

the service speed, the size of the queue increases extensively beyond the previously observed values. The increase in queue size is more stable under the same conditions for sensitivity-based schemes.

4) Source speed fluctuations R_{ds} are smaller for the sensitivity-based scheme than for the queue-based scheme. Analyzing the schemes based on sensitivity, we note that for the 3-step prediction, the feedback control signals (ie, the binary congestion bit) received in the data source from the network queue are insignificant in age and more closely reflect the network conditions compared to the 1-step prediction process. In feedback-based congestion control schemes with significant propagation delays, the control signals received at the sources may be outdated, and as a result, the control response will take effect only after some delay. The disadvantage of prediction based on the analysis of the state of the queue is that the longer the delay we make the prediction, the more difficult it is to obtain predictions with small errors.

Note that the results of the analysis according to p. 2, 3, 4 are valid for both functions of maintenance of the incoming flow of data (requests).

In this work, in contrast to traditional overload control systems for the maintenance of incoming data flow (requests) based on changes in the status and parameters of queues, the proposed system works according to optimal algorithms for setting weight parameters. Thanks to this, the accuracy of determining the control signals is increased, the impact of their delay is reduced and, as a result, the average resource consumption is minimized.

The elaborated telecommunication network control system essentially represents a static neural network, which includes feedback via a delay element for one cycle [13, 17]. This assumption for packet telecommunications networks is very logical.

Conclusions

The conducted studies show that the sensitivity-based approach is able to reduce the magnitude of queue fluctuations (as shown by the variance value in Table 1), but cannot completely eliminate fluctuations. Using the sensitivity of the system's performance function allows timely detection of congestion, and this leads to a timely feedback control response to the data sources. The use of neural architecture to implement the sensitivity function and the gradient of the objective function while increasing the prediction horizon provides acceptable values of the delay of feedback messages and thus improves the accuracy of prediction and detection of congestion in telecommunication networks.

A method of managing telecommunications network overloads using a neural network as a monitoring and control system has been developed. A proposed and substantiated scheme for multi-step prediction of the state of the queue. For prediction and early detection of overload, the apparatus of the general theory of sensitivity with indirect feedback and control of the activity of message sources is used. The results of this theory are used to build a control system with indirect feedback, which allows saving channel and computing resources.

As a result of the verification of theoretical results by means of computer simulation, quantitative comparative evaluations of the efficiency (accuracy and required computing resource) of the developed method and previously existing methods were obtained. It can be argued that with the perfect architecture of the neural network, suitable for modeling the dynamics of the system, it is possible to obtain a completely satisfactory performance of the telecommunication system as an object of control.

The resulting solutions make it possible to predict the appearance of congestion and, as a result, significantly reduce the risk of data loss during information exchange in the network.

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