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MATHEMATICAL MODELING OF INTERNET OF THINGS TRAFFIC IN AD-HOC NETWORKS WITH HYBRID ROUTING

І.В. Прокопович, О.С. Лопаков, В.В. Космачевский, Ю.І. Бабич, П.А. Швагирев, О.В. Денисова. **Математичне моделювання трафіку Інтернету Речей в AD-HOC мережах з гібридною маршрутизацією.** У даній роботі розглядається вплив трафіку Інтернету Речей, який формується системами моніторингу і диспетчерського управління або іншими системами, коли властивості цього трафіку описуються властивостями регулярного потоку. Оцінюється вплив цього трафіку на такі основні показники QoS як затримка доставки даних і вірогідність втрат. В якості моделі мережі зв'язку розглядається система масового обслуговування (СМО) з комбінованою дисципліною обслуговування. Аналіз тенденцій розвитку інфокомунікаційної системи показує, що в перспективних мережах зв'язку істотно збільшиться частка трафіку IP, що призведе до його впливу на якість обслуговування. З урахуванням того, що трафік в мережі буде містити і трафік телеметрії, цей вплив може чинити істотний вплив на якість його обслуговування. Сучасні мережі AD-HOC побудовані на основі принципу «усереднення». Згідно зі статистикою, безліч потоків даних з випадковими варіаціями щільності дадуть в результаті якийсь усереднений трафік. Але цей підхід не працює в мережах, схильних до прояву потужних пікових викидів. Такі своєрідні, локалізовані в часі «стовпотворіння» (congestions) викликають значні втрати пакетів, навіть коли сумарна потреба всіх потоків далека від максимально допустимих значень. Це негативно позначається на ефективності використання пропускної здатності мереж. Класична пуассонівська модель трафіку, яка використовувалася при проектуванні мережевих протоколів, не відображає реальної дійсності: дані реального мережевого трафіку мають властивість самоподібності.

Ключові слова: Інтернет Речей, (IoT), AD-HOC-мережа, функція автокореляції, математичне очікування, дисперсія, коефіцієнт Херста, найпростіший і самоподібний потік

I. Prokopovych, O. Lopakov, V. Kosmachevskiy, Y. Babych, P. Shvahirev, O. Denysova. **Mathematical modeling of Internet of Things traffic in AD-HOC networks with hybrid routing.** This paper considers the impact of Internet of Things traffic, which is formed by monitoring and control systems or other systems, when the properties of this traffic are described by the properties of the regular flow. The impact of this traffic on such key QoS indicators as data delivery delay and probability of loss is estimated. As a model of communication network the system of queuing (SMO) with the combined discipline of service is considered. The analysis of trends in the development of the infocommunication system shows that the share of IP traffic in promising communication networks will significantly increase, which will lead to its impact on the quality of service .Given that the traffic in the network will also include telemetry traffic, this impact can have a significant impact on the quality of its service. Modern AD-HOC networks are based on the principle of "averaging". According to statistics, many data streams with random variations in density will result in some average traffic. However, this approach does not work in networks prone to strong peak emissions. Such peculiar, time-localized "congestions" cause significant packet losses, even when the total demand of all flows is far from the maximum allowable values. This negatively affects the efficiency of network bandwidth utilization. The classical Poisson model of traffic, which was used in the design of network protocols, does not reflect the real reality: the data of real network traffic have the property of self-similarity.

Keywords: Internet of Things, (IoT), AD-HOC-network, autocorrelation function, mathematical expectation, variance, Hearst coefficient, simplest and self-similar flow

1. Introduction

One of the most promising areas of development of telecommunication networks and ICS in general is the implementation of the concept of the Internet of Things (IoT) [1], which appeared largely

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due to the development of technologies and networks of wireless communication and means of receiving and processing information. This concept assumes an increase in the availability of information, unlimitedly expanding the concept of accessibility, both in the spatial and temporal domains (the availability of information about everything, everywhere and at any time) [2, 3, 4]. This formulation, in practice, does not limit the scope of application of IoT technologies, which creates the prerequisites for an increase in the number of corresponding devices – IoT network nodes. Along with this, one should expect changes in the properties of traffic served in communication networks. In the present time, a change in a number of traffic properties is noted, which is due to an increase in the number of automatic devices connected to the network that generate traffic, the properties of which differ from the properties of traffic produced by people. Such changes require the development of appropriate approaches to solving the problems of building IoT both in terms of traffic servicing and in terms of choosing a network structure. In this concept, Internet things (or just things) are understood as objects of the world around us (physical objects) or the information world (virtual objects). These objects must be identifiable, and it must also be possible to integrate them into existing communication networks. Accordingly, every Internet thing must satisfy two conditions: identifiability (be able to be addressed) and the ability to interact with the network, i.e. must have an appropriate interface. In fact, if these two conditions are fulfilled, an Internet thing can be considered as an element of a communication network, and since, potentially, it can have all the functions of network nodes, it can be considered as a network node. Depending on the used communication technologies and methods of building the IoT network, this can be an end node, which is a source or receiver of information, or, for example, a node that performs traffic transit functions. This creates potential prerequisites for the formation of network structures with a significantly higher density of nodes than was previously the case in telecommunication networks.

2. Analysis of publications and problem statement

One of the priority directions of development of the infocommunication system is the organization of the Internet of Things (IoT) [5, 6], the concept of which is reflected in [7]. The development of the IoT is an extremely important step, as it affects almost all areas of human activity. The penetration of the IoT will contribute to the availability of more and more information, the growth of opportunities for its analysis, the formation of decisions and actions based on its results.

The second important direction in the development of the telecommunications system is expressed by the concept of the tactile Internet (TI) [8], which implies a significant increase in the requirements for the quality of service (QoS) of traffic, which are imposed by new interactive services. An example is the construction of monitoring and dispatch control networks [9], in terms of the development of IoT, telemedicine applications and unmanned vehicles. Comparing the construction of the IoT with the construction of telemetric and telemechanical systems [10], one can notice a lot in common. The fundamental novelty of these areas consists, first of all, in the potentially possible number of monitoring and control devices, in the possibilities of their penetration to the most varied levels of technological and other processes, as well as in the requirements for QoS, in particular, for probabilistic and temporal parameters. The need to deliver data between a large numbers of devices, which potentially can significantly exceed the number of subscribers of existing communication networks, sets the task of ensuring the availability, QoS, reliability and stability of the functioning of communication networks in such conditions.

3. Unresolved problem area

In view of the fact that the nature of IoT traffic, in general, differs from the traffic of other services, it makes sense to assess its characteristics and impact on the quality of service. According to [10, 11, 12], the traffic generated by devices of the Internet of Things can be conditionally divided into three characteristic types: deterministic – produced by devices operating according to a rigidly specified schedule; deterministic technological – necessary to maintain the functioning of the system and mediated, i.e. generated as a reaction to some external events. The traffic generated by IoT devices can be served in conjunction with traffic from other communication services, for example, with traffic

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from base stations of mobile communication systems, wireless broadband access points and other network nodes. Such traffic has the properties of aggregated and must be investigated and modeled.

4. Purpose of the article

The aim of the study is to develop a mathematical model of IoT traffic in AD-HOC networks with hybrid routing, which will differ from the known models in that it will allow assessing the quality of service differentiated for each of the traffic flows entering the common service system. The article also explores the definition of aggregated traffic for the Internet of Things in AD-HOC networks. The proposed model and method of servicing the traffic of the Internet of Things make it possible to take into account its influence on the quality of functioning when choosing the parameters of the communication network serving it.

5. Aggregated traffic in AD-HOC networks

Aggregation of traffic in the network solves the problem of fault tolerance and summation of the capacity of data transmission channels involved in the aggregation. Typically, most traffic flows in modern networks are aggregated. They consist of many streams that form them. These are streams from various devices (users), streams of various services, etc. In data transmission networks, there are a large number of queues (buffers) for transmission in network nodes, which affect each other in the sense that a stream leaving one queue enters one or several other queues, possibly after merging with parts of other streams from any other queues. From an analytical point of view, this complicates the nature of the processes of entering the queues located in the direction of flow. The main difficulty lies in the fact that when packets are transmitted outside the first queue in relation to the point of their entry into the network, the intervals between the moments of packet arrival become strongly dependent (correlated) with the packet lengths, or rather with the time of their transmission. In real networks, when packet lengths and intervals between arrival times are correlated, numerical modeling shows that at high loads, the average packet delivery delay is less than in the ideal case, when there is no described mutual dependence. However, in the case when the loads are small, the opposite is true. The development of data transmission networks has led to the widespread use and use of self-similar traffic models for modeling. The definition of self-similarity of traffic is often based on the autocorrelation function of the flow. Suppose that the target process is specified by the sequence $X=(X_1, X_2, ..., X_t)$, where $t=1, 2, ..., N$.

Then its autocorrelation function can be defined as:

$$r(k)=\frac{\sum_{i=1}^{N-K}(X_i-\bar{X})(X_{i+k}-\bar{X})}{(N-k)\sigma^2}, \quad (1)$$

where N is the number of elements in the sequence; σ^2 – dispersion.

An aggregated process (stream) means a process (stream) defined by a sequence of blocks. Blocks (elements of this sequence) are obtained from the original stream by averaging it over blocks of m consecutive elements. An aggregated process over blocks of length m can be written as:

$$X^m=(X_1^{(m)}, X_2^{(m)}, \ldots, X^m), \quad (2)$$

where $X_t^{(m)}=\frac{1}{m}(X_{tm-m-1}+...X_{tm})$.

Its autocorrelation function is $lm(k)$.

The flow X is strictly self-similar if $lm(k)=r(k)$, for $m=2, 3, .., N$. Also, the flow is strictly self-similar if the autocorrelation functions correspond to formula (1), and for aggregated streams correspond to formula (2) obtained from it when aggregating into blocks of arbitrary size. In this case, the autocorrelation functions of the original stream must be equal. In other words, the correlation coefficient does not change when the stream is averaged over blocks of arbitrary size. For example, combining multiple traffic sources with alternating periods A and B creates aggregated traffic that is self-similar. Aggregated data transfer traffic can be viewed as a superposition of sources that transfer the requested file during a certain period A, and period B corresponds to the time interval between transfers. The characteristics of such traffic appear to be robust to network operations such as splitting, aggregation, queuing, management, and shaping. Self-similarity is preserved when homogeneous and

heterogeneous, that is, independent, traffic sources are superimposed, and this property takes place under a wide range of conditions: both in cases of changes in bandwidth and buffer capacity and when mixing with other traffic.

In IoT networks, aggregation of flows occurs in relation to traffic flows produced by terminal devices, i.e. internet things. Depending on the structure of the IoT network, traffic aggregation can occur at different levels. For example, in a star structure, which is typical for data collection networks, traffic aggregation occurs at the gateway level (or gateways if there are several). In networks of a tree structure, aggregation of flows also occurs at the level of transit nodes of the network, which, in most cases, can be Internet things themselves. It is also worth noting the features that arise when using wireless technologies for organizing an IoT network. They consist in the fact that the properties of an aggregated traffic stream can be influenced by streams that are not actually part of this aggregated stream, but nevertheless affect its service. The reason for this is the use of a common distribution environment, which may be busy serving a third-party thread at some points in time. This effect complicates the analysis, but it can be taken into account when choosing the properties of the aggregated flow service system in the IoT network model.

For the analysis, the model shown in Fig. 1 was chosen. It consists of an IoT traffic generator that simulates the operation of one device and a traffic generator for traditional communication services and TI traffic, which is denoted as H2H + TI. The generated traffic flows arrive at a communication node, the model of which is represented by a queuing system with a combined service discipline (with waiting and failures). The average service time of a packet (message) is $\overline{t}$.

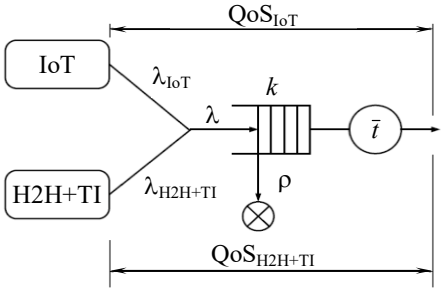

Fig. 1. Aggregated traffic service model

We will denote the traffic intensity of the Internet of Things as λ_{IoT} and the H2H traffic will be denoted as λ_{H2H}, the intensity of the aggregated flow $\lambda = \lambda_{IoT} + \lambda_{H2H}$. With a certain probability ρ, the packet arrives at the input of a system in which all positions in the queue are occupied and gets rejected (losses occur). At the output of the system, the aggregated flow has a total intensity $\overline{\lambda}$. The properties of the mixed stream at the input of the system are determined by the properties of both streams; therefore, in general, they differ from both the properties of traditional traffic and the properties of IoT traffic. The operation of this system will be characterized by indicators of the quality of service: the probability of losses (refusals) of packets (messages) and the delay in packet delivery (waiting time in the queue and service time). Various services generating traffic in the communication network have specific requirements for the values of the quality of service indicators. The process of servicing packets (messages) affects the properties of the served traffic, which then enters other network elements; therefore, the properties of the served traffic at the output of the system are also of significant interest.

When studying the mutual influence of the traffic flows, the quality of service indicators separately for IoT and H2H traffic flows will be evaluated.

IoT traffic service model

The model of the queuing system described above can be represented as the *G*/*G*/1/*k* system. For this system, there are no accurate analytical models that allow us to estimate the probability of packet loss and delivery delay (waiting time in the queue). In [13], the diffusion approximation method is used to estimate the probability of losses in such a system with known distribution parameters describing the traffic at the input and the packet service process, and the following expression for an approximate estimate is obtained:

$$p = \frac{1-\rho}{1-\rho^{\frac{2}{C_a^2+C_s^2}n_b+1}}\rho^{\frac{2}{C_a^2+C_s^2}n_b}, \quad (3)$$

where C_a^2 and C_s^2 – quadratic coefficients of variation of the distributions of the input flow and service time, respectively; n_b – buffer size; ρ – system boot.

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An approximate estimate of the average packet delivery time can be obtained using [14]:

$$T = \frac{\rho \overline{t}}{2(1-\rho)}\left(\frac{\sigma_a^2 + \sigma_s^2}{\overline{t}^2}\right)\left(\frac{\overline{t}^2 + \sigma_s^2}{\overline{a}^2 + \sigma_s^2}\right) + \overline{t}\ , \tag{4}$$

where σ_a^2, σ_s^2 – the variance of the time interval between packets and the service time; $\overline{a}$ – the average value of the interval between packets; $\overline{t}$ – average service time.

Formula (4) determines the average packet delivery time for the general type of traffic.

Since we are interested in a separate assessment of the quality of service of H2H traffic and IoT traffic, it makes sense to investigate the applicability of the above approximate solutions for assessing the quality of service of an aggregated traffic flow. We will assume that the human-to-human background traffic flow (H2H) has the properties of a self-similar flow (the value of the Hurst coefficient H = 0.7...0.9). This assumption is based on the fact that a large proportion of traffic in modern communication networks is video transmission. As a rule, video playback by modern players generates self-similar (burst) traffic. Thus, this assumption about the properties of subscriber traffic is quite acceptable. Let's also make the assumption that M2M traffic is a deterministic flow, defined as a periodic process of sending data to the monitoring system. This assumption is based on the fact that in many cases M2M traffic is generated by monitoring and supervisory control (SCADA) systems that periodically poll the status of the sensors.

Researching the Impact of IoT Traffic on Quality of Service

To build a simulation model, the AnyLogic simulation system was chosen [15], which allows creating discrete event simulation models. To simulate a self-similar flow, a generator of a sequence of independent events was used, the time intervals between which are random and have a Pareto distribution:

$$f(x) = \begin{cases} \dfrac{k x_m^k}{x^{k+1}}, & x \ge x_m; \\ 0, & x < x_m, \end{cases} \tag{5}$$

where x_m and k – distribution parameters.

Based on formula (5), we determine the moments of a random variable.

The mathematical expectation and variance are determined according to:

$$E(x) = \frac{k x_m}{k-1}, \quad D(x) = \left(\frac{x_m}{k-1}\right)^2 \frac{k}{k-2}. \tag{6}$$

Fig. 2 shows examples of the implementation of the simplest (H = 0.50) and self-similar flow (H = 0.75).

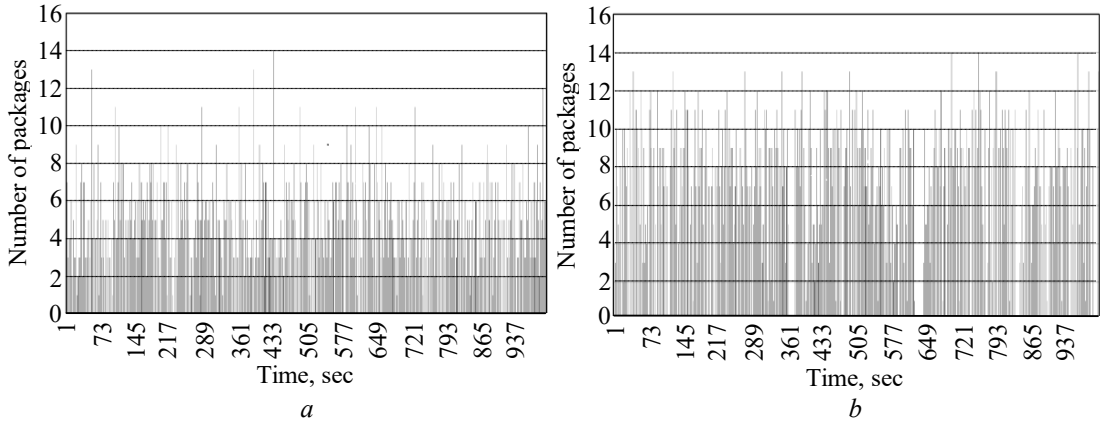

Fig. 2. The simplest (*a*) and self-similar (*b*) flows

A deterministic stream is a regular stream with a given packet rate. Figure 3 shows the implementation of aggregated traffic (H2H + M2M) with a Hurst coefficient value H = 0.8.

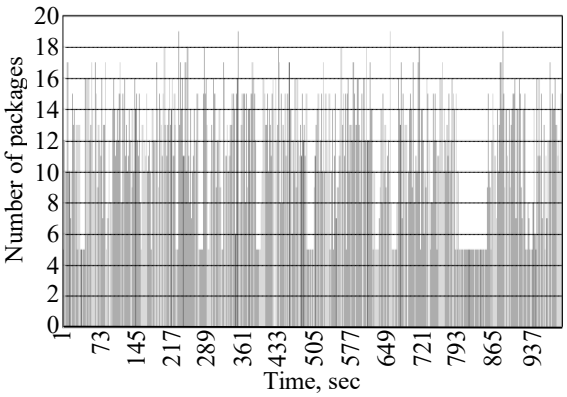

Fig. 3. Implementation of aggregated traffic (H = 0.7)

The Hurst coefficient is estimated by the method of analysis of variance changes [16] based on formulas (6). The graphs of the dependences of the variance of the incoming and outgoing flows on the flow aggregation interval are shown in Fig. 4.

This example is given for a relatively high traffic volume (0.9 Earl). As will be shown below, the value of the Hurst coefficient of the served flow depends on the load intensity, at a high value of which the properties of the output flow are determined by the properties of the service process. When constructing the model, it is assumed that the service time should reflect the time of packet transmission over the communication line [17]. The transmission time of a packet is determined by the packet size and the line rate. If the latter is constant (such an assumption can be made for wired communication lines), then the transmission time is determined only by the size of the packet and the distribution function is determined by the distribution function of the packet length. Let's assume that the minimum and maximum packet sizes are limited. Based on the analysis of the results of a sufficiently large number of measurements, it is concluded that a large proportion of packets in wired communication networks have either a maximum length or a relatively short length. Packages with intermediate lengths make up a significantly smaller percentage. Therefore, to approximate the distribution of the packet length for modeling purposes, the beta distribution is chosen [18]:

$$f(x) = \frac{1}{B(u,v)} x^{u-1}(1-x)^{v-1}, \tag{7}$$

where u, v – form parameters; $B(u, v)$ – beta feature.

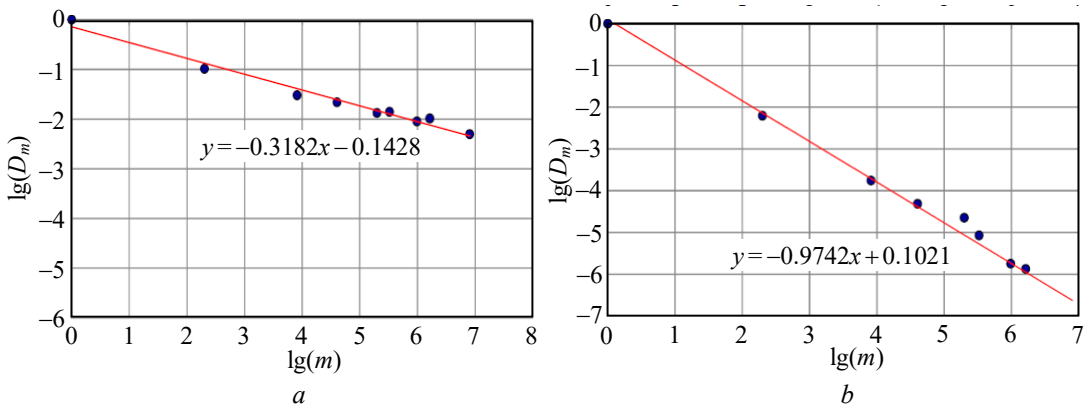

Fig. 4. Estimation of the Hurst coefficient for incoming (*a*) and served (*b*) streams (H = 0.80 and H = 0.51, respectively)

According to the above formula (7), we will use the beta distribution of the packet length typical for Internet traffic. Different IoT applications can create packets of different lengths, however, in this model, we focus on monitoring and dispatching services, the implementation of which currently uses packets of equal length (required to represent telemetry data). In this model, we assume that the length of the IoT packets is constant ("short" packets).

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6. Analysis of simulation results

As a result of simulation, empirical dependences of the probability of packet loss on traffic intensity were obtained, differentiated for IoT traffic and background traffic. These dependencies are shown in Fig. 5 for different buffer sizes. The red dashed line *1* indicates the Deterministic Flow for approximating the probability of packet loss and delivery delay using the diffusion approximation method using formula (3). The blue dashed line *2* indicates the Self-Similar Flow for approximate estimation of packet loss probability and delivery delay using the same method.

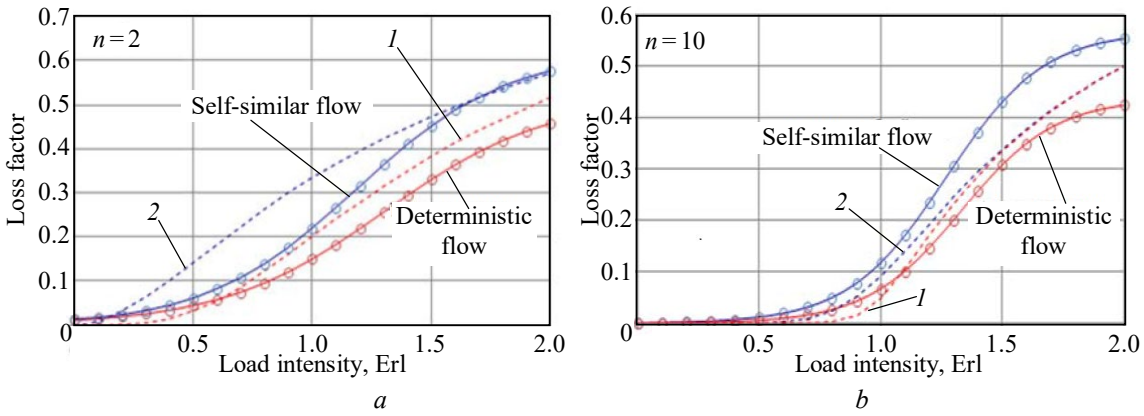

Fig. 5. Dependence of the probability of losses on the load intensity for different buffer lengths (*a*) $n = 2$ and (*b*) $n = 10$, $\rho \neq 1$

These figures also show the dependences obtained according to the approximate formula (3). The simulation results showed that the estimate using formula (3) gives a slightly overestimated value of the loss factor, and the largest error (about 2 times) occurs for a self-similar flow at average values of the load intensity. It can also be seen from the graphs above that the loss factor for regular flow (IV) claims is much less than the loss factor for self-similar flow claims in aggregated traffic.

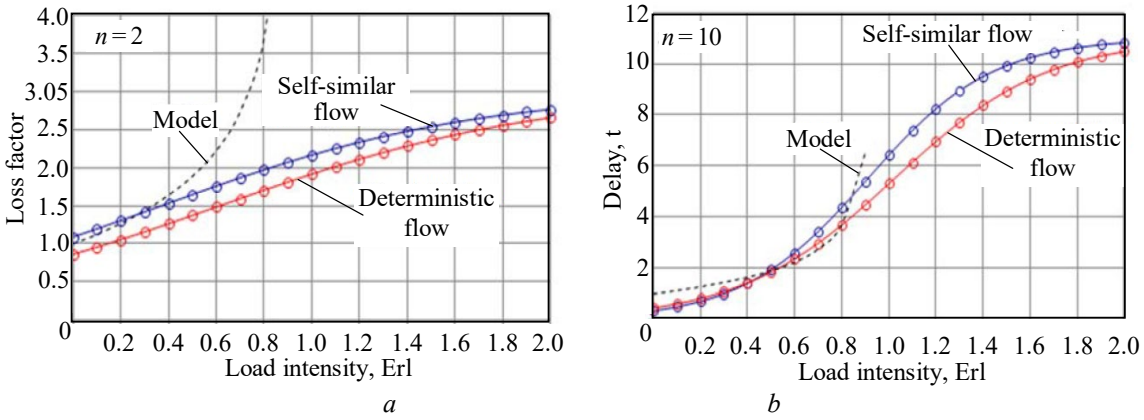

Fig. 6. Dependence of the packet delivery delay on the load intensity for different buffer lengths (*a*) $n = 2$ and (*b*) $n = 10$, $\rho \neq 1$

Fig. 6 shows the empirical dependences of the packet delivery delay for self-similar and regular flows in aggregated traffic on the load intensity for different buffer sizes ($n = 2$ and $n = 10$, respectively). These dependences were obtained from the results of simulation modeling. For comparison, these figures show the estimates obtained using the approximate model (dashed line). As can be seen from the above simulation results, the average delay of packet delivery for a self-similar flow is slightly higher than delivery delay of the regular flow packet. The difference in values does not exceed 20 %. The analytical model for the aggregated flow rather accurately describes the packet delivery delay in

the range of load intensity values, in which packet losses are close to zero (up to 0.5 Erl with a buffer length $n=2$ and 0.8 Erl with $n=10$), and its values are closest to the delay values for a self-similar flow. Thus, regular flow (IoT) claims are served with a higher quality, and this is mostly evident in an increase in the loss rate for shared traffic. When studying the properties of traffic at the output of the service system, the dependence of the Hurst coefficient [19] on the load intensity was investigated.

Table 1 shows the results of simulation modeling of the QS (queuing system) of the form $G/M/1/k$, the input of which receives an aggregated flow obtained by combining self-similar and regular flows. The value of the Hurst coefficient of the input stream $H_{in}=0.77$.

Table 1

Values of the Hurst coefficient of the served flow to the system outputs on the intensity of the flow load $G/M/1/k$

Load intensity, Erl	Hurst index values	
	Self-similar flow	Deterministic flow
0.5	0.75	0.71
0.6	0.725	0.73
0.7	0.71	0.722
0.8	0.68	0.667
0.9	0.66	0.651
1.0	0.649	0.625
1.1	0.625	0.63
1.2	0.6	0.625
1.3	0.58	0.65
1.4	0.56	0.552
1.5	0.549	0.525
1.6	0.525	0.551
1.7	0.519	0.47
1.8	0.49	0.46
1.9	0.472	0.472
2.0	0.465	0.465

With an increase in the load intensity at the QS input, a decrease in the Hurst coefficient of the serviced flow at the QS output is observed. At low and medium values of the load intensity at the input from 0 to 0.5 Erl, the Hurst coefficient of the output flow is practically equal to the analogous parameter of the input flow. The obtained dependence can be explained by the fact that for high values of the load intensity, the properties of the serviced flow are determined largely by the distribution law of the service time than by the properties of the input flow, which coincides with the results of the study [20]. At a high load intensity, the distribution of the duration of the time intervals between packet arrivals tends to the distribution of the service time, i.e. to the beta distribution, which is ultimate.

Consequently, the time intervals between packets take on a limited range of values, while a self-similar stream is characterized by a distribution having a “long tail” (for example, a Pareto distribution). Thus, for the chosen service time model, an increase in the load intensity leads to a decrease in the self-similarity properties of the served traffic.

7. Conclusions

1. The simulation results showed that when servicing an aggregated stream, the parameters of the quality of service of IoT traffic and background traffic differ significantly. Analysis of the results of modeling the process of servicing the aggregated stream showed that the probability of packet loss of the regular stream is less than that of the random stream (H2H + TI). Moreover, this difference increases with an increase in the intensity of the incoming load.

2. Analysis of the dependence of the self-similarity properties of the serviced flow on the load intensity showed that the properties of the output flow are close to the properties of the input flow at small and medium values of the input load intensity. At large values of the load intensity, the proper-

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ties of the served flow are determined by the distribution of the service time. The results obtained demonstrate the range of applicability of known approximate models for systems *G*/*G*/1/*k* and *G*/*G*/1 for describing the loss rate and packet delivery delay.

Література

1. Шелухин А.М., Тенякшев А.В., Осин А.В. Фрактальные процессы в телекоммуникациях / за ред. А.М. Шелухин, Москва : Радиотехника, 2003. 479 с.
2. Парамонов А.І. Управління трафіком машина-машина на основі розкладу. *Системи управління та інформаційні технології.* 2014. Т. 56, № 2. С. 84–88.
3. Кучерявий А.Е., Нуріллоев І.М., Парамонов А.І., Прокоп'єв А.В. Забезпечення зв'язності бездротових сенсорних вузлів гетерогенної мережі. *Інформаційні технології та телекомунікації.* 2015. Т. 3. № 1, С. 115–122.
4. Impact of machine-type communications on energy and de-lay performance of random access channel in LTE-advanced / M. Gerasimenko, V. Petrov, O. Galinina, S. Andreev, Y. Koucheryavy. *European Transactions on Telecommunications*. 2013. Vol. 24, Issue 4. P. 366–377.
5. Киричок Р.В., Парамонов А.І., Прокоп'єв А.В., Кучерявий А.Е. Еволюція досліджень в області бездротових сенсорних мереж. *Інформаційні технології та телекомунікації*. 2014. № 4 (8). С. 29–41.
6. Боронін П.Н., Кучерявий А.Е. Інтернет речей як нова концепція розвитку мереж зв'язку. *Інформаційні технології та телекомунікації.* 2014. № 3 (7). С. 7–30.
7. Бузюков Л.Б., Окунева Д.В., Парамонов А.І. Аналіз часових параметрів обслуговування трафіку бездротової самоорганізовуючої мережі. *T-Comm: Телекомунікації та транспорт.* 2016. Т. 10, № 10. С. 66 –75.
8. Дао Ч.Н., Парамонов А.І. Моделі концентрації трафіку M2M і оцінка його впливу на QOS в мережах 5G. *Електрозв'язок*. 2018. № 4. С. 47–54.
9. Євглевська Н.В., Парамонов А.І., Смирнов П.І., Шамілова Р.В. Модель архітектури програмно-конфігурованої мережі і когнітивний метод управління для організації множинного доступу в мережах інтернету речей. *Радіопромисловість*. 2018. № 4. С. 68–75.
10. Зелигер Н.Б., Чугреев О.С., Яновский Г.Г. Проектирование сетей и систем передачи дискретных сообщений. Москва : Радио и связь, 1984. 177 с.
11. Карпов Ю. Имитационное моделирование систем. СПб. : БЖД Петербург, 2005. 389 с.
12. Кендалл М., Стюарт А. Многомерный статистический анализ и временные ряды. Москва : Наука, 1976. 736 с.
13. Мутханна А.С., Виборнова А.І., Парамонов А.І. Дослідження перевантажень у проникаючих сенсорних мережах. *Електрозв'язок.* 2016. № 1. С. 53–59.
14. Парамонов А.І. Моделі потоків трафіку для мереж M2M. *Електрозв'язок*. 2014. № 4. С. 11–16.
15. Вадзинский Р.Н. Справочник по вероятностным распределениям. СПб. : Наука, 2001. 295 с.
16. Кокс Д., Льюис П. Статистический анализ последовательностей событий / Пер. с англ. под ред. Н.П. Бусленко. Москва : Мир, 1969. 312 с.
17. Ладыженский Ю.В., Моргайлов Д.Д., Юнис Моатаз. Моделирование самоподобного входного трафика сетевых процессоров в системе NS-2. *Наукові праці Донецького національного технічного університету. Серія : Інформатика, кібернетика та обчислювальна техніка*. 2012. № 16. С. 68–74.
18. Справочник по теории вероятностей и математической статистике / под ред. В.С. Королюк. Научная мысль, 1978. 582 с.
19. Фомін В.В. Статистичний аналіз IP і VoIP трафіку. *Інфокомунікаційні технології*. 2009. № 1, Том 7. С. 40–44.
20. Шелухін О.І. Моделювання інформаційних систем: навчальний посібник для вузів, 2-е вид., Перераб. і доп. Москва : Гаряча лінія – Телеком, 2014. 536 с.

References

1. Shelukhin, A.M., Tenyakshev, A.V., & Osin, A.V. (2003). *Fractal processes in telecommunications.* Moscow: Radiotechnics.
2. Paramonov, A.I. (2014). Traffic management machine-to-machine based on the schedule. *Control systems and information technologies,* 56, 2, 84–88.

3. Kucheryavy, A.E., Nurilloev, I.N., Paramonov, A.I., & Prokopiev, A.V. (2015). Ensuring the connectivity of wireless sensor nodes of a heterogeneous network. *Information Technologies and Telecommunications,* 3, 1, 115–122.
4. Gerasimenko, M., Petrov, V., Galinina, O., Andreev, S., & Koucheryavy Y. (2013). Impact of machine-type communications on energy and de-lay performance of random access channel in LTE-advanced. *European Transactions on Telecommunications,* 24, 4, 366–377.
5. Kirichek, R.V., Paramonov, A.I., Prokopiev, A.V., & Kucheryavyy, A.E. (2014). Evolution of research in the field of wireless sensor networks. *Information technologies and telecommunications*, 4 (8), 29–41.
6. Boronin, P.N., & Kucheryavyy, A.E. (2014). The Internet of Things as a New Concept for the Development of Communication Networks. *Information technologies and telecommunications,* 3 (7), 7–30.
7. Buzyukov, L.B., Okuneva, D.V., & Paramonov, A.I. (2016). Analysis of the time parameters of servicing the traffic of a wireless self-organizing network. *T-Comm: Telecommunications and Transport,* 10, 10, 66–75.
8. Tao, Ch.N., & Paramonov, A.I. (2018). Models of M2M traffic concentration and assessment of its impact on QOS in 5G networks. *Electrosvyaz*, 4, 47–54.
9. Evglevskaya, N.V., Paramonov, A.I., Smirnov, P.I., & Shamilova, R.V. (2018). Model of architecture of software-defined network and cognitive control method for organizing multiple access in networks of the Internet of things. *Radioindustry*, 4, 68–75.
10. Zeliger, N.B., Chugreev, O.S., & Yanovsky, G.G. (1984). *Design of networks and systems for the transmission of discrete messages.* Moscow: Radio and communication.
11. Karpov, Y. (2005). *Simulation of systems.* SPb.; BCHV Petersburg.
12. Kendall, M., & Stewart A. (1976). *Multivariate statistical analysis and time series.* Moscow: Nauka.
13. Muthanna, A.S., Vybornova, A.I., & Paramonov, A.I. (2016). Investigation of overloads in pervasive sensor networks*. Electrosvyaz,* 1, 53–59.
14. Paramonov, A.I. (2014). Traffic flow models for M2M networks. *Telecommunications,* 4, 11–16.
15. Vadzinsky, R.N. (2001). *Handbook of Probability Distributions.* SPb.: Science.
16. Cox, D., & Lewis, P. (1969). *Statistical analysis of sequences of events* / Transl. from English ed. N.P. Buslenko. Moscow: Mir.
17. Ladyzhensky, Yu.V., Morgailov, D.D., & Yunis, M. (2012). Modeling of self-similar input traffic of network processors in the NS-2 system. *Scientific studies DonNTU. Series "Informatics, cybernetics and numerical technology",* 16 (204), 68–74.
18. *Handbook of Probability and Mathematical Statistics* (1978). Ed. Korolyuk, V.S. Publisher. Naukova Dumka.
19. Fomin, V.V. (2009). Statistical analysis of IP and VoIP traffic. *Infocommunication technologies*, 1, 7, 40–44.
20. Shelukhin, O.I. (2014). *Information systems modeling. Textbook for universities*. 2nd ed., Revised and add. Moscow: Hot line – Telecom.

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