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DEVISING A METHOD FOR INCREASING DATA TRANSMISSION SPEED IN MONITORING SYSTEMS BASED ON THE MOBILE HIGH-DENSITY INTERNET OF THINGS

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The object of this study is the process that improves the efficiency of data transmission in monitoring systems that arrive from low-power devices within the mobile high-density Internet of Things. The task addressed was to reduce the average delay time of information transmission through the transmitting station of the monitoring system gateway. To this end, it was proposed to improve the multiple output procedure and use the technique for building temporary dynamic clusters of dependent sources.

During the research, a model of a monitoring system with multiple node outputs was built. Its process involved the procedure for constructing a temporary subset of active devices dependent on data. That made it possible to reduce the redundancy of data coming to the monitoring system gateway.

An approach has been proposed for finding the values of the upper and lower limits of the average data transmission delay. The approach is based on simplifying calculations by switching to a one-dimensional Markov chain. The use of a uniform distribution of active subscribers has made it possible to find an analytical expression for the upper limit of the average delay. A feature of the lower bound calculation process is the introduction of a fixed division of the receiving zone of the transmitting station into equal sectors.

The algorithm developed for multiple node output is aimed at reducing the average data transmission delay with a limited number of subscribers. A feature of the method is the limitation of the number of transitions when forming a stationary distribution of the Markov chain. As a result of using the method, the average delay is reduced and the speed of data transmission increases. Studies of the proposed method have shown that the speed of data transmission increases in comparison with existing methods from 5 to 50%. The research results are attributed to the use of the procedure of multiple subscriber output

Keywords: Internet of Things, Markov chain, high-density, random multiple access system

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1. Introduction

Internet of Things (IoT) systems are gaining popularity in various industries. They are already used in industry, agriculture, healthcare, and smart home systems [1]. One of the most common scenarios for implementing the Internet of Things is the massive Machine-Type Communications (mMTC) scenario [2]. This scenario describes the operation of systems with a large number of low-power devices and is the basis of most modern monitoring systems. Typically, mMTC scenarios are used to monitor changes in the system served by the IoT. Such systems are called monitoring systems, and changes occurring in the system are termed events. System changes are understood as changes in some environmental parameters, for example, changes in temperature, humidity, or air pollution [3].

When distributing channel resources between a large number of devices in any system, only random access can be used. Random multiple access systems (RMAS) are capable of providing stable system operation with a potentially unlimited number of subscribers [4]. The basic idea of random access is that subscribers who have data to transmit send them to the channel with some probability. Most IoT systems built according to the mMTC scenario use RMA at the lower level: when transmitting information about an event to the general communication channel.

But when choosing the number of devices necessary to ensure the efficiency of data delivery and other indicators of system performance, the following contradiction arises [5]:

– a large number of IoT devices increases the probability of event detection by individual devices;

– a large number of devices increases the number of conflicts in the general communication channel.

Therefore, the use of a large number of IoT devices reduces the probability of event data delivery. This can worsen the operation of the corresponding monitoring system, especially built on the basis of mobile high-density IoT.

It has been observed that in IoT systems, data transmitted from different sensors is highly correlated [6]. Research into such systems has begun to exploit data dependences to improve the quality of IoT operation. As a result, the mMTC scenario has been supplemented with a multiple-output procedure that is robust to any input flow intensities [7].

In monitoring systems based on mobile high-density IoT (MHIoT), IoT devices often detect the same event [8]. Such devices are located close to each other when an event is detected. In the mMTC scenario, this can lead to duplication of data transmission for some events. As a result of the transmission of such redundant information, transmission delays increase, and, accordingly, the quality of service (QoS) indicators decrease [9].

Therefore, the issue of reducing the redundancy of information received from MHIoT devices built according to the mMTC scenario is relevant. Solving this issue could improve the efficiency of the MHIoT system.

2. Literature review and problem statement

In [10], a model of a wireless sensor network is considered, in which the signals of IoT devices are highly correlated. For data transmission in this model, the random multiple access algorithm "multichannel ALOHA" is used. The paper proposes an adaptive approach to data transmission using Slepian-Wolf coding to increase the energy efficiency of the system. However, this approach does not take into account the emerging data redundancy, which, at a high sensor density, could lead to undesirable data transmission delays.

In [11], a random access model with dependent sources is considered. This model uses a modified "ALOHA" algorithm. The paper considers industrial Internet of Things systems. A model of a system with dependent sources is investigated, depending on which the calculation of Gaussian correlated random variables is described. Like the previous paper, the model is focused on energy efficiency but does not involve the use of the multiple output procedure.

The method for forming a mobile cluster, proposed in [12], is focused on increasing the stability of mobile components consisting of mobile MHIoT devices. However, the issue of improving the operability is not considered in the work. Therefore, with a high density of MHIoT nodes, QoS requirements may be violated.

The study reported in [13] considers a mobile system based on the Internet of Things, designed for monitoring air pollution. The advantages of this system are its cost-effectiveness, automation of data collection and operational analysis, and the possibility of real-time monitoring. However, with the increase in operational data, which occurs when the analyzed parameters change significantly, the real-time mode is violated.

The study conducted in [14] proposes a monitoring system that uses data analysis and forecasting to prevent communication system failures. In the event of abnormal situations, the monitoring system sends notifications to users, which allows for immediate problem resolution and prevention of serious problems. However, the study does not assume the presence of clusters of IoT devices, which is typical for MHIoT systems. And in the methods proposed in [15], the main criterion is not the speed of data processing but the stability of mobile clusters. In addition, these methods do not take into account the specific features of MHIoT systems.

Random multiple access with multiple dispatch is considered in [16]. A model of random multiple access systems with a non-standard dispatch policy is built. All incoming messages are evenly distributed over a finite circle. If a message is successfully transmitted, it leaves the system together with all neighbors within the circle centered at the location of the message. However, the specificity of MHIoT is not taken into account when choosing the radius of the circle. Similar problems arise when applying the random access procedure to support mass connectivity of Internet of Things devices, given in [17].

The algorithms proposed in [18] are aimed at reducing the number of losses of Internet of Things information packets by using stabilizing load control. However, in places where IoT devices are concentrated, an unacceptably large amount of information redundancy arises.

In [19], a model of an Internet of Things system with a large number of devices is considered. The issues of detecting active devices and estimating channel bandwidth due to the temporal correlation of device activity are investigated. However, this model does not reduce data redundancy.

The method presented in [20] is aimed at reducing the execution time of IoT transactions. To this end, part of the computational load is transferred to peripheral devices of the Internet of Things. However, under the conditions of low-power devices of the mobile high-density Internet of Things, this method is unacceptable.

Therefore, the reviewed scientific works on the proposed algorithms and methods for improving the efficiency of data transmission do not sufficiently take into account the characteristic features of monitoring systems based on MHIoT. In addition, the cited papers do not focus on the possible duplication of information when using RMA systems. This can lead to both increased delays in the transmission of operational processing information and reduced QoS indicators. Thus, it is advisable to conduct a study aimed at reducing the average delay time in the transmission of operational information from MHIoT devices to the monitoring system.

3. The aim and objectives of the study

The aim of our work is to devise a method for improving the efficiency of data transmission in monitoring systems that receive input information from mobile Internet of Things sensors. This would make it possible, at a high density of MHIoT devices, to meet the requirements of quality of service (QoS) by reducing the average delay time of information transmission.

To achieve this goal, the following tasks were set:

– to build a model of a monitoring system with multiple node outputs that will receive data from MHIoT devices;

– to propose an approach to finding the average data transmission delay with an unlimited number of active MHIoT devices;

– to develop an algorithm for multiple node outputs with a limited number of subscribers.

4. The study materials and methods

The object of our study is the process of improving the efficiency of data transmission in monitoring systems that come from low-power devices of the mobile high-density Internet of Things. The work considers the monitoring system gateways of a limited reception radius that receive data coming from MHIoT devices.

The main hypothesis of the study assumes that the implementation of a new method for improving the efficiency of data transmission in monitoring systems could make it possible to reduce the average data transmission delay time. The method is based on the construction of temporary dynamic clusters of dependent MHIoT sources. This would ensure an increase in the efficiency of the monitoring system, the data to which come from mobile MHIoT devices.

When devising the method, the following conditions were followed:

Condition 1. MHIoT mobile devices in the coverage area of the monitoring system gateway have a high density.

Condition 2. Receiving information from MHIoT devices occurs in discrete time intervals – time windows.

Condition 3. When opening a window, the gateway can receive information from only one MHIoT device.

Condition 4. The monitoring system gateway randomly selects the current device for receiving information.

Condition 5. The process of the appearance of active MHIoT mobile devices in the system is described by a point Poisson process with intensity l. At the moment of appearance, the mobile device contains a single message and after successful transmission leaves the system.

In the process of devising a method for improving the efficiency of data transmission in monitoring systems based on MHIoT, a number of different methods and algorithms were used.

When calculating the average data transmission delay in the monitoring system gateway coverage area, Little's formula was used [21]. Little's formula describes the relationship between the average number of requests in the system, the average time a request stays in the system, and the intensity of requests

$$L = \lambda \cdot W, \tag{1}$$

where L is the average number of requests in the queue for service or being serviced; λ is the average intensity of requests, i.e., the number of requests received per unit of time; W is the average time the request spends in the system.

When building a model of a monitoring system based on MHIoT with dependent mobile sources, the ALOHA algorithm was considered [22]. ALOHA is a simple protocol for accessing the data transmission environment. It allows several users to share one wireless communication channel. Two main versions of ALOHA are used:

– Pure ALOHA – the station transmits data at any time and waits for confirmation [23];

– Slotted ALOHA – time is divided into slots (windows), and transmission is possible only at the beginning of the window, which reduces the probability of collisions [24].

The Slotted ALOHA algorithm was chosen to simulate the operation of the monitoring system gateway.

This algorithm works as follows:

Action 1 – synchronization. All MHIoT mobile nodes and the monitoring system gateway are synchronized in time. Time is divided into equal slots (time windows), and transmission is possible only at the beginning of the window.

Action 2 – readiness to transmit. When the MHIoT node has data to transmit, it assumes the status of an active node and waits for the beginning of the next window.

Action 3 – transmission of a data packet. When the window opens, the MHIoT node transmits a data packet to the channel.

Action 4 – waiting for confirmation of receipt. The MHIoT node waits for confirmation of receipt from the gateway during the window opening.

Action 5 – success or collision. If the reception is confirmed and the data packet is delivered, the MHIoT node goes into inactive mode.

Action 6 – if the reception is not confirmed due to a collision with another transmission, the transmission is considered to have failed.

Action 7 – retry. The MHIoT node waits for a random time (random backoff) and returns to action 3 to retry in another window.

When comparing the proposed method of servicing MHIoT node requests with existing ones, the Group-based ALOHA algorithm, which is used in modern mobile IoT [25], was applied. In this algorithm, in the event of a collision, MHIoT nodes are divided into subgroups. Each subgroup in turn receives access to an open time window of the monitoring system gateway. This helps reduce collisions during data transmission.

The Group-based ALOHA algorithm is mainly used in high-density IoT. At the same time, it has the following advantages over similar algorithms:

– fewer collisions occur because fewer devices compete for each time window;

– horizontal scalability is allowed when working with a large number of devices;

– delays are predictable, i.e., access to the gateway can be controlled;

– in mobile IoT, energy consumption is reduced due to the fact that devices are active only in their phase.

But at the same time, this algorithm also has a number of disadvantages, among which the most important are the following:

– the complexity of implementing the grouping procedure, because centralized coordination or a decentralized group formation algorithm is required;

– the presence of an unacceptable delay if a device is in a group that is waiting for service for a long time;

– inefficiency with a small number of devices due to downtime between groups.

Non-Orthogonal Multiple Access (NOMA) technology was considered as the basic technology for MHIoT.

A set of MHIoT devices can be considered a system with multiple access (SMA) [4]. SMAs provide sharing of a resource between many users or devices. The specificity of MHIoT suggests the possibility of analyzing this set as a random multiple access system (RMAS). Devices in RMAS are usually called subscribers. Therefore, information collection devices (sensors) when analyzing MHIoT as RMAS are termed subscribers.

RMAS systems can be divided into two classes:

– class 1: models with the appearance of events [26];

– class 2: models with the appearance of subscribers [27].

For monitoring systems that receive information from mobile low-power IoT devices, second-class models are considered [28].

A fragment of a monitoring system model based on MHIoT with dependent sources is considered. Let's describe this model verbally.

The fragment receives data from MHIoT mobile devices using a gateway equipped with a base station for receiving information. MHIoT devices appear in the coverage area of the base station randomly. The number of MHIoT devices in the system is not limited. Random access without source identification is used for transmission.

In order to reduce information redundancy in the process of model operation, data dependence is taken into account. In case of successful transmission, MHIoT devices whose data are dependent simultaneously leave the system.

To determine the quality of the model, a number of indicators can be considered:

– average number of successful transmissions per unit of time;

– probability of delivering information about an event;

– average number of successfully transmitted messages about the same event;

– average data transmission latency (ADTL);

– average age of information (AoI);

– energy efficiency;

– average number of retransmissions.

In monitoring systems, when receiving operational information, the most significant indicator is ADTL [29]. Therefore, within the framework of this work, the average data transmission delay in a system with an unlimited number of users and dependent sources is investigated.

When finding the average data transmission delay with an unlimited number of active MHIoT devices, the Markov chain model with a uniform arrangement of subscribers [30] was used.

The set of subscribers is divided into Q sections. In the case of subscriber success, a multiple exit occurs, i.e., all subscribers of the corresponding sector leave the set.

Let us denote by $U(j, q)$ the set of coordinates of the locations of active subscribers that are in the q-th section of the base station reception boundary circle. The current number of active subscribers is recognized as $N(j, q)| = U(j, q)|$. Then the following partition holds

$$U(j)=\bigcup_{q=1}^{Q} U(j,q). \tag{2}$$

The behavior of the time process $T2$ can be represented as a Markov chain with Q dimensions and described by the following system of equations

$$\begin{cases} N(j+1,1)=N(j,1)- \\ -F_1\big(N(j,1),N(j,2),\ldots,N(j,Q)\big)+V(j,1); \\ N(j+1,2)=N(j,2)- \\ -F_2\big(N(j,1),N(j,2),\ldots,N(j,Q)\big)+V(j,2); \\ \ldots \\ N(j+1,Q)=N(j,Q)- \\ -F_Q\big(N(j,1),N(j,2),\ldots,N(j,Q)\big)+V(j,Q), \end{cases} \tag{3}$$

where $V(j, q)$ is the number of subscribers who entered the system in window j and got to section q. This system of equations will be valid for the time process $T2$ because the coordinates of the location of subscribers in each section q will be distributed uniformly. Since the random variable $V(j, q)$ has a Poisson distribution with parameter λd, then

$$M[V(j, q)] = \lambda d. \tag{4}$$

The random variables $F_q(N(j, 1), N(j, 2), \ldots, N(j, Q))$ are calculated in the model as follows

$$F_q\big(N(j,1),N(j,2),\ldots,N(j,Q)\big)= = \begin{cases} 1, & \big(\xi\in\big[0; N(j,q)/N(j)\big)\big)\&(\eta=1); \\ 0, & \text{else}, \end{cases} \tag{5}$$

where ξ is a continuous random variable uniformly distributed on a unit interval; η is a random Boolean function equal to unity with probability

$$p_\eta=\big(1-1/N(j)\big)^{N(j)-1}. \tag{6}$$

5. Results related to devising and investigating a method for improving the efficiency of data transmission in monitoring systems

5.1. Model of a monitoring system with multiple node outputs that receives data from MHIoT devices

In the Internet of Things systems operating under the mMTC scenario, neighboring devices often transmit similar information. The readings of neighboring sensors may be different but will have a high correlation. Devices whose data are the same or almost the same are called correlated sources (CSs). Devices that have been affected by the same event initiate correlated activation (CA). In both cases, their data may differ but will be close. Note that the absence of data correlation does not mean the absence of dependence between the information transmitted by nearby sources. Therefore, nearby sources are considered dependent sources. This concept will combine the concepts of correlated sources and correlated activation. Taking into account the dependence of data from different devices is one of the ways to solve some problems of MHIoT systems. In particular, this will help reduce the redundancy of information coming from MHIoT devices to the monitoring system.

As an indicator of quality, our model uses the value of the average data transmission delay in a system with an unlimited number of users and dependent sources.

Usually, when constructing models of SMA mobile systems, the surface of a sphere is considered as the boundary of the base station coverage area. In the following, to simplify the analysis of the monitoring system, we shall limit ourselves to a planar version.

Also, when building a model of a monitoring system based on MHIoT with dependent sources, a number of conditions and input data are considered.

The exchange of messages between subscribers (low-power mobile IoT devices) and the base station of the monitoring system occurs over a radio channel. The base station is able to receive messages from subscribers located at a distance R from it.

Therefore, the location of available subscribers can be depicted on a circle of length L with radius $R = L/2\pi$, as shown in Fig. 1.

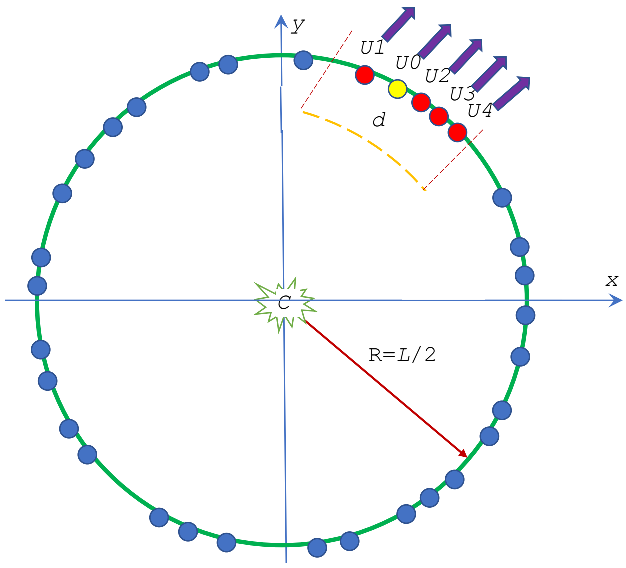

Fig. 1. Example of outputting dependent active subscribers

In Fig. 1, the points on the circle indicate the coordinates of the entries of active subscribers to the range of the gateway base station. The gateway base station C is located in the center of the coordinates. The yellow point corresponds to the entry point of the subscriber $U0$, which was served during the last open window. This subscriber has left the set of active subscribers. At the same time, all distance-dependent subscribers leave the set of active subscribers: $U1$, $U2$, $U3$, $U4$. These points are marked in red.

Subscribers enter the range of the base station according to a point Poisson process with parameter l. Each subscriber is characterized by the time of entry into the system and the coordinates of the location on the circle. Therefore, the time periods between the subscriber entries are random variables distributed according to the exponential law. Also, the coordinates of the subscriber positions on the circle are random variables distributed according to the uniform law.

The time for receiving messages from subscribers of the monitoring system by the base station is divided into equal time intervals. This interval is called the reception window. The time during which the message will be sent to the base station is equivalent to the duration of one window. Subscribers have information about the beginning of the next window, which is the time for sending messages.

All subscribers who have a message to send when they log in to the system are considered active subscribers. The base station determines the number of active subscribers $N(j)$ before the beginning of window j and sends this information to subscribers. Subscribers have the opportunity to send messages to the base station with the probability: $p(j) = 1/N(j)$.

When a window is opened, the following situations may occur:

– A0 or "success", if exactly one subscriber sends a message;
– A1 or "empty" (all subscribers do not send messages;
– A2 or "conflict" (the number of subscribers who sent messages is more than one).

When closing the window, subscribers learn what situation has arisen in the window.

The subscriber is removed from the set of active subscribers after successful transmission of the message. Other subscribers learn from the base station the coordinate of this subscriber's location on the circle – $U0$. Next, for each i-th active subscriber, l_i is calculated – the length of the arc of the circle from it to the point $c0$. Let d be the length of the arc that defines the subset of subscribers dependent on the data. If $l_i \leq d/2$, then the i-th subscriber is also removed from the set of active subscribers.

The discrete time process of opening windows of the base station is considered

$$T = \{t_j\}, j \in N, \tag{7}$$

where j is the current window number, t_j is the time of opening the current window, N is a set of natural numbers.

Let the following sets be defined:

$U(j)$ is the set of coordinates of the locations of active subscribers at the moment of opening the j-th window; $|U(j)| = N(j)$;

$X(j)$ is the set of coordinates of the positions of active subscribers who entered the system during the opening of window j; $|X(j)| = V(j)$;

$Y(j)$ is the set of coordinates of the locations of subscribers who left the system during the opening of window j; $|Y(j)| = W(j)$.

Then the functioning of the discrete time process T can be represented as a multidimensional Markov chain:

$$U(j+1) = (U(j) \backslash Y(j)) \cup X(j); \tag{8}$$

$$N(j+1) = N(j) - W(j) + V(j). \tag{9}$$

The intensity of subscriber appearance in the considered Markov process is a finite quantity. Therefore, the multidimensional Markov chain (8) is ergodic. Therefore, the Markov chain, reflecting the model of the monitoring system, has a stationary distribution regardless of the intensity of subscriber appearance in the system. In order to obtain the average delay in the monitoring system based on MHIoT, it is necessary to find the stationary distribution of the Markov chain (8). But solving this problem is quite difficult because the number of states of this Markov chain is uncountable. Therefore, further techniques for obtaining upper and lower estimates of the average delay are considered, which do not require consideration of Markov chains with an uncountable number of states.

5. 2. Finding the average data transmission delay with an unlimited number of active MHIoT devices

To find the upper estimate of the average delay, assume that after the event A0 the location of active subscribers on the circles changes accordingly with a uniform distribution. Such a time discrete process $T1$ will differ from process T. But the Markov chain for the process $T1$ will also have a stationary distribution.

Let the average number of subscribers in monitoring systems with process models T and $T1$ be N_{aver} and $N1_{aver}$, respectively. Then, regardless of the intensity of the appearance of subscribers in the system, the following inequality will hold

$$N1_{aver} \geq N_{aver}. \tag{10}$$

According to the process model $T1$, the coordinates of the location of subscribers will always be distributed evenly around the circle. Therefore, unlike the process model T, the operation of the process model $T1$ can be represented by a one-dimensional Markov chain.

Let us calculate the mathematical expectation from the left and right parts of expression (9)

$$\mathrm{M}[N(j+1)] = \mathrm{M}[N(j) - W(j) + V(j)]. \tag{11}$$

Consider processes T and $T1$ at $j \to \infty$. Then $\mathrm{M}[N(j+1)] = \mathrm{M}[N(j)]$, hence

$$\mathrm{M}[V(j)] = \mathrm{M}[W(j)]. \tag{12}$$

Since the random variable equal to the number of active subscribers who entered the monitoring system during window j has a Poisson distribution, then

$$\mathrm{M}[V(j)] = \lambda. \tag{13}$$

Let us denote by θ the indicator of the situation that has arisen in the current window j. The indicator θ can take the following values

$$\mathrm{M}\left[\theta(j)\right] = \begin{cases} 1, & \text{if A0;} \\ 0, & \text{if A1;} \\ 2, & \text{if A2.} \end{cases} \tag{14}$$

Then $\mathrm{M}[W(j)]$ can be calculated as follows

$$M[W(j)] = P\{\theta(j)=1\} \cdot \left(1 + d \cdot \left(M[W(j)] - 1\right)\right). \tag{15}$$

The probability that a "success" situation has arisen in the window can be calculated as

$$P\{\theta(j)=1\} = \left(1 - \frac{1}{N(j)}\right)^{N(j)-1}. \tag{16}$$

At large values of the intensity of the incoming flow λ, the number of active subscribers in window j begins to grow significantly. Therefore, at large values of $N(j)$, the probability of the situation A0 "success" will be approximately equal to

$$P\{\theta(j)=1\} = \left(1 - \frac{1}{N(j)}\right)^{N(j)-1} \approx e^{-1}. \tag{17}$$

Then

$$M\left[W(j)\right] = e^{-1} \cdot \left(1 + d \cdot \left(M\left[N(j)\right] - 1\right)\right). \tag{18}$$

Based on (11), (13), and (18), let's calculate the mathematical expectation of the number of active subscribers for window j

$$M\left[N(j)\right] = \frac{\lambda e + d - 1}{d}. \tag{19}$$

Considering $j \to \infty$ we obtain

$$\lim_{j \to \infty} M\left[N(j)\right] = N1_{aver}. \tag{20}$$

Hence

$$N1_{aver} = \frac{\lambda e + d - 1}{d}. \tag{21}$$

Knowing the average number of active subscribers in the system and the intensity of their arrival, we calculate the upper limit of the average delay using Little's formula

$$Z_{aver\_top} = \frac{N1_{aver}}{\lambda} = \frac{\lambda e + d - 1}{\lambda d}. \tag{22}$$

To find the lower estimate of the average delay, we shall change the procedure for removing subscribers from the set of active subscribers after a successful message transmission.

Suppose that the circle of the base station reception boundary is divided into several sectors. Let us denote their number by Q. The subscriber leaves the system after the successful transmission of the message. Other subscribers learn from the base station the coordinates of the location of this subscriber and determine in which sector s/he was. If s/he was in the same sector, then this subscriber also leaves the system. Let d denote the length of the sector of the circle on which subscribers are located, simultaneously leaving the system. Let us denote the time process with such conditions as $T2$.

An example of a schematic representation of the process model $T2$ for $Q = 4$ is shown in Fig. 2.

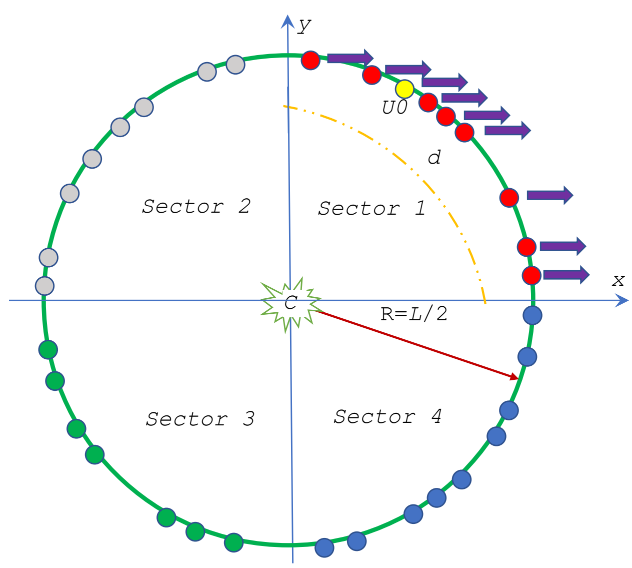

Fig. 2. Example of a model for process $T2$ at $Q = 4$

The subscriber from the first sector successfully transmitted the message (yellow color), so all other subscribers of the first sector leave the set of active subscribers (Fig. 2).

Let $N2_{aver}$ be the average number of subscribers in the monitoring system built according to the $T2$ model. Then, regardless of the intensity of the appearance of subscribers in the system, the following inequality will hold

$$N_{aver} \geq N2_{aver}. \tag{23}$$

Simulation modeling of the time process $T2$ by building a model of the above-described Markov chain makes it possible to obtain a lower estimate of the average delay of this process.

With an unlimited number of subscribers, the difference between the lower and upper estimates of the average delay increases with the number of subscribers. In addition, the computational complexity of the corresponding model begins to grow significantly. But in practical implementation, the number of subscribers that can be served by a fixed gateway is always limited.

5. 3. Algorithm for multiple node output with a limited number of subscribers

We consider the time discrete process $T1$. Let no more than K subscribers reach the coverage area of a specific gateway of the monitoring system. In order to find the limits of the average delay, it is necessary to find the stationary distribution of the Markov chain. The number of its states will be $K+1$ (Fig. 3).

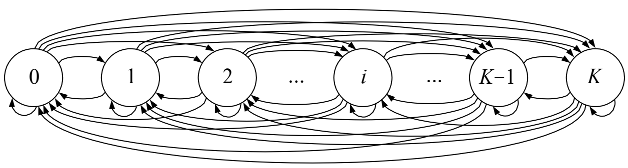

Fig. 3. Markov chain of bounded time discrete process $T1$

The transition probabilities of such a Markov chain p_{ij} for any two arbitrarily chosen states i and j depend on the main indicator of the formation of dependent subsets d. For a time-discrete process $T1$, they will take the following form:

$$\text{if } i=0 \text{ then } p_{i,j}=\frac{\lambda^j}{j!}e^{-\lambda}; \tag{24}$$

$$\text{if } (i>0)\&(j\geq i) \text{ then } p_{i,j}(d)=$$
$$=\left(1-\left(1-\frac{1}{i}\right)^{i-1}\right)\frac{\lambda^{j-1}}{(j-i)!}e^{-\lambda}+\left(1-\frac{1}{i}\right)^{i-1}\times$$
$$\times\sum_{m=1}^{i}\left(C_{i-1}^{m-1}d^{m-1}(1-d)^{i-m}\frac{\lambda^{j-i+m}}{(j-i+m)!}e^{-\lambda}\right); \tag{25}$$

$$\text{if } (i>0)\&(j<i) \text{ then } p_{i,j}(d)=$$
$$=\left(1-\frac{1}{i}\right)^{i-1}\sum_{m=0}^{j}\left(C_{i-1}^{i-j+m-1}d^{i-j+m-1}(1-d)^{j-m}\frac{\lambda^m}{m!}e^{-\lambda}\right). \tag{26}$$

Let τ_i be the probability that the system is in state i. It is equivalent to the probability that the number of subscribers in the system is i, that is

$$\omega_i=P\{N(j)=i\}. \tag{27}$$

In order to find the stationary probabilities of a given Markov chain, it is necessary to solve the following system of equations

$$\begin{cases}\omega_0(d)=\omega_0\cdot p_{0,0}+\omega_1\cdot p_{1,0}(d)+\ldots+\omega_K\cdot p_{K,0}(d);\\ \omega_1(d)=\omega_0\cdot p_{0,1}(d)+\omega_1\cdot p_{1,1}(d)+\ldots+\omega_K\cdot p_{K,1}(d);\\ \omega_2(d)=\omega_0\cdot p_{0,2}(d)+\omega_1\cdot p_{1,2}(d)+\ldots+\omega_K\cdot p_{K,2}(d);\\ \ldots\\ \omega_{K-1}(d)=\omega_0\cdot p_{0,K-1}(d)+\omega_1\cdot p_{1,K-1}(d)+\\ +\ldots+\omega_K\cdot p_{K,K-1}(d);\\ \omega_0(d)+\omega_1(d)+\omega_2(d)+\ldots+\omega_K(d)=1.\end{cases} \tag{28}$$

Having obtained the stationary probabilities, one can calculate the average number of subscribers in the system as follows

$$N_{aver}(d)=\sum_{i=0}^{K}i\cdot\omega_i(d). \tag{29}$$

Using expression (28), let's calculate the average delay in the system

$$Z_{aver\_top}(d)=\sum_{i=0}^{K}i\cdot\omega_i(d)\Big/\lambda. \tag{30}$$

Note that as the power of the subset of data-dependent subscribers increases, the average data transmission delay decreases. The power of the subset of subscribers increases with increasing parameter d. But at the same time, as the average data transmission delay decreases, the average probability of data loss $P_{aver}(d)$ increases. This parameter is the sum of two components

$$P_{aver}(d)=P_{aver1}(d)+P_{aver2}(d), \tag{31}$$

where P_{aver1} is the average probability of data loss due to the subscriber exceeding the maximum allowable waiting time for data transmission; P_{aver2} is the average probability of data loss due to the removal of a subscriber with event data that has not yet been received by the monitoring system from the set of active subscribers.

When the parameter d increases, the first term of the sum (31) decreases, and the second term increases. To find the optimal ratio between the average delay and the average probability of data loss, an indicator of data transmission efficiency is introduced

$$\eta(d)=\frac{1-P_{aver}(d)}{1+Z_{aver\_top}(d)}. \tag{32}$$

The indicator (32) takes values from the interval (0, 1]. The maximum value of the indicator $\eta(d)=1$ is achieved in the absence of data transmission delay and zero probability of data loss.

To assess the effectiveness of the proposed method, a simulation model of a gateway of a monitoring system with multiple outputs of mobile high-density Internet of Things nodes was used. The radius of stable reception of the base station is 1600 m. The length of the base station coverage circle is approximately 10 km. The maximum length of the arc that defines the subset of subscribers dependent on data on this circle is 450 m. MHIoT devices (subscribers) that must transmit data appear in the coverage area of the base station randomly.

The quality of the monitoring system that receives data from MHIoT devices was assessed based on the length of the interval for determining the subset of subscribers dependent on data. The value of the parameter d varied from 50 to 450 m. Three variants of the model were considered for restrictions on the maximum number of subscribers K: 100, 500, 900 subscribers. The simulation results for these values of K are shown in Fig. 4.

The effectiveness of the proposed method for increasing the speed of data transmission in monitoring systems based on MHIoT was evaluated in comparison with standard methods. For comparison, methods based on the ALOHA algorithm were considered. For mobile high-density IoT, the method based on the Group-based ALOHA algorithm is usually used, therefore this algorithm was chosen for modeling. The evaluation was carried out using the data transmission speed evaluation indicator $\eta(d)$ (expression (32)). Various options for limiting the maximum number of subscribers from 100 to 900 subscribers were simulated. The generalized modeling results are shown in the plots of Fig. 5.

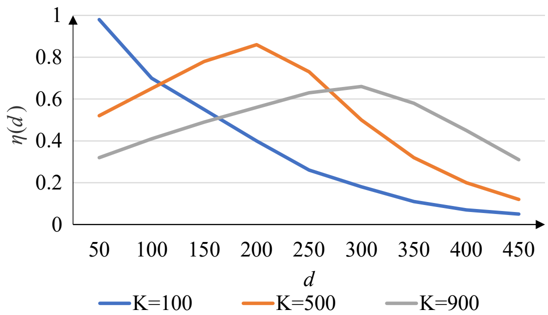

Fig. 4. Dependence of the indicator for assessing the efficiency of data transmission on the length of the interval for determining a subset of subscribers

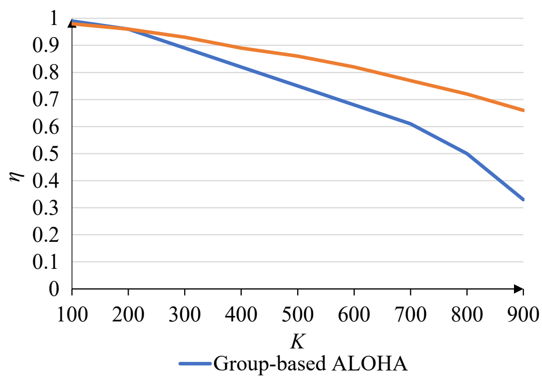

Fig. 5. Dependence of data transmission efficiency on restrictions on the maximum number of subscribers

During simulation, the limit on the maximum number of subscribers varied within the specified limits from the minimum to the maximum value with a step of $\Delta K = 20$.

6. Discussion of results based on investigating the method for improving the efficiency of data transmission in monitoring systems

A model of a monitoring system that will receive data from MHIoT devices with multiple node outputs has been proposed. The main difference of this model is the reduction of data redundancy entering the monitoring system gateway. The reduction occurs by forming a temporary subset of devices that depend on the data entering the current open window. When the current window is closed, all MHIoT devices that depend on the transmitted data leave the system (Fig. 1). The model is described as a multidimensional Markov chain (3), (4). This model takes into account the specific features of the mobile high-density Internet of Things.

We have proposed an approach for finding the limits of the average data transmission delay with an unlimited number of active MHIoT devices. A feature of this approach is a significant simplification of calculations by switching to a one-dimensional Markov chain. The use of a uniform distribution of active subscribers allowed us to find an analytical expression for the upper limit of the average delay – formula (17). A feature of the process of calculating the lower limit of the average delay is the introduction of a fixed division of the receiving zone of the transmitting station into equal sectors (Fig. 2, (17)).

A multiple node output algorithm has been developed, focused on reducing the average data transmission delay with a limited number of subscribers. The main difference of this algorithm is the limitation of the number of transitions when forming a stationary Markov chain distribution (Fig. 3). That has made it possible to determine the optimal indicator of the formation of dependent subsets d (28), (30) relative to the minimum of the average data transmission delay. When developing the algorithm, the characteristic features of the MHIoT system were taken into account. The proposed algorithm made it possible to reduce the average delay and improve the efficiency of data transmission in the case of a high-density arrangement of IoT devices.

Comparative testing of the standard and proposed methods (Fig. 4, 5) showed the following results:

– with an increase in the density of IoT devices, the optimal value of the length of the interval for determining a subset of subscribers increases, and the indicator of the efficiency of data transmission decreases (Fig. 4);

– with a low density of IoT devices ($K < 100$), the use of multiple subscriber output is impractical due to an increase in the probable data loss;

– at a high density of IoT devices ($K > 300$), the use of the proposed method makes it possible to improve the efficiency of data transmission from 5 ($K = 300$) to 50% ($K \sim 1000$).

Our results of the study on the method for improving the efficiency of data transmission in monitoring systems based on MHIoT are attributed to the use of the procedure of multiple subscriber exit.

Unlike [10], in which a model of a wireless sensor network is considered, in which the signals of IoT devices have a high correlation, our method takes into account the emerging data redundancy. Also, data redundancy is reduced when using the modified ALOHA algorithm [11]. This becomes possible due to the use of the multiple node output procedure.

Unlike [12, 13], in the case of an increase in operational data, the real-time mode is not violated when using the proposed method. Unlike [14, 15], our method assumes the presence of clusters of IoT devices, which is typical for MHIoT systems. Unlike [16, 17], the proposed method can be used with a high-density location of IoT devices. Also, unlike [18], in places where IoT devices are concentrated, information redundancy is significantly reduced. This becomes possible due to the reduction of delays in the transmission of operational information.

Unlike [19], in which a model of the Internet of Things system with a large number of devices is proposed, our method has made it possible to reduce the average data transmission delay. This becomes possible due to the consideration of the specific features of monitoring systems based on the mobile high-density Internet of Things. Unlike [20], the proposed method allows the use of low-power devices of the mobile high-density Internet of Things. This becomes possible due to the acceleration of the information flow to the base station.

Thus, our results have made it possible to improve the efficiency of data transmission from MHIoT devices through the monitoring system gateway. Depending on the density of MHIoT devices, the efficiency of data transmission increased from 10 to 50%.

But it is worth noting that the proposed results should be applied only at a high density of IoT devices ($K > 300$).

In addition, a significant limitation of the study is the restriction on the sequential passage of messages through the monitoring system gateway.

As a drawback of this study, it is necessary to note the lack of analysis of possible correlation between individual monitoring system gateways. To eliminate this drawback, it is necessary to conduct additional research on the possibility of interaction of neighboring gateways in order to reduce data transmission delay.

As a development of this study, the following can be noted.

First, it is necessary to conduct a separate study to reduce delays in monitoring systems that use intelligent gateways to receive information from MHIoT sensors. Secondly, it is necessary to consider the possibility of load balancing of monitoring system gateways.

7. Conclusions

1. A model of a monitoring system that will receive data from mobile high-density Internet of Things devices with multiple node outputs has been built. The model is based on a dynamic change in the set of active MHIoT devices. During the current window, the set is replenished with new activated elements. When the window is closed, all MHIoT devices that depend on the transmitted data are removed from the set. The main difference of this model is the reduction of data redundancy entering the monitoring system gateway. To this end, a procedure for forming a temporary subset of devices that depend on the data entering the currently open gateway window was used. This model allowed for an estimate of the average data transmission delay.

2. An approach to finding the average data transmission delay with an unlimited number of active MHIoT devices has been proposed. In particular, algorithms are suggested for obtaining upper and lower estimates of the average data transmission delay. A feature of this approach is a significant simplification of calculations by switching to a one-dimensional Markov chain. The use of a uniform distribution of active subscribers allowed us to find an analytical expression for the upper limit of the average delay. To find the lower limit, a fixed division of the reception area of the gateway transmitting station into equal sectors was proposed. This approach was used in the development of a multiple node output algorithm with a limited number of subscribers.

3. A multiple node output algorithm has been developed, focused on reducing the average data transmission delay with a limited number of subscribers. The main difference of this algorithm is the limitation of the number of transitions when forming a stationary Markov chain distribution. That has made it possible to determine the optimal indicator of the formation of dependent subsets relative to the minimum of the average data transmission delay. Taking into account the characteristic features of MHIoT has made it possible to improve the efficiency of data transmission by reducing the average delay. The results of the study have made it possible to compare the efficiency of the standard and proposed methods by the criterion of data transmission efficiency. At a low density of MHIoT devices ($K < 100$), the proposed method has no advantages over standard ones, therefore its use is inexpedient. At a high density of MHIoT devices ($K > 300$), the use of the proposed method allows one to improve the efficiency of data transmission from 5 to 50%. It has been also proven that the maximum efficiency of the proposed method is achieved at the highest values of the density of MHIoT devices, $K \sim 1000$.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Kuchuk, H., Malokhvii, E. (2024). Integration of IoT with Cloud, Fog, and Edge Computing: a Review. Advanced Information Systems, 8 (2), 65–78. https://doi.org/10.20998/2522-9052.2024.2.08
2. Amitu, D. M., Akol, R. N., Serugunda, J. (2025). Hybrid access control mechanism for massive machine type communications. Discover Internet of Things, 5 (1). https://doi.org/10.1007/s43926-025-00106-8
3. Zhao, D., Wang, H., Du, H., Cheng, H., Peng, L., Liang, Y. et al. (2025). An intelligent bridge multi-dimension deflection IoT monitoring system based on laser datum and imaging. Journal of Traffic and Transportation Engineering (English Edition), 12 (2), 269–287. https://doi.org/10.1016/j.jtte.2023.06.006
4. Harwahyu, R., Cheng, R.-G., Liu, D.-H., Sari, R. F. (2021). Fair Configuration Scheme for Random Access in NB-IoT with Multiple Coverage Enhancement Levels. IEEE Transactions on Mobile Computing, 20 (4), 1408–1419. https://doi.org/10.1109/tmc.2019.2962422
5. Kuchuk, H., Kalinin, Y., Dotsenko, N., Chumachenko, I., Pakhomov, Y. (2024). Decomposition of integrated high-density IoT data flow. Advanced Information Systems, 8 (3), 77–84. https://doi.org/10.20998/2522-9052.2024.3.09
6. Vaiyapuri, T., Parvathy, V. S., Manikandan, V., Krishnaraj, N., Gupta, D., Shankar, K. (2021). A Novel Hybrid Optimization for Cluster-Based Routing Protocol in Information-Centric Wireless Sensor Networks for IoT Based Mobile Edge Computing. Wireless Personal Communications, 127 (1), 39–62. https://doi.org/10.1007/s11277-021-08088-w

7. Shokeen, S., Singh, H. (2023). Multiple Input Multiple Output: An IOT based Application. 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), 634–638. https://doi.org/10.1109/incacct57535.2023.10141742
8. Kuchuk, H., Mozhaiev, O., Kuchuk, N., Tiulieniev, S., Mozhaiev, M., Gnusov, Y. et al. (2024). Devising a method for the virtual clustering of the Internet of Things edge environment. Eastern-European Journal of Enterprise Technologies, 1 (9 (127)), 60–71. https://doi.org/10.15587/1729-4061.2024.298431
9. Singh, S. P., Kumar, N., Kumar, G., Balusamy, B., Bashir, A. K., Dabel, M. M. A. (2025). Enhancing Quality of Service in IoT-WSN through Edge-Enabled Multi-Objective Optimization. IEEE Transactions on Consumer Electronics. https://doi.org/10.1109/tce.2025.3526992
10. Choi, J. (2018). On Multichannel Random Access for Correlated Sources. IEEE Transactions on Communications, 66 (8), 3444–3454. https://doi.org/10.1109/tcomm.2018.2823318
11. Chetot, L., Egan, M., Gorce, J.-M. (2023). Active User Detection and Channel Estimation for Grant-Free Random Access with Gaussian Correlated Activity. 2023 IEEE 97th Vehicular Technology Conference (VTC2023-Spring), 1–6. https://doi.org/10.1109/vtc2023-spring57618.2023.10199877
12. Kuchuk, H., Mozhaiev, O., Tiulieniev, S., Mozhaiev, M., Kuchuk, N., Tymoshchyk, L. et al. (2025). Devising a method for forming a stable mobile cluster of the internet of things fog layer. Eastern-European Journal of Enterprise Technologies, 1 (4 (133)), 6–14. https://doi.org/10.15587/1729-4061.2025.322263
13. Alqasimi, A., Al Marzouqi, K., Alhammadi, A., Aljasmi, A., Alnabulsi, A., Al-Ali, A. R. (2025). An IoT-Based Mobile Air Pollution Monitoring System. Proceedings of IEMTRONICS 2024, 221–233. https://doi.org/10.1007/978-981-97-4784-9_16
14. Wing Lo, Y., Ho Tsoi, M., Chow, C.-F., Mung, S. W. Y. (2025). An NB-IoT Monitoring System for Digital Mobile Radio With Industrial IoT Performance and Reliability Evaluation. IEEE Sensors Journal, 25 (3), 5337–5348. https://doi.org/10.1109/jsen.2024.3512859
15. Kuchuk, H., Husieva, Y., Novoselov, S., Lysytsia, D., Krykhovetskyi, H. (2025). Load balancing of the layers IoT Fog-Cloud support network. Advanced Information Systems, 9 (1), 91–98. https://doi.org/10.20998/2522-9052.2025.1.11
16. Foss, S., Turlikov, A., Grankin, M. (2017). Spatial random multiple access with multiple departure. 2017 IEEE International Symposium on Information Theory (ISIT), 2728–2731. https://doi.org/10.1109/isit.2017.8007025
17. Moon, S., Lee, H.-S., Lee, J.-W. (2018). SARA: Sparse Code Multiple Access-Applied Random Access for IoT Devices. IEEE Internet of Things Journal, 5 (4), 3160–3174. https://doi.org/10.1109/jiot.2018.2835828
18. Kuchuk, H., Mozhaiev, O., Tiulieniev, S., Mozhaiev, M., Kuchuk, N., Tymoshchyk, L. et al. (2025). Devising a method for stabilizing control over a load on a cluster gateway in the internet of things edge layer. Eastern-European Journal of Enterprise Technologies, 2 (9 (134)), 24–32. https://doi.org/10.15587/1729-4061.2025.326040
19. Zhu, W., Tao, M., Yuan, X., Guan, Y. (2023). Message Passing-Based Joint User Activity Detection and Channel Estimation for Temporally-Correlated Massive Access. IEEE Transactions on Communications, 71 (6), 3576–3591. https://doi.org/10.1109/tcomm.2023.3261382
20. Kuchuk, N., Kashkevich, S., Radchenko, V., Andrusenko, Y., Kuchuk, H. (2024). Applying edge computing in the execution IoT operative transactions. Advanced Information Systems, 8 (4), 49–59. https://doi.org/10.20998/2522-9052.2024.4.07
21. Aqeel Abdulhussein M, A.-M., Smirnova, T., Buravchenko, K., Smirnov, O. (2023). The method of assessing and improving the user experience of subscribers in software-configured networks based on the use of machine learning. Advanced Information Systems, 7 (2), 49–56. https://doi.org/10.20998/2522-9052.2023.2.07
22. Asvadi, S., Ashtiani, F. (2023). Peak Age of Information in Slotted ALOHA Networks. IEEE Transactions on Communications, 71 (10), 6018–6030. https://doi.org/10.1109/tcomm.2023.3296590
23. Semenov, S., Mozhaiev, O., Kuchuk, N., Mozhaiev, M., Tiulieniev, S., Gnusov, Y. et al. (2022). Devising a procedure for defining the general criteria of abnormal behavior of a computer system based on the improved criterion of uniformity of input data samples. Eastern-European Journal of Enterprise Technologies, 6 (4 (120)), 40–49. https://doi.org/10.15587/1729-4061.2022.269128
24. Munari, A. (2021). Modern Random Access: An Age of Information Perspective on Irregular Repetition Slotted ALOHA. IEEE Transactions on Communications, 69 (6), 3572–3585. https://doi.org/10.1109/tcomm.2021.3060429
25. Tzeng, S.-S., Lin, Y.-J., Wang, S.-W. (2025). Age of Information in IoT Devices with Integrated Heterogeneous Sensors under Slotted ALOHA. IEEE Sensors Journal, 1–1. https://doi.org/10.1109/jsen.2025.3563452
26. Petrovska, I., Kuchuk, H., Kuchuk, N., Mozhaiev, O., Pochebut, M., Onishchenko, Y. (2023). Sequential Series-Based Prediction Model in Adaptive Cloud Resource Allocation for Data Processing and Security. 2023 13th International Conference on Dependable Systems, Services and Technologies (DESSERT), 1–6. https://doi.org/10.1109/dessert61349.2023.10416496
27. Zhang, Y., Jing, R., Zou, Y., Cao, Z. (2025). Optimizing power allocation in contemporary IoT systems: A deep reinforcement learning approach. Sustainable Computing: Informatics and Systems, 46, 101114. https://doi.org/10.1016/j.suscom.2025.101114
28. Sobchuk, V., Pykhnivskyi, R., Barabash, O., Korotin, S., Omarov, S. (2024). Sequential intrusion detection system for zero-trust cyber defense of IoT/IIoT networks. Advanced Information Systems, 8 (3), 92–99. https://doi.org/10.20998/2522-9052.2024.3.11
29. Cui, Y., Shi, G., Xu, L., Ji, J. (2023). Average dwell time based networked predictive control for switched linear systems with data transmission time-varying delays. IMA Journal of Mathematical Control and Information, 40 (2), 210–231. https://doi.org/10.1093/imamci/dnad007
30. Czapla, D. (2024). On the Existence and Uniqueness of Stationary Distributions for Some Piecewise Deterministic Markov Processes with State-Dependent Jump Intensity. Results in Mathematics, 79 (5). https://doi.org/10.1007/s00025-024-02195-3