UDC 004.41:519.7
DOI: 10.15587/1729-4061.2025.336111

DEVISING A METHOD FOR ENERGY-EFFICIENT CONTROL OVER A DATA TRANSMISSION PROCESS ACROSS THE MOBILE HIGH-DENSITY INTERNET OF THINGS

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This study's object is the process that controls data transmission across the mobile high-density Internet of Things. The task addressed is to reduce energy consumption when transmitting mobile IoT transactions to fog gateways was by devising a method for energy-efficient data transmission control.

To this end, it was proposed to optimize the distribution of active mobile devices across the fog layer gateways. In the process of research, the architecture of the data transmission subsystem between the boundary and fog layers of the Internet of Things was formed. During the development, an intermediate level of support infrastructure was selected – Communication Layer. That has made it possible to build a mathematical model of the data transmission process control process. The main difference of this model from existing ones is a significant acceleration of calculations when finding a Pareto-optimal solution. To this end, the method of successive concessions was used. It has made it possible to solve a three-criteria optimization problem with objective functions ordered by significance.

The mathematical model has made it possible to devise a method for energy-efficient control over the data transmission process across the mobile high-density Internet of Things. The main difference of this method from existing ones is the optimization of the process simultaneously according to three criteria: energy efficiency, priority, and time. In this case, preference is given to the criterion of energy efficiency of data transmission by mobile IoT devices. That has made it possible to significantly reduce the time of searching for a Pareto-optimal solution when transmitting transactions to a cloud data processing center.

The research results are attributed to the application of the successive concessions method together with the ant colony algorithm with a limited number of iterations. The method proves effective when concessions on the energy resource of mobile devices are from 5 to 15%

Keywords: Internet of Things transactions, energy resource, fog gateway, Pareto-optimal solution, boundary computations

Received 14.05.2025
Received in revised form 02.07.2025
Accepted 22.07.2025
Published 30.08.2025

How to Cite: *Kuchuk, H., Mozhaiev, O., Tiulieniev, S., Mozhaiev, M., Kuchuk, N., Lubentsov, A., Onishchenko, Y., Gnusov, Y., Brendel, O., Roh, V. (2025). Devising a method for energy-efficient control over a data transmission process across the mobile high-density internet of things. Eastern-European Journal of Enterprise Technologies, 4 (4 (136)), 46–57. https://doi.org/10.15587/1729-4061.2025.336111*

1. Introduction

In today's digital world, the rapid development of mobile communication technologies and computing devices is contributing to the active implementation of the Internet of Things (IoT) concept. It unites various devices into a single IoT network [1]. The interaction of mobile devices with the IoT network opens up new opportunities for data collection, transmission, and processing [2]. Modern mobile gadgets can act not only as user interfaces but also as nodes in a distributed IoT infrastructure [3].

Mobile devices can act not only as user interfaces. In combination with the mobile Internet, they can also perform other roles in the IoT ecosystem. Mobile devices can provide functions such as communication, data processing, and interaction with other devices [4, 5]. Due to their mobility and functionality, they expand the capabilities of IoT in various areas of life. Thus, in the mobile high-density Internet of Things (MHDIoT), mobile IoT devices provide the functioning of the boundary layer of the IoT ecosystem [6].

MHDIoT is one of the key directions of mobile network development. It provides mass connectivity of Internet of Things (IoT) devices in limited space.

Typically, IoT devices have low power consumption and high reliability. However, a large number of IoT devices that constantly send small requests can overload communication channels. MHDIoT edge layer mobile devices filter, aggregate or, if possible, process data on-site. This reduces the load on the network core [7, 8].

Complex requests are aggregated and sent by edge layer devices to cloud data centers (CDCs). Communication with CDCs is carried out through fog gateways (FGs) [9].

Stationary edge devices are usually divided into stable clusters. Each cluster is served by a specific fog gateway.

In MHDIoT, aggregation of complex requests at the edge layer is performed by mobile devices. This does not allow for a stable binding of a mobile edge device to a specific fog gateway.

Each fog gateway has a limited information reception area via wireless communication channels. A mobile device can transmit a transaction to any fog gateway in whose reception area it is located at a fixed point in time. However, the following problematic issues specific to MHDIoT arise [10]:

– transaction transmission is associated with additional energy costs;

– the presence of a large number of devices increases the number of possible conflicts during transmission;

– when distributing transactions across gateways, priorities must be taken into account.

The vast majority of edge layer mobile devices have limited energy resources. Therefore, the issue of reducing energy consumption when transmitting mobile IoT transactions to fog gateways is relevant. Solving this issue will increase the efficiency of the MHDIoT system.

2. Literature review and problem statement

In [11], the results of research on the control over the data transfer process between the edge and fog layers of the IoT support network are reported. A method for building a virtual cluster of the edge environment of the Internet of Things was proposed. Each cluster provides a constant connection with a dedicated fog gateway. It is shown that such clustering provides effective control of the data transfer process. However, issues related to the mobility of edge devices, energy consumption for data transmission, and high density of IoT devices remain unresolved. The likely reason is the restrictions imposed on the structure of the virtual cluster. An option to address these issues is to remove restrictions on the number of cluster elements. This approach is used in [12], in which an algorithm is proposed that effectively manages the resources of high-density Internet of Things networks. This leads to improved system performance. However, as in [11], that algorithm does not take into account the features of mobile devices and energy consumption for data transmission. This is the approach proposed in [13, 14], which reports the results of research on managing the data transmission process using mobile edge devices. In [13], a new resource planning method is proposed taking into account energy efficiency for the mobile Internet of Things using a hybrid optimization algorithm. This method integrates the optimization algorithm with the search algorithm, improves energy consumption, and reduces latency compared to conventional methods. The cluster formation method devised in [14] is focused on mobile IoT devices. Transaction management using this method allows for dynamic selection of a gateway for further data transmission. However, in [13, 14], the issue related to the high density of IoT devices remains unresolved. This may be due to the significant increase in the computational complexity of the corresponding algorithms with a high density of IoT devices. Options for overcoming these difficulties may include data stream decomposition, as done in [15], or short-term forecasting, as in [16]. However, the proposed methods are designed only to reduce the total transaction processing time, so the energy consumption of mobile devices is not taken into account when managing the data transfer process.

All the above issues were resolved in the study reported in [17]. That paper proposes an energy-saving method for resource allocation across the mobile Internet of Things using node ranking and an optimization algorithm. The results show significant changes in energy consumption when using the proposed method. However, unacceptable time delays occur during the transmission of operational transactions. Therefore, when transmitting data in high-density mobile IoT, it is necessary to solve a multi-criteria optimization problem in terms of energy efficiency, time, and task priorities.

The authors of [18] reports the results of research on controlling the data transmission process using a multi-criteria optimization problem. The paper considers an algorithm for distributed resource allocation for many nodes based on a deep deterministic policy gradient. The algorithm combines the advantages of distributed and centralized algorithms, and mobile Internet of Things nodes save energy consumption for information transmission. But the criterion of the algorithm is not the maximum possible reduction of energy consumption but the minimization of the age of information across the mobile Internet of Things. A similar problem arose in [19]. The work analyzes in detail the problems of data transmission when performing mobile peripheral computing for the Internet of Things. Three aspects of this problem were considered and solved, which yielded the following results:

– a common model for optimizing task offloading and power distribution has been proposed;

– a centralized algorithm for implementing this model has been developed;

– based on the equalization delay and the impact of energy consumption on data and task offloading, the algorithm uses free resources.

The developed algorithm can not only effectively coordinate task offloading and power distribution but also improve the balance between system latency and energy consumption. This makes it possible to significantly reduce the time of data transmission and calculation execution and reduce transmission latency. However, as in [18], the issue of reducing the energy consumption of mobile devices is relegated to the background.

The reason for this is an attempt to find an optimal solution to a multi-criteria optimization problem. An option to resolve the issue is to find a solution that is optimal according to Pareto. This approach is used in [20]. The work proposes a multi-objective resource allocation method for IoT. The Pareto archived evolution strategy is used to optimize time costs, load balancing and energy consumption of boundary layer servers. To obtain an optimal multi-objective resource allocation strategy, decision-making according to several criteria and the method of ordering by similarity to the ideal solution are used. However, issues related to the energy consumption by mobile devices for transmitting IoT transactions remain unresolved. All this gives grounds to argue that it is advisable to conduct research aimed at reducing energy consumption when transmitting mobile high-density IoT transactions to fog gateways.

3. The aim and objectives of the study

The aim of our research is to devise a method for energy-efficient control over the data transmission process coming from sensors across the mobile high-density Internet of Things. This will make it possible to meet the requirements of quality of service (QoS) at a high density of mobile devices by reducing energy consumption when transmitting IoT transactions to fog gateways.

To achieve this aim, the following objectives were accomplished:

– to propose an architecture of the data transmission subsystem between the edge and fog layers of the Internet of Things;

– to build a mathematical model of the data transmission process control process;

– to develop an ant colony algorithm for distributing IoT transactions across fog layer gateways.

4. The study materials and methods

The object of our study is the process of controlling data transmission across the mobile high-density Internet of Things. Our paper considers active mobile devices of the boundary layer that have formed transactions for processing in cloud data centers. Transactions are transmitted through gateways to the fog layer. The mobile device chooses one of several gateways within the reach of which it is currently located.

The principal hypothesis of the study assumes the implementation of a new method for energy-efficient control over the data transmission process could reduce energy consumption when transmitting mobile IoT transactions. The method is based on finding a Pareto-optimal solution to a three-alternative optimization problem. This would ensure an increase in the functioning efficiency of the mobile high-density Internet of Things.

When devising the method, the following conditions were set:

Condition 1. The mobile device in a boundary layer enters the active state immediately after the formation of a transaction for processing in the cloud layer.

Condition 2. Active mobile devices in a boundary layer transmit data through the fog gateway, in the reach of which they are located.

Condition 3. The energy consumption for data transmission is proportional to the distance from the mobile device to the fog gateway.

Condition 4. One fog gateway channel can accept only one transaction at a time.

In the process of controlling the data transmission process across the mobile high-density Internet of Things, a number of different methods and algorithms have been applied.

When building a mathematical model of the process that controls data transmission, the principle of multi-criteria Pareto optimization was considered [21]. Solving a multi-criteria optimization problem is understood as an approximation or calculation of a representative set of Pareto optimal solutions. Pareto optimization is a search in domain X, which is associated with mathematical optimization problems with several functions to be optimized simultaneously [22].

Pareto optimality is defined as follows. Point x^* is termed Pareto optimal for function $f(x)$ if the following condition is satisfied when finding its maximum

$$f(x) \le f(x^*) \forall x \in X, \tag{1}$$

and when minimizing the function

$$f(x) \ge f(x^*) \forall x \in X. \tag{2}$$

In this case, vector x^* is termed Pareto optimal.

In multi-objective optimization, there is usually no acceptable solution that would minimize all objective functions simultaneously. Therefore, when solving it, a solution is sought that is Pareto optimal. In the case of a single-criteria problem, the Pareto-optimal point becomes the maximum point of the objective function. It follows that the definition of the Pareto-optimal point is a generalization of the point of the extremum of a scalar numerical function for the variant with a vector criterion.

To find a Pareto-optimal solution for a three-criteria minimization problem, the lexicographic method or the successive concessions method was used [23]. A prerequisite for its use is the distribution of all criteria in order of decreasing importance [24].

At the initial stage, a single-criteria optimization problem is solved by the first criterion

$$y_1 = \min_{x \in X} f_1(x). \tag{3}$$

After that, a concession is introduced, determined on the basis of any conditions or conclusions. Due to this concession, the region of admissible solutions is narrowed, that is, we obtain a new region $X_1 \subset X$. Taking it into account, a single-criteria optimization problem is formed and solved by the second criterion

$$y_2 = \min_{x \in X_1} f_2(x). \tag{4}$$

At the third and final stage of Pareto optimization, another concession is made to the second criterion. This further narrows the range of feasible solutions, i.e., $X_2 \subset X_1$. After solving the single-criteria optimization problem according to the third criterion

$$y_3 = \min_{x \in X_2} f_3(x), \tag{5}$$

the final result of Pareto optimization is expected to be vector y_3.

To find solutions to single-criteria problems (3) to (5), the Ant Colony Algorithm (ACA) [25] was used. This algorithm is an imitation of the organization of the behavior of an ant colony. A colony is a multi-agent system in which each individual representative of the system acts independently according to some specific rules. The algorithm of work represents a probabilistic heuristic in which probabilities are set according to information about the quality of the solution based on previous solutions [26].

ACA can be described by the following sequence of actions:

1. Creation of ants. The methodology of placing ants is basic and is tied to the conditions of the problem. Depending on the chosen methodology, the ants of the colony can be located both in one place and in different ones. Also, at the time of creating ants, it is necessary to specify the initial level of pheromone, which is characterized by some small positive number. This is necessary in order to ensure a non-zero possibility of moving to the next point in the first step.

2. Finding a solution. A route is a set of graph vertices connected by paths – edges. The probability of an ant moving from vertex i to vertex j is determined from the following formula

$$p_{ij} = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum\limits_{h \notin tabu_k} \left(\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta} \right)}, & \text{if } j \notin tabu_k; \\ 0, & \text{if } j \in tabu_k, \end{cases} \qquad (6)$$

where t_{ij} is the amount of pheromone on edge (i, j), the ant's "smell"; h_{ij} is the attractiveness of edge (i, j), $h_{ij} = 1/d_{ij}$, where d_{ij} denotes the distance between vertices i and j, the ant's "sight"; a, b are adjustable parameters that determine the importance of the components (edge weight and pheromone level) when choosing a path; h is an element of the set of possible ant routes; $tabu_k$ is a list of already visited vertices, the ant's "memory".

3. Pheromone update. When all ants have completed their path, the amount of pheromone should change. This process includes two stages:

– reducing the pheromone value on all arcs by a certain fixed value;

– increasing the pheromone level on those edges that the ants visited.

The simulation of pheromone evaporation is carried out according to the following formula

$$\tau_{ij} = (1 - \rho) \cdot \tau_{ij}, \qquad (7)$$

where parameter ρ is responsible for controlling the rate of pheromone evaporation. This parameter makes it possible to level the situation with continuous accumulation of pheromones on the edges of the path. The accumulation of pheromone can lead to the fact that the algorithm will not "forget" unsatisfactory solutions obtained at previous stages. If the path was not chosen by the ants, then the level of pheromone associated with it will decrease exponentially with each subsequent iteration. After the final evaporation, all ants change the level of pheromone on the edges they visited.

For edge (i, j), the amount of pheromone deposited on it is given by

$$\tau_{ij} = \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \qquad (8)$$

where $\Delta\tau_{ij}^{k}$ denotes the amount of pheromone left by the k-th ant on the edge it visited, and is calculated from the following formula

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L, & \text{if } (i, j) \in L; \\ 0, & \text{if } (i, j) \in L, \end{cases} \qquad (9)$$

where Q is a constant that artificially adds pheromone, and L is the total length of the path traveled.

Formula (9) shows that the better the path, the greater the amount of pheromone will be located on the edges of this path. Therefore, those edges along which a larger number of ants move, and which are part of the shortest path receive more pheromones. For this reason, such edges will most often be chosen by ants in subsequent iterations.

This iterative process will continue until one of the following termination conditions is met:

– a given number of iterations has been made;

– all the specified number of ants have completed the search;

– a solution has been obtained that is necessary or closest to the required quality;

– the time allotted for calculations has expired.

The algorithm is tuned for a specific task by choosing coefficients a and b. The coefficient a determines how strongly the amount of pheromone affects the ant's choice. The coefficient b determines how strongly an ant will focus on the proximity of the next vertex when making a decision, as well as the number of ants in the colony.

A modification of this algorithm, which is designed to improve the efficiency of solving routing problems, is the ant colony system. This modification differs from the classical ACA in the following features [27]:

– path selection strategy: it is modified to ensure the possibility of achieving a balance between exploring a new edge and using accumulated knowledge about the problem;

– global pheromone update rule: it is applied only to edges that belong to the best solutions;

– local pheromone update rule: it will be applied only when the agent completes the route.

The path selection strategy in the ant colony system consists of two separate strategies, namely, exploitation and exploration of the track. The path exploitation strategy is a deterministic rule that always selects the edge with the largest value of the product of the pheromone weight and the visibility of the vertex. On the other hand, the exploration strategy is a stochastic rule for determining the probability

$$P_{ij}^{k}(t) = \frac{\left(\tau_{ij}(t)\right)^{\alpha} \cdot \left(\eta_{ij}(t)\right)^{\beta}}{\sum\limits_{l \in J_{i,k}} \left(\tau_{il}(t)\right)^{\alpha} \cdot \left(\eta_{il}(t)\right)^{\beta}}, \quad j \in J_{i,k}, \qquad (10)$$

where $P_{ij}^{k}(t)$ is the probability of agent k moving from vertex i to vertex j; $h_{i,j}$ – attractiveness of the path from vertex i to vertex j is the a priori degree of transition, $h_{i,j} = 1/D_{i,j}$; $D_{i,j}$ – geometric distance in two-dimensional space between vertices i and j

$$D_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}, \qquad (11)$$

where (x_i, y_i) are the coordinates of vertex i, and (x_j, y_j) are the coordinates of vertex j; $J_{i,k}$ is the set of vertices that have not yet been visited by agent k, located at vertex i; α, β are parameters defined by the user.

When $\alpha = 0$, the agent focuses on the shortest edge; when $\beta = 0$, the agent chooses the edge with the largest amount of pheromone.

The use of the term path attractiveness implies that vertices that are close to each other have a higher probability of being chosen for visit by the agent. It is worth noting that this factor is not observed in the behavior of real ants but is used as an artificial means to increase the efficiency of the algorithm.

When finding a new solution, a strategy is used, which is the stage of making a decision to move from current vertex i to j. Such a transition strategy is formed as

$$s = \begin{cases} \arg\max\left(\tau_{ij}(t)\right)^{\alpha} \cdot \left(\eta_{ij}(t)\right)^{\beta}, q \le q_0 \text{ (exploitation)}; \\ P_{ij}^{k} \text{ (exploration)}, \end{cases} \quad (12)$$

where $q_0 \in (0; 1)$ is a user-defined parameter responsible for the transition probability; q is an arbitrary number uniformly distributed in the interval [0; 1].

5. Results of devising and investigating the method for energy-efficient control over the mobile Internet of Things data transmission process

5. 1. Forming the architecture of the data transmission subsystem between the edge and fog layers on the Internet of Things

The fog layer of the IoT support infrastructure is a distributed decentralized structure [28]. The main components of the fog layer are local computing nodes, temporary data stores, and fog gateways.

Local computing nodes are designed to implement a number of actions that require execution in real time, in particular [29]:

– performing simple analytics;
– launching containerized services or microservices;
– distributed task processing;
– local resource optimization.

Temporary data stores of the fog layer have small volumes and are usually used for the following actions [30]:

– temporary storage of IoT data for buffering or backup;
– caching to reduce calls to the cloud;
– logging of events and actions.

In the context of supporting high-density mobile IoT in the fog layer, fog gateways are coming to the fore. The main reason is the significant increase in the number and complexity of IoT transactions. Therefore, the processing of most transactions is expected to be carried out in the cloud layer data centers. Accordingly, the following tasks fall to fog gateways [31]:

– reception and aggregation of data from active edge layer devices;
– preliminary minimal processing of received data if possible (filtering, normalization, compression);
– ensuring data compatibility by converting protocols (for example, from MQTT to HTTP);
– transmission of relevant data to cloud data centers;
– local adoption of simple decisions in real time.

Therefore, fog gateways for high-density mobile Internet of Things should be intelligent nodes that perform communication and analytical functions and combine [32]:

– multi-protocol;
– local data processing;
– mobility resilience;
– secure communication;
– adaptation to network changes.

To communicate with mobile edge devices, each gateway has a certain number of physical channels:

– 10–20 real interfaces such as Wi-Fi, USB, 5G, etc.;
– 3–16 radio channels operating simultaneously, for example, LoRa or BLE.

Such fog gateways can simultaneously process dozens or even hundreds of logical connections, for example, MQTT sessions or HTTP sessions.

When operating high-density mobile IoT, the importance of the intermediate support infrastructure layer – Communication Layer – increases significantly. This layer is responsible for transmitting data to the fog layer gateways. It is designed for stable, efficient, and adaptive communication between mobile edge devices and the fog layer computing infrastructure. This layer must:

– adapt to changes in mobility;
– ensure secure, reliable, and efficient data transmission;
– support a wide range of communication protocols and technologies.

Typically, protocols such as MQTT, CoAP, WebSockets, and LwM2M are used to transfer data between mobile devices and gateways.

The physical transmission of packets depends significantly on the characteristics of the Internet of Things and the supporting infrastructure. In local networks with short distances, Wi-Fi or Bluetooth/BLE technology with low energy consumption is used if available. When using sensor networks with a short range, Zigbee/Thread technology is used. At long distances, depending on the availability and IoT tasks, 5G/6G, LoRa/LoRaWAN, or NB-IoT/LTE-M technologies are chosen.

When forming this layer, it is necessary to take into account the peculiarities of transmission under mobility conditions:

– frequent switching between gateways (handover event);
– delays and loss of communication, which must be compensated for by buffering, overwriting, or duplication;
– the need for adaptive routing, which is usually associated with changing the delivery route depending on the availability of fog gateways;
– the need to conserve energy, so energy-saving protocols are usually used to minimize energy consumption.

The considered layer receives information from mobile devices of the edge layer of IoT. These devices under the conditions of high-density IoT operate in an environment with a large number of other IoT devices, often in a limited space. Therefore, they have special requirements that allow them to work effectively under conditions of interference, competition for network resources, and the need for quick response. As a result, mobile devices of the edge layer under the conditions of high-density IoT must:

– be compact, energy-efficient, adaptive to changes;
– support lightweight protocols and dynamic routing;
– work in a complex environment with minimal human intervention;
– provide a scalable and reliable network.

Therefore, when designing the architecture of a data transmission subsystem between the edge and fog layers across the mobile high-density Internet of Things, the following levels are mandatory:

– the highest, cloud level, which accepts IoT transactions for centralized processing;
– the level of ensuring the reception of IoT transactions for transmission for further processing in the cloud layer;
– the level of providing data transmission to the gateways of the fog layer;
– the level of mobile devices of the fog layer, which receive information from devices for direct receipt of information from physical objects;
– the lower level of the IoT system, which consists of devices for direct receipt of information from physical objects.

A fragment of the proposed architecture is shown in Fig. 1.

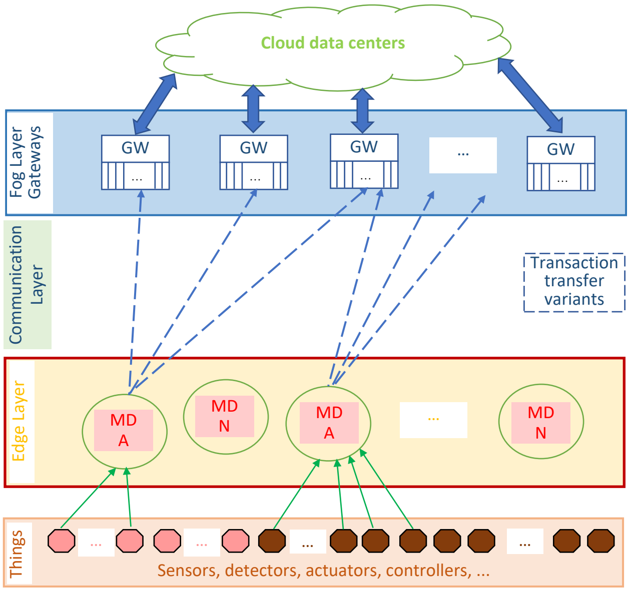

Fig. 1. Fragment of the architecture of a data transmission subsystem between the boundary and fog layers across the mobile high-density Internet of Things

Fig. 1 shows the following:

– Things – the device layer of the Internet of Things;

– MD A – an active mobile device of the boundary layer;

– MD N – an active mobile device of the boundary layer;

– GW – a gateway of the fog layer.

The efficiency of the data transmission subsystem between the boundary and fog layers of the mobile high-density Internet of Things depends significantly on the quality of the process. This process is influenced by many indicators. But in this case, energy efficiency indicators come first, for the study of which it is necessary to build an appropriate mathematical model.

5. 2. Mathematical model of the data transmission control process

Let at a fixed time there be $t \in K$ active fog layer gateways. At the same time, mobile IoT devices have generated J transactions for processing in the cloud infrastructure supporting the Internet of Things. Each k-th gateway ($k = 1...K$) has current coordinates $(x_k(t), y_k(t), z_k(t))$ and m_k independent channels for receiving information. Each j-th transaction ($j = 1...J$) is transmitted from a mobile device with current coordinates $(x_j(t), y_j(t), z_j(t))$. In addition, each j-th transaction has a fixed time interval in which it must arrive at the cloud data center

$$t_j^* = \left[t_j^{begin}; t_j^{end}\right], \tag{13}$$

where t_j^{begin} is the time of transition of the transaction to the active state; t_j^{end} – limit time of transaction activity.

Let us introduce function $r(k, j, t)$, which will determine the distance from the k-th gateway to the j-th mobile device at time t. We shall also introduce the energy resource cost functions:

– $j_1(k, r(k, j, t))$ – cost of transmitting information to the k-th gateway;

– $j_2(k, j, t)$ – cost of transmitting information to the IoT cloud data processing center.

In parallel, we can define the functions of the time spent on transmitting information packets of the j-th transaction:

– $t_1(k, r(k, j, t))$ is the time of transmitting information to the kth gateway;

– $t_2(k, j, t)$ – time of transmitting information to the IoT cloud data processing center.

The matrix of distribution of IoT transactions between fog gateways takes the following form

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1J} \\ \cdots & \cdots & \cdots \\ x_{K1} & \cdots & x_{KJ} \end{pmatrix}, \tag{14}$$

where any element x_{kj} is Boolean, and $x_k = 1$ if the j-th transaction ($j = 1...J$) is served by the k-th gateway ($k = 1...K$).

Also considered is the priority matrix

$$H = \begin{pmatrix} h_{11} & \cdots & h_{1J} \\ \cdots & \cdots & \cdots \\ h_{K1} & \cdots & h_{KJ} \end{pmatrix}, \tag{15}$$

where each element $h_{kj} \in (0; 1]$ denotes the degree of importance of the route between the corresponding transaction and the selected gateway. Accordingly, the larger the value of the element, the higher the priority of the selected route.

Additionally, the time matrix is considered

$$T = \begin{pmatrix} t_{11} & \cdots & t_{1J} \\ \cdots & \cdots & \cdots \\ t_{K1} & \cdots & t_{KJ} \end{pmatrix}, \tag{16}$$

where the elements $t_{kj} \geq 0$ characterize the time of arrival of the corresponding transaction to the cloud data center through the k-th gateway. If $t_{kj} = 0$, it is implied that the corresponding route cannot be used.

The first objective function of the task is formulated based on the condition of minimizing the spent energy resource. The specificity of this task is the factor of its solution at any time due to the possibility of changing the coordinates of mobile devices. The objective function takes the following form

$$f_1(t) = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{kj} \cdot \left(\varphi_1(k, r(k,j,t)) + \varphi_2(k,j,t)\right) \xrightarrow[X]{} \min. \tag{17}$$

If we adopt the orientation of considering routes with the highest priorities, then we can formulate the second objective function as follows

$$f_2(t) = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{kj} \cdot h_{kj} \xrightarrow[X]{} \max. \tag{18}$$

It is also necessary to take into account the time costs of the process of sending transactions to the cloud data center, i.e., the third objective function will take the following form

$$f_3(t) = \sum_{k=1}^{K}\sum_{j=1}^{J} x_{kj} \cdot \left(t_{kj} \middle| t_{kj} > 0\right) \xrightarrow[X]{} \min. \tag{19}$$

In addition to the formulated objective functions, there are restrictions on the process of information receipt to cloud data centers.

First, at a fixed time t, each k-th gateway can serve no more than m_k transactions, i.e.

$$\sum_{j=1}^{J} x_{kj} \leq m_k, \ \forall k \in \overline{1,K}, \ x_{kj} \in \{0;1\}. \tag{20}$$

Secondly, each transaction under consideration must be serviceable, i.e.

$$\sum_{k=1}^{K} x_{kj} = 1,\ \forall j \in \overline{1,J},\ x_{kj} \in \{0;1\}. \tag{21}$$

Thirdly, each transaction in question must be active by the time it arrives at the fog gateway, i.e.

$$x_{kj} \cdot \tau_1\left(k, r\left(k, j, t\right)\right) \in t_j^*,\ \forall k \in \overline{1,K},\ \forall j \in \overline{1,J}. \tag{22}$$

In addition, time limits for each transaction must be observed, i.e.

$$\sum_{k=1}^{K} x_{kj} \cdot \left(\tau_1\left(k, r\left(k, j, t\right)\right) + \tau_2\left(k, j, t\right)\right) \le t_j^{end},\ \forall j \in \overline{1,J}. \tag{23}$$

It is also necessary to ensure that there are sufficient resources in the fog layer to serve IoT transactions, i.e.

$$\sum_{k=1}^{K} m_k \ge J. \tag{24}$$

So, we obtained a multi-criteria optimization problem with three objective functions (17) to (19) and constraints (20) to (24). Solving such a problem involves finding a representative set of Pareto optimal solutions. To find it, we shall use the lexicographic method. This method implies that all criteria of the multi-criteria problem must be distributed in order of decreasing importance.

For mobile devices, in most cases, the energy conservation criterion is the most important. Therefore, the objective function (17) in the tuple of objective functions of the problem will be considered the most important, and the Pareto optimization task is reduced to finding minimal solutions.

In the case of a lack of resources for transmitting a batch of transactions, it is desirable that transactions with the highest priorities be transmitted. Therefore, the objective function (18) will take the next place in the tuple, and the inverse function is minimized.

The time spent on transmitting a transaction is also important. But for each problem there is a constraint (23). Therefore, time optimization can be put in the last place in the tuple that is formed.

So, the tuple of objective functions for Pareto optimization by the successive concessions method will be as follows

$$F(t) = \min\left\langle f_1(t), -f_2(t), f_3(t)\right\rangle. \tag{25}$$

This method requires determining the size of possible concessions for higher priority tasks. The larger the concession size, the faster the final solution will be obtained. But the solution will differ more from the theoretical Pareto-optimal solution.

Let the size of the concession in energy consumption be for the first objective function D_1 conditional units. When optimizing over time, the size of the priority error is added – D_2.

According to the Pareto-optimization principle, in the first step of the algorithm, a single-criteria optimization problem is solved to find the minimum in energy consumption, taking into account constraints (20) to (24)

$$y_1 = \min_{D(t)} f_1(t), \tag{26}$$

where $D(t)$ is the set of all possible options for distributing transactions across the gateways of the fog layer at fixed time t.

In the second step of the algorithm, due to the concession in energy consumption, another constraint is added to the system of constraints

$$f_1(t) \le y_1 + \Delta_1. \tag{27}$$

Given this constraint and constraints (20) to (24), the minimum of the second objective function is found

$$y_2 = \min_{D(t)}\left(-f_2(t)\right). \tag{28}$$

Before the third step of the algorithm, we have a rational solution to the problem, taking into account the first and second objective functions

$$Y = \left(y_1^*, y_2\right),\ y_1 \le y_1^* \le y_1 + \Delta_1. \tag{29}$$

In the third step of the algorithm, a constraint is added that takes into account concession D_2

$$-f_2(t) \le y_2 + \Delta_2, \tag{30}$$

that is,

$$f_2(t) \ge -y_2^* - \Delta_2. \tag{31}$$

Taking into account constraints (20) to (24), (27), and (31), the minimum of the third objective function is

$$y_3 = \min_{D(t)}\left(f_3(t)\right), \tag{32}$$

and the result obtained is the final rational solution to the optimization problem with three objective functions (17) to (19) and constraints (20) to (24):

$$Y^* = \left(y_1^{**}, y_2^*, y_3\right),$$
$$y_1 \le y_1^{**} \le y_1 + \Delta_1,\ y_2 \le y_2^* \le y_2 + \Delta_2. \tag{33}$$

Therefore, to obtain solution (31), it is necessary to solve optimization problems (26), (28), and (32). Focusing on the features of mobile IoT devices and fog layer gateways, the main criterion for choosing an algorithm was the speed of finding the optimal solution.

5. 3. Ant colony algorithm for distributing IoT transactions across fog layer gateways

Evolutionary algorithms are an effective and promising tool used to solve optimization problems in various fields of activity. The effectiveness of evolutionary algorithms depends on the task set before them. For example, one will be successful when working with tasks with a small number of parameters but turns out to be inoperable when processing large data sets. Another, on the contrary, works great with tasks based on the need for multi-criteria optimization but is unable to provide a satisfactory solution for less complex tasks.

A separate issue for evolutionary algorithms is the time to find a solution. To accelerate, it is necessary to set constraints within which the algorithm provides a solution or a set of solutions that fit into these constraints. There is also the problem of ensuring a balance between the speed of finding a solution and the diversification of the search.

Fast convergence of the algorithm usually means a decrease in population diversity.

When choosing an evolutionary algorithm, the main criterion was the criterion of the speed of finding a solution to a large-dimensional multi-criteria problem. The most popular algorithms were considered [33]:

– genetic algorithm;
– ant colony algorithm (ACA);
– bee swarm algorithm (BA);
– flock of birds algorithm (FOA);
– gravitational search algorithm (GSA).

With a high combinatorial complexity of the problem, the time to find a solution by genetic algorithms increases exponentially. The bird flock and gravity search algorithms show good time results only on local clusters of objects. With a number of elements in the search more than a thousand, the best time results were obtained using the ACA and BA algorithms. But with a search area of more than five thousand elements, the ant colony algorithm won in terms of time to find a solution.

Considering the peculiarities of the fog layer of mobile IoT, the ACA algorithm was chosen as the basic algorithm for solving single-criteria optimization problems.

Tuning the ACA parameters is aimed at modifying the mechanism of the algorithm's operation to ensure an increase in the speed of convergence with the quality of the solution.

The main known modifications of ACA were considered [34]:

– Max-Min Ant System (MMAS);
– Elite Ant System (EAS).

Its offer to speed up the search process by reducing the number of routes by influencing the formation and change of the principles of pheromone deposition and evaporation. The consequence of this process is an increase in the convergence rate. But changing the main coefficients of the algorithm also directly affects the speed of the algorithm. The following coefficients were directly considered:

– α and β – coefficients of "visibility" of the base ant and "sensitivity" to the left pheromone, respectively;
– p and q – coefficients of "leftover" and "evaporation" of the pheromone.

Within the framework of this study, both the possibilities of changing the coefficients of the classical algorithm and the application of the elite ant system were used. Such adjustment allowed us to highlight the most favorable routes more clearly, which contributed to an increase in the convergence rate.

Formula (9) is taken as the basis for the formation of the pheromone of elite ants, which takes the following form

$$\Delta\tau_{ij}^{(k_{elite})} = A_{elite} \cdot Q / L, \tag{34}$$

where k_{elite} is the number of the current ant, and the added coefficient A_{elite} characterizes its "authority".

By varying coefficient A_{elite}, it is possible to influence the elite of the colony on other ants.

It is also worth noting that there are several methods for the initial location of the colony:

– "shotgun" when the ants are distributed randomly;
– "intensification" when all the ants of the colony are placed at one point (vertex of the graph);
– "blanket", which is considered the standard location of the colony in the format "one ant – one vertex";
– "wandering colony when the initial position of the colony changes with each subsequent iteration of the algorithm.

Taking into account the statement of the problem with time constraints, a more acceptable option for calculations would be to use a hybrid method. This method combines elements of all methods since the location of mobile IoT objects can be both significantly separated and grouped.

The search for a rational solution, taking into account the above remarks, is as follows.

At the moment of system start, a colony is formed from a certain number of ants. In addition, the number of iterations within which the entire colony is traversed is limited.

After each step, the k-th ant forms a pheromone, the strength of which is calculated as

$$f^{(k)} = \frac{v}{b} \cdot c, \tag{35}$$

where v is the value of the corresponding objective function obtained by the ant, b is the last best result in the system at the time of calculation, c is the coefficient obtained from the system configuration to stimulate the strength of pheromones in case of obtaining a too small value of the function.

At the beginning of the ant's movement, a probabilistic function is called to determine the ant's movement vector, according to which, over several iteration cycles, it will move towards one of the pheromones or randomly. The principle of operation of this function is implemented as follows.

The probabilities of the intensities of all "foreign" pheromones are distributed in the range from zero to the difference between unity and the chance of the ant choosing a movement route randomly according to the formula

$$p(k) = (1-\delta) \cdot f^{(k)} \Big/ \sum_{i=0,\, i\neq k}^{n} f^{(i)}, \tag{36}$$

where $f^{(k)}$ is the strength of the received pheromone; d is the chance of the ant to choose a movement route randomly; n is the number of existing pheromone classes.

The value d is a non-negative static value less than unity. The probability function for determining the pheromone is formed depending on value $p(k)$ as follows

$$\xi(j) = \begin{cases} k_1, & \text{if } j \in [0; p(k_1)); \\ k_2, & \text{if } j \in [p(k_1); p(k_2)); \\ \cdots \\ k_n, & \text{if } j \in [p(k_{n-1}); p(k_n)); \\ 0, & \text{if } j \in [1-\delta; 1], \end{cases} \tag{37}$$

where k_i is an instance of the i-th pheromone class, j is a generated random real non-negative value not greater than 1. If $x(j) = 0$, then the ant chooses the movement route randomly.

Therefore, the probability function (37) receives as input a random, uniformly distributed value within the range [0; 1] and returns either a pheromone or a zero value for an arbitrary movement.

The ant forms the next step vector independently depending on its target point. In the presence of a pheromone, finding new coordinate values occurs according to the following formula

$$\eta_{new}^{(k)} = \left| \eta_{\psi}^{(k)} - \eta^{(k)} \right| w, \tag{38}$$

where $\eta_{new}^{(k)}$ is the new coordinates of the ant location, $\eta_{\psi}^{(k)}$ – coordinates of the pheromone location, $\eta^{(k)}$ – current coordinates of the ant location, w – speed of the ant, which is generated randomly.

After the movement, the ant receives new values of its coordinates, which become new arguments of the objective function. The values of the objective function are calculated using these coordinates. If the obtained value is less than the current one, then it is recorded in the corresponding class as the best result.

The algorithm has three main classes: Ant, AntColony, and Pheromone.

The Ant class forms an ant subject containing the current location in the form of a vector of values that limit the following values:

– task conditions;

– value of the objective function at the time of work;

– functions for movement.

In addition, the body of the ant class calculates the coordinates of the ant's next step during movement.

Pheromone, from the point of view of the algorithm, is a special chemical substance that ants lay down on their path. When an ant chooses a direction of movement, it takes into account both its own preferences in finding the shortest path and the experience of other ants. It receives this experience directly through the level of pheromones left on each route. It follows that the concentration of pheromone is an indicator of the ant's desire to choose a certain path. Therefore, ants, following the routes already traveled by other ants, can make more informed decisions and find optimal routes.

The Pheromone class is responsible for the operation of pheromones, which stores information about the host ant and the force of influence, which decrements with each iteration step.

The main calculations of the algorithm are performed in the AntColony class, which contains information about the task: basic functions, configuration variables, input data, and constraints.

So, in the process of performing iterations, a procedure of traversing all ants of the formed colony is performed, during which a path is selected. After the path is selected, the value of the objective function is calculated for each ant. If the ant has surpassed the best result, the value is updated. After completing the traversal, the ants initialize a new pheromone. After the ants pass, the value of each pheromone is updated by decrementing the intensity value.

To assess the effectiveness of the proposed method, a simulation model of the boundary and fog layers of the mobile high-density Internet of Things support network was used. At a fixed point in time, 12 active fog layer gateways were considered in the network. Each active gateway had 20 independent channels for receiving information from mobile IoT devices. The length of the reception range for each gateway was approximately 10 km. 150 active IoT mobile devices were considered, which formed transactions for transmission to the cloud. The coordinates of active mobile devices were generated randomly.

The quality of the data transmission process was assessed in terms of energy efficiency, priority, and transmission time depending on the size of the concessions and the number of algorithm iterations. The value of the number of algorithm iterations varied from 5 to 0 iterations. Three concession options were considered: 5%, 10%, 20%. The values obtained as a result of the simulation were normalized in the interval (0; 1). In this case, the maximum single value was obtained by the optimal result for the separately considered objective function. The simulation results for the above parameter values are shown in Fig. 2–4.

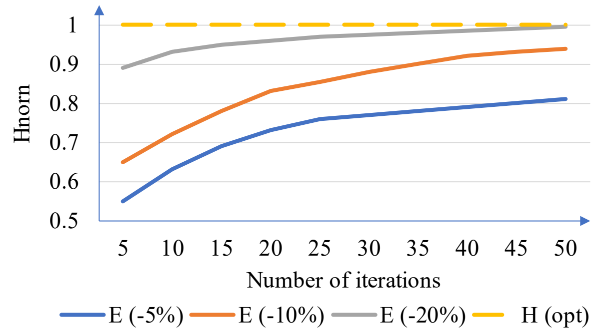

Fig. 2. Dependence of the normalized priority consideration indicator on energy resource concessions and the number of iterations

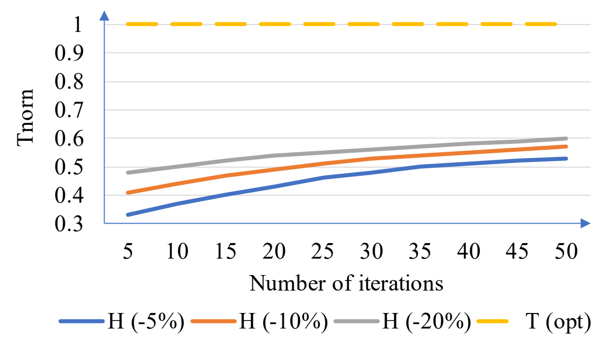

Fig. 3. Dependence of the normalized time cost indicator on concessions by the priority consideration indicator and the number of iterations with a fixed concession on the energy resource of 5%

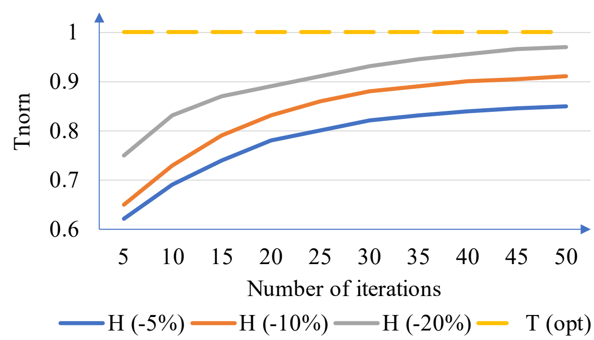

Fig. 4. Dependence of the normalized time cost indicator on concessions by the priority consideration indicator and the number of iterations with a fixed concession for energy resource of 20%

In the mathematical model, each concession adds an additional constraint. When the size of the concession increases, such a constraint passes from critical to non-critical, that is, it begins to have a reserve. Therefore, the final value of the spent energy resource may be less than that calculated taking into account the corresponding concession. The decrease in the final energy efficiency of the data transmission process with an increase in the size of concessions after the first step of the algorithm was analyzed. The generalized results of the analysis are shown in the plots of Fig. 5.

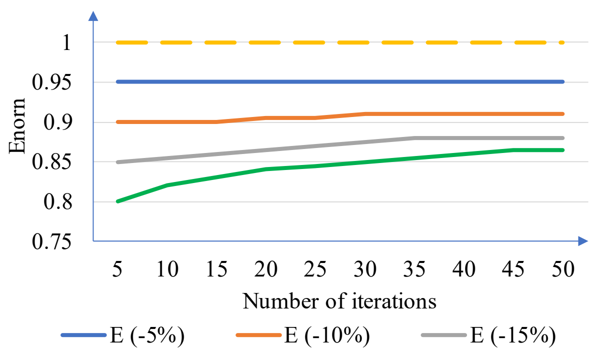

Fig. 5. Dependence of the final normalized energy saving indicator on energy resource concessions and the number of iterations

During the simulation, the number of operations performed varied within the specified limits from the minimum to the maximum value with a step of $\Delta l = 5$. The normalized indicators of energy consumption, priority consideration, and total time costs are denoted as Enorm, Hnorm, and Tnorm, respectively.

6. Discussion of results based on investigating the method of energy-efficient control over a data transmission process across the mobile high-density Internet of Things

The architecture of the data transmission subsystem between the boundary and fog layers of the Internet of Things has been formed. This architecture is focused on mobile high-density IoT (Fig. 1). The main difference of this architecture is the ability to reduce the energy consumption by mobile devices when transmitting transactions from the boundary layer to the gateways of the fog layer. After the transaction is formed to the cloud data processing center, the corresponding mobile device enters the active state for communication with the fog gateways. The reduction occurs due to the modification of the "handover" event. The active mobile device gets the opportunity to choose the fog gateway for transmitting the transaction in order to reduce energy consumption.

A mathematical model of the data transmission process control process has been proposed. A feature of this model is a significant simplification of calculations when finding the Pareto-optimal solution. The application of the successive concessions method made it possible to solve a three-criteria optimization problem with objective functions (17) to (19) ordered by significance. A feature of the iterative calculation process is the successive narrowing of the domain of admissible solutions by replacing the current concessions with equivalent constraints (27) and (31).

When devising a method for energy-efficient control over data transmission process across the mobile high-density Internet of Things, the ant colony algorithm was used. The main difference of this algorithm is the limitation of the number of iterations when solving a partial single-criteria problem. This has made it possible to significantly reduce the time for searching for a Pareto-optimal solution when transferring transactions to a cloud data center. The algorithm is tuned for a specific task by changing the coefficients of the classical algorithm and using the elite ant system (34). This contributed to an increase in the convergence rate.

The assessment of the effectiveness of the proposed method (Fig. 2–5) showed the following results:

– with a small amount of concession for the energy resource (about 5%, Fig. 2, 3) the loss in terms of priority and time costs will be significant;

– with a significant concession for the energy resource (about 20%, Fig. 2, 4) the values of other indicators approach the maximum possible with an increase in the number of iterations;

– an energy concession of around 10% provides a result close to Pareto-optimal, even with a small number of iterations;

– with an increase in the number of iterations in the case of energy concessions of more than 15% (Fig. 5), the value of energy consumption decreases in comparison with the size of the concession.

The results of our research into the method of controlling the mobile IoT data transmission process are attributed to the use of the composition of the sequential concession method with a modified ant colony algorithm.

Unlike [11], in which a resource planning method is proposed taking into account energy efficiency for mobile IoT, the proposed method takes into account the features of high-density IoT. Also, the proposed method, unlike [19], allows us to simultaneously process a large amount of data, which is a specific feature of high-density IoT. This becomes possible due to the use of the Pareto multi-criteria optimization principle.

Unlike [12], in which an algorithm for managing resources of high-density IoT networks was developed, our method takes into account the features of mobile devices. Also, unlike [13], in which only stationary devices are considered, the proposed method considers mobile devices. This becomes possible due to the modification of the "Handover" event.

Unlike [14], in which only the energy consumption of mobile devices was minimized, our method is also aimed at reducing time delays. When performing load balancing, calculated in [15] and [16] only to reduce data transfer time, the proposed method takes into account energy consumption. Similarly, unlike [18], energy consumption is taken into consideration. This becomes possible due to finding a Pareto-optimal solution according to three criteria simultaneously.

Unlike [17], in which a multi-objective method for resource allocation for IoT was proposed, our method takes into account the energy consumption by mobile devices for transmitting transactions. Also, unlike [20–22], the energy consumption of mobile devices is a priority objective function in energy-efficient management of the data transmission process.

Therefore, our results allowed us to reduce energy consumption when transmitting mobile IoT transactions to fog gateways. Depending on the energy resource/time ratio, energy consumption is reduced from 5 to 20%.

But it is worth noting that the proposed results should be applied only at a high density of IoT mobile devices. In addition, a significant limitation of the study is the restriction on the mandatory intersection of the coverage areas of several fog gateways.

As a drawback of this study, it is necessary to note the lack of analysis of the influence of distances between fog gateways on the change in energy consumption. To eliminate this drawback, additional research should be conducted on choosing the optimal distance between fog gateways in order to reduce energy consumption during data transmission.

The following is the prospect for future studies.

First, a separate study should be conducted on the optimal number of fog gateways for mobile high-density IoT. Second, it is necessary to investigate the possibility of organizing IoT transaction queues to fog gateways in the event of a shortage of data transmission channels.

7. Conclusions

1. We have designed the architecture of a data transmission subsystem between the edge and fog layers across the Internet of Things. The levels of the mobile high-density Internet of Things involved in data transmission to cloud data centers have been determined. Special attention has been paid to the intermediate level of the support infrastructure – Communication Layer. When forming the architecture, the specific features of mobile devices of the edge layer and fog gateways were taken into account. Based on the resulting architecture, a mathematical model of the data transmission process control process has been built.

2. A mathematical model of the data transmission control process has been proposed. The main difference of this model from existing ones is a significant acceleration of calculations when finding a Pareto-optimal solution. To this end, the successive concessions method was used. It allowed us to solve a three-criteria optimization problem with objective functions ordered by significance. In addition, to accelerate the solution, a successive narrowing of the region of admissible solutions was carried out by replacing the current concessions with equivalent constraints. This mathematical model has made it possible to devise a method for energy-efficient control over a data transmission process across the mobile high-density Internet of Things.

3. An ant colony algorithm has been developed to distribute Internet of Things transactions across fog layer gateways. The main difference of this algorithm is the limited number of iterations when solving a partial single-criteria Pareto optimization problem. In addition, the algorithm is tuned for a specific task by changing the coefficients of the classical algorithm in parallel with the use of the elite ant system. That has made it possible to significantly reduce the time for searching for a Pareto-optimal solution when transmitting transactions to a cloud data center. The process is optimized simultaneously according to three criteria: energy efficiency, priority, and time. In this case, preference is given to the criterion of energy efficiency of data transmission by mobile IoT devices. The results of our study have made it possible to assess the effectiveness of the devised method. With a small amount of concession in terms of energy resources, about 5%, the loss in terms of priority and time costs will be significant. But with a significant concession in energy resources of about 20%, the values of other indicators approach the maximum possible with an increase in the number of iterations. A concession in energy resources of about 10% provides a result close to Pareto-optimal, even with a small number of iterations. At the same time, depending on the energy resource/time ratio, energy consumption decreases from 5 to 20%.

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.

Funding

The study was conducted without financial support.

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.

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