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LOAD BALANCING OF THE LAYERS IoT FOG-CLOUD SUPPORT NETWORK

Abstract. Topicality. Nowadays, the concept of the Internet of Things (IoT) is developing rapidly. In recent years, mobile devices have been used as elements of the IoT. But when using mobile devices, a number of problems arise. The main ones are the following: – limited computing resources; the need to maintain an energy-saving mode. Therefore, there is a need to balance the distribution of resources between all layers of the IoT support network. In this case, it is necessary to comply with all the time and structural constraints imposed by the IoT system with mobile devices. **The subject of study** in the article is methods of distributing IoT tasks between support network layers. **The purpose of the** article is to reduce the energy consumption of mobile IoT devices. The reduction occurs by transferring part of the load of mobile devices from the edge layer of the IoT support network. Time limits on IoT transactions must also be enforced. **The following results** were obtained. A model of the mobile computing unloading process has been developed. Proposed approach to calculating the average response time for components of different layers of the IoT support network: mobile device, fog node, cloud computing node. The task of choosing the optimal energy consumption option for mobile devices in the IoT support network is formulated. **Conclusion.** The dependence of the probability of unloading tasks from mobile IoT devices on the unloading threshold was analyzed. The conditions under which the minimum energy consumption is obtained when meeting time requirements were determined.

Keywords: Internet of Things; computer system; cloud environment; fog and edge computing; energy consumption; mobile devices; computing resources.

Introduction

Problem relevance. Nowadays, the concept of the Internet of Things (IoT) is developing rapidly [1]. In recent years, mobile devices have been used as elements of the IoT [2]. Some mobile IoT devices have their own computing power. Such devices are used to process IoT information at the edge layer of the IoT support network [3]. However, the computing resources of edge layer devices are severely limited. Therefore, most tasks are transferred to the cloud environment for execution. This results in large time delays in the information exchange process [4].

To reduce time delays, an intermediate layer of the IoT support network is used: Fog computing. The term “Fog computing” was proposed in 2012 by Cisco Systems. Fog computing extends cloud services to the device layer of the Internet of Things [5]. Cloud computing is used in the mobile IoT support network. Fog computing, in accordance with the IoT concept, is used at the level of connected things [6]. In a fog computing environment, devices also have small computing capabilities. Fog computing servers manage multiple devices and gateways [7]. They are responsible for communication between heterogeneous components of the fog environment. They also communicate with cloud components of the IoT support network [8].

For operational IoT transactions, an important parameter is response time [9]. Of course, the shortest response time will be obtained when processing the transaction at the edge layer. But when using mobile devices, a number of problems arise. The main ones are the following [10]:

– limited computing resources;
– the need to maintain an energy-saving mode.

Therefore, there is a need to balance the distribution of resources between all layers of the IoT support network. In this case, it is necessary to comply with all the time and structural constraints imposed by the IoT system with mobile devices.

Literature review. Let's consider some scientific works on this topic.

Research on resource allocation in fog-cloud infrastructures supporting IoT has been conducted in many scientific papers. In [11, 12], resource allocation methods for fog-cloud platforms are proposed. The methods take into account the capacity of virtual machines and the request processing time. However, the algorithm is not focused on the features of mobile devices. In [13, 14], models for a trade-off between energy consumption and delays are developed. However, the complexity of the load and resources is not considered in these papers. In [15–17], tools are proposed to take into account service requirements. They take into account the quality of communication, but ignore availability and waiting time.

Many scientific works are focused on the optimal allocation of resources in fog computing. In [18, 19], algorithms for deploying IoT applications in fog-cloud systems are described. The works take into account RAM and bandwidth. However, response time and resource availability are also important, but energy consumption costs are not taken into account. In [20], big data processing using fog computing is studied. The method minimizes the computational load through dynamic resource allocation. However, this method does not take into account the peculiarities of mobile devices. In [21, 22], a resource estimation algorithm using user history is proposed. However, these works do not focus on the energy consumption of mobile devices. Therefore, all the considered works do not take into account the energy consumption of mobile devices when distributing resources between all layers of the IoT support network.

The purpose of the research is to reduce the energy consumption of mobile IoT devices. The reduction occurs by transferring part of the load of mobile devices from the edge layer of the IoT support network. Time limits on IoT transactions must also be enforced. To achieve the purpose, the following tasks are solved:

1) development of a model of the mobile computing unloading process;

2) calculation of average response time for devices of different layers of the IoT support network;

3) choosing the optimal energy consumption option for mobile devices supporting the IoT network.

1. Unloading tasks to the fog-cloud infrastructure

The most common scenarios for using task offloading mechanisms are considered. Some applications require a fog computing infrastructure for uninterrupted service. These include intelligent transportation systems, AR, VR, healthcare. Also, this is streaming video, smart houses and smart cities. Platform and application requirements are also necessary for services. Below is an overview of research on the use of fog computing.

1. Intelligent Transportation System. A number of studies cover intelligent transportation systems using fog computing. For example, in [23], a VANET architecture is proposed that combines SDN and fog computing. SDN provides programmability, scalability, flexibility, and global knowledge. The advantage of such a combination is the presence of location-based and fast response. This system improves the communication between vehicles, infrastructure, and base stations. Research on VANET networks is also described in [24]. This work focuses on modeling applications for VANET architecture.

2. Vehicles in a fog computing infrastructure. In [25], the idea of vehicular fog computing (VFC) was proposed. The VFC architecture uses vehicles for computing and communication [26]. This allows for pooling the resources of moving vehicles and improving the quality of services.

3. Augmented and virtual reality. AR applications are very time-sensitive; delays can cause errors [27]. Solutions based on fog computing have great potential in this area. This also applies to VR games, which require high accuracy and speed. In [28], a VR game with brain-computer integration is proposed. Fog computing analyzes brain signals and performs real-time processing.

4. Healthcare. Fog computing enables real-time healthcare services [29] Network latency, energy consumption, and communication optimization for healthcare services are discussed in [30].

5. Smart cities. Smart city applications require real-time data processing [31]. An architecture supporting smart city applications is proposed in [32]. Noise mapping, drainage networks, and smart streets are considered.

The examples considered are typical examples of fog computing. Fog computing performs critical analysis at the edge of the network. It is resistant to delays when transferring to cloud computing. Fog computing can be considered as an extension of cloud computing.

The growth of the number of applications increases the intensity of calculations and energy consumption [33]. Therefore, the fog layer is well suited for critical resource-intensive applications.

This technology reduces the load on mobile devices and saves energy. The main difference from the cloud is the proximity to the end user. This significantly reduces response time and increases efficiency.

2. Choosing an IoT support network architecture

To deploy fog computing, it is necessary to define the architecture of the IoT support network. There are many different variants of such architectures [34–37].

Fog computing uses resources along with networks between the cloud and devices. This ensures high-quality and fast processing of applications and services. In addition to fog computing, there are several similar paradigms.

Among them is mobile cloud computing (MCC) [38]. There is also mobile peripheral computing (MEC). This also includes peripheral computing (Edge Computing). Dew Computing is another similar technology. There is also fog-dew computing (Fog-dew Computing) [39]. In cloud computing, IoT devices are directly connected to the cloud. Computing is completely dependent on the cloud in this approach. Similar technologies use intermediate devices, not depending on the cloud. Some of them don't even require a connection to the cloud.

Next, we'll briefly discuss each of the above schemes separately.

1. Mobile Cloud Computing (MCC) is a technology for remote service execution. This technology provides access to data, applications, and the cloud. Access is provided to mobile users over the Internet. Offloaded mobile services are executed using MCC near users. MCC helps to overcome the resource limitations of mobile devices and their power consumption. It also expands the possibilities of data storage and computing power. For this, a small cloud server is usually used at the edge of the network. It is expected that in the future MCC will be used in various fields. These are education, urban and rural development, healthcare, and social networks. Computing-intensive applications such as augmented reality (AR) are gaining popularity. Also, it is speech recognition, machine learning, planning, and decision-making. Natural language processing is also a promising area of use for MCC.

2. Mobile Edge Computing, MEC. MEC combines computing and storage resources at base stations. It is an evolution of base stations that combines telecommunications and IT networks. MEC can be connected to cloud data centers. It supports two- or three-

tier deployment of mobile device-based applications. The MEC server is deployed near the base stations to process and store data.

3. Edge or Edge Computing, EC. The “edge” is a network or resource near the data transmission. It is located between the cloud centers and the data sources. Smart devices or sensors can be the data sources. Cloud storage is the edge between the mobile application and the cloud. IoT gateway is the edge between the IoT sensors and the cloud. The main goal of EC is to perform computing closer to the data sources.

4. Dew Computing, DC. DCs are located at the lower level between cloud and fog computing. They are transformed into a sub-platform based on the microservice concept. The DC hierarchy is distributed vertically, facilitating the use of sensors and smartphones. This includes ad-hoc network technologies.

5. Fog computing, FDC. In the FDC architecture, IoT devices do not require an active Internet connection. The FDC server interacts with the cloud and provides services to IoT devices. Cloud computing requires a constant Internet connection, which is its disadvantage. FDC allows you to work offline without the Internet.

Let's consider the most generalized, three-tier version of the architecture. In this architecture, fog computing is an intermediate layer between edge and cloud computing. This layer consists of all intermediate computing devices. Virtualization technologies can be used on it. Data generated by IoT sensors is accumulated at this level. Fog servers maintain a constant connection to the cloud layer. This layer can also be used for small amounts of big data processing.

Fig. 1 shows a generalized diagram of fog-cloud computing for IoT.

The lowest layer is the IoT layer. It consists of all connected devices. Devices at this layer perform reading and processing. For time-sensitive applications, processing is done using fog computing. The cloud performs other tasks that are not time-critical. The fog computing layer manages the data sent to the cloud. Users can receive services from the fog and cloud layers.

The cloud layer is responsible for complex data processing and storage.

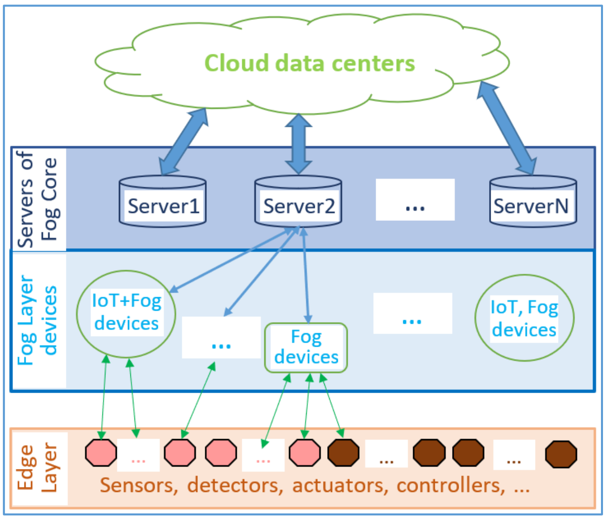

Fig. 1. Fog and cloud computing scheme

3. Modeling the mobile computing unloading process

The model considers a mobile computing offload scheme. The main elements of the scheme are a fog computing node and a remote cloud computing system. IoT devices run applications that consume a large amount of computing resources. Most tasks are offloaded to a fog computing node. A fog computing node has limited capacity, so overloading may occur. In this case, the offloaded task is sent to a remote cloud computing node.

The main goal of the task is to minimize the power consumption of mobile devices. In this case, it is necessary to fulfill strict constraints on the response time.

Fig. 2 shows an example of offloading calculations in an IoT support system. The system has m mobile devices that have low computing power and battery life. In addition, the system has a fog computing node F and a cloud computing node C.

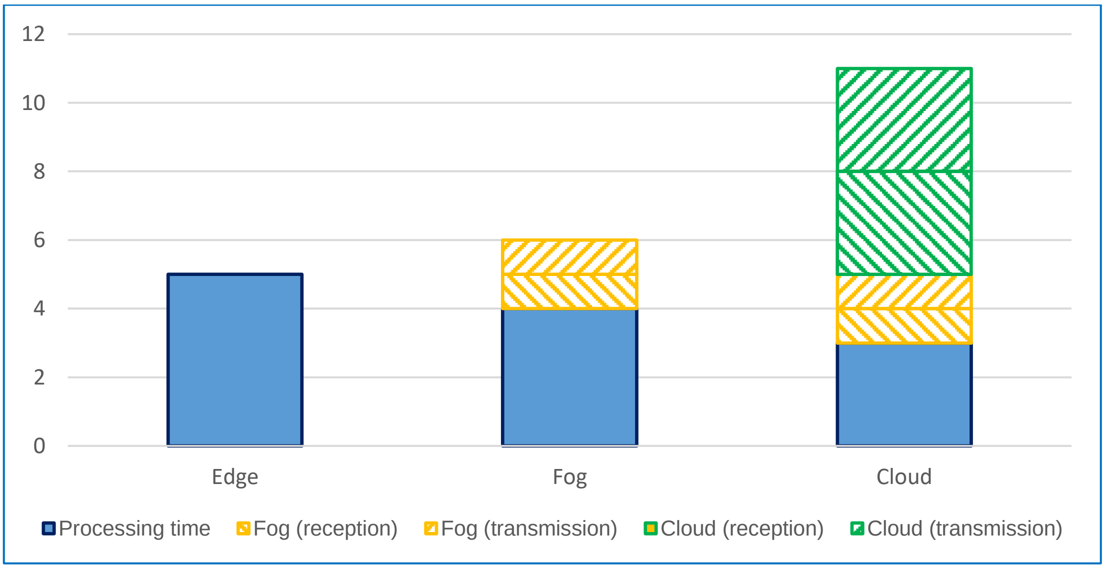

Fig. 2. Mobile computing unload example

The random variable response time γ_i ($i = 1..m$) when solving a task on node i corresponds to the processing time of unloaded tasks. In this case, the mobile device consumes a lot of energy. But the node has the smallest response time, which consists only of the processing time, $\gamma_i = t_i$. In the case of offloading a task to a fog computing node, the mobile device spends energy only on sending the task over the wireless channel. But it saves energy on performing calculations.

The resulting response time is the sum of the delay time for transmitting and processing the task in the fog computing node:

$$\gamma_i = t_F + 2\Delta_F, \quad i = m + 1, \tag{1}$$

where t_F is task execution time by a fog node, Δ_F is time spent exchanging information with a fog node.

If the unloaded task cannot be processed on the fog node, it is forwarded to the remote cloud. In this case, the energy consumption of the mobile device is the same as in the previous case.

But the response time will be much longer, since the transmission delay to the cloud computing node is added:

$$\gamma_i = t_C + 2\Delta_F + 2\Delta_c, \quad i = m + 2, \tag{2}$$

where t_c is task execution time in a cloud environment; Δ_F is time spent exchanging information with a fog node.

The computational offloading scheme can be described in terms of queuing networks. Let m be the number of mobile devices in the coverage area of a fog computing node F.

A mobile device i ($i = 1..m$) generates a stream with an intensity of λ_i requests per second. Each task requires a certain amount of computation. Let v_i be a random variable that specifies the required amount of computation for device i. The distribution function:

$$V_i(x) = P(v_i < x), \tag{3}$$

where x – current value of the required amount of calculations.

Let μ_i be the constant processing speed of tasks on device i ($i = 1..m + 2$). Let v_i^* be the threshold of the amount of computation for mobile IoT devices and the fog node. Then the task is offloaded to the fog node when the condition is met:

$$v_i > v_i^* \tag{4}$$

Otherwise, the task is processed locally on the mobile device. The probability of unloading the i-th mobile device is defined as

$$p_i = 1 - V_i\left(v_i^*\right). \tag{5}$$

A fragment of the mathematical model of the system, which is built taking into account formulas (1) – (5), is presented in Fig. 3. 4.

4. Average response time calculation

Let's calculate the average response and processing time of the task for different task execution options:
– on a mobile device (option 1);
– in a fog computing node (option 2);
– in a cloud computing node (option 3).

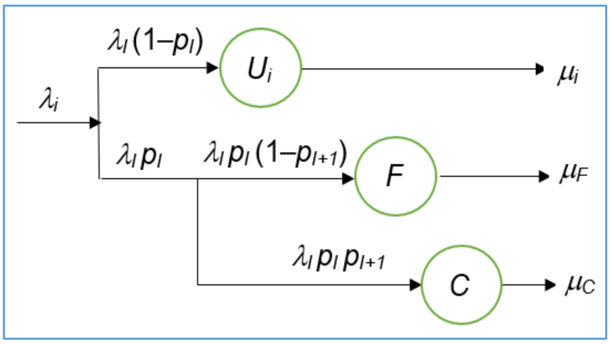

Fig. 3. Mobile IoT device upload model

4.1. Option 1: mobile device. Let $q_{i,j}$ be the probability that j operations will be required to process a task from the i-th mobile computing node, and

$$\sum_{j=0}^{\infty} q_{i,j} = 1. \tag{6}$$

Then the distribution function (3) is defined as

$$V_i(x) = \sum_{j=0}^{x} q_{i,j}. \tag{7}$$

The computation volume distribution function for a task processed locally on the i-th mobile device is defined as

$$\Xi_i(x) = \begin{cases} V_i(x)/(1-p_i), & x \le v_i^*; \\ 1, & x > v_i^*. \end{cases} \tag{8}$$

Substituting (7) into expression (8):

$$\Xi_i(x) = \begin{cases} \sum_{j=0}^{x} q_{i,j} \Big/ (1-p_i), & x \le v_i^*; \\ 1, & x > v_i^*. \end{cases} \tag{9}$$

The processing time on the i-th mobile device is defined as the ratio of the amount of computation and the speed of task processing λ_i.. Then the distribution function is defined as

$$T_i(x) = \begin{cases} \Xi_i(\mu_i x), & x \le v_i^* / \mu_i; \\ 1, & x > v_i^* / \mu_i. \end{cases} \tag{10}$$

Next, formula (9) is substituted

$$T_i(x) = \begin{cases} \sum_{j=0}^{\mu_i x} q_{i,j} \Big/ (1-p_i), & x \le v_i^* / \mu_i; \\ 1, & x > v_i^* / \mu_i. \end{cases} \tag{11}$$

Therefore, the average response time of the i-th mobile device is equal to

$$t_i^{(average)}(x) = \frac{1}{\mu_i \cdot (1-p_i)} \cdot \sum_{j=1}^{v_i^*} j \cdot q_{i,j}. \tag{12}$$

4.2. Option 2: Fog Node. All tasks from mobile devices (where $v_i > v_i^*$) are sent to the fog node.

Tasks arrive at the fog computing node with intensity

$$\lambda_F = \lambda_{m+1} = \sum_{j=0}^{m} \lambda_i \cdot p_i . \qquad (13)$$

The amount of computation on the i-th mobile device is determined by the distribution function:

$$\Xi_{m+1,i}(x) = P\left(v_i < x \middle| v_i > v_i^*\right). \qquad (14)$$

For $\forall j \le v_i^*$ $\Xi_{m+1,i}(x) = 0$. Then,

$$\Xi_{m+1,i}(x) = \begin{cases} 0, & x < v_i^* + 1; \\ \sum_{j=v_i^*}^{x} p_{m+1,i,j} & x \ge v_i^* + 1. \end{cases} \qquad (15)$$

Let $\mu_F = \mu_{m+1}$.is constant task processing speed on a virtual machine of a fog computing node. Let n is number of virtual machines, $v^* = \min_{i \in 1,m} v_i^*$. Then the task processing time distribution function on a fog node is as follows:

$$T_{m+1}(x) = T_F(x) = \\ = \begin{cases} 0, & x < \left(v^* + 1\right) / \mu_{m+1}, \\ \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_{m+1}} \cdot \sum_{j=v_i^*}^{\mu_{m+1} x} q_{i,j}, & x \ge \left(v^* + 1\right) / \mu_{m+1}. \end{cases} \qquad (16)$$

Then the average processing time of a task in a fog computing node from any mobile device is as follows:

$$t_F^{(average)} = t_{m+1}^{(average)} = \\ = \frac{1}{\mu_{m+1}} \cdot \sum_{j=v_i^*+1}^{\infty} j \cdot \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_{m+1}} \cdot q_{i,j} . \qquad (17)$$

When a fog node is overloaded, tasks are redirected to the cloud environment. The probability of overload is

$$p_F = p_{m+1} = \\ = \left(\sum_{s=1}^{n} \frac{\lambda_{m+1} \cdot t_F^{(average)}}{s!} \right)^{-1} \cdot \frac{\left(\lambda_F \cdot t_F^{(average)} \right)^n}{n!} . \qquad (18)$$

4.3. Option 3: Cloud environment. All tasks blocked on a fog node are redirected to the cloud environment.

The intensity of requests is $\lambda_{m+1} \cdot p_{m+1}$.

The distribution of processing time on has the following probability distribution function:

$$T_{m+2}(x) = T_C(x) = \\ = \begin{cases} 0, & x < \left(v^* + 1\right) / \mu_{m+2}, \\ \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_{m+1}} \cdot \sum_{j=v^*}^{\mu_{m+2} x} q_{i,j}, & x \ge \left(v^* + 1\right) / \mu_{m+2}. \end{cases} \qquad (19)$$

Then the average processing time of a task from any mobile device in a cloud environment is equal to

$$t_C^{(average)} = t_{m+2}^{(average)} = \\ = \frac{1}{\mu_{m+2}} \cdot \sum_{j=v^*+1}^{\infty} j \cdot \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_{m+2}} \cdot q_{i,j} . \qquad (20)$$

5. Formulation of the optimization task

The objective function of the optimization problem is to reduce the load and energy consumption of mobile devices. To do this, it is necessary to maximize the total probability of unloading, which is equal to

$$\Im = \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_\Sigma} p_i , \qquad \lambda_\Sigma = \sum_{i=1}^{m} \lambda_i . \qquad (21)$$

However, as the probability of offloading increases, the load on the fog node also increases. This can lead to overloading of the fog node. As a result, the response time will increase sharply.

Let the average processing times of tasks on each layer of the IoT cloud environment be known for each mobile node. For i-th mobile node, this time will be $t_i^{(average)}$ (the processing probability is $t_i^{(average)}$). For the fog node this time will be $t_F^{(average)} + 2\Delta_F$ (the processing probability is p_i $(1 - p_{m+1})$. For the cloud environment this time will be $t_C^{(average)} + 2\Delta_F + 2\Delta_C$ (the processing probability is p_i p_{m+1}.

Then, the average response time of the i-th node is as follows:

$$\gamma_i^{(average)} = \left(1 - p_i\right) \cdot t_i^{(average)} + \\ + p_i \cdot \left(1 - p_{m+1}\right) \cdot \left(t_F^{(average)} + 2\Delta_F \right) + \\ + p_i \cdot p_{m+1} \cdot \left(t_F^{(average)} + 2\Delta_F + 2\Delta_C \right). \qquad (22)$$

The average response time of the current task is

$$\gamma^{(average)} = \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_\Sigma} \gamma_i^{(average)} . \qquad (23)$$

For critical applications, the probability of exceeding a predefined threshold t^* is as follows:

$$\Gamma\left(t^*\right) = P\left(\gamma > t^*\right); \\ P\left(\gamma > t^*\right) = \sum_{i=1}^{m} \frac{\lambda_i}{\lambda_\Sigma} P\left(\gamma_i > t_i^*\right). \qquad (24)$$

The probability of exceeding the response time on the i-th mobile device is defined as

$$P\left(\gamma > t^*\right) = \left(1 - p_i\right)\left(1 - T_i\left(t^*\right)\right) + \\ + p_i\left(1 - p_i\right)\left(1 - T_{m+1,i}\left(t^* - 2\Delta_F\right)\right) + \\ + p_i\, p_{m+1}\left(1 - T_{m+2}\left(t^* - 2\Delta_F + 2\Delta_C\right)\right). \qquad (25)$$

Then the task of finding the optimal threshold for unloading from mobile devices is formulated as follows:

$$\Im\left(v^*\right) \to \max; \quad (26)$$

$$\gamma_i^{(average)}\left(v^*\right) \le \gamma^* \quad \forall i \in \overline{1,m}; \quad (27)$$

$$\Gamma\left(v^*, t^*\right) \le \Gamma^*, \quad (28)$$

where γ^*, Γ^* are predefined threshold values of response time and probability of its exceeding.

6. Discussion of results

The averaged results of the dependence of the probability of unloading tasks from mobile IoT devices on the unloading threshold are given in Table 1.

Table 1 – **Probability of task unloading**

v^*	100	120	140	160	180	200
$\Im(v^*)$	**0,9**	0,7	0,5	0,4	0,2	0,1

Table 1 shows that the probability of unloading decreases depending on the unloading threshold.

The averaged results of the dependence of the average response time on the unloading threshold and the number of virtual machines in the fog node are given in Table 2.

Table 2 – **Results of the average response time study**

n \ v^*	100	120	140	160	180	200
2	1,5	1,4	1,3	1,1	**0,8**	1,7
4	1,0	0,9	0,8	**0,6**	1,1	1,6
6	0,8	0,6	**0,4**	0,7	0,8	0,9
8	0,7	**0,5**	**0,5**	0,6	0,7	0,8
10	0,6	**0,4**	0,5	0,5	0,6	0,7

When v^* is small, almost all tasks are unloaded to the fog node. As a result, it becomes overloaded. Therefore, many tasks are redirected to a remote cloud computing node with a relatively large transmission delay. As the unloading threshold v^* increases, the probability of the fog node being overloaded becomes smaller. This leads to a decrease in the average response time. However, at some point, the average response time starts to increase. This is because the probability of unloading becomes too small. Therefore, most of the requests are processed locally on mobile devices with relatively small capacity. Therefore, at the points of local minimum, the load is optimally balanced between mobile devices and the fog node.

Conclusions

The paper develops a method for balancing the load of the fog-cloud layers of the IoT support network. The method is focused on reducing the energy consumption of mobile IoT devices.

The approaches to unloading tasks to the fog or cloud layers are analyzed. It is shown that, compared to the cloud, the use of fog nodes reduces the response time and increases the efficiency of the network. The increase in the number of applications increases the intensity of calculations and energy consumption. A three-level architecture option is proposed. In this architecture, fog computing is an intermediate layer between edge and cloud computing. A model of the mobile computing offloading process is developed. An approach to calculating the average response time for individual components of different layers of the IoT support network is proposed: a mobile device, a fog node, a computing node of the cloud environment. The task of choosing the optimal option for the energy consumption of mobile devices of the IoT support network is formulated. The dependence of the probability of unloading tasks from mobile IoT devices on the unloading threshold was analyzed. The conditions under which the minimum energy consumption is obtained when meeting time requirements were determined.

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Балансування навантаження шарів туманно-хмарної мережі підтримки IoT

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Анотація. Актуальність. В наш час концепція Інтернету речей (IoT) розвивається швидкими темпами. В останні роки в якості елементів IoT використовуються мобільні пристрої. Але при задіянні мобільних пристроїв виникає низка проблем. Серед них головними є такі: обмеженість обчислювальних ресурсів; необхідність підтримання режиму енергозбереження. Отже, виникає необхідність балансування при розподілі ресурсів між всіма шарами мережі підтримки IoT. При цьому потрібно виконувати всі часові та структурні обмеження, що накладені системою IoT з мобільними пристроями. **Предметом вивчення** в статті є методи розподілу завдань IoT між шарами мережі підтримки. **Метою статті** зменшення енергоспоживання мобільних пристроїв IoT. Зменшення відбувається за рахунок перенесення частини навантаження мобільних пристроїв з граничного шару мережі підтримки IoT. При цьому виконуються часові обмеження на транзакції IoT. Отримано **такі результати**. Розроблена модель процесу вивантаження мобільних обчислень. Запропонований підхід до розрахунку середнього часу відгуку для окремих компонент різних шарів мережі підтримки IoT: мобільний пристрій, туманний вузол, обчислювальний вузол хмарного середовища. Сформульовано завдання вибору оптимального варіанту енергоспоживання мобільних пристроїв мережі підтримки IoT. **Висновок.** Проаналізовані залежності ймовірності вивантаження завдань з мобільних пристроїв IoT від порогу вивантаження. Визначені умови, за яких отримується мінімум витрат енергії при виконанні часових вимог.

Ключові слова: Інтернет речей; комп'ютерна система; хмарне середовище, туманні та периферійні обчислення; енергоспоживання; мобільні пристрої; обчислювальні ресурси.