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ADAPTIVE RESOURCE ALLOCATION METHOD FOR THE MOBILE FOG LAYER OF HIGH-DENSITY INDUSTRIAL INTERNET OF THINGS IN INDUSTRY 5.0 NETWORKS

Relevance of the article. The modern concept of Industry 4.0 laid the foundation for complete digitalization through the industrial Internet of Things. However, the transition to Industry 5.0 requires greater flexibility and resilience of systems. High-density mobile industrial IoT with a fog layer is a critical element of this transformation, as it provides not only automation but also the adaptability of production to human needs and environmental standards. **The object of study** is the process of pre-processing transactions of the HDIoT edge layer. **The main hypothesis of the study:** the implementation of a new adaptive method of resource allocation for mobile devices of fog clusters will reduce the average pre-processing time of transactions of the HDIoT edge layer. **The goal of the work** is to reduce the average time a transaction of the HDIoT peripheral layer spends in the fog layer by developing an adaptive method for distributing the resources of mobile devices in fog clusters. **Research objectives:** to identify the architectural features of fog computing in HDIoT networks; to create a mathematical model of the process of optimal resource allocation for mobile cluster devices in the fog layer; to formalize a multi-agent approach to cluster resource allocation; to develop and investigate a theoretical game model for managing the resources of a mobile fog cluster of a multi-layer IoT. **Methods used:** multi-agent approach, game theory, in particular, optimization of a cooperative stochastic game, computer modeling**. Results.** An adaptive method for distributing resources of mobile devices in fog clusters has been developed. Within the framework of the method, the architecture of a mobile fog cluster has been proposed and a mathematical model of the process of optimal distribution of its resources has been created. In addition, a multi-agent approach is used to find an approximate solution to the formulated two-parameter nonlinear optimization problem, and a game-theoretical approach is implemented to reduce computational complexity and accelerate the search for an approximate solution. **Conclusion.** As a result of applying the developed method, the average time a transaction of the peripheral layer of a high-density IoT spends in the fog layer has been reduced, which, given the high density of mobile devices, has made it possible to meet QoS requirements.

Keywords: Industry 5.0; Internet of Things; fog cluster; mobile node; computer system; agent-based approach; intelligent agent; stochastic game.

1. Introduction

The Internet of Things (IoT) is one of the key paradigms for the development of modern information and communication technologies, enabling the integration of physical objects into the digital space [1]. Thanks to the IoT, billions of sensors, actuators, and embedded systems are capable of collecting, transmitting, and processing data in near real time [2]. This opens up vast opportunities for building intelligent environments in various areas, such as industry [3], transportation [4], healthcare [5], energy [6], and others. IoT systems generate enormous amounts of data, which in some cases requires instant collection, transmission, and analysis for operational decision-making [7]. Traditional cloud computing, despite its power, faces critical delays when transporting traffic from the periphery to remote data centers [8]. In addition, network bandwidth limitations and data transfer delays reduce the efficiency of centralized processing [9]. That is why there is an urgent need to decentralize computing power and bring it closer to the sources of information.

To overcome these problems, a fog computing layer is actively used, which is located between peripheral devices and the cloud [10]. Fog computing allows part of the data processing to be moved closer to its source. This reduces delays, increases reliability, and reduces the load on backbone networks [11]. In addition, the fog layer provides better support for mobility and geographic distribution, which is critical for modern dynamic systems [12]. The use of fog node resources enables the implementation of real-time computing, which is vital for industrial automation and critical infrastructure [13]. Thus, the fog layer becomes a key element of scalable IoT systems.

Fog computing is particularly relevant in the context of High-Density IoT (HDIoT) [14]. High-density networks are characterized by an extremely large number of active nodes in a limited area. For example, the concept of high-density Industrial IoT (IIoT) involves the deployment of thousands of sensors in a limited area,

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which creates a huge load on the network. The addition of a Mobile Fog Layer (MFL) allows data to be processed directly near the source, even if that source or computing node is constantly moving. For example, this could be a large automated warehouse covering 50,000 m^2, where thousands of pallets with RFID tags, vibration and temperature sensors, and hundreds of autonomous mobile robots are operating simultaneously. Each unit of goods and each rack is equipped with sensors. Due to their large number (high density), transferring all data directly to the cloud would cause delays (latency) and overload communication channels. The fog node (robot) makes most decisions without connecting to the cloud, coming to the sensors itself, which allows the sensors to operate at very low power (saving battery life).

Mobile fog environments HDIoT are characterized by high transaction intensity, dynamic topology, and traffic heterogeneity [15]. The huge number of simultaneous requests from sensors and actuators requires the infrastructure to be highly adaptable and capable of rapid scaling [16]. High-density conditions make centralized management virtually impossible due to the exponential growth in coordination complexity. In addition, high-density IoT significantly increases the requirements for response speed and data processing stability [17]. At the same time, the resources of individual fog nodes remain limited. This makes it difficult to ensure guaranteed quality of service.

Under such conditions, there is a need for territorial clustering of fog layer devices. Clustering allows fog nodes and peripheral devices to be grouped according to spatial proximity and load characteristics [18]. Division into territorial segments helps to localize traffic within a certain area, preventing overload of the entire network. This contributes to more efficient use of available computing and network resources [19]. Territorial clusters also simplify data flow management and load balancing [20].

A complicating factor is that a mobile fog layer cluster functions as a decentralized system with limited resources [21]. The mobility of nodes leads to constant changes in available resources and network connections. The lack of a single control center forces nodes to self-organize and make decisions based on local information [22]. In such conditions, static approaches to resource management prove ineffective. The system must adapt to the current state of the cluster and the intensity of transaction flow.

Therefore, preprocessing transactions at the edge layer requires a change in traditional approaches to resource allocation. Adaptive allocation methods focused on the dynamics of mobile devices in a fog cluster are becoming a prerequisite for the effective functioning of a high-density Internet of Things. This determines the relevance of research on the adaptive allocation of fog cluster resources in modern HDIoT systems.

2. Analysis of literature and problem statement

Recently, there have been many works addressing the issue of optimal distribution of communication and computing resources in mobile systems. Article [23] addresses the problem of optimizing computations at the network edge. The main optimization task is to minimize the total energy consumption of mobile devices, taking into account the current requirements of Internet of Things transactions. However, the issue of optimal resource allocation is not addressed, as in the classical approach, the nearest available resource is always allocated. In [24], the problem of minimizing the total delay of HDIoT transactions that arises during data processing is considered. An algorithm for making decisions on resource allocation is presented, taking into account the presence of several base stations and computing servers in the network. However, the HDIoT mobile cluster is a decentralized system. In [25], the task of minimizing delay is considered for decentralized systems, but the proposed approach does not allow for the requirements of HDIoT transactions to be taken into account. In [26], procedures are given for organizing resource allocation in decentralized computing networks that use a weighted utility function for energy and transaction delays. However, these procedures are also not focused on optimal resource allocation. To solve the problem of dynamic changes in the mobile IoT environment, there are also other computing models described in [27, 28], but they also do not take into account all the requirements of HDIoT transactions.

In [29], the process of data transfer between the edge and fog layers of the IoT ecosystem is investigated. The proposed method is effective for managing the data transfer process. However, issues related to the mobility of fog devices, energy consumption for data transfer, and the high density of IoT devices remain unresolved. This is due to restrictions imposed on the number of elements in a virtual cluster. In [30], there are no such restrictions on the number of cluster elements. However, as in [29], this algorithm does not take into account the characteristics of mobile devices.

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This approach is proposed in [31, 32], which present the results of research on the transmission of data using mobile devices. Work [31] proposes a resource planning method for the mobile Internet of Things, focused on energy efficiency. The method of forming a fog layer cluster developed in work [32] is also focused on mobile IoT devices. However, these works leave unresolved the issue related to the high density of IoT devices. The main reason is the significant increase in the computational complexity of the proposed algorithms as the density of IoT devices increases.

In [33], data transmission is controlled using a multi-criteria optimization problem. The authors propose a fast resource allocation algorithm for many nodes based on a deterministic gradient. However, this algorithm is aimed at minimizing the age of information in the mobile Internet of Things. A similar problem is found in [34], which analyzes in detail the problems of data transmission when performing mobile computing for the Internet of Things. The proposed algorithm improves the balance between system latency and energy consumption, which reduces transmission delays. However, as in [33], the issue of optimal resource allocation for mobile devices takes a back seat.

Thus, all the analyzed works leave unresolved issues related to the optimal distribution of limited resources of the fog layer of the high-density Internet of Things. resources of the fog cluster of the high-density Internet of Things.

This gives reason to argue that it is expedient to conduct research aimed at reducing the time indicators associated with the transmission and pre-processing of information sent from the IoT periphery to the fog layer.

3. Purpose and objectives of the study

The purpose of the study is to reduce the average time a HDIoT peripheral layer transaction spends in the fog layer by developing an adaptive method for allocating resources of mobile devices in fog clusters. This will make it possible to meet quality of service (QoS) requirements even with a high density of mobile devices.

The object of the study is the process of preprocessing transactions of the HDIoT peripheral layer. The main hypothesis of the study is that the implementation of a new adaptive method for allocating resources of mobile devices in fog clusters will reduce the average preprocessing time of transactions in the HDIoT peripheral layer.

The following conditions were used as a basis for developing the method.

Condition 1. Mobile fog devices belonging to the same HDIoT territorial cluster are considered.

Condition 2. Mobile fog devices of the territorial cluster are considered as a completely decentralized system.

Condition 3. The peripheral layer transaction is transmitted to the nearest available mobile fog device.

Condition 4. Additional computing resources of another device located within the range of the base device may be used to pre-process the transaction.

To achieve the goal, the following tasks were set:

– to identify the architectural features of fog computing in HDIoT networks;

– to develop a mathematical model of the process of optimal resource allocation for mobile fog cluster (MFC) devices;

– to formalize a multi-agent approach for MFC resource allocation;

– to develop a theoretical game model for managing MFC HDIoT resources;

– to describe in the form of a sequence of steps and investigate the developed adaptive method for distributing resources of mobile devices in fog clusters.

4. Development and investigation of an adaptive method for distributing resources of mobile devices in fog clusters

4.1. Architectural features of fog computing in HDIoT networks

The development of the Internet of Things (IoT) concept has led to a transition to a three-tier architecture through the introduction of a fog layer [35].

This layer acts as an intermediary between end devices and cloud data processing centers (DPC), where the IoT level is responsible for data collection and the cloud is responsible for long-term storage. Fog layer nodes provide pre-processing and instant transmission of critical information to operational control points. Vertical integration of such computing significantly improves quality of service (QoS) [36], ensuring minimal response time, reduced load on communication channels, and increased system fault tolerance through decentralization.

Architecturally, the fog layer is based on the principles of modularity and virtualization [37], which allows for flexible system scaling. The hardware platform includes computing, memory, security, and management modules, as well as containerization tools for service deployment [38]. Communication with data centers is maintained through a distributed decentralized core that combines the resources of IoT devices into a single aggregation network. In such conditions, the clustering of spatially dispersed nodes becomes critical, optimizing the use of network resources and increasing the energy efficiency of the system.

Promising IoT networks are characterized by high node mobility, which involves placing fog capabilities on mobile platforms, including unmanned aerial vehicles. In such systems, fog devices can act as both last-mile network components and user terminals, which facilitates network slicing. The formation of mobile clusters is based on critical parameters: the speed vector of devices or the time of task execution. For ultra-high-density architectures with mobile components, a four-level hierarchy is mandatory: cloud level (DPC), fog layer core servers, clustered fog devices, and the lower level of direct information collection.

A fragment of the ultra-dense IoT architecture with a dedicated mobile fog layer cluster is shown in Fig. 1.

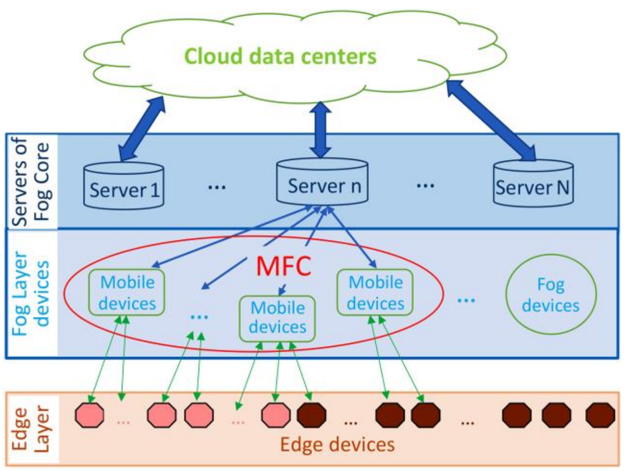

Fig. 1. MFC's place in the vertical structure of HDIoT

One of the main factors affecting the efficiency of HDIoT is the quality of clustering of mobile fog devices. For mobile clusters, stability indicators, which are analyzed in detail in article [39], are essential. However, given the limited computing resources of mobile devices, time criteria are no less important, especially for operational transactions of the peripheral layer. Among the many time criteria for evaluating the quality of multi-node decentralized mobile systems, the criterion of minimizing the maximum data processing delay has been selected [40, 41]. This criterion helps to reduce the time transactions spend in the fog layer.

4.2. Mathematical model of the optimal MFC resource allocation process

A set of mobile computing nodes (Mobile Fog Computing Node, MFCN) MFC $N=\{N_1,N_2,\ ...,N_k,\ ...,N_K\}$, represented by K mobile devices, card $N=K$, is considered. Each node $N_k \in N$ has the ability to accept transactions from the edge layer of HDIoT, which, depending on the source, constitute a set of types $M=\{M_1,M_2,\ ...,M_s,\ ...,M_S\}$, card $M=S$. During the operation of HDIoT, the flow of transactions of type M_s arriving at MFC is distributed according to the Poisson distribution with an average intensity of λ_s, and the average intensity of task processing at the k-th node is μ_k.

Let node N_k accept transaction HDIoT M_s, which is characterized by the following parameters:

G_s – computing resource required to execute transaction M_s;

B_s – size of transaction M_s.

When processing this transaction, node N_k provides the required computing resource at a rate of f_k. Then, the delay in computing during the execution of transaction M_s on node k is determined as follows:

$$t_{k,s}=G_s/f_k. \tag{1}$$

Let the following conditions be satisfied:

$$f_k\cdot t_{k,s}\le F_{k,\max}; \tag{2}$$

$$\lambda_s<\mu_k, \tag{3}$$

where $F_{k,\max}$ – the maximum possible amount of computing resources that node N_k can provide per unit of time.

When these conditions are met, the transaction can be fully resolved on the node that accepted it, and the time the transaction spends on this node is determined as

$$T_k(M_s)=t_{k,s}\cdot\left(\frac{1}{\mu_k-\lambda_s}\right). \tag{4}$$

However, if at least one of conditions (2) and (3) is not met, the computing resources of node k are insufficient to execute the transaction, let node j be selected as the auxiliary node. Let the share of transaction M_s processed on node k be denoted as $z_{k,s}$, 0 £$z_{k,s,j}$£ 1. When conditions (2) and (3) are met, $z_{k,s,j}=1$, and if $z_{k,s,j}=0$, the transaction is completely transferred to another mobile node j for execution.

In the case of $0 < zk,s,j < 1$, the transaction is executed jointly by mobile nodes k and j. The delay in transmitting the necessary information is calculated using the formula

$$\tau_{k,s,j} = \left(1 - z_{k,s,j}\right) \cdot \frac{B_s}{C_{k,j}}, \tag{5}$$

where $C_{k,j}$ – the throughput capacity of the channel between the k-th and j-th mobile nodes.

Then, in the general case, the time spent by transaction M_S in the MFC environment is calculated using the following formula:

$$T_k\left(M_s \mid z_{k,s,j}\right) = z_{k,s,j} \cdot t_{k,s} \cdot \left(\frac{1}{\mu_k - z_{k,s,j} \cdot \lambda_s}\right) + \left(1 - z_{k,s,j}\right) \cdot \left(\tau_{k,s,j} + t_{j,s}\left(\frac{1}{\mu_j - \left(1 - z_{k,s}\right) \cdot \lambda_s}\right)\right). \tag{6}$$

Let us introduce a set of possible states of the system that satisfy conditions (1)–(5), depending on the distribution of transactions and the options for their processing:

$$\Gamma = \left\{\gamma_\eta\right\}, \quad \gamma_\eta = \left\{z_{k_s,s,j_s}\right\}, \quad \mathrm{card}\left(\gamma_\eta\right) = S, \quad s \in \overline{1,S};\, k_s, j_s \in \overline{1,K},$$

where γ_η – η-th option of fixed distribution of a set of transactions between computing nodes of a mobile cluster.

Using expression (6) and the criterion of minimizing the maximum transaction processing delay, we can formulate the objective function of the problem of optimal distribution of MFC computing resources:

$$\gamma_\eta^* = \arg\left(T\left(\gamma_\eta\right) \middle| T\left(\gamma_\eta\right) < T\left(\gamma_\eta^*\right) \ \forall \gamma_\eta \in \Gamma; \gamma_\eta \neq \gamma_\eta^*\right), \tag{7}$$

where $T\left(\gamma_\eta\right) = \max\limits_s\left(T_{k_s}\left(M_s \mid z_{k_s,s,j_s}\right)\right), \quad z_{k_s,s,j_s} \in \gamma_\eta$.

At the same time, a number of restrictions must be observed:

$$0 \le z_{k_s,s} \le 1 \quad \forall s \in \overline{1,S}; \tag{8}$$

$$\lambda_s < z_{k_s,s} \cdot \mu_{k_s}, \quad \forall s \in \overline{1,S}, \forall k_s \in \overline{1,K}; \tag{9}$$

$$\left(1 - z_{k_s,s}\right) \cdot \lambda_s < \mu_{j_s}, \quad \forall s \in \overline{1,S}, \forall j_s \in \overline{1,K}; \tag{10}$$

$$f_{j_s} \cdot \tau_{j_s,s} \cdot \left(1 - z_{k_s,s}\right) \le F_{j_s,\max}, \ \forall s \in \overline{1,S}, \forall j_s, k_s \in \overline{1,K}. \tag{11}$$

Thus, based on the resource allocation model (expressions (8)–(11)), it is possible to optimize the process of allocating MFC computing resources relative to the criterion of minimizing the maximum transaction processing delay by minimizing the objective function (7).

4.3. Formalization of a multi-agent approach for MFC resource allocation

MFC HDIoT is a stochastic decentralized system. Therefore, to find an approximate solution to a two-parameter nonlinear optimization problem, it is advisable to use an agent-based approach.

In the work of M. Wuldridge and N. Jennings, Intelligent Agents: Theory and Practice [42], the concept of an intelligent agent (IA) was systematized for the first time in the context of multi-agent systems. The authors define a separate IA as an autonomous system capable of perceiving the environment, making decisions, and behaving purposefully, which is ensured by reactivity, proactivity, and the ability to interact socially, i.e., an IA must meet a number of specific properties. These properties in HDIoT systems correspond to mobile fog computing nodes (MFCN, Table 1).

Table 1. *Compliance of mobile fog HDIoT nodes with the canonical definition of IA*

IA characteristics	Canonical interpretation	Compliance of MFCN with HDIoT
Autonomy	Independent choice of actions	The node itself controls transmission, sleep modes, and offloading
Reactivity	Function of reaction to the environment	Reaction to events, channel changes, load
Pro-activeness	Purposeful behavior	Local traffic prediction, task migration, fog node change
Social ability	Communication with other agents	MQTT/CoAP/DDS, coordination with fog nodes
Situatedness	Placement in the environment	Physical location + network topology + decentralized system element
Rationality	Maximization of utility	Energy/latency/QoS optimization

Therefore, any MFCN that has accepted a peripheral layer transaction for processing can be considered as an IA, and the set of nodes with which it interacts at this time can be considered as the operating environment of this IA [43].4 For MFC devices, there is no reward criterion for IA actions (utility function). This requires the IA to implement random actions and learn to select those that maximize the utility function. It should be noted that none of the MFC mobile devices can control the entire process and has no complete picture of the global state of the system [44]. Therefore, MFC HDIoT cannot be classified as a fully observable environment, so a reinforcement learning approach should be used.

Single-agent reinforcement learning by trial and error shapes the behavior of the IA that will be necessary to achieve the set goal [45]. A generalized diagram of this process is shown in Fig. 2.

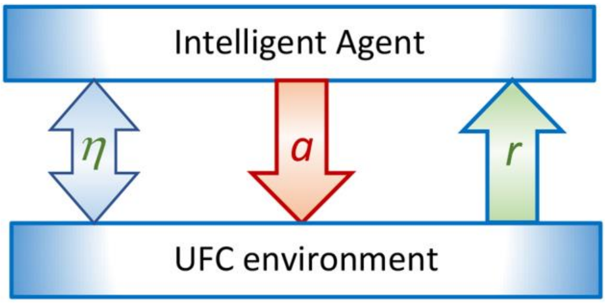

Fig. 2. Interaction IA and UFC

According to the concept of reinforcement learning, the AI interacts with the environment, having some observation η, on the basis of which it performs action a and receives reward r, which depends on the results of the impact on the environment. The reward received in accordance with the reinforcement learning algorithm increases or decreases the probability of performing the action under the same conditions in the future.

The formal model of such interaction is given by the tuple:

$$\theta = \langle S, A, H, R \rangle, \tag{12}$$

where set $S = \{s\}$ is the set of all possible states of the environment; set $A = \{a\}$ is the set of all possible actions of the IA; $H = \{h\}$ is the set of all possible observations of the environment available to the computing node; $R = \{r\}$ is the set of all possible values of the IA's gain, where each element is a reward function.

$$r = r(s_t, a_t, s_{t+1}) : S \times A \times S \to R, \tag{13}$$

which is determined at a discrete moment in time t and which is obtained by the IA when performing action a_t in state s_t of the environment and transitioning the environment to state s_{t+1}.

Tuple θ elements at a discrete moment in time t determine the transition function

$$\nu = \nu(s_t, a_t, s_{t+1}) : S \times A \to [0;1], \tag{14}$$

which returns the probability of the environment transitioning from state s_t to state s_{t+1} when the agent performs action a_t, and the observation function

$$\nu = \nu(s_t, a_t, s_{t+1}) : S \times A \to [0;1], \tag{15}$$

which returns the probability of an agent receiving observation o_t in state s_t.

When considering several IA models (12)–(15), it is transformed into multiagent reinforcement learning (MRL) [46]. When transitioning from single-agent reinforcement learning to multiagent reinforcement learning, the corresponding mathematical model transitions from scalar values to vectors, which are elements of the corresponding sets.

The number of states of the environment S grows exponentially with the increase in the number of IA, because the states of the environment, except for state σ (without mobile nodes that have become intelligent agents), are supplemented by the states of the set of IA. Thus, in the tuple (48)

$$S = \{s\} = \left\{ \left\langle \sigma, s^{(1)}, \ldots, s^{(i)}, \ldots s^{(n_k)} \middle| s^{(i)} \in S_k, i = \overline{1, n_k} \right\rangle \right\}, \tag{16}$$

where S_k – the set of possible states of mobile node k, which belongs to the set of intelligent agents, card $S_k = n_k$.

The set of all possible actions of an IA becomes a set of action tuples, i.e.

$$A = \{a\} = \left\{ \left\langle a_i \middle| a_i \in A_k \right\rangle \right\}, \tag{17}$$

where each tuple is a set of actions of a separate IA of the corresponding mobile computing node N_k, which form the corresponding set of actions A_k.

Similarly, when transitioning from single-agent to multi-agent reinforcement learning, sets H and R are formed with the corresponding tuples:

$$H = \{h\} = \left\{ \left\langle h_i \middle| h_i \in H_k \right\rangle \right\}, \tag{18}$$

$$R = \{r\} = \left\{ \left\langle r_i \middle| r_i \in R_k \right\rangle \right\}. \tag{19}$$

The power of the sets $A_k = \{a_i\}$ of possible actions of IA, which is the k-th mobile computing node, increases due to the additional capabilities of interaction between agent nodes. The number of components of a single element and $h_i \in H_k$ possible observations of the environment of the k-th IA increases because the nodes observe not only the state of the environment without intelligent agents, but also the states of other agents.

Thus, multi-agent reinforcement learning (MARL), described by formal models (12), (16)–(19) and

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functions (13)–(15), allows us to find an approach to solving the optimization problem (7)–(11). Given the characteristics of MFC HDIoT, it is necessary to take into account such features of the process as complete decentralization, heterogeneity, the possibility of simultaneity, and individualization of gains [47]. Due to the absence of information in the observations about the actions that other computing nodes plan to take, tasks were selected without IA knowledge of the planned actions of other agents. Based on the simultaneity of actions a_i, a multi-agent reinforcement learning task was selected, where the actions of all computing nodes are performed simultaneously. Based on the criterion of individualization of gains, tasks with different individual gains were selected. In order to have information generated by other agents in the observation, tasks with communication were selected. In order to have homogeneity of the sets of available actions and observations q, tasks with physically heterogeneous computing nodes were selected.

4.4. Theoretical game model of MFC HDIoT resource management

Mobile computing nodes (MCN) MFC can pursue different interests. Therefore, the above-considered MFC functioning scheme, taking into account MARL, does not fully reflect the dynamics of its functioning. In order to refine this scheme, it is proposed to move to a modification of the MARL scheme, within which a cooperative stochastic game (CSG) is implemented.

The priority is calculated as a win for the AI, which allows MCN tasks to be redistributed according to their priority. Thus, the higher the priority of the MCN, the faster its task will be assigned for distribution and solution in the system.

Let $z^{(k)} = (z_1, \ \ldots, z_{k-1}, z_{k+1}, ..., z_K)$ is the decision to provide its resources by all nodes except node k. Taking into account the decisions $z^{(k)}$ for other nodes, computing node k would seek to choose the correct decision z_k regarding whether to provide its resources to other nodes in order to achieve a common goal, so as to minimize resource costs and the time the task spends in the network, i.e.

$$\min_{z_k} \psi_k \left(z_k, z^{(k)}\right) \forall k \in \overline{1,K}, \tag{20}$$

where $z_k = 0$, if node k does not provide computing resources to other nodes, in this case $\psi_k \left(z_k, z^{(k)}\right) = E^{(k)}$ – computing resource costs when performing a transaction independently; $z_k = 1$ if node k is ready to provide its own resources, in this case $\psi_k \left(z_k, z^{(k)}\right) = Y^{(k)}$ – computing resource costs when using the assistance of other mobile nodes.

Let's formulate problem (20) as a strategic game

$$\Im = \left(K, \left\{F_k^{'}\right\}, \left\{\psi_k\right\}\right) \forall k \in \overline{1,K}, \tag{21}$$

where the set of K computing nodes is considered as a set of players; $F_k^{'}$ is a set of strategies for user k; $\psi_k \left(z_k, z^{(k)}\right)$ is considered as a service function, which is a cost function that player k must minimize. The game $\Im$ will perform a decentralized distribution of resources. The solution to the game lies in the region of rational solutions to the optimization problem (7)–(11) that are close to the optimal. The solution to this game is an equilibrium point that can be found using Nash equilibrium [48, 49]. Let there be a strategy profile

$$z^* = \left(z_1^*, z_2^*, \ldots z_K^*\right), \tag{22}$$

which is a Nash equilibrium in a game with decentralized resource allocation, if, in a state of equilibrium, no computing node can further reduce its own computing resource costs by unilaterally changing its own strategy, i.e.,

$$\psi_k \left(z_k^*, z^{*(k)}\right) \le \psi_k \left(z_k, z^{*(k)}\right) \forall z_k \in F_k^{'}, k \in \overline{1,K}, \tag{23}$$

Nash equilibrium has the property of self-stability, so computing nodes that are in equilibrium can reach a mutually acceptable solution, and no node has an incentive to deviate. Considering the strategies $z^{(k)}$ of other players, the strategy $z^{*(k)} \in F_k^{'}$ of the k -th player is the best if

$$\psi_k \left(z_k^*, z^{*(k)}\right) \le \psi_k \left(z_k, z^{(k)}\right) \forall z_k \in F_k^{'}, k \in \overline{1,K}. \tag{24}$$

According to (23) and (24), in Nash equilibrium, all players use the best response strategies in relation to each other. Due to the property of Nash equilibrium, no player has an incentive to deviate from the decisions reached. Thus, the iterative algorithm for finding the Nash equilibrium of the game allows us to quickly find a resource allocation that is close to optimal in terms of minimizing the maximum data processing delay.

4.5. Research on an adaptive method for distributing resources among mobile devices in fog clusters

The results obtained in sections 4.1–4.4 allow us to propose an adaptive method for distributing resources

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among mobile devices in fog clusters, which can be described as a sequence of the following steps:

Stage 0. Determination of initial time characteristics $t = t_0$ and discretization step $\Delta t = \Delta t_0$, fixation of a stable core of a fuzzy cluster.

Stage 1. Determination of average values of key characteristics of mobile devices and HDIoT transaction flows using a mathematical model of the MFC optimal resource allocation process.

Stage 2. Determination of sets of possible states of a fog cluster and possible actions of mobile nodes that accept HDIoT transactions as intelligent agents using the proposed multi-agent approach for MFC resource allocation.

Stage 3. If $\operatorname{card}(\Gamma) \neq \varnothing$, then the transition to the next stage of the method is carried out. Otherwise, the discretization step must be reduced by 2 times. If the obtained discretization step value is less than the minimum permissible value, then control is transferred to the classical method of resource allocation of the fuzzy cluster of the high-density Internet of Things.

Stage 4. Use of the MFC HDIoT resource management theoretical game model, which implements a cooperative stochastic game based on the data generated in the previous stages of the method.

Stage 5. The distribution of fog cluster resources is carried out based on game equilibrium strategies.

Stage 6. We form the beginning of the next interval $t = t + \Delta t$.

Stage 7. Correction of multiple possible states of a fog cluster and possible actions of mobile nodes that accept HDIoT transactions. Transition to stage 3.

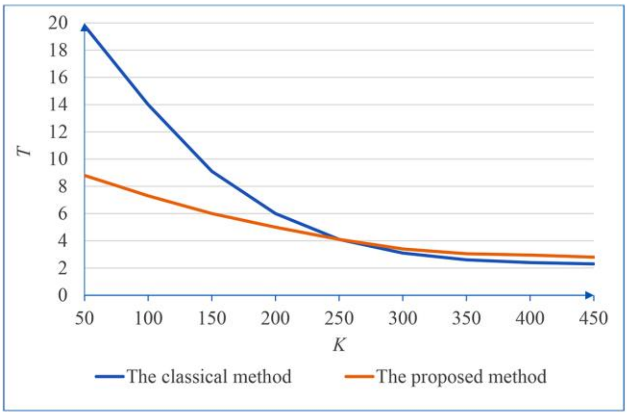
Unlike the methods discussed above, the proposed method does not require the use of cloud technologies and remote server-type nodes. The method involves solving computational tasks directly on mobile devices in the fog layer. To do this, the computing resources of devices located in the same cluster are used. If a mobile device lacks its own resources, such as memory or processor time, it redirects its task or part of it to another device or devices that have the necessary resources to solve it. To evaluate the performance of the method, the criterion of minimizing the maximum data processing delay is used. Therefore, the worst delay caused by data transfer and processing should be as small as possible.

To evaluate the effectiveness of the proposed resource allocation method, a simulation model of the MFC HDIoT mobile cluster operation was used. The average time a transaction from the edge layer spends in the HDIoT fog layer during a fixed time interval was chosen as the performance indicator. To compare transaction processing methods, two methods were modeled:

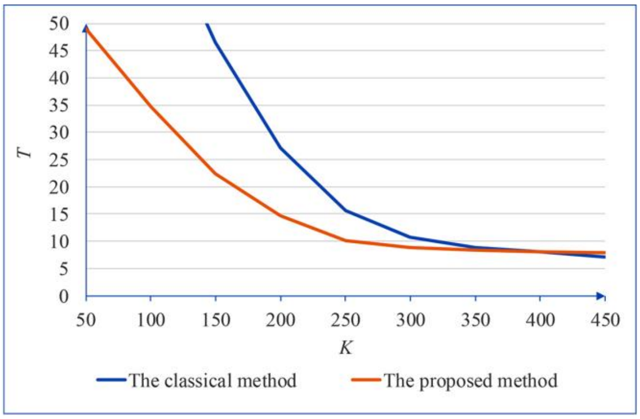
– the classic method, which distributes the transaction for execution to a mobile device that has sufficient computing resources to execute it and sent the first response to the request; the transaction is fully processed by this device;

– the proposed method.

The generalized results of modeling the dependence of the transaction residence time in the fog layer on the number of mobile devices in the cluster and the intensity of transaction arrival are shown in Fig. 3.



a) $\lambda = 100$ trans./s



b) $\lambda = 250$ trans./s

Fig. 3. Dependence of the transaction residence time in the fog layer $(T,\ s)$ on the number of mobile devices in the cluster (K) and the intensity of transaction arrival

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In high-density IoT, even stable mobile fog clusters have a variable structure with some stable core. Therefore, important characteristics when analyzing the dynamic stability of a cluster are both the intensity of adding new nodes to the system and the intensity of nodes leaving the cluster. Fig. 4 shows the dependence of the average transaction residence time in the fog layer on the ratio of the intensity of adding nodes to the intensity of nodes leaving the cluster.

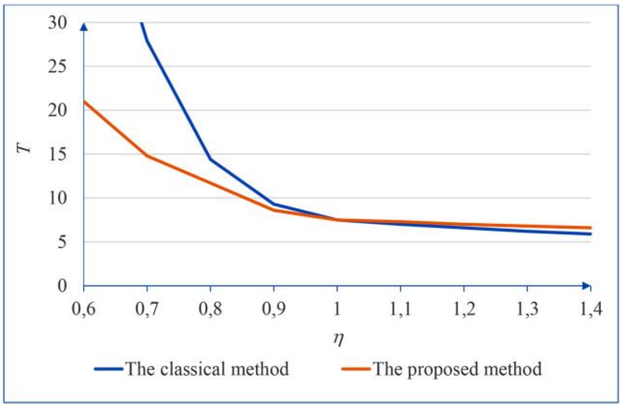

Fig. 4. Dependence of the transaction residence time in the fog layer (T, s) on the ratio of node addition intensity to node exit intensity (η)

When modeling the dependence shown in Fig. 4, system parameters were selected for which, for a constant fog cluster structure, the time value T coincides for both methods under analysis: $\lambda = 250$ trans./s ; $K = 350$ nodes.

5. Discussion of the results of research on an adaptive method for distributing resources among mobile devices in fog clusters

The architecture of the high-density IoT ecosystem subsystem has been developed, which performs pre-processing of peripheral layer transactions on fog layer mobile devices (Fig. 1). A distinctive feature of this architecture is its focus on the cluster structure of the fog layer. After receiving a transaction, the fog mobile device, unlike the classical method, can select another available node to participate in the preprocessing of the transaction. This allows for more flexible use of the limited computing resources of fog layer devices.

The proposed mathematical model of the MFC optimal resource allocation process allows minimizing the maximum delay in preprocessing transactions of the HDIoT peripheral layer. A distinctive feature of this model is that it takes into account the possibility of distributing preprocessing between fog mobile devices. The use of an agent-based approach made it possible to take into account the decentralized structure of the fog mobile cluster. The use of the mathematical apparatus of cooperative stochastic games made it possible to significantly speed up the search for an approximate solution to the formulated optimization problem (7)–(11) in the context of implementing an agent-based approach for a decentralized system.

The evaluation of the effectiveness of the proposed method (Figs. 2–4) showed the following results:

– when the mobile cluster is loaded by no more than 30%, the proposed method is not significantly inferior to the classical one in terms of time indicators;

– when the mobile cluster is loaded by more than 50%, the proposed method provides better results in terms of time indicators than the classical one; at the same time, the higher the load of the mobile cluster devices, the better the time indicators become when using the proposed method;

– in the case of an unstable mobile cluster structure, the proposed method provides better results in most cases, especially with a relative decrease in the number of mobile devices.

The results of the study can be explained by a more rational use of the limited resources of mobile fog devices, which reduces the volume of transaction queues to the fog layer.

Unlike [23, 24], which proposes optimization algorithms for centralized systems, the proposed method is focused on decentralized systems. In addition, the proposed method, unlike [25–28], takes into account the requirements of HDIoT transactions.

Unlike [29, 30], which uses methods for controlling the IoT data transmission process, the proposed method takes into account the characteristics of mobile devices. Also, unlike [31, 32], where methods for resource planning for the mobile Internet of Things are developed, the proposed method solves issues related to the high density of IoT devices by reducing computational complexity. Unlike [33, 34], where the energy consumption of mobile devices is optimized, the proposed method is also focused on the optimal distribution of limited resources.

Thus, the developed adaptive method for allocating resources of mobile devices of fog clusters of high-density Internet of Things made it possible to reduce the average transaction residence time of the HDIoT peripheral layer in the fog layer. This made it possible to meet QoS requirements even with a high density of mobile devices.

However, the proposed results should be applied with the following restrictions:

– high density of IoT mobile devices;

– presence of territorial clustering of fog devices.

It is also advisable to use the proposed method when the average load of fog layer devices is at least 50%.

A drawback of this study is that it does not consider the analysis of the possible interaction of mobile virtual clusters of the HDIoT fog layer. To eliminate this, the simulation model of the fog layer of the HDIoT support ecosystem should be expanded with the appropriate procedure.

6. Conclusions

An adaptive method for distributing the resources of mobile devices in fog clusters has been developed, which has made it possible to reduce the average time a HDIoT peripheral layer transaction spends in the fog layer. The following results were obtained in the process of developing the method:

– the architecture of the high-density IoT ecosystem subsystem has been formed, which pre-processes peripheral layer transactions on fog layer mobile devices and allows for more flexible use of the limited computing resources of fog layer devices;

– a mathematical model of the MFC optimal resource allocation process was proposed, which allows minimizing the maximum delay in preprocessing HDIoT peripheral layer transactions. A distinctive feature of this model is that it takes into account the possibility of distributing preprocessing between fog mobile devices;

– a multi-agent approach was used to find an approximate solution to the formulated two-parameter nonlinear optimization problem, which made it possible to take into account the decentralized structure of the fog mobile cluster;

– a theoretical game model for managing the resources of a mobile fog cluster of a multi-layer IoT has been developed and researched. The use of its mathematical apparatus has made it possible to significantly speed up the finding of an approximate solution to the formulated optimization problem in the context of implementing an agent-based approach for a decentralized system.

The proposed method can be used to create flexible and scalable production facilities in accordance with the Industry 5.0 concept, such as a smart logistics hub with autonomous robots. As a development of this research, the development of a method for priority processing of HDIoT operational transactions can be considered.

Conflict of interest

The authors declare that they have no conflict of interest with respect to this research, including financial, personal, authorship, or other conflicts that could influence the research and its results presented in this article.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technology in the creation of this work.

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АДАПТИВНИЙ МЕТОД РОЗПОДІЛУ РЕСУРСІВ МОБІЛЬНОГО ТУМАННОГО ШАРУ ВИСОКОЩІЛЬНОГО ПРОМИСЛОВОГО ІНТЕРНЕТУ РЕЧЕЙ У МЕРЕЖАХ INDUSTRY 5.0

Актуальність дослідження. Сучасна концепція Індустрії 4.0 заклала фундамент для повної цифровізації через індустріальний Інтернет речей. Але перехід до Індустрії 5.0 вимагає більшої гнучкості та стійкості систем. Високощільний мобільний індустріальний IoT з туманним шаром є критичним елементом цієї трансформації, оскільки забезпечує не лише автоматизацію, а й адаптивність виробництва до людських потреб і екологічних стандартів. **Об’єктом вивчення** є процес передоброблення транзакцій периферійного шару HDIoT. **Основна гіпотеза дослідження**: упровадження нового адаптивного методу розподілу ресурсів мобільних пристроїв туманних кластерів дасть змогу зменшити середній час передоброблення транзакції периферійного шару HDIoT. **Метою роботи** є зменшення середнього часу перебування транзакції периферійного шару HDIoT в туманному шарі завдяки розробленню адаптивного методу розподілу ресурсів мобільних пристроїв туманних кластерів. **Завдання дослідження**: визначити архітектурні особливості туманних обчислень у мережах HDIoT; створити математичну модель процесу оптимального розподілу ресурсів пристроїв мобільного кластера туманного шару; формалізувати багатоагентний підхід для розподілу ресурсів кластера; розробити й дослідити теоретико-ігрову модель управління ресурсами мобільного туманного кластера багатощільної IoT. **Застосовані методи**: багатоагентний підхід, теорія ігор, зокрема оптимізація кооперативної стохастичної гри, комп’ютерне моделювання. **Досягнуті результати**. Розроблено адаптивний метод розподілу ресурсів мобільних пристроїв туманних кластерів. У межах методу запропоновано архітектуру мобільного туманного кластера, створено математичну модель процесу оптимального розподілу його ресурсів. Крім цього, застосовано багатоагентний підхід для знаходження наближеного рішення сформульованої двопараметричної нелінійної оптимізаційної задачі, а для зменшення обчислювальної складності та прискорення знаходження наближеного рішення впроваджено теоретико-ігровий підхід. **Висновок.** Унаслідок застосування розробленого методу зменшено середній час перебування транзакції периферійного шару високощільного IoT в туманному шарі, що за умови високої щільності мобільних пристроїв уможливило виконання вимог QoS.

Ключові слова: Індустрія 5.0; Інтернет речей; туманний кластер; мобільний вузол; комп’ютерна система; агентний підхід; інтелектуальний агент; стохастична гра.

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