IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

SPECIAL SECTION ON SMART CACHING, COMMUNICATIONS, COMPUTING AND CYBERSECURITY FOR INFORMATION-CENTRIC INTERNET OF THINGS

Received December 28, 2018, accepted January 9, 2019, date of publication January 22, 2019, date of current version February 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2894172

Optimizing the Coverage via the UAVs With Lower Costs for Information-Centric Internet of Things

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This work was supported in part by the National Natural Science Foundation of China under Grant 61772554, and in part by the Fundamental Research for the Master Free Explorations and Innovations Projects of Central South University under Grant 2018zzts564.

ABSTRACT The recent developments in the areas of the Internet of Things (IoTs) have provided a rapid growth in the epoch of the novel information-centric collections (IC-IoTs). In the IC-IoTs, expanding the ranges of information collections and reducing the costs are important issues for the information required platform. In the previous scenarios, the information is collected in a random manner, which leads to lower coverages and higher costs. Thus, a ''optimizing the coverage via the unmanned aerial vehicles (UAVs) with lower costs for information-centric Internet of Things'' (OCLC-IoTs) approach is established, which targets to improve the coverage ratio and to reduce the costs of the information-required platform via the cooperation of the information collectors and the UAVs. First, to improve the coverage ratio, an intensive strategy is proposed to inspire the information collectors to bid for the tasks published by the platform and an improved rolling horizon strategy (IRHS) strategy is designed to plan the flying routes of the UAVs to reach more coverage ranges. Then, to reduce the costs factor, the IRHS strategy is designed to shorten the flying routes of the UAVs under the prerequisite of guaranteeing coverage ratio to achieve fewers costs. Finally, a comprehensive theoretical analysis and experiments are provided, which indicates the advancements of the OCLC-IoTs scheme. Compared with the previous studies, the OCLC-IoTs scheme can improve the coverage ratio of information by 21.42% approximately and can reduce the cost ratio by 13.335% to 34.32%.

INDEX TERMS Coverage, costs, unmanned aerial vehicle, information-centric Internet of Things.

I. INTRODUCTION

Recently, the Internet of things (IoTs) which can support the information exchanges among human-to-human, human-to-applications and applications-to-applications by utilizing the communications among various of smart sensor devices have gained enough attentions in a smart city [1]–[4]. With the rapid growth of the various information [5], a novel communication model named information-center networking (IC) is arisen [6], [7], which concentrates to collect the information with a novel and effectively manner. Problems arise in plenty of aspects in the IC-IoTs networks, such as the energy-consumption issue [8]–[10], novel communication methods [11], [12], time-consumption issue [13], [14], transfer-efficiency issue [15], security issue [16]–[19], privacy issue [20]–[23] and delay issue [24], [25], etc. Those schemes have given novel thoughts in promoting the advancements of the IC-IoTs networks.

In the IC-IoTs, both the applications and the humans with smart sensor devices, such as the mobile-phones, the iPads and the computers, can accomplish the processes of the receptions, sensors and transmissions [26]. A virtual application can publish the tasks and require information. This virtual application is called ''platform'' in this paper. Obviously, the IC-IoTs have provided a novel environment for the platform which requires information of the whole smart city. It is convenient for the platform to reach the information (such as the fog-haze condition monitoring) by both the applications and the humans with smart sensor devices [11]. And the platform will pay for the information collectors.

However, there are many issues accrued during the information collection processes. Without selections, the collected information will be redundant [26] and the coverage ratio of them will be lower [27]–[30]. The rewards of the information collectors will directly lead to the costs of the platform, without a suitable selection method. In addition, the deficiencies of the previous researches are reflected as follows.

(1). In the IC-IoTs networks, because of the nonuniform distributions of both the applications and humans with sensor devices, the information in the urban regions will be redundant and the information in some of the suburban regions cannot be collected timely. Meanwhile, arranging plenty of the static sensor devices will lead to huge costs for the IC-IoTs, which is unrealistic. Therefore, if a platform published a task, such as the weather monitoring and the fog-haze conditions, the data in some suburban regions may not be obtained by the applications or the humans, which would have a great impact on the analysis results of the platform. The platform might make a wrong decision on the weather or the fog-haze predictions. Therefore, in the IC-IoTs, improving the coverage ratio of the information collections is an urgent problem.

(2). In the previous approaches, few of them have a research on the redundant issue of the information collections in one region. In some conditions, such as the weather monitoring or the fog-haze condition monitoring, clearly, a piece of information can represent a limited region. In some regions, especially in the urban regions, there will have much collected information due to the large number of humans in those regions. Therefore, there is no need to collect more information in one limited region. In addition, more information collections in this region will lead to the redundant issue and will have a directly influence on the costs of the platform. Simplifying the information collections can reduce the costs of the platform in an efficiency way. Therefore, considering the cost issue, it is important to handle with the data redundant problem while guaranteeing the coverage

Obviously, the platform which publishes the tasks targets to require for more information of a smart city. And the platform needs to reach the information within a limited time period. Based on the precious schemes, the coverage ratio of the information cannot reach to an ideal level and the costs of the platform are high.

Therefore, based on the previous schemes, this paper proposes a novel approach named ''Optimizing the Coverage via the UAVs with Lower Costs for Information-Centric Internet of Things'' (OCLC-IoTs) to handle with the coverage issue in the information-collection processes, as well as minimize the costs of the platform. The main contributions of this paper are shown in the following.

(1). The OCLC-IoTs approach improves the coverage ratio by the utilizations of the unmanned aerial vehicles (UAVs). To satisfy the coverage ratio, the UAVs which have the characteristic of high-mobility, can be utilized as the information collectors. Firstly, based on the incentive strategy and the selection method, with the participations of the sensor-devices people, the platform can obtain the data information in some regions via the wireless networks. Then for the rest of the regions in a city, the information cannot be achieved by the platform. Therefore, in the OCLC-IoTs approaches, the UAVs are used to collect the information in the rest of the regions. With the participations of UAVs, the platform can obtain the information in the regions without participants of sensor-devices people, which will improve the coverage ratio of information collections to a great extent.

(2). The OCLC-IoTs approach also focus on the way to reduce the costs of the platform. For the sensor-devices people, the redundant information collections in a limited region will cause more costs of the platform, because the platform need to pay those participant people rewards. Therefore, the OCLC-IoTs approach focuses on reducing the costs paid for the people by selecting the one with minimum distance. In the intensive strategy, the rewards of the urban regions are less than those of the suburban regions. In a limited region, the one with smallest distance (between this people and the platform) will be chosen as the information collector to reach minimum costs. Moreover, with the utilizations of the UAVs, how to organize them to reach lower costs is a significant issue. Considering the costs of the UAVs, the OCLC-IoTs proposes an improved rolling horizon strategy (IRHS) to minimize the flying routes of them. With the optimized IRHS, when guaranteeing the coverage factor, the UAVs can reduce the travelling distances. Thus, the energy consumptions of the UAVs are reduced, which will decrease the costs of the UAVs and reduce the costs of the platforms in an effectively manner.

(3). Through a comprehensive evaluation and experiment, we demonstrate that both the performances of the coverage ratio and the cost factor can be optimized by the OCLC-IoTs approach. Compared with the previous schemes, our approach can make a better performance in the aspect of information collections. To be specific, with the OCLC-IoTs, the coverage ratio of the information collections can be improved by 21.42% approximately, and the cost factor of the platform can be reduced by 13.33% to 34.32% approximately. The OCLC-IoTs approach can improve the coverage ratio as well as reducing the costs of platform, which has achieved the initial requirements and is difficult to be achieved in other schemes.

The remainders of this paper are organized as follows. In the Section II, the related works are described. In the Section III, we explain the system models and problem statements. In the Section IV, the research motivations and the designs of the OCLC-IoTs scheme are presented. Both the experimental settings and the simulation performances are analyzed in the Section V. Finally, Section VI concludes the whole paper.

II. BACKGROUND AND RELATED WORK

The IC-IoTs are highly correlated systems among things to things. Thus, the optimization of the information collections implies a comprehensive consideration of both the coverage ratio and the costs. In the recent years, there are many researches proposed to deal with this problem, many of them optimize the performances in the aspects of network framework [31]–[34] and new transmission protocol [35]–[37], etc.

The information can be collected by people with sensor devices like mobile-phones in the IoTs networks [38]. The paper [39] proposed a novel framework to optimize the mobility of the UAVs as well as reduce the uplink power. It firstly utilized the locations of the active devices in the IoTs to optimize the locations of the UAVs, and determine the associations among those UAVs. Then it analyzed the mobility patterns of the UAVs to serve the IoT devices with a dynamically with a minimize energy consumptions. This approach mainly focuses on reducing the transmission power by redefining the mobility patterns and associations of the UAVs. However, it didn't take the issue of the transmission power for the UAVs into considerations. Collecting the information of amounts of active devices will lead to large costs of the UAVs. Manuscript [40] proposed a new framework which relying on the modified Louvain method for the communications of the UAVs. It targeted to save the power of the information collectors. However, in the most situations, the users, with the characteristics of uncertainty and emotional, are hard to be clustered. Even they are clustered in a time period, in the next time period, those clustered results may not satisfy the real situation. Therefore, it is hard for the UAVs to define the locations and collect the information in the centroids of the user clusters. To make a balance between the transmission energy of the sensor devices and the consumptions of the UAVs. Paper [41] proposed a novel and effective framework to control the UAVs with the deep reinforcement learning. With the convolutional neural networks, the features of information can be obtained. With the guidance of deep learning networks, it indicated that the UAVs can travel in the smart city without controls. However, the neural networks are lack of interpretations and this framework will be crushed by the adversarial examples easily, which will lead to the network crash issue without a reasonable security solution. Those existed problem can lead to increasing the energy costs of the UAVs and reducing the coverage ratio. Bujari *et al.* [42] consider to use the coordinates to route greedily by the nodes' locations, and expanded the location-based packet routing mind to the 3-D UAVs' environments, which built a novel framework for the transmission process.

The above researches are based on the framework constructions. In the paper [43], it studied the UAVs-information collection system by assuming the situation that a UAV is dispatched to collect the information at a fixed location. This scheme proposed a novel mind which is to make a tradeoff between those two energy factors in the transmission processes to improve the system performances. However, it didn't consider the problem of how to reach higher coverage ratios with less energy consumptions. In the paper [44] targeted to maximize the energy efficiency via optimizing the flying routes of the UAVs. With general constraints of the trajectories, it could optimize the energy efficiency of the UAVs. And it didn't consider the coverage ratio. And paper [45] introduced a scheme to reduce the energy consumptions and make full use of the energy of the UAVs. Firstly, it solved the route planning problem by either dynamic programming or genetic algorithms, and then solved the task assignment problem by the Gale-Shapley algorithm. The method in the [45] researched the revenue of the information carriers. With the method in the [45], the energy consumptions of the UAVs can be reduced and the revenue of the information carriers is improved. Baek and Lim [46] discussed the usages of the UAVs in the area of the military and commercial domains, for the UAVs can be seen as the relay nodes while transmitting information. This paper researched on building a future UAV-relay tactical information link. However, those above schemes didn't consider the coverage factor of information. And if the platform requires for the information distributed in the whole city, only with the collections of the UAVs' will lead to a high cost.

A new framework in the paper [47] introduced an approach to improve the stationary coverage of the target region by three sub schemes, the centralized optimal solution, the distributed game-theory-based strategy and the bio-inspired scheme. This paper optimized the performances of the transmission processes between the UAVs and the information owners in many aspects, including the UAV positioning and deployments, and the cost-benefit tradeoff of information exchange. And derived the approximation of the centrally computed optimum.

However, less of the above schemes studied on reaching the information by utilizing both the UAVs and the smart-devices humans or applications in the IoTs networks. Therefore, in the IC-IoTs, it is significant to develop a novel scheme to improve the coverage ratio, as well as reduce the platform costs by using the UAVs and the smart-devices humans. In the OCLC-IoTs scheme, both the smart-devices people and the UAVs are utilized to sense the information. With the participation of UAVs and the incentive strategy, we believe that our works can improve the coverage ratio of collected information, and reduce platform costs with an effectively manner.

III. THE SYSTEM MODEL AND PROBLEM STATEMENT

A. THE SYSTEM MODEL

In this subsection, the system model of the OCLC-IoTs scheme is provided.

In the OCLC-IoTs scheme, suppose that there is one platform in a smart city. The platform is responsible for publishing different kinds of tasks (such as the weather condition monitoring and fog-haze monitoring), which requires higher coverage ratios. In the IoTs, firstly, with the intensive strategy, the users with smart phones can take part in the published tasks and then get rewards from the platform. The information in the rest of regions with less users' collections will be obtained by the UAVs, the system model is provided in the Fig. 1.

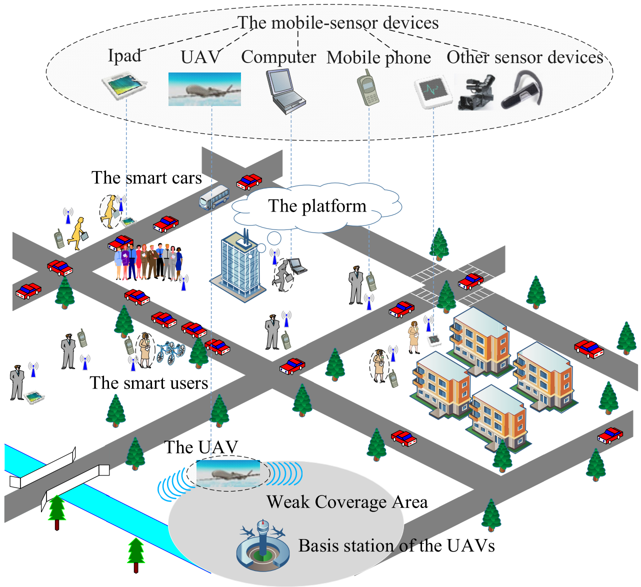

FIGURE 1. The system model.

At time T, with the intensive strategy, the platform publishes a task Ø (such as gathering the information of the haze conditions in a city). Then part of the users distributed in the city will bid for the task Ø. The set of bidding users for the task Ø is defined as $U_{\emptyset}$, where $U_{\emptyset} = (u_{\emptyset 1}, u_{\emptyset 2}, u_{\emptyset 3}, \ldots\ldots u_{\emptyset(n-1)}, u_{\emptyset n})$. Then the platform will select several users to participant in the task Ø. At time $T+1$, the selected users will sense the information, which is required by the platform. And transmit the information to the platform. Then the platform will pay for the selected users according to the intensive strategy. At time $T+2$, we can obtain the regions without information. The information in those regions can be collected by the UAVs.

If several users bid for the task in a region, then the platform will choose the nearest one. Then, the regions with less mobile-phone users will be collected by the UAVs.

B. THE PROBLEM STATEMENT

There are many researches that have focused on the information-collections issue [8], [21], [29], [41]. However, the distribution characteristic of the mobile-phone users is nonuniform, which will lead to missing the information in the regions without user participations. This will have a great impact on the collection performances of a task.

Thus, the problem statements focused on in this paper is shown as follows: in the IoTs, a platform can publish different kinds of tasks. Most tasks, such as the air condition monitoring and the fog-haze conditions, need to achieve more regions' information in a city. The users with mobile-phones can bid for the tasks and obtain the surrounding information within the limited sensor region r. In the regions without users' participants, the platform will arrange the UAVs to get the information in those regions. With the cooperation of those two types of sensor applications, the coverage ratio of the collected information can be expanded.

To inspire the users with mobile-phones to take part in the tasks, the platform utilizes an intensive strategy. For the regions without the collection users, the UAVs are utilized to sense and collect the information. To keep a balance between the cost ratio and the coverage ratio, the flying trajectories of the UAVs are defined by the IRHS strategy in the OCLC-IoTs scheme. The experimental results illustrate that with the intensive strategy and the IRHS strategy, both the performances of coverage and costs have been optimized. The set of UAVs is defined as $UAV = (uav_1, uav_2, \ldots\ldots, uav_{m-1}, uav_m)$. And the set of tasks published by the platform is defined as $Tas = (task_1, task_2, \ldots\ldots, task_{\emptyset-1}, task_{\emptyset})$.

(1). Coverage improvement.

$$Cov = \frac{N\left(\underset{i\in I}{Cov}(u_i)\right) + N\left(\underset{i\in I}{Cov}(U_j)\right)}{N(range)} \tag{1}$$

where $N(range)$ represents the total number of ranges, $N\left(\underset{i\in I}{Cov}(u_i)\right)$ is the number of coverage regions of the users with mobile-phones. And $N\left(\underset{i\in I}{Cov}(U_j)\right)$ is the number of coverage regions of the UAVs. In the OCLC-IoTs scheme, the city is divided into several small regions, which is defined as $range = (r_1, r_2, r_3 \ldots\ldots, r_{k-1}, r_k)$. Each small region is a data collection area. The size of each region in the set *range* is the same, defined as $n \times m$.

(2). Cost reduction.

$$Cos = C_{user} + C_{UAV} = \sum_{i=1}^{\emptyset}\sum_{k=1}^{n} \min\left(\frac{dis_{ki}}{D}\right) \times Cost_{ki} + \sum_{i=1}^{\emptyset}\sum_{j=1}^{m} Time_{ij} \times \omega \tag{2}$$

where C_{user} is the costs of the mobile-phone users and the C_{UAV} is the costs of the UAVs. The dis_{ki} represents the distance between the user u_k and the platform in a task $task_i$, and D is a constant number. For a task $task_i$, the $Cost_{ki}$ is the reward basis in the region where the user u_k is in. The $Time_{ij}$ represents the flying time of the UAV uav_j for the task $task_i$. And ω is a static value, which represents the costs of UAVs in a time interval.

To make it convenient for the readers to understand this paper, the related parameters and some notations have been listed in the Table 1.

IV. THE DESIGN OF OCLC-IOTS SCHEME

A. RESEARCH MOTIVATIONS

The research motivations of OCLC-IoTs scheme are based on the comprehensive analysis in the Internet of Things (IoTs). The main two motivations are shown as follows:

TABLE 1. Related parameters and notations.

Symbol	Descriptions
UAV	The set of the UAVs
$range$	The set of data collection ranges
r	The sensor range of smart devices
Tas	The set of tasks published by the platform
α	The number of city divisions according to the density degree
L	The set of the basis stations of the UAVs
C_{user}	The costs of the users
C_{uav}	The costs of the UAVs
$C_{\emptyset}$	The total costs of the platform for the task $task_{\emptyset}$
cos_f	The costs of the platform based on the former scheme
$a \times b$	The range definition of the small regions
$A \times B$	The range definition of the big regions
TS_{r_k}	The time stamp of the small region r_k
v	The static speed of the UAVs
ω	The costs of the UAVs in a time interval
I_{cov}	The improved coverage ratio
ς	The air mass density
ℓ_{R_q}	The set of connected graphs in the region R_q
ϕ	The evaluation standard
σ_{R_q}	The threshold number in the region R_q

1) MOTIVATION ONE

The first motivation is to reduce the costs of the platform. In the previous cost distribution schemes, the costs are paid to participants according to a static cost basis, which cannot inspire users to take part in. Moreover, without selections, this can lead to the data redundancy issue. Therefore, in the OCLC-IoTs scheme, a model to reduce the cost ratio is introduced.

2) MOTIVATION TWO

The second motivation is to improve the coverage ratio of the information-collection ranges of a task published by the platform. In the previous scheme, the information in many regions cannot be obtained, owing to many kinds of reasons. Therefore, in the OCLC-IoTs scheme, both the users and the UAVs are utilized to collect the information required by the platform. In the regions without users' participations, the UAVs are arranged to reach the information, routing by the IRHS strategy in the OCLC-IoTs scheme. With the cooperation of users and UAVs, the coverage ratio can be optimized to a large scale.

Based on the above two research motivations, the OCLC-IoTs scheme is proposed to achieve the purposes of coverage improvements and cost reductions by means of the utilizations of both the mobile-phone users and the UAVs.

B. COST REDUCTIONS

In this subsection, the method to reduce the cost ratio in the OCLC-IoTs scheme is introduced.

The city is divided into several big ranges, defined as $R = (R_1, R_2, R_3 \ldots\ldots, R_{q-1}, R_q)$. The size of each region division is static, defined as $A \times B$. The basis stations of the UAVs are in the intersections of the big regions, defined as $L = (L_1, L_2, \ldots\ldots, L_{p-1}, L_p)$. The locations of the UAVs' basis are shown in the Fig. 2.

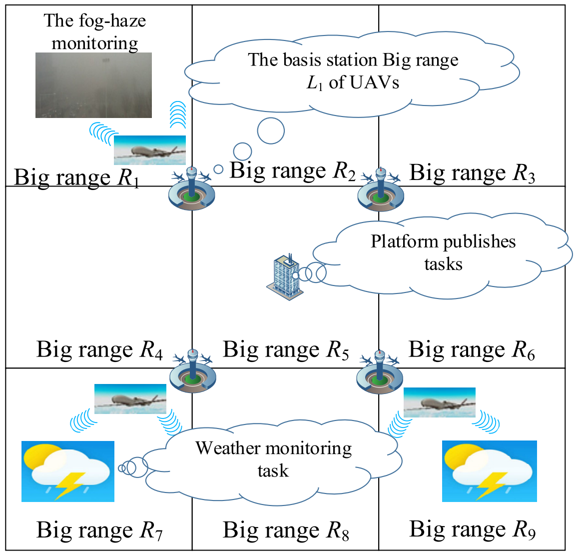

FIGURE 2. The location of the UAVs' basis station.

As defined above, there are many small regions in a big region. The information in each small region is required to be collected. The size of a small region is static, defined as $a \times b$. To be specific, a small region division is the basic unit of information collection. And there are $\frac{A \times B}{a \times b}$ small region divisions in a big region division, which indicates that there should have $\frac{A \times B}{a \times b}$ pieces of information in a big region division.

In the cost reduction model, the city is divided into α regions, according to the density degree of a city, defined in the equation (3).

$$Cost = \begin{cases} Cost_1, & \text{in the density class1 } D_1 \\ Cost_2, & \text{in the density class 2 } D_2 \\ & \cdots \\ Cost_{\alpha}, & \text{in the density class} \alpha \ D_{\alpha} \end{cases} \tag{3}$$

The costs of the platform for the users can be also called the rewards of users. Therefore, improving the rewards of users can inspire the users to participant in the tasks, especially in the suburban regions. For a task $\emptyset$, the costs of the platform for a user u_z is defined in the equation (4).

$$C_{u_{\emptyset z}} = \frac{dis_{u_{\emptyset z}}}{D_{u_{\emptyset z}}} \times Cost_{u_{\emptyset z}}, \quad u_{\emptyset z} \in U_{\emptyset} \tag{4}$$

where the $dis_{u_{\emptyset z}}$ is the distance between the user u_k and the platform in the task $\emptyset$, the $D_{u_{\emptyset z}}$ is a static value in a region division, defined as half of the maximum distance in the density class D_α where the user u_k is in. And the $Cost_{u_{\emptyset z}}$ is a basis cost value in the region division where the user $u_{\emptyset z}$ is in. The definition of $D_{u_{\emptyset z}}$ is same as the $Cost_{u_{\emptyset z}}$, shown as $D = (D_1, D_2, \ldots\ldots, D_{\alpha-1}, D_\alpha)$.

Then for the users in a small region r_k, the one with minimum distance is selected, shown in the equation (5).

$$\underset{\substack{u_{\emptyset 1}\rightarrow u_{\emptyset n}\\ z\in[1,n]}}{MIN} C_{u_{\emptyset z}}, \quad \forall u_{\emptyset z} \in r_k \tag{5}$$

Then we can derive the costs of the platform paying for the users for the task $\emptyset$, shown in the equation (6).

$$C_{user} = \sum_{r_1}^{r_k} \underset{\substack{u_{\emptyset 1}\rightarrow u_{\emptyset n}\\ z\in[1,n]}}{MIN} C_{u_{\emptyset z}} C_{u_{\emptyset z}}, \quad \forall u_{\emptyset z} \in r_g and r_g \in [r_1, r_k] \tag{6}$$

With the selection scheme of users' participants, the platform can reduce the costs of users to a great extent. And with the intensive strategy, the users can be inspired to bid for the tasks.

However, the information in many regions still cannot be collected, owing to two reasons. The first reason is, the users in those regions cannot be inspired because they think the rewards aren't enough. The second reason is that there are no users in those regions. For the first reason, the platform can improve the rewards within a limited range to inspire the users to participant in, shown in the equation (7). For the second reason, the platform will hire the UAVs to collect the information.

$$C'_{u_{\emptyset z}} = \frac{dis_{u_{\emptyset z}}}{D_{u_{\emptyset z}}} \times Cost_{u_{\emptyset z}} + \beta, \quad u_{\emptyset z} \in U_\emptyset \cap C'_{u_{\emptyset z}} < \varphi \tag{7}$$

$$\varphi = \omega\theta = \frac{\omega \times \frac{\sqrt{a^2+b^2}}{v}}{\eta} \tag{8}$$

where the φ is the maximum costs of the UAVs in a region and v is the static speed of a UAV. When the employment cost of a UAV is less than the $C'_{u_{\emptyset z}}$, the platform will hire the UAVs to collect the information. η is a static value to restrain the value of φ.

And for the value of ω of a UAV uav_f, the definition is shown in the equation (9).

$$\omega(v) = \vartheta_{f,1} v^3 + \frac{\vartheta_{f,2}}{v} \tag{9}$$

In the simulations, the v of each UAV is a constant value. The $\vartheta_{f,1} v^3$ in the equation (9) is the required power to balance the parasitic drag and the $\frac{\vartheta_{f,2}}{v}$ is the required power to balance the drag force of air redirections. The calculations of the $\vartheta_{f,1}$ and $\vartheta_{f,2}$ are shown in the equation (10).

$$\begin{aligned} \vartheta_{f,1} &\triangleq \frac{1}{2}\varsigma G Q_f \\ \vartheta_{f,2} &\triangleq \frac{2H_f^2}{(\pi e \epsilon_f)\varsigma Q_f} \end{aligned} \tag{10}$$

where the Q_f is the region of the UAV uav_f and the G is the coefficient of zero-lift drag force. The ς is the air mass density. ϵ_f is the wing aspect ratio of the uav_f and the Q_f is the weight for the uav_f.

After improving the rewards of users, the extra costs of those users can be derived, shown in the equation (11).

$$C'_{user} = \sum_{u_{\emptyset z}\in U_\emptyset} MIN\left(\frac{dis_{u_{\emptyset z}}}{D_{u_{\emptyset z}}} \times Cost_{u_{\emptyset z}} + \beta\right) \tag{11}$$

In a time period, the costs of the UAVs are the same, defined as ω. Therefore, with the time increases, the costs of a UAV will increase at the same time. Thus, the flying time of the UAVs needs to be minimized. For a task $\emptyset$, the costs of the UAVs are defined in the equation (12). Because the costs of the uav_f when changing its heading direction is much smaller than the flying costs, therefore, the head-changing costs of the UAVs will be ignored.

$$C_{uav} = \sum_{uav_{\emptyset 1}}^{uav_{\emptyset m}} \omega T_{uav_{\emptyset f}}, \quad uav_{\emptyset f} \in [uav_{\emptyset 1}, uav_{\emptyset m}] \tag{12}$$

where the $T_{uav_{\emptyset f}}$ represents the time of the UAV uav_f spend for the task $\emptyset$. To reduce the costs of the UAVs, a routing method is proposed to minimize the flying time of the UAVs, which is introduced in the next subsection.

Then the costs of the platform for a task $\emptyset$ can be derived, shown in the equation (13).

$$\begin{aligned} C_\emptyset &= C_{user} + C_{uav} + C'_{u_{\emptyset z}} \\ &= \sum_{r_1}^{r_k} \underset{\substack{u_{\emptyset 1}\rightarrow u_{\emptyset n}\\ z\in[1,n]}}{MIN} C_{u_{\emptyset z}} C_{u_{\emptyset z}} + \sum_{uav_{\emptyset 1}}^{uav_{\emptyset m}} \omega T_{uav_{\emptyset f}} \\ &\quad + \sum_{u_{\emptyset z}\in U_\emptyset} MIN\left(\frac{dis_{u_{\emptyset z}}}{D_{u_{\emptyset z}}} \times Cost_{u_{\emptyset z}} + \beta\right) \end{aligned} \tag{13}$$

In general, the details of the OCLC-IoTs scheme in this subsection are summarized in the Algorithm 1.

C. COVERAGE IMPROVEMENTS

In this subsection, the method of coverage improvement model in the OCLC-IoTs scheme is introduced.

The OCLC-IoTs scheme utilizes both the users with mobile-phones and the UAVs to optimize the coverage ratio of information required by the task. For the users, the OCLC-IoTs scheme inspires them to collect information via improving the rewards, which is introduced in the above subsection. And for the UAVs, the OCLC-IoTs scheme defines the improved rolling horizon strategy (IRHS) scheme to optimize the coverage ratio of the information, which is introduced in the following.

The main target is how to organize the flying routings of the UAVs to collect the information in the regions which haven't been collected. As defined above, the basis stations of the UAVs are located in the intersections of the big regions. In the IRHS scheme, for a task $\emptyset$, the regions which have been collected by the users can be treated as blocks, the number of

Algorithm 1 Algorithm to Reduce the Costs in the OCLC-IoTs Scheme

Input: p, $task_{\emptyset}$, a, b, A, B, q
Output: costs of platform $cost_p$
For a task $\forall task_i \in task_{\emptyset}, i : 1 \rightarrow \emptyset$
  For users of $task_i$ range: $u_{iz} \in U_i, z : 1 \rightarrow n$
    For$X = X + a \cap X \leq qA$ // the range of X
      For$Y = Y + b \cap Y \leq qB$ // the range of Y
        If the $u_{iz}.x \leq X \cap u_{iz}.y \leq Y$
          Record the u_{iz} in the list r_{XY}
            // plot the users in each small region
        End if
      End for
    End for
  End for
  // for the small region $r_1 \rightarrow r_k$
  For$X = X + a \cap X \leq qA$
    For$Y = Y + b \cap Y \leq qB$
      For the users in a small region
        Calculate the distance
        Select the minimum distance min_d
  End for
  Calculate the costs cos of the selected one
  $c = c + cos$//calculate the user' costs
  End for
  End for
  $cost_{pi} = c + c_{uavi} = c + \sum_{uavi1}^{uav_{im}} \omega T_{uav_{if}}$
    // the costs of task $task_i$
  $cost_p = cost_{pi} + cost_p$
End for
End algorithm 1

them is defined as x. Then the number of regions without data information is $k - x$.

In the IRHS scheme, the next step of a UAV is decided according to the distance priority and then the time-stamp priority. The number of neighbor regions of each small region ranges from 0 to 4. If a small region has been collected, them this region will be treated as a block. Each step of a UAV will record the nearest regions' ID to a list. The definition of IRHS scheme is show in the equation (14).

$$\begin{cases} time_{\varepsilon+0} = list\left\{nei_{\varepsilon_1}, nei_{\varepsilon_2}, \ldots\ldots, nei_{\varepsilon_\sigma}\right\}; \\ time_{\varepsilon+1} = list\left\{\begin{matrix} nei_{\varepsilon+1_{\varepsilon_1}}, nei_{\varepsilon+1_{\varepsilon_2}}, \ldots\ldots, nei_{\varepsilon+1_{\varepsilon_\sigma}}, \\ list\left(time_{\varepsilon+0}\right) \end{matrix}\right\}; \\ \ldots\ldots\ldots; \\ time_{\varepsilon+\lambda} = list\left\{\begin{matrix} nei_{\varepsilon+\lambda_{\varepsilon_1}}, nei_{\varepsilon+\lambda_{\varepsilon_2}}, \ldots\ldots, nei_{\varepsilon+\lambda_{\varepsilon_\sigma}}, \\ list(time_{\varepsilon+0}) \rightarrow list(time_{\varepsilon+\lambda-1}) \end{matrix}\right\}; \end{cases}$$
$$where\ \sigma \in [0, 4]\ and\ MIN\left[dis\left((\varepsilon+\lambda) \rightarrow nei_{\varepsilon+\lambda_{\varepsilon_\sigma}}\right)\right] \cap MIN\left[TS\left(list\left(nei_{\varepsilon+\lambda_{\varepsilon_\sigma}}\right)\right)\right] \quad (14)$$

The $nei_{\varepsilon+\lambda_{\varepsilon_1}}$ in the equation (14) indicates the neighbors of the small region number $r_{\varepsilon+\lambda}$. The TS is the time stamp of the neighbors in the $list\left(nei_{\varepsilon+\lambda_{\varepsilon_\sigma}}\right)$. To sum up, the next step of a UAV will choose the minimum distance and the maximum time stamp.

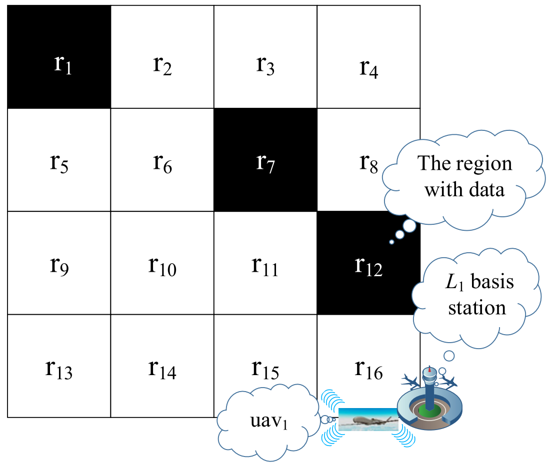

FIGURE 3. An example of IRHS scheme.

For a big region R_1, an example is introduced in the Fig. 3.

In the Fig. 3, suppose that there are 16 small regions (ranging from r_1 to r_{16}) in a big region R_1. The information in the small region r_1, r_7 and r_{12} has been collected by the users with mobile phones. The r_1, r_7 and r_{12} can be looked as blocks. According to the definition, the basis station of the UAVs is set in the bottom right corner. The UAV needs to collect the information in the rest of the small regions.

The collection route of the UAV uav_1 follows the IRHS scheme. The uav_1 chooses the least distance to start. In the Fig. 3, obviously, the uav_1 will fly at the small region r_{16}. In the r_{16}, the neighbor-region is only r_{15}, recorded as $\{r_{15}\}$, thus the next region is r_{15}. In the r_{15}, there are two small regions, r_{14} and r_{11} respectively. Both the distance priority and the time-stamp priority of the r_{14} and r_{11} are the same, recorded as $\{r_{11}, r_{14}\}$. Thus the uav_1 will randomly select a small region in the and the set $\{r_{11}, r_{14}\}$. Suppose the uav_1 chooses the r_{11} as the next step. Then the rest of the list is $\{r_{14}\}$. For the r_{11}, the neighbor region is $\{r_{10}\}$, then add the $\{r_{10}\}$ to the list $\{r_{14}\}$. In the list $\{r_{10}, r_{14}\}$, according to the distance priority firstly, the uav_1 will choose the r_{10} as the next step. The rest of the list is $\{r_{14}\}$. Then the uav_1 will move to the small region $\{r_{10}\}$. At r_{10}, there are three neighbor regions, the r_6, r_9 and r_{14} respectively. Add the three regions to the list and then we can obtain $\{r_6, r_9, r_{14}\}$. The distance priorities of them are the same, thus according to the time priority, the time-stamp of r_{14} is larger. Thus, the next step of the uav_1 is r_{14}.

To sum up, at each small region, the UAV decides the next step according to the distance priority and then the time-stamp priority.

Via the IRHS scheme, the flying routing of the uav_1 in the Fig. 3 can be organized as follows: $\{r_{16}, r_{15}, r_{11}, r_{10}, r_{14}, r_{13}, r_9, r_5, r_6, r_2, r_3, r_4, r_8\}$.

If a small region r_k is in the list at time t_1, the time-stamp of the r_k is defined in the equation (15).

$$TS_{r_k} = 1 + t_2 - t_1 \tag{15}$$

where the t_2 indicates the next step of the UAV is r_k.

In reality, after the users' participants, the rest of regions may cannot form into a connected graph. Therefore, the IRHS scheme defines a threshold number σ for each big region. The value of σ in a big region R_q is defined in the equation (16).

$$\sigma_{R_q} = \frac{1}{2} \times \underset{\ell_1 \to \ell_\tau}{MAX}\, N(\ell_\gamma), \quad \ell_\gamma \in [\ell_1, \ell_\tau] \tag{16}$$

where the ℓ_γ is a connect graph in the big region R_q, and τ is the total number of the connect graph in the region R_q. If the number of the small regions in a ℓ_γ is larger than the threshold σ_{R_q}, then a UAV is hired to collect the information. Else the information will be dropped; the trade-off strategy is shown in the equation (17).

$$\begin{cases} N\left(\ell_\gamma\right) \geq \sigma_{R_q}, & arrange\ UAVs \\ N\left(\ell_\gamma\right) < \sigma_{R_q}, & drop\ the\ \ell_\gamma \end{cases} \tag{17}$$

The IRHS scheme can reach an ideal coverage ratio as well as reduce the costs of platform in hiring the UAVs. With the intensive strategy of users and the IRHS scheme of the UAVs, the coverage ratio of the information required by the platform can be improved to a large scale.

After defining the trade-off strategy in the IRHS scheme, the connected graphs in a big region R_q can be selected, shown as $\ell_{R_q} = (\ell_1, \ell_2, \ldots\ldots, \ell_\delta)$. The station which needs to arrange the UAVs to the ℓ_{R_q} in the big range R_q is discussed. The selection definition of the basis station L_{R_q} is defined in the equation (18).

$$\begin{aligned} L_{R_q} &= \underset{\substack{\ell_1 \to \ell_\delta \\ L_1 \to L_p}}{MIN}\ Dis\left(\ell_\mu, L_\rho\right) \\ &= \underset{\substack{\ell_1 \to \ell_\delta \\ L_1 \to L_p}}{MIN} \sqrt{\left(x_{\ell_\mu} - x_{L_\rho}\right)^2 + \left(y_{\ell_\mu} - y_{L_\rho}\right)^2} \end{aligned} \tag{18}$$

With the equation (14), the basis station which need to serve the big region R_q can be obtained.

In the OCLC-IoTs scheme, the IRHS scheme is introduced in the Algorithm 2.

Algorithm 2 Algorithm to Improve the Coverage Ratio in the OCLC-IoTs Scheme

Input: p, x, R_q, L
Output: coverage ratio cov

n $= x$;
For big regions R_ξ: $R_1 \to R_q$
  Record the connect graph in the R_ξ to $list_{R_\xi}$
  For the connect graph in $list_{R_\xi}$
    Calculate the value of σ_{R_ξ}
    Form a new list $list'_{R_\xi}$
  End
  For the L_ρ in the L
    Calculate the distances among $list'_{R_\xi}$ and L_ρ
     Record the minimum distance $dis_{R_\xi} \to list'_{R_\xi}$
     Record the L_i
  End
  For the connect graph ℓ_γ in the $list'_{R_\xi}$
     While (ℓ_γ is not empty)
     Record the neighbor of the current small region r_{t_j} at time t_j in the list $l^{\ell_\gamma}_{R_\xi}$
     Decide the next step at time t_{j+1} via the distance priority and the time priority
     $\varrho =$ the number of small regions
     n $=$ n $+ \varrho$;
     End while
  End
End
cov $= \frac{\text{n}}{k}$ //k is the total number of small regions
Return cov;
End algorithm 2

V. THE EXPERIMENTAL RESULTS AND ANALYSIS

A. EXPERIMENTAL SETTINGS

In this subsection, the experiment settings and evaluation environments are introduced detailly. The experiments are made based on the Beijing T-driver datasets in the 2008. The T-drivers are the users with mobile phones in a smart city. In the T-driver datasets, there are 10,357 taxis (which are the users) which are recorded by the GPS services. The time period ranges from Feb. 2 to Feb. 8, 2008 and the dataset includes 15 million geographical points, which can provide a suitable environment to carry on the simulations.

In the simulations, the abscissa of the map is from 116.07 to 116.7 and the ordinate is from 39.68 to 40.22. And the costs of the region divisions are determined according to the density degree of the Beijing city, shown in the equation (19).

$$Cost = \begin{cases} Cost_1 = 90, & in\ the\ density\ class\ 1 \\ Cost_2 = 130, & in\ the\ density\ class\ 2 \\ Cost_3 = 170, & in\ the\ density\ class\ 3 \end{cases} \tag{19}$$

where the region division 1 ranges from 116.295 to 116.52 and 39.853 to 40.036. The region division 2 ranges from 116.22 to 116.595 and 39.7615 to 40.0909, except for the range division 1. And the rests are the region division 3.

The abscissa of the map is from 116.07 to 116.7 and the ordinate is from 39.68 to 40.22, which is equals to the abscissa value is 50km and the ordinate value is 60km.

The size of the big range is defined as $A \times B$, where $(A = 18\ km) \times (B = 20\ km)$. And the size of the small range is defined as $a \times b$, where the $(a = 2\ km) \times (b = 2\ km)$. Thus, for example, in a big range L_1, there are $\frac{A \times B}{a \times b} = \frac{18 \times 20}{2 \times 2} = 90$ small regions, which indicates that there are 90 collection units. Therefore, in the simulations, there are 750 small collection regions in general. And the platform is located in the center of the Beijing city, the coordinate of it is (116.385, 39.945).

TABLE 2. The coordinate of the basis stations.

Basis stations	x	y
L_1	116.295	40.036
L_2	116.52	40.036
L_3	116.295	39.853
L_4	116.52	39.853

According to the definitions of the basis station, there are four basis stations of the UAVs in the simulations. The coordinates of the basis stations L_1, L_2, L_3 and L_4 are shown in the Table 2.

The basis stations are responsible for arranging the UAVs to collect information of the small regions.

1) CALCULATIONS OF COVERAGE IMPROVEMENTS

In the simulations, to verify the coverage factor, the Beijing city is divided into 750 small regions according to the abscissas and the ordinates.

Based on the realistic situations, the definition of calculation for the coverage improvements is shown in the equation (20).

$$I_{cov} = \frac{N\left(u_{cov1} + uav_{cov1}\right) - N\left(u_{cov2}\right)}{N\left(u_{cov1} + uav_{cov1}\right)} \tag{20}$$

where the $N\left(u_{cov1} + uav_{cov1}\right)$ is the number of the regions covered by both the users u_{cov1} and the UAVs uav_{cov1} in the OCLC-IoTs scheme. And the $N\left(u_{cov2}\right)$ indicates the regions that the users u_{cov2} covers in the previous scheme. The evaluation results will be described clearly in the following subsections.

2) CALCULATIONS OF COST REDUCTIONS

In this subsection, the calculation methods of cost reductions will be provided. Based on the traditional methods, the costs of the platform are the rewards to the users without selections, which will cause the data redundancy. Without selections of the mobile-phones users, the costs of the platform are large. In the OCLC-IoTs scheme, the costs of the platform are both the rewards to the mobile-phone users with selections and the employment costs of the UAVs.

The calculation methods of the costs based on the former methods is summarized in the equation (21).

$$cos_f = \sum_{u_1 \to u_m} cos_{u_i}, \quad u_i \in [u_1, u_m] \tag{21}$$

where the cos_{u_i} indicates the costs of the user u_i that has participated in the task of the platform, on the basis of the former method. The total number of the participant mobile-users is m.

Then the costs of the platform based on the OCLC-IoTs scheme is defined in the equation (22).

$$cos_{oc} = C_{user} + C_{uav} + C'_{u_z} \tag{22}$$

where the C_{user} is the costs of users in the first selection round, the C_{uav} is the costs of UAVs and the C'_{u_z} is the costs of users in the second selection round.

Then the calculation method of the cost reductions is shown in the equation (23).

$$I_{cos} = \frac{cos_f - cos_{oc}}{cos_f} \tag{23}$$

To compare the performances of the OCLC-IoTs scheme comprehensively, the evaluation standard ϕ is proposed in the equation (24).

$$\phi = \frac{2 \times I_{cov} \times I_{cos}}{I_{cov} + I_{cos}} \tag{24}$$

The value of ϕ illustrates the efficiency and advancement of the proposed scheme.

B. THE COVERAGE IMPROVEMENTS

In this subsection, the coverage ratio of both the OCLC-IoT scheme and the former scheme is compared. In the simulation, a task is published at time 17: 49: 16. The mobile-phones users in the T-driver datasets will participate in the task. With the simulations, there are 3683 mobile-phones users bid for the task one, shown in the Fig. 4.

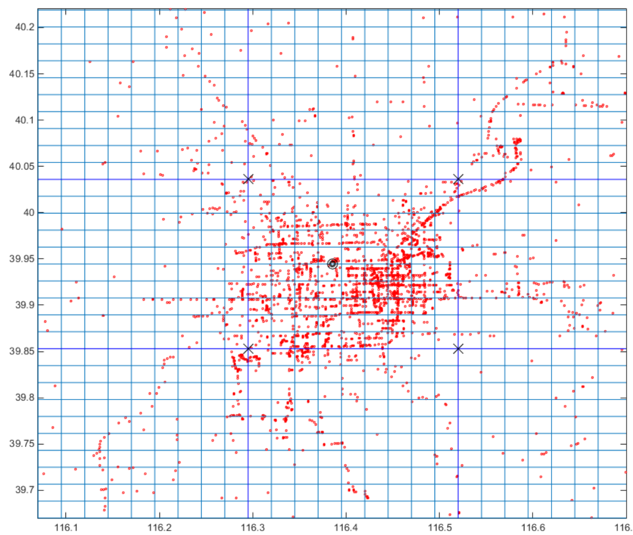

FIGURE 4. The mobile-phones users bids for the task.

In the Fig. 4, the horizontal purple lines and the in the vertical purple lines are the division lines of the big regions. According to the definitions, there are nine big regions in the Beijing city. The intersections of the four lines are the locations of the basis stations of the UAVs. With the intensive strategy, the number of users who bid for the task is 3683, distributed in each small region ununiformly. The mobile-phones users in the Fig. 4 include two types. One is the users bid for the task in the first selection round, the other is the users who are inspired by the platform in the second selection round. The number of mobile-phones users in the first situation is 3577, the number of mobile-phone users in the second situation is 106. Based on the proposed selection scheme, the users who are selected to finish the task is shown in the Fig. 5.

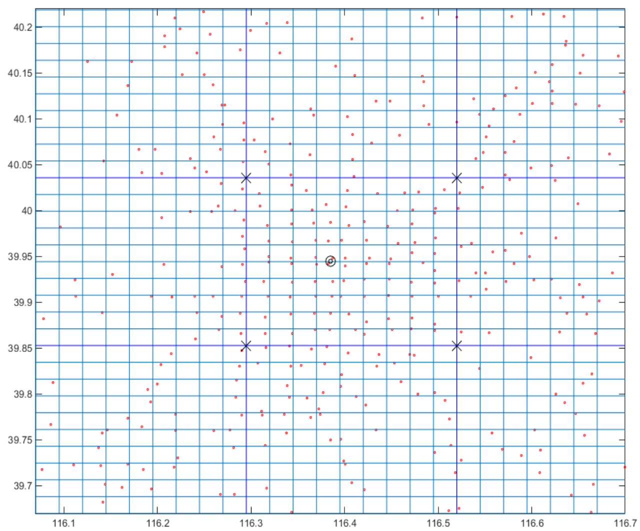

FIGURE 5. The distributions of the mobile-phones users with selections.

With the selection scheme in the OCLC-IoT scheme, the Fig. 5 shows the distributions of the mobile-phones users after selections. There are 353 small regions in which the information can be collected by the users. If only with the participants of the mobile-phones users, the coverage ratio of the information required by the task is 47.067%.

In the former scheme, the coverage regions are shown in the Fig. 6.

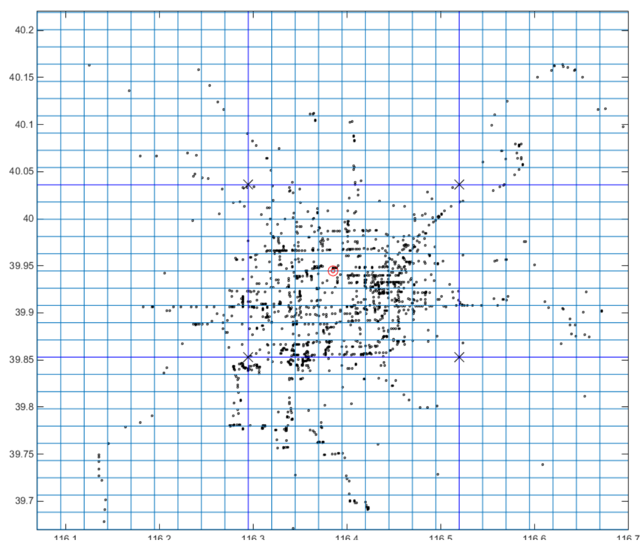

FIGURE 6. The distributions of the mobile-phone users based on the previous scheme.

In the previous scheme, the rewards to the users are the same, which cannot meet the demands of some mobile-phone users. The static value of the rewards is defined as 100. With the simulations, there are 2699 mobile-phone users who participant for the task. With the intensive strategy, the participant improvement of the user is 26.72%. On the basis of the previous scheme, the platform will choose the nearest one in each small region to serve for the task. The distributions of the selected users based on the former scheme are shown in the Fig. 7.

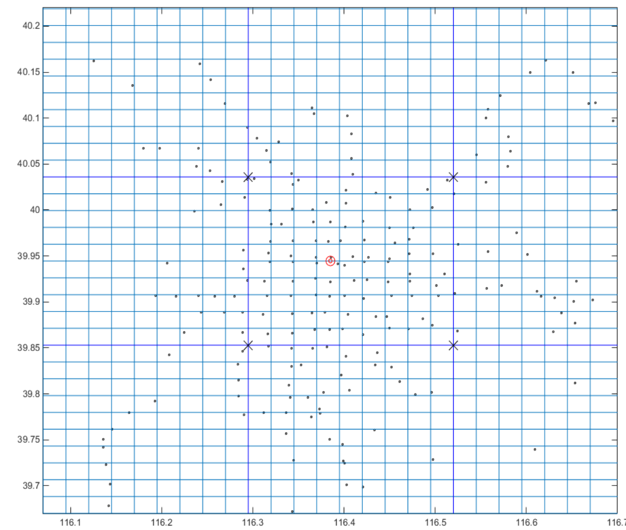

FIGURE 7. The distributions of the mobile-phones users on the basis of the former scheme.

Based on the former scheme, the number of the coverage regions is 208. With the intensive strategy in the proposed scheme, the coverage ratio of the information can be improved by 41.07 %. Some regions especially in the suburban regions cannot be covered by the mobile-phone users based on the previous scheme. It is because that the rewards of the platform cannot meet the demands of some mobile-phone users. Therefore, they won't bid for the task. In the proposed scheme, the platform will pay more rewards for the mobile-phone users in the suburban regions to inspire the them to bid for the task. Therefore, there are more mobile-phone users take part in the task and the coverage ratio of the information will be improved.

Then the comparisons of the number of the collected small regions in each big region is shown in the Fig. 8.

In the Fig. 8, it shows that with the intensive strategy, the number of coverage regions is increased. The improved coverage ratio is shown in the Fig. 9.

For the rest of the small regions, the platform will arrange the UAVs to collect the information in them. The collection routings of the UAVs follow the IRHS strategy in the OCLC-IoTs scheme. With the UAVs, the number of the coverage regions in each big region is shown in the Fig. 10.

In the Fig. 10, it can be seen that with the UAVs, most of the uncovered small regions can be collected. With the IRHS strategy, the connected graph of some small regions will be dropped to reduce the flying time of the UAVs, under the condition of keeping the coverage ratio. In general,

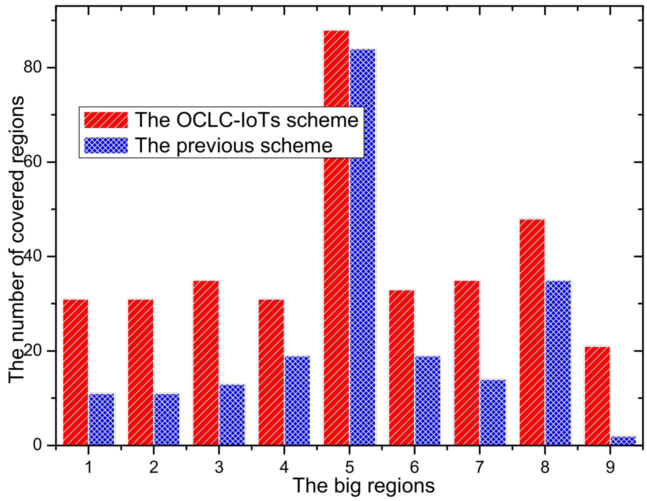

FIGURE 8. The coverage number in each big region divisions.

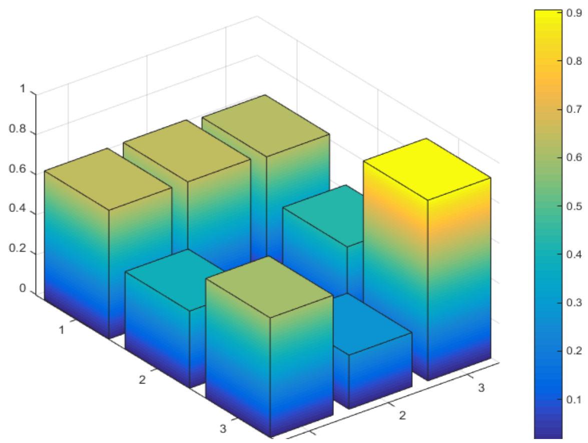

FIGURE 9. The improved coverage ratio based on the intensive scheme.

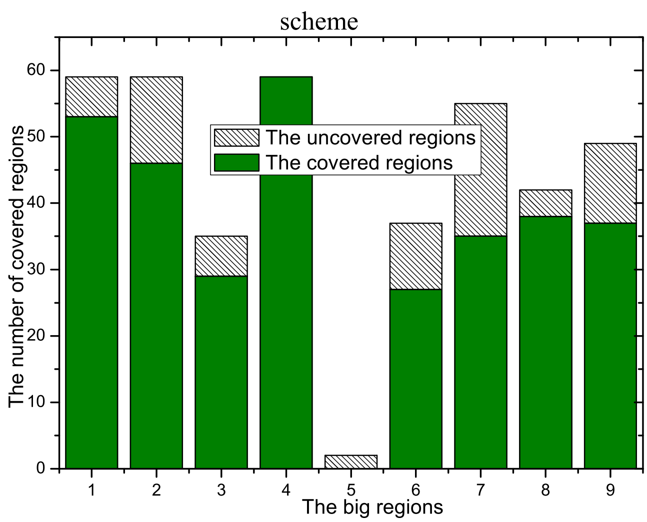

FIGURE 10. The covered regions of the UAVs in each big region.

the coverage ratio of the UAVs can reach to 72.583%. With both the mobile phone users and the UAVs, the number of the small regions which can be covered is 677, the coverage ratio of the OCLC-IoTs scheme can reach to 90.267%, which has been expanded to a large scale. Compared with the previous scheme which only utilizes the mobile-phone users to collect the information, the OCLC-IoTs scheme can improve the coverage number in each big range with the usage of both the mobile-phone users and the UAVs. The improved coverage number is shown in the Fig. 11.

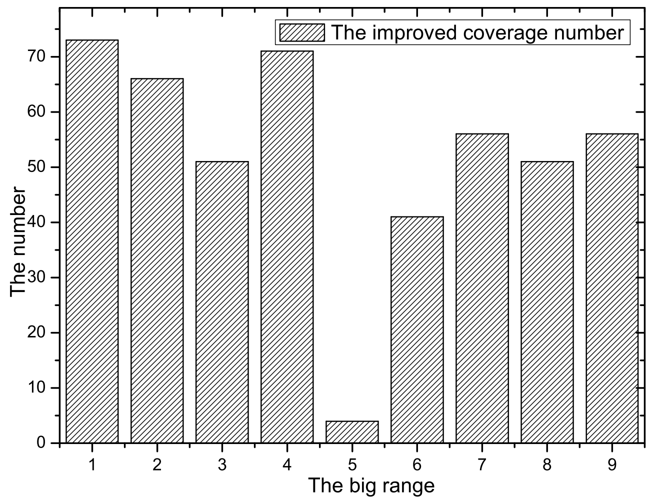

FIGURE 11. The improved coverage number based on the OCLC-IoTs scheme.

The Fig. 11 shows that with both the cooperation of the mobile-phone users and the UAVs, the number of coverage regions can be improved by a large scale, compared with the previous scheme which pays for the participants with static rewards. Some users with mobile sensor devices may not bid for the published tasks because of lower rewards, and there are less mobile-devices users in the suburban regions. Due to the two reasons, the information of the suburban regions is hard to be obtained. Therefore, with improving the rewards in the suburban regions, there are more probability for the mobile-sensor-device users to take part in the tasks, which will increase the total coverage number. For the rest of the regions, the OCLC-IoTs scheme utilizes the UAVs to collect the information under the plan of IRHS scheme. With the two approaches, the number of coverage regions can be improved to a large scale. The improved coverage ratio is shown in the Fig. 12.

The Fig. 12 shows that the OCLC-IoTs scheme has a better performance on the aspect of coverage ratio. We then compared the performances of the OCLC-IoTs scheme with the previous scheme which utilized both the mobile-sensor-devices users without the intensive strategy and the UAVs with the random route planning or the greedy route planning. Based on the number of collection regions for the UAVs is the same, the improvements of the coverage ratio are shown in the Fig. 13.

In the urban regions, the ratio of coverage improvements is less, as shown in the Fig. 13 when the value of vertical coordinates is 5. It is because that there are many mobile-sensor-devices users in the urban regions, as shown in the

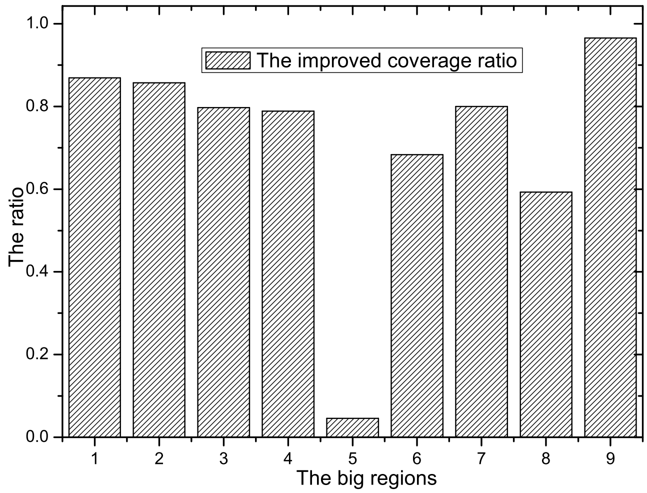

FIGURE 12. **The improved coverage ratio compared with the previous scheme which only utilizes the mobile-sensor-devices users.**

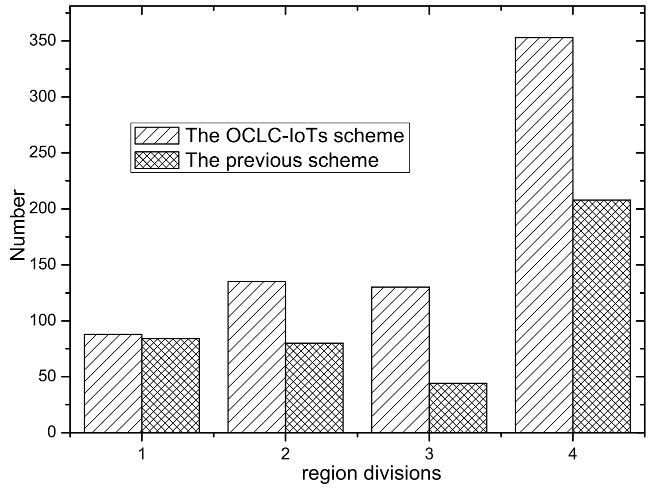

FIGURE 14. **The distributions of mobile-phone users in each density class of the Beijing city.**

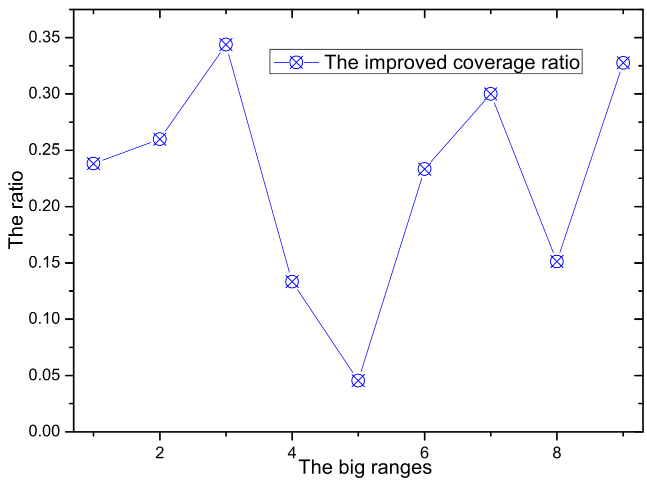

FIGURE 13. **The improvements of the coverage ratio based on the OCLC-IoTs scheme.**

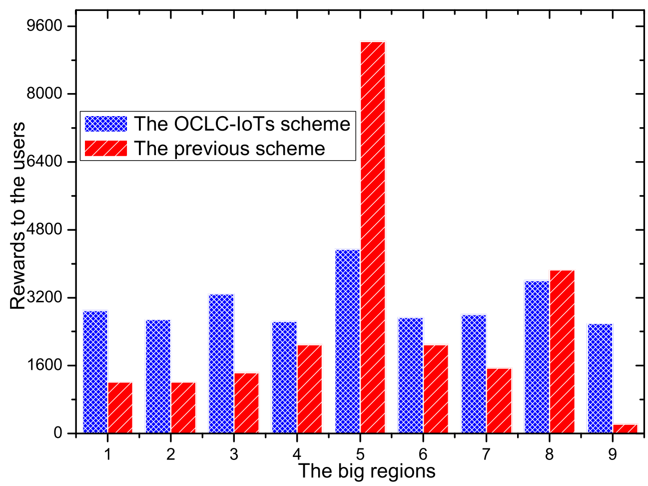

FIGURE 15. **The rewards to the mobile-phone users.**

Fig. 4 and Fig. 6. Therefore, the information of almost each small region in the urban regions can be collected by the mobile-sensor-devices users, as shown in the Fig. 5 and Fig. 7. Thus, the improvement space of coverage in the urban regions is less. The OCLC-IoTs scheme mainly targets to improve the coverage ratio in the suburban regions, for example, when the value of the vertical coordinates is 3, 7 and 9. In general, the coverage ratio can be improved from 5% to 34.38% approximately.

To further evaluate the performances, the number of mobile-phone users in each density degree is compared in the Fig. 14.

According to the experiment settings, there are three density classes in the Beijing city, shown in the Fig. 14. Clearly, in the density class 1, the number of the mobile-phone users of the two schemes is similar to each other. In the density class 2 and the density class 3, the number of the mobile-phone users on the basis of the OCLC-IoTs scheme is more than that on the basis of the previous scheme. It is because that with the intensive strategy, there are more likely that the mobile-phone users in the low-density regions taking part in the task, which will increase the coverage ratio. And in the previous scheme, the standards of the rewards may cannot satisfy the demands of the users in the edges of a city, which will lead to a low coverage ratio. The comparisons of the total number of the users are shown in the fourth column in the Fig. 14.

C. THE COSTS REDUCTIONS

In this subsection, the performances of the cost reductions of the OCLC-IoTs scheme are evaluated. When the time is 17: 49: 16, the comparisons of the mobile-phone users' rewards are shown in the Fig. 15.

Fig. 15 shows that in the proposed scheme, the users who participate in the task can achieve more rewards compared with the users in the previous scheme, which will inspire the users to bid for the published tasks. The ratio of the improved rewards is 17.037%. Even with the cost reduction scheme, the costs of the platform paid for the mobile-phone users are still increasing, because the number of users who take part in the task increases. In the Fig. 15, the tendency of the OCLC-IoTs scheme is smoother than that of the previous scheme. It is because that in the urban regions, there are more mobile-phone users who can take part in the task, therefore, the reward standards in the urban regions are less. Therefore, even the participants' number in the urban regions is more, the costs of the platform won't grow that much.

Based on the degree classes, the comparisons of the rewards for the participant users are shown in the Fig. 16.

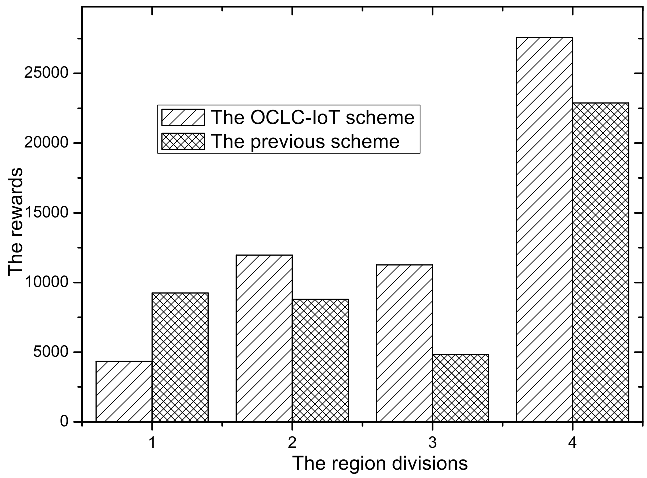

FIGURE 16. The rewards in each region division.

The first three columns in the Fig. 16 shows the rewards of the participant users in each region division. The platform pays more rewards for the participant users in the more remote regions, which can utilize less costs to achieve more coverage ratio. And on average, the costs of a participant user in the OCLC-IoTs scheme are less than those in the previous scheme by 28.97% approximately.

Based on the IRHS strategy in the OCLC-IoTs scheme, we then compared the costs of the UAVs with the costs in the previous scheme. Based on the same collection number, firstly, the energy consumptions of the UAVs in the eight big regions are shown in the Fig. 17.

Fig. 17 shows the energy consumptions of the three routing schemes. The information in the fifth big region has been collected enough, the coverage ratio of information collections can reach to more than 90%. Thus, there is no need to hire the UAVs to that region. Therefore, the value of the fifth column is empty, shown in the Fig. 17. And with the IRHS strategy in the OCLC-IoTs scheme, the energy consumptions of the UAVs can be reduced. It is because that with both the distance priority firstly and then the time priority, the collection routes of the UAVs will be planned well to decrease the trajectory time. Based on the same velocity, the energy consumptions of the UAVs are related to the time consumptions. With the flying time increases, the energy consumptions will be increased. The IRHS strategy optimizes the routing of the

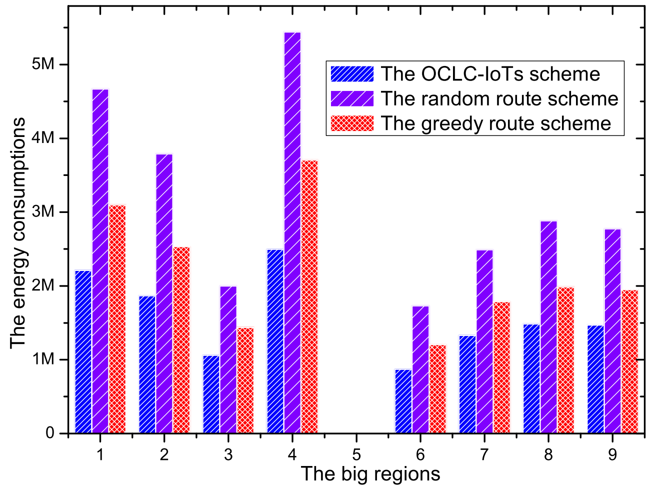

FIGURE 17. The energy consumptions of the nine big regions.

UAVs, thus the energy consumptions will be reduced, compared with the other schemes.

Then the average energy consumptions of each small region are shown in the Fig. 18, based on the three route schemes.

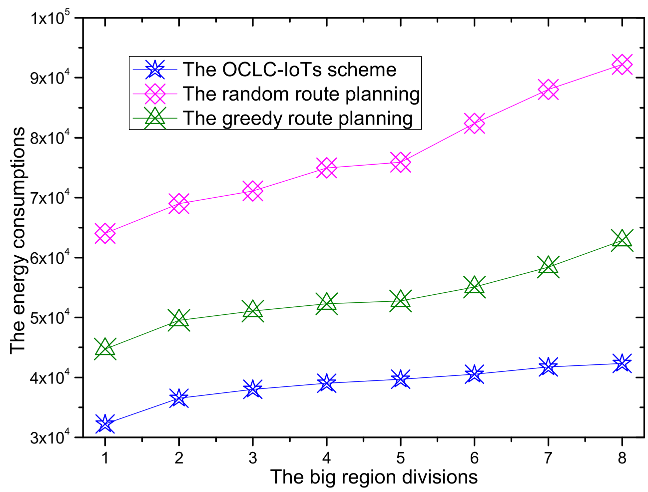

FIGURE 18. The energy consumptions of the UAVs in each big region.

Based on the mobile-phone users' collections, there are eight big regions which information need to be collected by the UAVs, because the information in the urban big region has been fully obtained. For the eight big regions, the average energy consumptions of the UAVs based on the OCLC-IoTs scheme are compared with both the random route planning and the greedy route planning. The tendencies of the three routing schemes are the same. Then the comparisons of the reduced energy consumptions are shown in the Fig. 19.

Fig. 19 shows the reduced energy consumptions of the OCLC-IoTs scheme compared with the random route planning. The reduction ratio ranges from 46.57% to 54.08%.

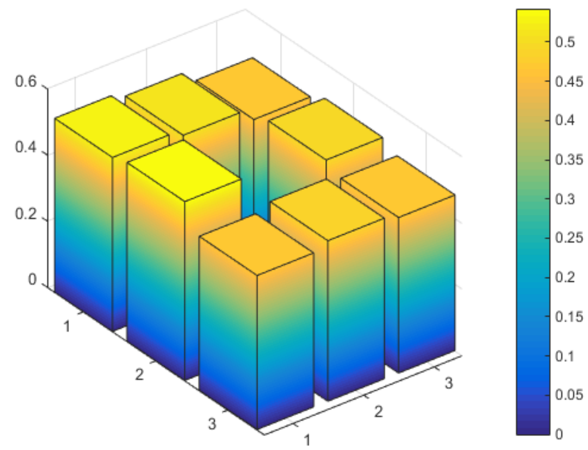

FIGURE 19. **The ratio of reduced energy consumptions compared with the random route planning.**

Compared with the greedy route planning, the ratio of the reduced energy consumptions is shown in the Fig. 20.

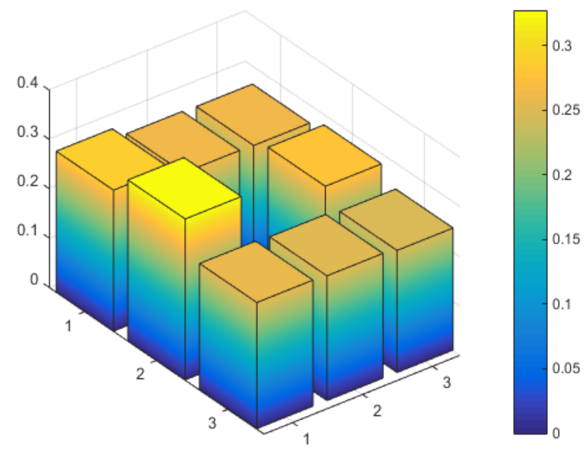

FIGURE 20. **The ratio of reduced energy consumptions compared with the greedy route planning.**

Compared with the greedy route planning, the Fig. 20 shows the reduced ratio of the OCLC-IoTs scheme. The reduction ratio ranges from 24.74% to 32.61%.

Then based on the three-routing schemes, the costs of the UAVs are compared. In the simulation, the value of the η is set as 330. Therefore, the costs of the UAVs at a big range can be obtained. The comparisons of the three routing schemes are shown in the Fig. 21.

In the Fig. 21 it shows the costs of the UAVs in each big region. Compared with the three schemes, the costs of the OCLC-IoTs scheme is less than the other two schemes. It is because that in the IRHS strategy, with both the distance priority and the time priority, the flying distances of the UAVs are decreased. With the static speed, flying time of the UAVs can be reduced. There is a positive correlation between the flying time and the energy consumptions. Therefore, time reductions will have a direct effect on reducing the energy

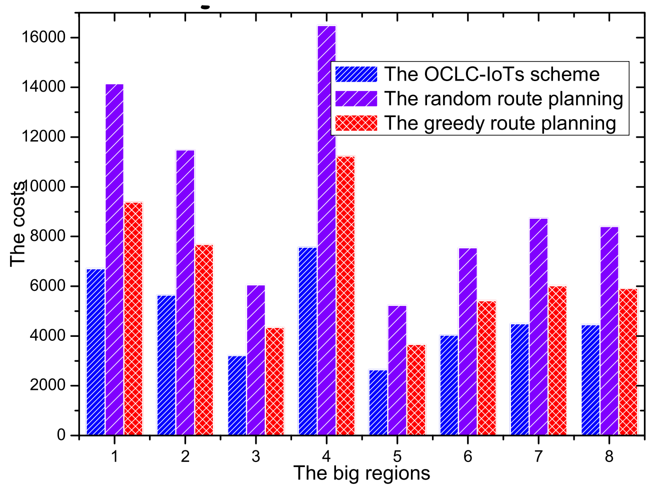

FIGURE 21. **The costs of the UAVs in each big region.**

consumptions. The costs of the UAVs will be reduced with less energy consumptions. The reduced ratio of costs is shown in the Fig. 22.

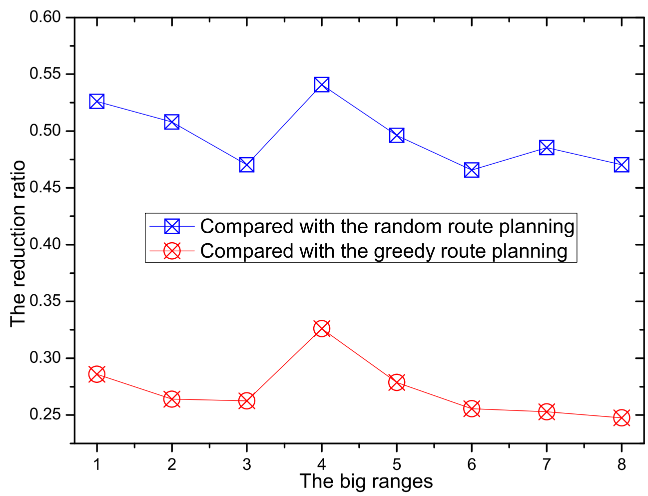

FIGURE 22. **The reduction ratio of costs for the UAVs based on the OCLC-IoTs scheme.**

The Fig. 22 shows the reduction ratio of the costs based on the OCLC-IoTs scheme, compared with the random route planning and the greedy route planning respectively. With the IRHS scheme, the energy consumptions of the UAVs are decreased, which lead to the reductions of the costs for the UAVs.

To further evaluate the performances of the cost reductions, for the energy consumptions of each small region in the eight big regions, the comparisons of the three routing schemes are shown in the Fig. 23.

In each big region, the average costs in each small region are evaluated, shown in the Fig. 23. With the number of the collected small regions increases, the UAV has a higher probability to choose a longer flying route. Thus, the average energy consumptions of each small region will increase, and

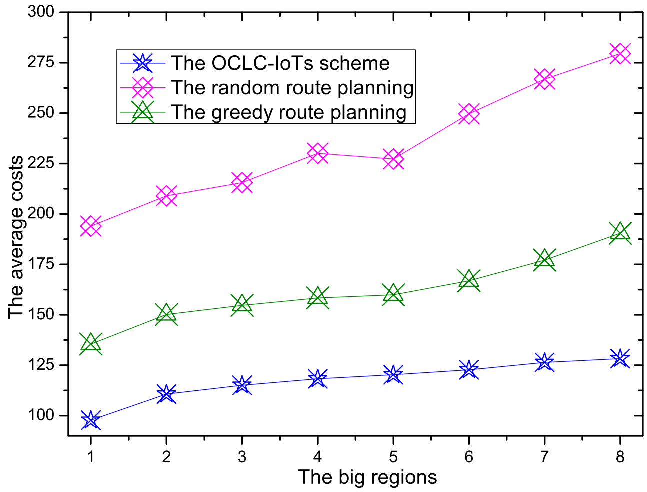

FIGURE 23. The average costs of the UAVs.

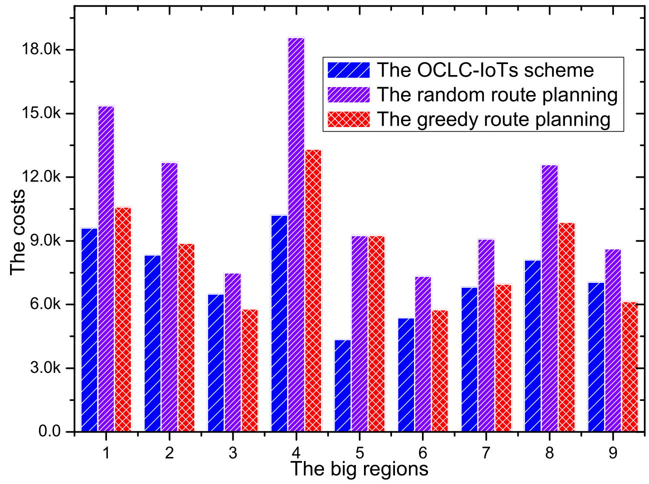

FIGURE 25. The comparisons of the total costs in the three schemes.

the average costs of a small region will increase. But with the OCLC-IoTs scheme, the UAVs can shorten the flying route and reduce the probability of choosing the false way. Thus, the average costs of each small region increase slowly, compared with the random route planning and the greedy route planning.

With both the mobile-phone users' participants and the UAVs, the coverage ratio can reach to 90.267%, which has been introduced above. Then the total costs of the platform are evaluated, shown in the Fig. 24.

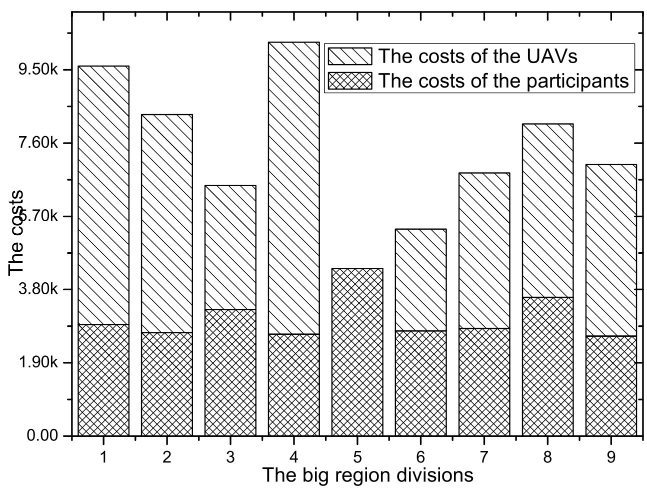

FIGURE 24. The total costs of the platform.

Fig. 24 shows the total costs of the platform paid for the tasks. With both the previous schemes of the mobile-phone users' selection and the random route planning or the greedy route planning of the UAVs, the costs' comparisons among the three schemes are shown in the Fig. 25.

Fig. 25 shows the costs of the three schemes in each big region, which shows the effectiveness of the proposed scheme. Based on the OCLC-IoTs scheme, compared with the random route planning and the greedy route planning, the costs can be reduced by 34.32% and 13.335% respectively. The cost reduction ratio is shown in the Fig. 26.

schemes

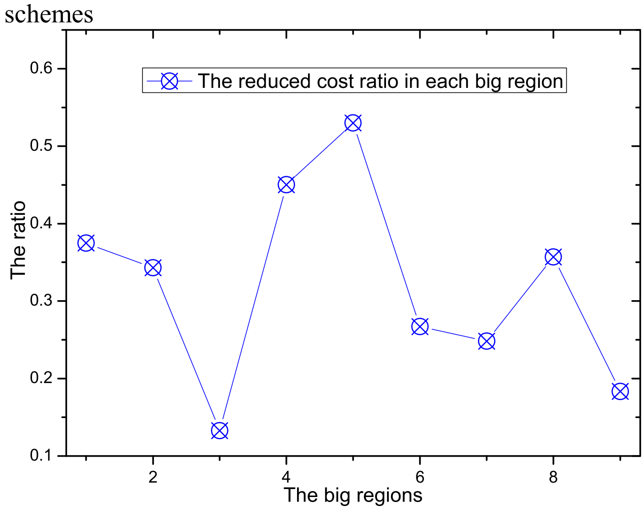

FIGURE 26. The total reduction costs of the big ranges compared with the previous scheme with the random route planning.

The Fig. 26 shows the reduction ratio of costs in each big region, compared with the previous scheme with random route planning. Based on the previous selection scheme of the mobile-phone users and the random route planning, the comparisons of coverage ratio are shown in the Fig. 27.

The Fig. 27 shows the comparisons of the covered regions. Compared with the previous scheme with random route planning, the OCLC-IoTs scheme can improve the coverage ratio of the required information by 21.42% approximately.

The number of the coverage regions in the greedy route planning is the same as that in the random route planning. Therefore, the improved coverage ratio of the OCLC-IoTs scheme is also 21.42%, compared with the previous scheme with greedy route planning.

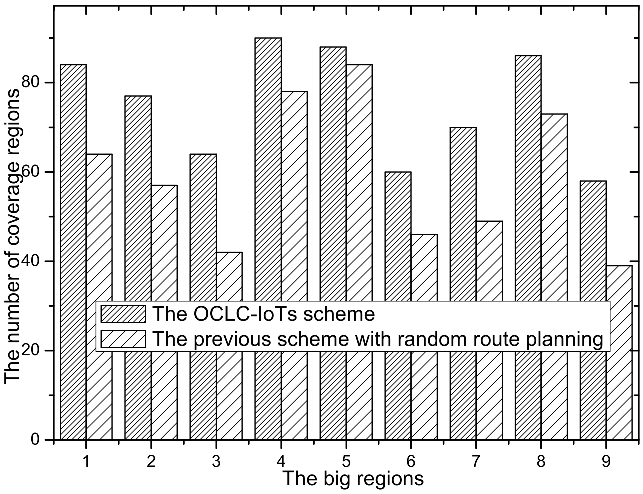

FIGURE 27. The number of covered regions.

TABLE 3. The experimental results of the coverage number.

V	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9
OC	84	77	64	90	88	60	70	86	58
P	64	57	42	78	84	46	49	73	39
I_{cov}	0.29	0.26	0.34	0.13	0.1	0.23	0.3	0.15	0.33

TABLE 4. The number of UAVs.

V	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9
I_{cov}	1	1	2	1	0	1	2	1	1

To evaluate the performances of the OCLC-IoTs scheme comprehensively, the value of ϕ is 26.38% and 16.44% compared with the previous scheme based on the random route planning and the greedy route planning respectively, which shows the effectiveness of the proposed scheme. The number of the covered regions is shown in the Table 3.

Where the OC indicates the OCLC-IoTs scheme and the P indicates the previous scheme in the Table 2.

And the number of the UAVs in each big region is shown in the Table 3.

VI. CONCLUSION

Information collections in the IC-IoTs system are critical issues in guaranteeing the quality of services for the platform, such as the fog-haze monitoring and the weather condition monitoring. Therefore, the coverage ratio of the information collection needs to be expanded. On the basis of improving the coverage ratio, the platform expects to reduce the costs in hiring both the information collectors and the UAVs.

Therefore, the OCLC-IoTs scheme is proposed in this study. For the information collectors, an intensive strategy is designed to inspire them to bid for the published tasks via improving the rewards in the suburban regions and reducing the rewards in the urban regions. For the UAVs, an IRHS strategy is designed to plan the flying routes to reach more coverage ranges, and shorten the flying time to reduce the energy consumptions via utilizing the distance priority firstly and time priority secondly. Under the prerequisite of guaranteeing coverage ratio, with less energy consumptions of UAVs, the rewards the platform paid for hiring them are less. The simulation results indicate that the OCLC-IoTs scheme can reach better performances on both the information-coverage improvements and the cost reductions, compared with the previous schemes.

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