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RESEARCH ARTICLE

A Potential Game Approach to Multi-UAV Accurate Coverage Based on Deterministic Radio Wave Propagation Model in Urban Area

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ABSTRACT Existing methods based on statistical models ignore the detail effect of the real environment on path loss, leading to some discrepancies with the actual results in real urban environments. In order to reduce the discrepancies and improve the unmanned aerial vehicle (UAV) coverage effect, a multi-UAV coverage method based on deterministic radio wave propagation is proposed. First, the ray-tracing method, as one of the deterministic models, is used to simulate the path loss. Next, the cooperative search and coverage problem of multiple unmanned aerial vehicles is modeled as a potential game model, and the utility function is designed by path loss. After that action set is designed to constrain the motion of unmanned aerial vehicles. Then, the coverage problem is solved using a binary log-linear learning algorithm, which combines ray-tracing method and deterministic model. Finally, experiments are conducted in local areas of two cities, Haikou and Guangzhou by proposed method and statistic models. The experimental results show that the proposed method is capable of multi-UAV cooperative search and coverage tasks in urban areas and can achieve better performance than the statistical model-based methods.

INDEX TERMS Multi-UAV cooperative coverage, deterministic radio wave propagation model, potential game, binary log-linear learning algorithm, urban areas.

I. INTRODUCTION

In recent years, unmanned aerial vehicle (UAV) has been widely used in cooperative search tasks due to their small size and high mobility. Compared with a single UAV, multi-UAV cooperation can achieve higher efficiency and complete more complex search and coverage tasks. With the development of game theory, many problems in wireless communication can be solved by it, such as UAV power control, spectrum resource allocation and UAV coverage deployment [1], [2], [3]. Potential game is used for UAV coverage and spectrum resource allocation, matching game is used for UAV relay, coalition game and Stackelberg game are used for spectrum resource planning and power control, etc.

Especially the potential game, as a significant branch of game theory, has a good performance in the area coverage problem of UAVs [4], [5], [6], [7]. Ruan et al. proposed a communication-based multi-UAV low-energy coverage model and used a spatially adaptive game-based multi-UAV energy-efficient coverage deployment algorithm to achieve maximized coverage and control power to ensure optimal energy-efficient coverage [8]. Li et al. proposed a game model for cooperative multi-UAV search and used a binary log-linear learning (BLLL) algorithm for motion control to ensure optimal coverage [9]. Ni et al. proposed an improved BLLL algorithm to obtain better cooperative

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search performance [1]. The above-mentioned articles modeled the problem as a potential game model and showed good results in their tasks. Besides that, there are also some articles use different algorithms [10] to solve the optimal problems. Particle swarm optimization and ant colony optimization algorithm, often used in path planning and coverage problem [11], [12], [13],and artificial bee colony algorithm is used in UAV and base station deployment and path planning [14].

There are also many articles that designed different UAV coverage and deployment methods according to their tasks. Li et al. used UAVs as mobile base stations and used UAV hovering relay technique for node deployment and achieved dynamic adaptive coverage by considering frequency reuse, interference, backhaul re-source allocation and coverage [15]. Wen et al. proposed a novel heuristic algorithm strategy to achieve energy efficiency by obtaining the optimal hovering position of UAVs in the mission area [16]. Li et al. maximized system energy efficiency by jointly optimizing sub-channel selection, uplink transmission power control, and UAV relay deployment [17]. These methods can optimize the UAV deployment strategy and effectively reduce energy consumption. Indeed, most coverage problems require dynamic and distributed interactions of UAVs. Homogeneity, connectivity and environmental threats are important factors that affect the deployment of UAV swarm communication coverage [18], [19], [20]. To address these issues, Khuwaja et al. investigated the impact of the number of UAVs, operating environment, deployment coordinates and separation distance among UAVs on coverage utility [21]. Nguyen proposed a fast user clustering model based on K-means and distributed control power coefficients, and embedded the model into a real system to achieve real time recovery and maintenance of post-disaster networks by using UAV relay communications [22]. Liu et al. [23]constructed a many-to-one bilateral matching market to simulate the interaction between the mast UAV and the small UAVs, and a distributed matching algorithm is proposed to solve the problem of disconnection of UAV network.

For the multi-UAV cooperative search and coverage problem, most of the existing studies are based on the environmental parameters of statistical models [1], [8], [9]. However, due to the complex environment in urban areas, the utility functions constructed based on statistical models cannot reflect the real situation of multi-UAV coverage. In addition, the density of buildings in urban areas has a great influence on the signal field strength and the path loss between UAVs and ground users [24], [25]. On the contrary, the path loss in urban areas can be obtained by ray-tracing method, so using deterministic propagation models can yield results that are more realistic [26], [27], [28], [29], [30].

To improve the accuracy of cooperative search and coverage tasks, a multi-UAV coverage method based on a deterministic radio wave propagation model is proposed by using ray-tracing method to calculate the path loss. First, an urban area scenario is modeled to obtain the corresponding path loss and obtain the coverage utility of multi-UAV. Then, we model the cooperate search and coverage problem as a potential game. At the same time the transmission power and density functions are combined to construct the coverage utility function of multi-UAV which is used to measure coverage effect. Moreover, action set is constructed to control the movement of UAVs and the BLLL algorithm is used to solve the coverage problem. Finally, the effectiveness of the proposed method is validated by simulation in real urban areas.

The remainder of this paper is organized as follows. In Section II, a potential game model is constructed to describe the problem studied in this paper and solved using the BLLL algorithm. In Section III, simulations are conducted in real urban scenarios and the results are compared with statistical models.

II. SYSTEM MODEL

Game theory is an important optimization theory that has been widely used in the field of communication in recent decades [29], [30]. Potential games, as a kind of game theory, ensure that the local utility of each player is correlated with the global utility and play a prominent role in the cooperative control of distributed multi-agent systems [8], [9]. The exact potential game (EPG) is one of the most important potential games and is defined as follows:

Definition 1 (Exact Potential Game [33]): A game model $G = \left[N, S, \{U_n\}_{n \in N}\right]$ is called an exact potential game if there exists following function:

$$\begin{aligned} U_n\left(a_n^*, a_{-n}\right) &- U_n\left(a_n, a_{-n}\right) \\ &= F_n\left(a_n^*, a_{-n}\right) - F_n\left(a_n, a_{-n}\right), \\ &\quad \forall a_n, a_n^* \in A_n,\ \forall a_{-n} \in A_{-n} \end{aligned} \tag{1}$$

where N represents the player set; S is the strategy space of all players; U_n represents the utility function of the n player; a_n and a_n^* are the set of action strategies and the set of predicted action strategies of the nth player, respectively; a_{-n} is the set of action strategies of all players except the nth player; A_n is strategy set for the nth player; $F_n\left(a_n, a_{-n}\right)$ is the potential function.

Definition 2 (Nash Equilibrium [8], [9]): If a strategy set $a^* = (a_n^*, a_{-n}^*)$, $a^* \in S$ was known as the Nash Equilibrium, if and only if the following formula is met:

$$U_n\left(a_n^*, a_{-n}^*\right) \le U_n\left(a_n, a_{-n}^*\right), \quad \forall n \in N,\ \forall a_n \in A_n \tag{2}$$

Based on the descriptions above, when the game achieves to Nash Equilibrium, no player can increase its benefit by changing its strategies when other players keep their strategies unchanged, and a potential game may process several Nash Equilibrium [1].

A. PROBLEM STATEMENT

This paper focuses on multi-UAV performing cooperative search and coverage tasks in urban areas. The coverage effectiveness of UAVs is determined by the power of UAVs and

FIGURE 1. **The mission area in Haidian island, Haikou city.**

environmental factors, and the received power P_r is considered as a major factor to judge the coverage effectiveness of UAVs. The coverage effectiveness of UAVs is evaluated by constructing a global utility function of UAVs, and the influence of coverage effectiveness of other UAVs is excluded to avoid unnecessary recalculation of coverage utility.

In previous papers on cooperative UAV search and coverage [1], [8], [9], empirical formulas or simulations by establishing virtual mission areas are usually used to calculate the path loss. Considering the effects of diffraction and reflection of signal in urban areas, this paper calculates the path loss data by simulation.

Taking Haidian island in Haikou city shown in Fig. 1 as an example, the mission area Ω is delineated by red lines and covers an area of 5 km, and the destiny function $\eta(i)$ is set as:

$$\eta(i) : \Omega \rightarrow R_+ \tag{3}$$

where i represents the cell in mission area.

The coverage effect of the UAV is determined by the path loss, noise, the transmit power of UAVs, the carrier frequency and the receive threshold of the receivers, where the path loss L is obtained from the difference between the transmit power P_s and the receive powerP_r, which is given by the following equation:

$$P_r = P_s - L \tag{4}$$

The corrected received power P_r^* is shown below, taking into account the effect of the actual environmental factors on the calculated path loss.

$$P_r^* = P_r + \sigma^2 = P_s - L + \sigma^2 \tag{5}$$

where σ^2 represents the variance of white Gaussian noise.

The received power of the receiver can be obtained by comparing it with the threshold value of the received power, as shown below:

$$f\left(\left\|P_r^*(i) - Th\right\|\right) = \begin{cases} 1, & P_r^*(i) \geq \ Th \\ 0, & otherwise \end{cases} \tag{6}$$

where Th represents the threshold of received power of receivers.

Therefore, the global utility function is constructed as follows:

$$U\left(a_n, a_{-n}\right) = \int_{i\in\Omega} \eta(i) * f\left(\min_{n\in N} \left\|P_r^*(n) - Th\right\|\right) di \tag{7}$$

And the local utility function is:

$$\begin{aligned} U_n\left(a_n, a_{-n}\right) = &\int_{i\in\Omega} \eta(i) * f\left(\min_{n\in N} \left\|P_r^*(n) - Th\right\|\right) di \\ &- \int_{i\in\Omega_n} \eta(i) * f\left(\min_{n\in N\backslash\xi} \left\|P_r^*(n) - Th\right\|\right) di \end{aligned} \tag{8}$$

where $P_r(n)$ is the received power set of each unit of UAV n in the mission area. Ω_n is the coverage area of UAV n; ξ is the neighbor of UAV n; $N\backslash\xi$ is the set of UAVs that do not overlap with the coverage of neighbor of UAV n;

According to description above, we can know that if the local utility function is constructed as (8), the cooperative search and coverage problem of UAVs can be modeled as an EPG, and has at least one NE point. The proof procedure is described as follows:

First, the global potential function is constructed as follows:

$$F\left(a_n, a_{-n}\right) = \int_{i\in\Omega} \eta(i) * f\left(\min_{n\in N} ||P_r^*(n) - Th\|\right) di \tag{9}$$

Equation (8) can be converted to (10) according to (9):

$$\begin{aligned} U_n\left(a_n, a_{-n}\right) = &F\left(a_n, a_{-n}\right) \\ &- \int_{i\in\Omega_n} \eta(i) * f\left(\min_{n\in N\backslash\xi} \left\|P_r^*(n) - Th\right\|\right) di \end{aligned} \tag{10}$$

Therefore, when the UAV n changes its action strategy from a_n to a_n^*, the change in its utility function is represented as follows:

$$\begin{aligned} &U_n\left(a_n^*, a_{-n}\right) - U_n\left(a_n, a_{-n}\right) \\ &= \left[F\left(a_n^*, a_{-n}\right) - \int_{i\in\Omega_n} \eta(i) * f\left(\min_{n\in N\backslash\xi} \left\|P_r^*(n) - Th\right\|\right) di\right] \\ &\quad - \left[F\left(a_n, a_{-n}\right) - \int_{i\in\Omega_n} \eta(i) * f\left(\min_{n\in N\backslash\xi} \left\|P_r^*(n) - Th\right\|\right) di\right] \\ &= F\left(a_n^*, a_{-n}\right) - F\left(a_n, a_{-n}\right) \end{aligned} \tag{11}$$

According to (1), (2), the problem is an EPG with at least one NE point.

In order to get the NE solution better, the BLLL is used in this paper. The algorithm can improve iteration efficiency through a certain self-decision mechanism, and can be solved under the game structure.

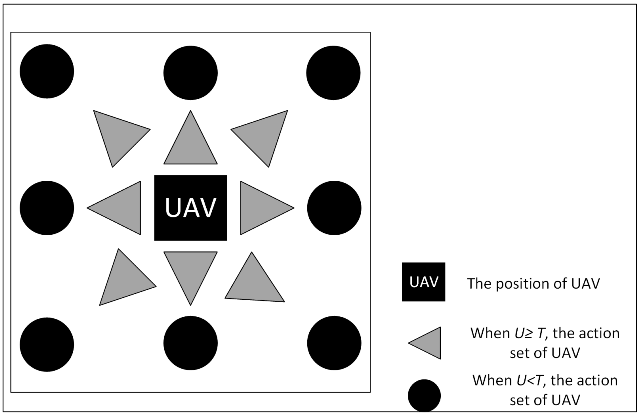

FIGURE 2. The action set: it has two different motion sets to be chosen.

B. UAV ACTION SELETION AND DEPLOYMENT

In order to improve the efficiency of iteration and avoid UAVs running out of the mission area in unreasonable movement direction, we design the UAV action set, as shown in Fig. 2. The algorithm can choose action set according to the value of global utility. When $U \leq$ T, the UAV adopts the larger motion set to move. When $U >$ T, the action set of smaller steps is used for the move. The UAV will be chosen randomly by the equal probability, it will take a trail action in the current constraint action set $L\left(a_n(t-1)\right)$, and the rest of UAVs will remain their actions. The strategy is following:

$$\begin{cases} P\left(a_n^* = a_n\right) = 1/z_n, a_n \in L\left(a_n(t-1)\right) \backslash a_n(t-1) \\ P\left(a_n^* = a_n(t-1)\right) = 1 - \left(\left|L\left(a_n(t-1)\right)\right| - 1\right)/z_n \end{cases} \tag{12}$$

where z_n denotes the maximum number of actions in $L\left(a_n(t-1)\right)$.

After selecting the trail action, the UAV updates its action at time t according to the following strategy:

$$\begin{cases} p\left(a_n(t) = a_n(t-1)\right) \\ = \frac{\exp(\beta * U_n(a_n(t-1)))}{\exp(\beta * U_n(a_n(t-1))) + \exp\left(\beta * U_n\left(a_n^*(t-1)\right)\right)} \\ p\left(a_n(t) = a_n^*\right) = \frac{\exp\left(\beta * U_n\left(a_n^*(t-1)\right)\right)}{\exp(\beta * U_n(a_n(t-1))) + \exp\left(\beta * U_n\left(a_n^*(t-1)\right)\right)} \end{cases} \tag{13}$$

where β is the learning exponent.

The algorithm shows in Table.1, and the process of implementing the BLLL algorithm is as follows:

Step 1: Set the mission scenario and related parameters, and initialize the location of UAVs;

Step 2: Randomly select a UAV whose action strategy at the current position is a_n and choose the corresponding action set according to the selected UAV. The trail action a_n^* can be randomly selected from the action set according to (12);

Step 3: Calculate the utility of UAV by (8), and the chosen UAV updates its position according to (13);

Step 4: Use (7) to calculate the global utility under the new location to measure the coverage effect of UAVs;

Step 5: Repeat steps 2, 3, and 4 until the algorithm converges.

Algorithm 1 Binary Log-Linear Learning Algorithm

Input: Th,L,T,t
Output: U

```
Scenario creation ();
% Create scenario and divide it to cells;
Parameters initial ();
% Initial parameters;
Action set initial ();
while (The mission area is not fully covered) do
    for (all UAVs in UAV set) do
        Random select(UAV);
        % Select UAV randomly from UAV set.
        Random select(UAV action);
        % Select a trail action from action set.
        Utility compute();
        % Utility compute according to (7).
        Statement update();
        % Select motion strategy according to (13).
    end for
    Iteration = Iteration + 1;
    if (Iteration ≥ IterationMax) then
        Break;
    end if
end while
return global utility
```

III. RESULTS AND DISCUSSIONS

To verify the effectiveness of the proposed method, the following experiments are conducted. The relevant experimental settings are as follows: the transmit power of the UAV is 30 dBm for Haidian island and 40 dBm for Guangzhou, the height of the UAV is 200 m, the receiver height is 1.5 m, the carrier frequency of the UAV is 2 GHz, the threshold value of received power Th is -85 dBm, the mission area is 50×50 cells, and the length of each cell is 100 m. All the experiments are performed on a personal computer equipped with an intel core i5-10210U, 16G RAM and Windows 11.

A. SIMULATIONS IN HAIDIAN ISLAND

The radio frequency (RF) model [28] and the COST231-Hata model [34] are chosen for comparison, both of which can predict path loss at 2 GHz. The RF model is applicable to low-altitude platforms with altitudes between 200 and 3000 m. The COST231-Hata model is an extension of the Okumura Hata model [35], with a transmitter and receiver can be up to 20 km away from each other, and the antenna height of the receiver is between 1 and 10 m. We also list free space (FS) path loss model and log-distance path loss model [36] for comparison. Ray tracing method is a deterministic model which has no limits in application scenarios.

To show good coverage, the initial positions of UAVs are placed at the edge of the mission area, as shown in Fig. 3. The effect of the number of UAVs on the coverage effectiveness is considered. In Table 1, the results show that the method

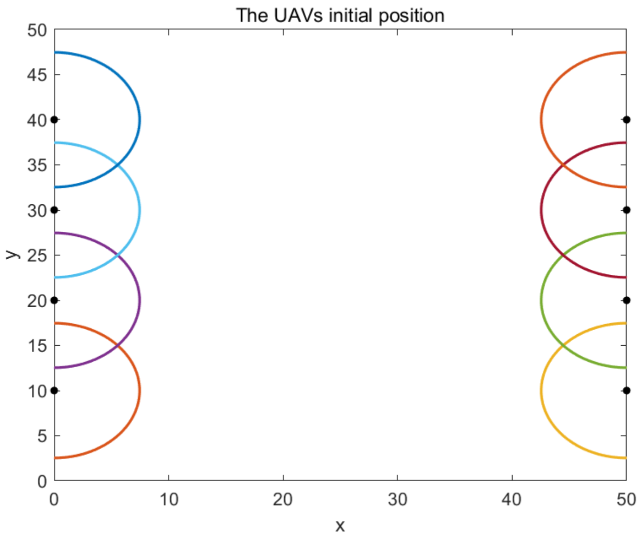

FIGURE 3. The UAVs initial positions.

proposed in this paper performs better than other models, and compared utility values with other utility values, we find the utility based on statistic models can not well reflect the coverage effect in real urban area, which means they are not suitable for the real urban areas. When the number of UAVs increases from 6 to 8, the utility values of the coverage increase rapidly. Because it is difficult for too few UAVs to completely cover the whole urban area, and as the number of UAVs increases, their coverage utility increases. However, 8 UAVs can basically satisfy the signal coverage needs of the area. Therefore, as the number of UAVs increases further, their utility grows slowly. On the contrary, the coverage utility values of UAVs obtained by other methods continue to grow with the increase of the number of UAVs, indicating that the coverage in urban areas is still not maximized. In conclusion, the method in this paper can achieve better coverage results in experiments with 6 to 10 UAVs.

Fig. 4 shows the evaluation coverage distribution of Haidian island by multi-UAV under the RF model. The color in the figure indicates the intensity of the received power. The threshold value of the received power *Th* is set to -85 dBm, which is shown as dark blue, and the color gradually tends to red as the intensity of the received power increases. From the figure, it can be seen that the RF model tends to achieve good results in most areas. However, there are still some shortcomings in the coverage effect in built-up areas. For example, in the area in the lower right corner of Fig. 5, the received power intensity in this area is poor due to the high density of nearby buildings. Fig. 5-7 shows the coverage effect of multi-UAV under the COST231-Hata model, FS model and log-distance model. The global utility values are 59.49%, 58.70% and 60.01%, those utility values are lower than utility based on ray-tracing method. Fig. 8 shows the coverage effect of the proposed method in this paper. Compared with Fig. 4-7, we can find that the mission are have less green and blue areas which means the proposed method have higher receive power, and it has better communication

TABLE 1. The global coverage utility of muti-UAVs in Haidian island, Haikou city.

The numbers of UAVs	The utility of RF model	The utility of COST231-Hata model	The utility of FS model	The utility of log-distance model	The utility of ray-tracing method
6	52.13%	51.14%	51.23%	51.79%	58.35%
7	56.49%	54.31%	55.61%	55.89%	62.85%
8	60.07%	59.49%	58.70%	60.01%	68.27%
9	62.87%	63.01%	62.39%	62.78%	71.27%
10	66.36%	66.96%	65.73%	66.51%	71.92%

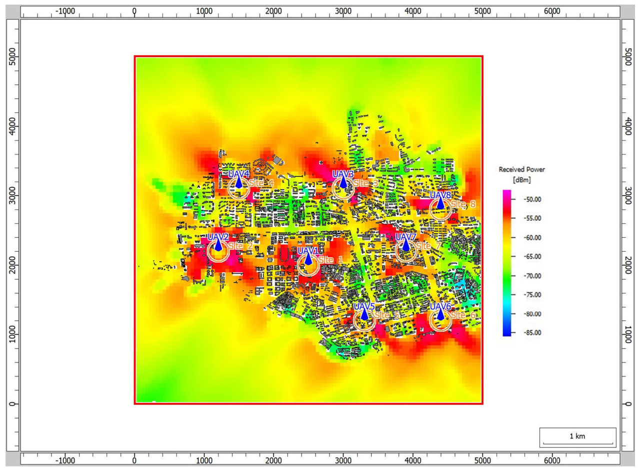

FIGURE 4. The coverage effect of 8 UAVs based on RF model in Haidian island, Haikou city. The global utility is 60.07%.

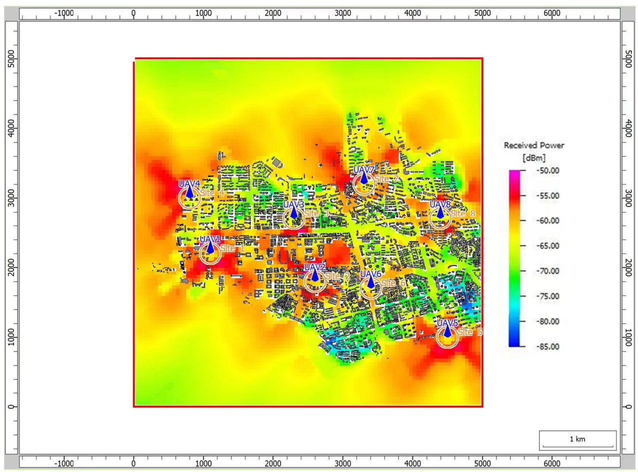

FIGURE 5. The coverage effect of 8 UAVs based on COST231-Hata model in Haidian island, Haikou city. The global utility is 59.49%.

condition. The results show the coverage effect are better than the method based on the statistical model, which effectively improves the reception of the signal in the dense building area. Fig. 9 shows that the method proposed in this paper can achieve relatively stable iterative results and get a good utility value.

B. SIMULATIONS IN GUANGZHOU

Simulation of multi-UAV coverage in the urban area of Guangzhou, China is also conducted. The mission is to cover the urban area while ignoring hills, lakes and parks.

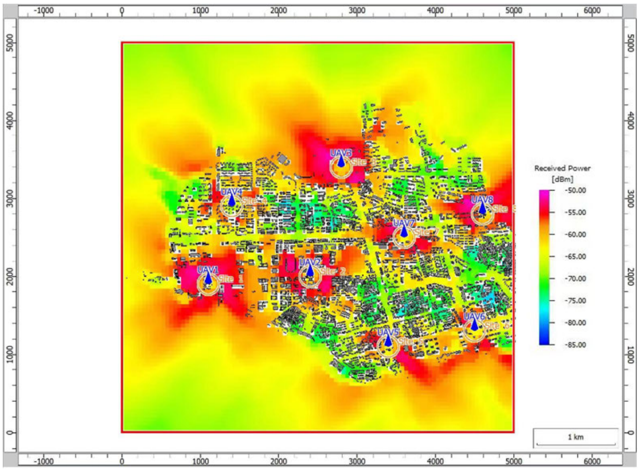

FIGURE 6. The coverage effect of 8 UAVs based on FS model in Haidian island, Haikou city. The global utility is 58.70%.

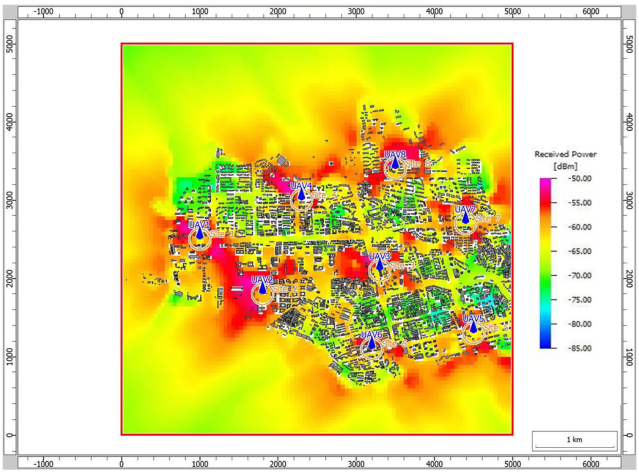

FIGURE 7. The coverage effect of 8 UAVs based on log-distance model in Haidian island, Haikou city. The global utility is 60.01%.

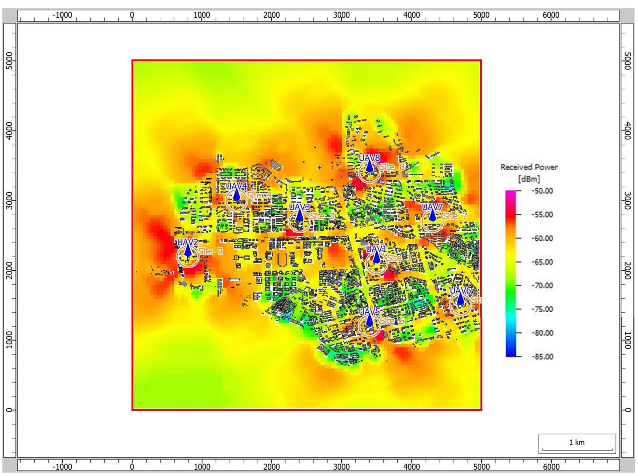

FIGURE 8. The coverage effect of 8 UAVs based on ray-tracing method in Haidian island, Haikou city. The global utility is 68.27%.

In Table 2, the utility values under different numbers of UAVs are listed. We can know the utility values of statistic

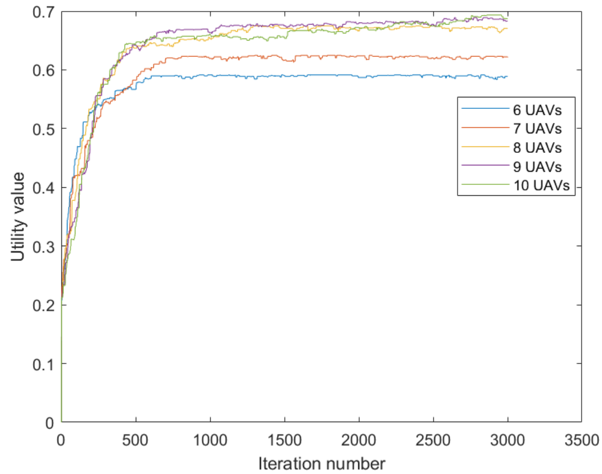

FIGURE 9. The iterations of 6-10 UAVs: it shows proposed method can achieve stable iterative results.

TABLE 2. The global coverage utility of muti-UAVs in Guangzhou.

The numbers of UAVs	The utility of RF model	The utility of COST231-Hata model	The utility of FS model	The utility of log-distance model	The utility of ray-tracing method
6	56.43%	55.63%	55.14%	55.07%	58.20%
7	58.63%	57.43%	57.63%	59.51%	60.62%
8	63.60%	62.76%	62.64%	63.99%	66.92 %
9	64.53%	63.65%	64.32%	65.48%	68.78%
10	66.53%	65.39%	65.24%	66.15%	69.83%
11	68.22%	67.64%	67.54%	68.21%	70.20%

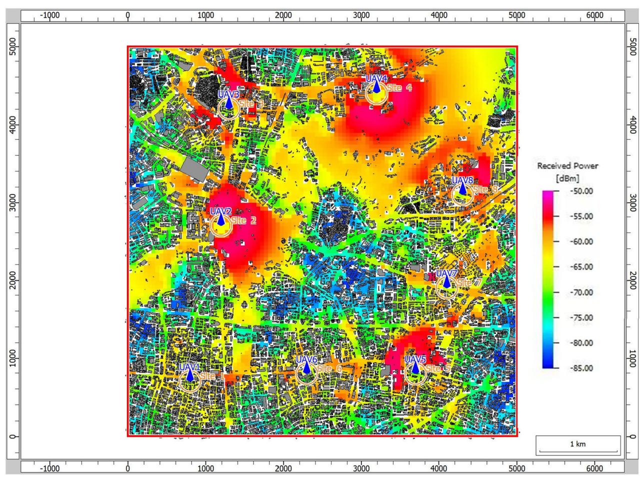

FIGURE 10. The coverage effect of 8 UAVs based on RF model in Guangzhou. The global utility is 63.60%.

model and deterministic method are lower than in Haidian island due to the much higher density of buildings in Guangzhou. However, we can draw similar conclusions to those in Haidian island: the results show the utility based on statistical models are not suitable for real urban areas. When the number of UAVs increases to a certain number, the increase in utility value is slow and the global utility value is

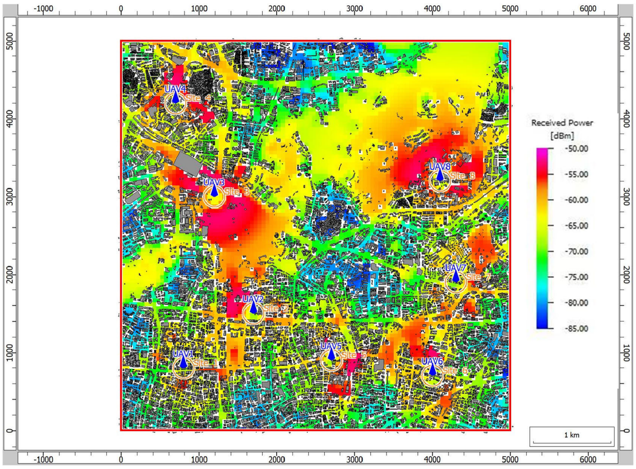

FIGURE 11. The coverage effect of 8 UAVs based on COST231-Hata model in Guangzhou. The global utility is 62.76%.

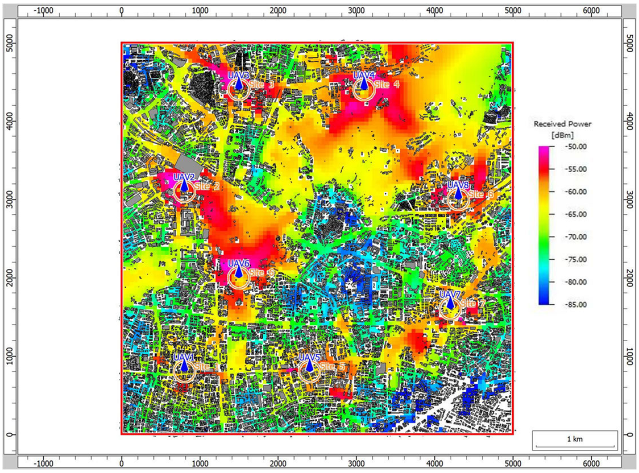

FIGURE 12. The coverage effect of 8 UAVs based on FS model in Guangzhou. The global utility is 62.64%.

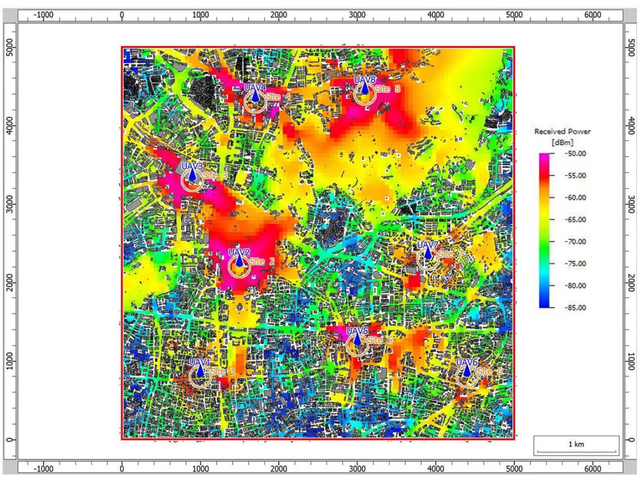

FIGURE 13. The coverage effect of 8 UAVs based on log-distance model in Guangzhou. The global utility is 63.99%.

low because of the higher density of buildings. This also indicates that more UAVs are needed to meet the communication

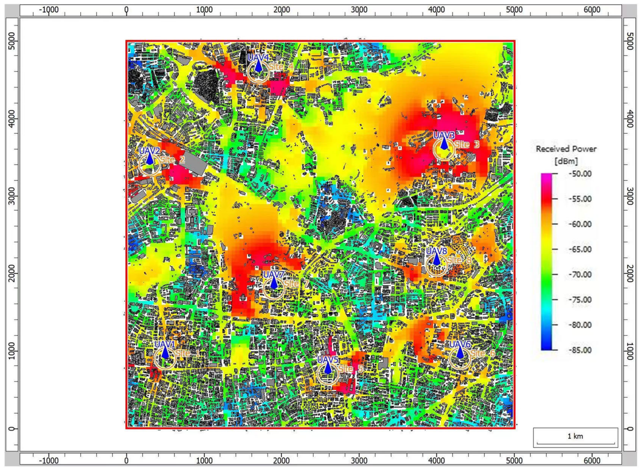

FIGURE 14. The coverage effect of 8 UAVs based on ray-tracing method in Guangzhou. The global utility is 68.78%.

requirements in large cities. The overall results show that the proposed method in this paper can perform the communication coverage task more accurately than the methods based on the statistical models.

Fig. 10-14 show the intensity distribution of the received power under the five models. The experimental results differ greatly from those of Haidian island, and there are dark areas where UAVs signal cannot meet the communication conditions. According to Fig. 10-13, multi-UAV can cover most areas of the city, but there are still some areas with unsatisfactory coverage compared to the results shown in Fig. 14. In Fig. 12, the white areas mean the received power are lower than -85 dBm, the coverage effect become worse due to the positions of UAVs. We can also find that the coverage of UAVs is not as effective as Haidian island. Because the high density of buildings in the city increases the path loss between UAVs and ground receivers and make the communication condition worse than Haidian island. However this dose not change the fact that the proposed method have higher utility values and better coverage effect.

IV. CONCLUSION

The modular framework of the approach proposed in this paper has the ability to design utility functions and task areas individually, thus providing a flexible and accurate way to adapt to different areas and tasks. The coverage effectiveness of UAVs grows with the number of UAVs. Based on the verification of the convergence of the proposed algorithm, the proposed method is compared with the statistical model methods in three aspects: the number of UAVs, the location of UAVs, and the maximum receiving power of ground equipment. The experimental results show that the utility based on statistical models can make a certain difference with actual situations. Compared with the statistical model-based methods, the proposed method is more effective and accurate, and overcomes the signal attenuation problem caused by urban buildings to a certain extent.

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