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Multi-UAV-assisted Internet of Remote Things communication within satellite–aerial–terrestrial integrated network

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Abstract
Due to the limited transmission capabilities of terrestrial intelligent devices within the Internet of Remote Things (IoRT), this paper proposes an optimization scheme aimed at enhancing data transmission rate while ensuring communication reliability. This scheme focuses on multi-unmanned aerial vehicle (UAV)-assisted IoRT data communication within the satellite–aerial–terrestrial integrated network (SATIN), which is one of the key technologies for the sixth generation (6G) networks. To optimize the system's data transmission rate, we introduce a multi-dimensional coverage and power optimization (CPO) algorithm, rooted in the block coordinate descent (BCD) method. This algorithm concurrently optimizes various parameters, including the number and deployment of UAVs, the correlation between IoRT devices and UAVs, and the transmission power of both devices and UAVs. To ensure comprehensive coverage of a large-scale randomly distributed array of terrestrial devices, combined with machine learning algorithm, we present the Dynamic Deployment based on *K*-means (DDK) algorithm. Additionally, we address the non-convexity challenge in resource allocation for transmission power through variable substitution and the successive convex approximation technique (SCA). Simulation results substantiate the remarkable efficacy of our CPO algorithm, showcasing a maximum 240% improvement in the uplink transmission rate of IoRT data compared to conventional methods.

Keywords: Internet of Remote Things (IoRT), Satellite–aerial–terrestrial integrated network (SATIN), Unmanned aerial vehicle (UAV), Low earth orbit (LEO) satellite, Data transmission

1 Introduction
In recent years, the Internet of Things (IoT) technology has made tremendous progress. The emergence of IoT-based smart scenarios has significantly enhanced the convenience of our daily lives. Nevertheless, the dramatically increasing number of IoT devices and the associated data transmission impose increasingly stringent requirements on parameters such as data rate, communication range, and network latency [1, 2]. With the standardization of the fifth generation-advanced (5G-A) networks, the sixth generation (6G) networks is being developed by academia and industry. Envisioned as a technological

leap beyond its predecessor, 6G is expected to deliver faster data rates, lower latency, higher reliability, and wider coverage with key technologies such as Artificial Intelligence (AI) and satellite–aerial–terrestrial Integrated Network (SATIN). These advancements are poised to create new avenues for the development and expansion of IoT applications [3]. Especially, environmental monitoring data of deserts, oceans, and remote areas provides important information for humans to further explore the world. Therefore, under these special scenarios, IoT services have been extensively studied, such as remote monitoring systems for monitoring climate change, natural disasters, and wildlife. The IoT in these scenarios is named as the Internet of Remote Things (IoRT). However, due to geographical limitations, Ground Base Stations (GBS) are often difficult to deploy, and most IoT devices, such as buoys in the ocean and sensors in remote areas, are hard to be covered by GBSs [4]. Therefore, ground communication is difficult to meet the communication needs of IoRT, and there is a pressing need to study and develop reliable and efficient communication solutions specifically tailored for IoRT scenarios. By addressing these challenges, the connectivity and communication capabilities of IoRT devices can be enhanced, enabling more effective environmental monitoring and exploration.

Satellite communication systems have the characteristic of providing seamless wireless access for vast geographical areas, making satellite-assisted ground IoRT communication possible [5]. In satellite communication, satellites include Geostationary Earth Orbit (GEO), Medium Earth Orbit (MEO), and Low Earth Orbit (LEO), which are important components for improving global communication services. LEO satellites, in particular, serve as vital components for gathering and relaying data generated by terrestrial devices [6]. Nevertheless, adverse weather conditions can render ground-satellite connections susceptible to disruption. Considering the constraints in terms of device number and power consumption, achieving long-distance transmission becomes challenging since the data transmission delays, and devices typically have difficulty establishing direct communication with satellites. Consequently, ensuring both high reliability and robust throughput in data transmission performance becomes a formidable task.

Recently, unmanned aerial vehicle (UAV) communication technology has developed rapidly, and has been widely applied in various fields, such as precision agriculture, traffic control, aviation inspection, search and rescue, etc. The ultra-high speed, ultra-low latency, and ultra-high reliability of the fifth generation wireless system (5G) have further promoted the development of UAVs [7]. UAVs have advantages of high mobility, flexible deployment, and low-cost. Simultaneously, compared to the ground link, line of sight transmission enables better channel conditions for the air-to-ground link, providing higher data transmission rate [8]. Thus, UAVs can serve as aerial base stations or relays to assist ground communication, providing temporary communication services, especially in the emergency communication and rescue. However, UAVs encounter challenges related to limited backhaul link capacity and restricted transmission range, making it challenging to fulfill communication requirements and ensure Quality of Service (QoS) standards solely with UAVs. Therefore, further advancements are necessary to address these limitations and fully harness the potential of UAVs in communication scenarios.

The deployment of UAVs in satellite-ground communication can bring numerous benefits, such as high throughput, flexibility and reliability. UAVs have the capability to establish communication links with both satellites and terrestrial devices concurrently, enabling the seamless transfer of data from devices to satellites [9]. On the other hand, using UAVs as relays can reduce ground wireless signal interference, provide effective communication connection, and improve the transmission quality for the ground-satellite network. This integration of UAVs as relays in satellite-ground communication holds great potential for optimizing communication performance and enhancing overall network efficiency.

UAVs operate at low altitudes and can dynamically navigate around IoT devices, offering flexible and ubiquitous accessibility, thus can be effectively applied in IoRT communication scenarios. UAVs can help LEO satellites improve the channel capacity of SATIN, achieving seamless reception [10]. However, due to the different channel characteristics of UAV-ground links and UAV-satellite links, as well as the high mobility of UAVs, introducing UAVs as relays to assist the ground-satellite network still poses great challenges. These challenges need to be addressed in order to effectively leverage UAVs as relays and fully realize their potential in optimizing the performance of the ground-satellite network.

1.1 Related work

The existing literature has extensively studied the scenarios of satellite-assisted ground communication. In [11], Huang et al. studied how to efficiently collect IoT data from distributed IoT networks through LEO satellites, an online algorithm based on Lyapunov optimization theory is proposed, and the power consumption and capacity issues of data collection and forwarding are investigated. In [12], Wang et al. researched satellite-assisted ground communication, where LEO satellite networks collect sensing data from terrestrial devices, and then forward the data to ground stations through GEO satellite networks. A transmission scheduling algorithm combining simulated annealing and Monte Carlo algorithm (SA-MC) is proposed to achieve the dynamic optimal scheduling scheme. These above literatures focus on utilizing satellite networks with extensive coverage to support data transmission for large-scale terrestrial devices. Nevertheless, the limitations imposed by the power consumption of terrestrial devices cannot be solved relying solely on algorithm optimization. Meanwhile, the significant transmission link loss between satellite systems and terrestrial devices still needs to be emphasized.

UAVs are being considered as relays for satellite-ground link communication to achieve better communication performance. In [13], Qiu et al. first conducted a comprehensive comparison and research on various communication service UAVs. Then an integrated air-ground heterogeneous network architecture is proposed to study the network throughput and outage probability under different UAV deployment scenarios. In the cognitive environment with satellite reception communication, Pervez et al. [14] considered an integrated satellite–aerial–terrestrial network (I-SAT) network, in which multiple UAVs and a GBS are deployed to provide communication services for intelligent vehicles on the ground. User associations, BS/UAVs transmission power and UAV trajectories are jointly optimized to maximize average throughput between users. In [15], Tran et al. studied the scenario of content transmission in LEO satellite and UAV-assisted ground networks. Caching is provided by UAV to reduce backhaul congestion, and LEO satellite supports UAV backhaul link. With limited cache capacity and flight time, cache placement, resource allocation and the trajectory of UAV are jointly optimized to maximize the minimum achievable throughput of each ground user (GU). In [16], Wang et al. investigated a resource allocation problem for SAG-IoRT network and proposed a SAG-IoRT framework, where UAV acts as relay, uploading data collected from terrestrial devices to LEO satellite, and maximizing system capacity by jointly optimizing the connection scheduling of terrestrial devices, power control, and UAV trajectory. In [17], Li et al. examined the energy-saving resource allocation problem in two-hop uplink communication in UAV-assisted IoRT network. Sub-channel selection, uplink transmission power control and UAV relay deployment are jointly optimized to maximize system energy efficiency. These above literatures explores the utilization of single or multiple UAVs to enhance satellite-ground communication, and focus on optimizing the flight trajectory of UAV to improve communication performance. However, practical scenarios pose challenges due to limited UAV coverage and energy constraints, leading to inadequate coverage for large-scale distributed terrestrial devices. This paper considers deploying multiple UAVs as relays, collaborating with satellite network, to achieve full coverage of devices, and improve data transmission rate.

In addition, achieving full coverage of terrestrial devices is crucial in practical scenarios, which can be accomplished by dynamically deploying 3D spatial positions of UAVs. In [18], Lyu et al. proposed a polynomial time algorithm for continuous mobile base station positions, which optimizes the horizontal deployment of UAVs, and achieves the minimum number of UAVs by fixing the height. In [19], Zhang et al. presented a rapid deployment scheme for UAVs under emergency scenarios. Two trajectory planning algorithms based on *k*-means are proposed to optimize the trajectory of UAVs, aiming to achieve full coverage of Device to Device Communication (D2D) users, while maximizing system throughput. These above literatures focus on optimizing UAV deployment locations, but overlook the randomness of user distribution, making it impossible to dynamically deploy the appropriate number of UAVs and optimize their locations accordingly. For example, in [19], the number of initial clustering clusters is the number of initial clustering clusters is typically pre-determined, limiting flexibility and rendering it unsuitable for complex and ever-changing communication environments.

1.2 Contributions

In summary, studying the optimization problem of IoRT communication within SATIN is of highly valuable. This paper considers using multiple UAVs as relays collaborating with LEO satellite to assist in IoRT terrestrial devices communication, and conducts research on data transmission rate optimization.

Based on the above considerations, the main innovation points of this paper are summarized as follows:

1. An optimization scheme using multiple UAVs as relays to assist IoRT communication within SATIN is proposed. The scheme focuses on the joint optimization of several key parameters, including the number and deployment of UAVs, the correlation between UAVs and devices, the transmission power of both IoRT devices and UAVs. The overarching goal of this optimization is to maximize the data transmission rate.

2. A dynamic deployment scheme for multiple UAVs is proposed, which uses the Dynamic Deployment based on K-means (DDK) algorithm to select the appropriate number of UAVs and conducting UAV 3D deployment accordingly. This scheme can achieve full coverage of large-scale randomly distributed terrestrial devices. Meanwhile, two access strategies are proposed for devices located in redundant coverage areas, which are based on the maximum channel power gain criterion, and the maximum signal-to-noise ratio criterion, respectively, making the deployment scheme more versatile in complicated and changeable practical application scenarios.
3. For the optimization of data transmission rate, combined with the DDK algorithm mentioned above, a multi-dimensional optimization Coverage and Power Optimization (CPO) algorithm is proposed, which applies variable substitution and successive convex approximation (SCA) technique to solve the non-convexity problem. Then by leveraging the block coordinate descent (BCD) method, the number and deployment of UAVs, the correlation between devices and UAVs, the transmission power of IoRT devices and UAVs are jointly optimized to maximize the data transmission rate. Finally, the proposed algorithm is compared with traditional algorithms through simulation.

The remainder of the paper is arranged as follows. The system model and problem formulation are described in Sect. 2. The proposed DDK algorithm and CPO algorithm are elaborated in Sect. 3. The simulation results and analysis are explained in Sect. 4. Section 5 summarizes the research in this paper.

2 System model

In Fig. 1, this paper explores the utilization of multiple UAVs as relays to enhance IoRT communication within the framework of SATIN. The scenario assumes a substantial population of terrestrial devices distributed randomly across remote regions where traditional infrastructure deployment is unfeasible, such as deserts or oceans. Initially, data from these devices is relayed to LEO satellite through a network of multiple UAVs. Subsequently, this

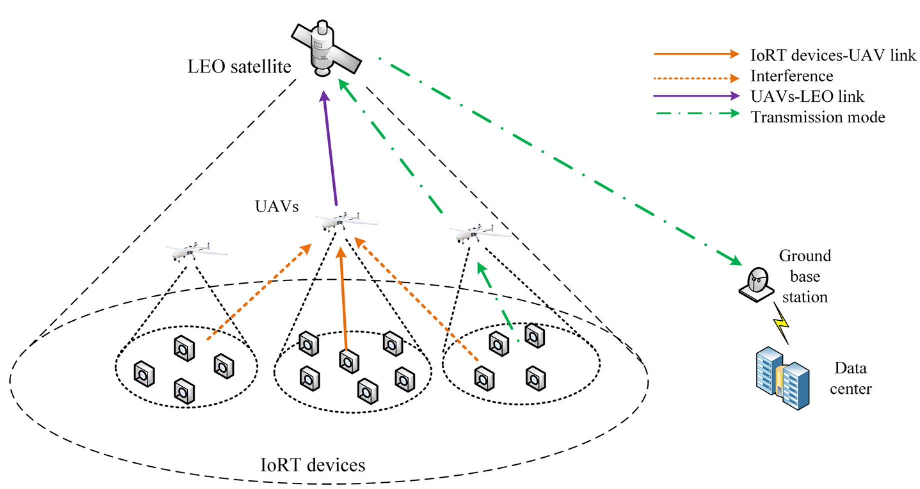

Fig. 1 Communication model of multiple UAVs assisted IoRT terrestrial devices within SATIN.

data is transmitted via satellite to GBSs and eventually routed to data centers for comprehensive processing and analysis.

Supposing that there are K IoRT devices distributed in a particular area, one LEO satellite and U UAVs are considered to facilitate terrestrial devices communication. The collection of IoRT devices is represented as $\mathcal{K} = \{1, 2, ..., K\}$. Suppose the location of each IoRT device is fixed, denoted by $\mathbf{w}_k \in \mathbb{R}^2$. The set of UAVs is represented by $\mathcal{U} = \{1, 2, ..., U\}$, the horizontal scale is represented by $\mathbf{w}_u \in \mathbb{R}^2$, and their flight altitude is H_u. The altitude of the LEO satellite is expressed as H_s.

This paper focuses on the communication problem of the uplink data transmission from IoRT devices to LEO satellite with the help of UAV relays. The goal is to maximize the total uplink transmission rate by jointly optimizing the number and 3D deployment of UAVs, the correlation between UAVs and devices, the transmission power of IoRT devices and UAVs. The system parameters are shown in Table 1.

2.1 G2A data transmission model

G2A data transmission refers to the uploading of data from the terrestrial device to the UAV connected to that device. Since there are almost no obstacles in the special scenarios considered (such as deserts, oceans, etc.), and UAVs operate at high altitudes, with line-of-sight (LoS) dominating, this paper uses the free space path loss model where the effects of shadows and small-scale are not considered [20]. Consequently, the channel power gain from the k-th IoRT device to the u-th UAV is

$$h_{k,u} = \rho_0 (d_{k,u})^{-2} = \frac{\rho_0}{\|\mathbf{w}_u - \mathbf{w}_k\|^2 + H_u^2}, \tag{1}$$

Table 1 Main notation

Notation	Definition
K	Number of IoRT devices
U	Number of UAVs
$\mathbf{w}_k$	2D coordinates of the k-th IoRT device
$\mathbf{w}_u$	2D coordinates of the u-th UAV
H_u	Flight altitude of the u-th UAV
H_s	Height of LEO satellite
ρ_0, β_0	Channel power gain at reference distance of 1m
σ^2, δ^2	Power spectral density of Additive Gaussian White Noise (AWGN)
$d_{k,u}$	The distance between the k-th IoRT device and the u-th UAV
$d_{\min}$	Minimum safe distance between UAVs and IoRT devices
$h_{k,u}$	Channel power gain from the k-th IoRT device to the u-th UAV
$h_{u,s}$	Channel power gain from the u-th UAV to LEO satellite
p_k	The transmission power of the k-th IoRT device uploading data to UAV
p_u	The transmission power of the u-th UAV uploading data to LEO satellite
$\gamma_{k,u}$	The SINR of the k-th IoRT device transmitting data to the u-th UAV
$\gamma_{u,s}$	The SNR of the u-th UAV transmitting data to LEO satellite
$P_k^{\max}, P_u^{\max}$	Maximum transmission power of IoRT devices and UAVs
B	System bandwidth
r_u	Coverage radius of the u-th UAV
$r_u^{\max}$	Maximum coverage radius of UAVs

where ρ_0 represents the reference channel gain at $d_0 = 1m$. $d_{k,u}$ denotes the distance between the k-th IoRT device and the u-th UAV. In addition, to avoid collisions, the following distance constraint need to be met

$$d_{k,u} \geq d_{\min}, \tag{2}$$

and $d_{\min}$ represents the minimum safe distance between IoRT devices and UAVs.

Supposing that the total available spectrum is completely reused in each UAV, when each UAV communicates with terrestrial devices served within its coverage area, it will be subject to Co-frequency interference caused by the devices served by the other UAVs. Additionally, provided that each UAV performs Orthogonal Frequency Division Multiplexing (OFDM) transmission when communicating with the served devices, thus the interference between the devices served within the coverage range of each UAV is not considered.

Assuming that the correlation between devices and UAVs is marked as $c_{k,u}$. $c_{k,u} = 1$ indicates that the u-th UAV serves the k-th device, on the contrary $c_{k,u} = 0$. Furthermore, considering the limited coverage range of UAVs, the coverage radius of the u-th UAV is r_u, and the maximum coverage radius of UAVs is $r_u^{\max}$. Providing that each device can only be connected to one UAV, one UAV can simultaneously serve multiple devices within its limited coverage range, and all devices are within the coverage range of UAVs. Thus, to meet the above assumptions, the following constraints need to be satisfied

$$c_{k,u} \in \{0, 1\} \tag{3}$$

$$\sum_{u=1}^{U} c_{k,u} = 1, \forall k \tag{4}$$

$$\sum_{u=1}^{U} \sum_{k=1}^{K} c_{k,u} = K \tag{5}$$

$$0 \leq r_u \leq r_u^{\max}. \tag{6}$$

Providing that the transmission power of the k-th IoRT device uploading data to the UAV is p_k. Accordingly, the Signal-to-Interference plus Noise Ratio (SINR) of the k-th device transmitting data to the u-th UAV is

$$\gamma_{k,u} = \frac{p_k h_{k,u}}{\sigma^2 + \sum_{m=1, m \neq u}^{U} \sum_{i=1}^{K} c_{i,m} p_i h_{i,u}}, \tag{7}$$

where σ^2 is the noise power spectral density of Additive White Gaussian Noise (AWGN). Moreover, the transmission power of devices must fulfill the following constraints

$$0 \leq p_k \leq P_k^{\max}. \tag{8}$$

2.2 A2S data transmission model

A2S data transmission refers to the data uploading from UAVs to LEO satellite. Similarly, LoS dominates the UAV-satellite link. To simplify the analysis, it is presumed that this channel is mainly affected by free space loss. Thus, the channel power gain from the u-th UAV to the LEO satellite is denoted as

$$h_{u,s} = \beta_0 (d_{u,s})^{-2} = \frac{\beta_0}{(H_s - H_u)^{-2}} \approx \frac{\beta_0}{H_s^2}, \tag{9}$$

where β_0 means the channel gain at the reference distance of 1 m from UAV to LEO satellite.

For simplicity, this paper considers using OFDM transmission between different A2S communication links to avoid Co-channel interference caused by strong LoS channels. Assuming the transmission power of the u-th UAV that uploading data to the LEO satellite is p_u. Therefore, the Signal-to-Noise Ratio (SNR) of the u-th UAV transmitting data to the LEO satellite is

$$\gamma_{u,s} = \frac{p_u h_{u,s}}{\delta^2}, \tag{10}$$

the transmission power of UAVs should be satisfied

$$0 \le p_u \le P_u^{\max}. \tag{11}$$

2.3 Uplink transmission rate

According to the Shannon formula and AF (Amplify and Forward) protocol [21], the achievable rate of data transmission from the k-th device to the LEO satellite through the u-th UAV is

$$R_{k,u,s} = B \log_2 \left(1 + \frac{\gamma_{k,u}\gamma_{u,s}}{1 + \gamma_{k,u} + \gamma_{u,s}}\right), \tag{12}$$

where $\gamma_{k,u}$ is obtained from formula (7), and $\gamma_{u,s}$ is obtained from formula (10). B indicates the system bandwidth.

Hence, the objective function, that is the total transmission rate of the entire uplink, is

$$R = \sum_{k=1}^{K} R_{k,u,s} = \sum_{k=1}^{K} B \log_2 \left(1 + \frac{\gamma_{k,u}\gamma_{u,s}}{1 + \gamma_{k,u} + \gamma_{u,s}}\right). \tag{13}$$

2.4 Problem formulation

Based on the research scenario mentioned above, to maximize the total data transmission rate of the entire uplink, we proposes a joint optimization problem, which involves jointly optimizing the number U and 3D deployment Q of UAVs, the correlation between UAVs and devices C, the transmission power of IoRT devices p_k, and the transmission power of UAVs p_u. The corresponding optimization problem (P) is given by the following equation

$$\begin{aligned} \max_{U,Q,C,p_k,p_u} \quad & R \\ \text{s.t.} \quad & C_1{:}d_{k,u} \geq d_{\min} \\ & C_2{:}c_{k,u} \in \{0,1\} \\ & C_3{:}\sum_{u=1}^{U} c_{k,u} = 1, \ \ \forall k \\ & C_4{:}\sum_{u=1}^{U}\sum_{k=1}^{K} c_{k,u} = K \\ & C_5{:}0 \leq r_u \leq r_u^{\max} \\ & C_6{:}0 \leq p_k \leq P_k^{\max} \\ & C_7{:}0 \leq p_u \leq P_u^{\max}, \end{aligned} \tag{14}$$

where the objective function is the total uplink transmission rate of data from all devices uploaded to the LEO satellite through UAV relays. Constraint C_1 is the safety distance constraint that ensures UAVs and devices do not collide. Constraint C_2 and C_3 are constraints on the connection relationship between devices and UAVs. Constraint C_4 ensures that all terrestrial devices are within the coverage range of UAVs. Constraint C_5 is the coverage radius constraint of UAVs. Constraint C_6 and C_7 are constraints on the transmission power of devices and UAVs, respectively. By solving the problem (P), the data transmission rate of IoRT devices communication collaboratively assisted by satellite and UAVs can be maximized.

3 Algorithm design

This paper proposes a multi-dimensional optimization CPO algorithm, which utilizes SCA technique to solve the non-convexity of the optimization problem. Then, based on BCD method [22], the number U and deployment Q of UAVs, the correlation between UAVs and devices C, the transmission power of IoRT devices p_k, and the transmission power of UAVs p_u are iteratively optimized to maximize the total data transmission rate R. In this section, the optimization problem (P) is divided into two sub-problems, namely sub-problem (P1): deployment optimization U, Q, C, and sub-problem (P2): power optimization p_k, p_u. Specifically, for deployment optimization, the DDK algorithm based on k-means algorithm is proposed to dynamically optimize UAV deployment. For power optimization, variable substitution and SCA technique are applied to solve the non-convexity problem, and the optimal power allocation is obtained. The processing process of the CPO algorithm is shown in Fig. 2. Firstly, how to solve these two sub-problems separately is discussed, and then based on the proposed CPO algorithm, we solved the optimization problem (P).

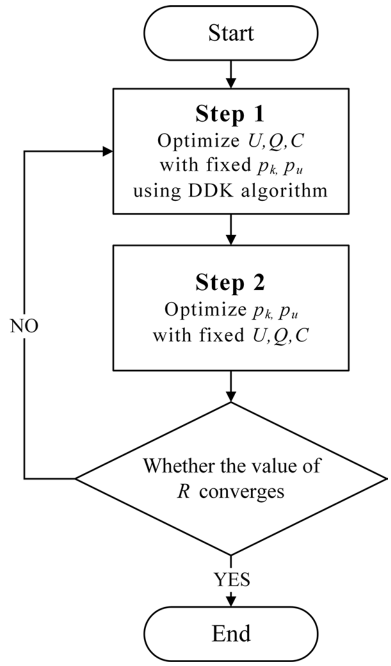

Fig. 2 The processing process of CPO algorithm.

3.1 Deployment optimization

A multi-UAV dynamic deployment scheme DDK algorithm is proposed to select the number of UAVs and conduct 3D deployment of UAVs, as well as complete the correlation between UAVs and devices, and achieve dynamic deployment of multiple UAVs in sophisticated and variable actual scenarios.

3.1.1 Initialization of 2D deployment of UAVs

The K-means Clustering Algorithm is used to initialize the 2D position of UAVs, which is a classical unsupervised learning algorithm, as well as a typical clustering algorithm that uses distance as the similarity evaluation indicator [23]. That is to say, objects with shorter distances between them are considered more similar. The similarity criterion assigns data objects to the closest cluster center, thus defining distinct classes. According to the above principle, terrestrial devices are divided into different clusters by the k-means algorithm; while, the center of each cluster is initialized, i.e., the horizontal coordinates of UAVs are met

$$\|\mathbf{w}_u - \mathbf{w}_k\| < \|\mathbf{w}_j - \mathbf{w}_k\|, \tag{15}$$

where $\mathbf{w}_j$ represents the horizontal position coordinates of the j-th UAV in other clusters. If the k-th device is associated with the corresponding u-th UAV, then $c_{k,u} = 1$.

3.1.2 2D deployment update for UAVs

For the fixed transmission power p_k and p_u, the optimization problem (P) can be transformed to obtain the sub-problem (P1) as

$$\begin{aligned} \max_{U,Q,C} \quad & R \\ \text{s.t.} \quad & C_1{:}d_{k,u} \geq d_{\min} \\ & C_2{:}c_{k,u} \in \{0,1\} \\ & C_3{:}\sum_{u=1}^{U} c_{k,u} = 1, \quad \forall k \\ & C_4{:}\sum_{u=1}^{U}\sum_{k=1}^{K} c_{k,u} = K \\ & C_5{:}0 \leq r_u \leq r_u^{\max}. \end{aligned} \tag{16}$$

When the initial clustering of IoRT devices is completed, according to the constraints C_2–C_5, once any of the constraints are not satisfied, the number of clusters should be increased. Then, it is necessary to re-cluster users and calculate the updated UAV coordinates.

After completing the 2D coordinate deployment of UAVs, the radius of the coverage area of each UAV r_u can be obtained. If there exist IoRT devices in the redundant coverage area of UAVs, noted by $\mathcal{O} = \{1, 2, ..., O\}$, the location is indicated as $\mathbf{w}_o \in \mathbb{R}^2$. Then, the UAV associated with the redundant device will be re-selected based on different access strategies, which will be described in Sect. 3.1.4.

3.1.3 Determination of UAV altitude

With the 2D deployment of UAVs mentioned above, the radius of the coverage area of each UAV r_u is known. As shown in Fig. 3, assuming the coverage angle of UAVs is θ, the height of the u-th UAV is

$$H_u = \frac{r_u}{\tan\theta} \tag{17}$$

Therefore, the 3D coordinates of the u-th UAV is $\mathbf{q}_u = (\mathbf{w}_u, H_u)$.

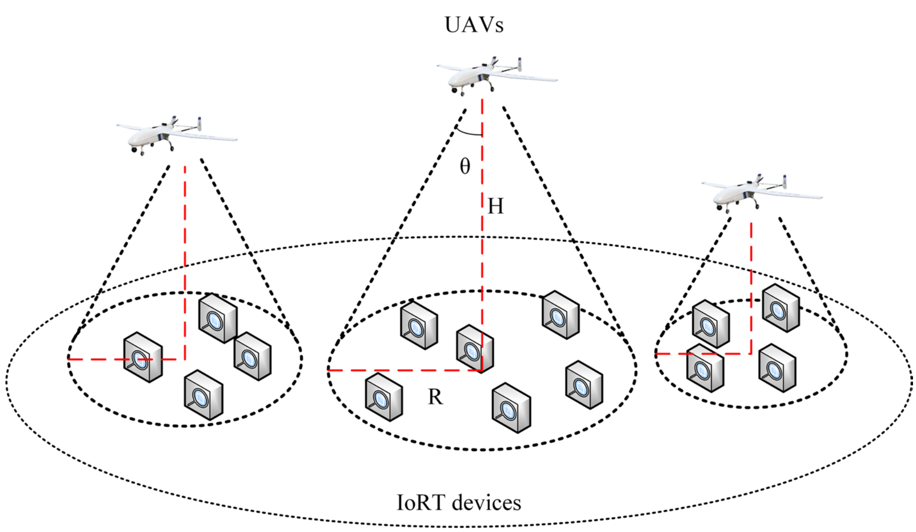

Fig. 3 Coverage example of UAV-assisted ground devices communication.

3.1.4 Access policy for devices in overlapping areas

With the 2D deployment of UAVs that mentioned above, there may exist IoRT devices located within the redundant coverage area of UAVs. Therefore, two access policies (AP) are proposed, which are based on the channel power gain maximization criterion (GM) and the SINR maximization criterion (SM), respectively.

1. GM-AP According to formula (1), the channel power gain between the o-th device and each UAV is calculated and compared with each other. When the o-th device is associated with the v-th UAV, the maximum channel power gain can be obtained as

$$h_{o,v} = \max\{h_{o,1}, h_{o,2}, ..., h_{o,U}\}. \tag{18}$$

Thus, the connections between UAVs and all devices located in the redundant coverage area of UAVs are updated, that is $c_{o,v} = 1, o \in \mathcal{O}$.

2. SM-AP According to formula (7), the SINR between the o-th device and each UAV is calculated and compared with each other. When the o-th device is associated with the v-th UAV, the maximum SINR can be obtained as

$$\gamma_{o,v} = \max\{\gamma_{o,1}, \gamma_{o,2}, ..., \gamma_{o,U}\}. \tag{19}$$

Thus, the connections between UAVs and all devices located in the redundant coverage area of UAVs are updated, that is $c_{o,v} = 1, o \in \mathcal{O}$.

3.1.5 3D deployment of UAVs

In practical scenarios, the number of deployed UAVs cannot be pre-determined due to that the number and distribution of terrestrial devices are random. Simultaneously, to accomplish the full coverage of devices, the coverage radius of each UAV needs to be dynamically adjusted according to the variability of the realistic requirements of different scenarios. Thus, with the proposed DDK algorithm, we can select the number of UAVs and deploy 3D positions, and complete the correlation between UAVs and devices, which demonstrates a remarkable degree of adaptability and flexibility in practical application scenarios. Algorithm 1 illustrates the details of the DDK algorithm.

Algorithm 1 DDK algorithm.

Input: device coordinate $\mathbf{w}_k$, maximum coverage radius of UAVs r_u^{max};
Cluster devices into U UAVs to obtain the correlation between UAVs and devices C;
Obtain the coverage radius of each UAV r_u to ensure that devices are within the coverage range of UAVs;
Determine the height of UAVs H_u;
Obtain 3D coordinates of each UAV $\mathbf{q}_u = (\mathbf{w}_u, H_u)$;
Obtain redundant device $\mathcal{O}$ and corresponding coordinates $\mathbf{w}_o$;
Update the correlation between the *o-th* device and UAV according to GM-AP or SM-AP;
if $r_u > r_u^{max}$ **then**
  execute $U = U + 1$, and jump to 1;
end
Obtain the number of UAVs $U^* = U$, UAV 3D deployment $Q^* = \{\mathbf{q}_1, \mathbf{q}_2, ..., \mathbf{q}_U\}$, correlation between devices and UAVs $C^* = C$;
Output: number of UAVs U^*, UAV 3D deployment Q^*, correlation between devices and UAVs C^*.

3.2 Power optimization

Deployment optimization is achieved through the DDK algorithm, that is, under the conditions of determining the number and deployment of UAVs, as well as the completion of correlation between devices and UAVs, the optimal transmission power of devices and UAVs can be obtained by solving problem (P). The problem (P) can be transformed to sub-problem (P2) as follows

$$\begin{aligned} &\max_{p_u, p_k} \quad R \\ &\text{s.t.} \quad C_6{:}0 \le p_k \le P_k^{\max} \\ &\qquad\ C_7{:}0 \le p_u \le P_u^{\max}, \end{aligned} \tag{20}$$

where the achievable rate $R_{k,u,s}$ from the k-th IoRT device to LEO satellite through the u-th UAV can be expressed as

$$\begin{aligned} R_{k,u,s} &= B\log_2(1+\frac{\gamma_{k,u}\gamma_{u,s}}{\gamma_{k,u}+\gamma_{u,s}}) \\ &= B(\log_2(\sigma^2\delta^2+\delta^2\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}p_i h_{i,u}) \\ &\quad +\delta^2 p_k h_{k,u}+\sigma^2 p_u h_{u,s}+p_u h_{u,s}\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}p_i h_{i,u}) \\ &\quad + p_k h_{k,u} p_u h_{u,s})-\log_2(\sigma^2\delta^2+\delta^2\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}p_i h_{i,u}) \\ &\quad +\delta^2 p_k h_{k,u}+\sigma^2 p_u h_{u,s}+p_u h_{u,s}\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}p_i h_{i,u})). \end{aligned} \tag{21}$$

It can be seen that $R_{k,u,s}$ is a non-convex and non-concave function of p_k and p_u. Then, the variable substitution method is used to simplify the equation. Due to the condition $p_k, p_u > 0$, and introducing auxiliary variables $e^{\alpha_k} \triangleq p_k, e^{\beta_u} \triangleq p_u$, $R_{k,u,s}$ can be represented as

$$\begin{aligned} R_{k,u,s} &= B(\log_2(\sigma^2\delta^2+\delta^2\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}e^{\alpha_i} h_{i,u}) \\ &\quad +\delta^2 e^{\alpha_k} h_{k,u}+\sigma^2 e^{\beta_u} h_{u,s}+e^{\beta_u} h_{u,s}\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}e^{\alpha_i} h_{i,u}) \\ &\quad + e^{\alpha_k} h_{k,u} e^{\beta_u} h_{u,s})-\log_2(\sigma^2\delta^2+\delta^2\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}e^{\alpha_i} h_{i,u}) \\ &\quad +\delta^2 e^{\alpha_k} h_{k,u}+\sigma^2 e^{\beta_u} h_{u,s}+e^{\beta_u} h_{u,s}\sum_{m=1,m\neq u}^{U}\sum_{i=1}^{K}c_{i,m}e^{\alpha_i} h_{i,u})). \end{aligned} \tag{22}$$

Therefore, the total data transmission rate R can be expressed as

$$R = \sum_{k=1}^{K} R_{k,u,s} = \sum_{k=1}^{K} B(\varphi_1 - \varphi_2). \tag{23}$$

Problem (P2) can be equivalent to problem (P3) as follows

$$\begin{aligned} &\max_{\alpha,\beta} \quad R \\ &\text{s.t.} \quad C_6{:}0 \le \alpha_k \le P_k^{\max} \\ &\qquad\;\; C_7{:}0 \le \beta_u \le P_u^{\max} \end{aligned} \tag{24}$$

where

$$\begin{aligned} \varphi_1 = \log_2(&\sigma^2\delta^2 + \delta^2 \sum_{m=1,m\neq u}^{U} \sum_{i=1}^{K} c_{i,m} e^{\alpha_i} h_{i,u} + \delta^2 e^{\alpha_k} h_{k,u} \\ &+ \sigma^2 e^{\beta_u} h_{u,s} + e^{\beta_u} h_{u,s} \sum_{m=1,m\neq u}^{U} \sum_{i=1}^{K} c_{i,m} e^{\alpha_i} h_{i,u} + e^{\alpha_k} h_{k,u} e^{\beta_u} h_{u,s}), \end{aligned} \tag{25}$$

$$\begin{aligned} \varphi_2 = \log_2(&\sigma^2\delta^2 + \delta^2 \sum_{m=1,m\neq u}^{U} \sum_{i=1}^{K} c_{i,m} e^{\alpha_i} h_{i,u} + \delta^2 e^{\alpha_k} h_{k,u} \\ &+ \sigma^2 e^{\beta_u} h_{u,s} + e^{\beta_u} h_{u,s} \sum_{m=1,m\neq u}^{U} \sum_{i=1}^{K} c_{i,m} e^{\alpha_i} h_{i,u}). \end{aligned} \tag{26}$$

Due to Hessian matrix $H_1 = \begin{pmatrix} \frac{\partial^2 \varphi_1}{\partial {\alpha_k}^2} & \frac{\partial^2 \varphi_1}{\partial \alpha_k \partial \beta_u} \\ \frac{\partial^2 \varphi_1}{\partial \beta_u \partial \alpha_k} & \frac{\partial^2 \varphi_1}{\partial {\beta_u}^2} \end{pmatrix}$ and $H_2 = \begin{pmatrix} \frac{\partial^2 \varphi_2}{\partial {\alpha_k}^2} & \frac{\partial^2 \varphi_2}{\partial \alpha_k \partial \beta_u} \\ \frac{\partial^2 \varphi_2}{\partial \beta_u \partial \alpha_k} & \frac{\partial^2 \varphi_2}{\partial {\beta_u}^2} \end{pmatrix}$ are positive definite matrices, both φ_1 and φ_2 are convex functions of α_k and β_u. Therefore, R is the difference of convex programming problems, whose convexity is uncertain. We use SCA technique [24] to solve the non-concavity.

Lemma 1 *For a convex function $f(x)$, its lower bound can be expressed as*

$$f(x) \ge f(x_0) + \nabla f(x_0)(x - x_0) \tag{27}$$

where x_0 is a given point in the domain of f, and $f(x) = f(x_0)$ if and only if $x = x_0$.

Based on Lemma 1, in the i-th iteration, for given variables α_k^i, β_u^i, there is a lower bound of φ_1

$$\begin{aligned} \varphi_1 \ge \widetilde{\varphi}_1 \triangleq \varphi_1(\alpha_k^i, \beta_u^i) &+ \frac{\partial}{\partial \alpha_k} \varphi_1(\alpha_k^i, \beta_u^i)(\alpha_k - \alpha_k^i) \\ &+ \frac{\partial}{\partial \beta_u} \varphi_1(\alpha_k^i, \beta_u^i)(\beta_u - \beta_u^i). \end{aligned} \tag{28}$$

From the above equation, it can be seen that $\widetilde{\varphi}_1$ is the concave function of α_k and β_u. Thus, the total data transmission rate can be converted into

$$\widetilde{R} = \sum_{k=1}^{K} \widetilde{R}_{k,u,s} = \sum_{k=1}^{K} B(\widetilde{\varphi}_1 - \varphi_2). \tag{29}$$

Therefore, problem (P3) can be changed to problem (P4) represented as follows

$$\begin{aligned} \max_{\alpha,\beta} \quad & \widetilde{R} \\ \text{s.t.} \quad & C_6{:}0 \le \alpha_k \le P_k^{\max} \\ & C_7{:}0 \le \beta_u \le P_u^{\max}. \end{aligned} \tag{30}$$

The problem (P4) is a convex optimization problem which can be solved using standard convex optimization methods or convex optimization tools such as CVX.

3.3 Unified solution CPO algorithm

Based on the above analysis of deployment optimization and power optimization, the solution of problem (P) is optimized based on the proposed CPO algorithm in this paper. Firstly, given the initial transmission power p_k and p_u, the DDK algorithm is used to optimize problem (P1), obtaining the number and 3D deployment of UAVs, as well as the correlation between UAVs and devices. Then, on this basis, the optimal power allocation is obtained by optimizing problem (P2). This process is repeated iteratively, with the optimization output of each iteration serving as the input for the next iteration until convergence or reaching the maximum number of iterations. The specific details are shown in Algorithm 2.

Algorithm 2 CPO algorithm.

Input: Initial number of UAVs $U^{(0)}$, UAV deployment $Q^{(0)}$, correlation between devices and UAVs $C^{(0)}$, transmission power of devices $p_k^{(0)}$ and transmission power of UAVs $p_u^{(0)}$, data transmission rate $R^{(0)}$, initial iteration number $s = 0$, maximum number of iterations s_{max}, prescribed threshold ε, initial difference $\lambda^{(0)} = \varepsilon + 1$;

while $s < s_{max}$ *and* $\lambda \ge \varepsilon$ **do**
- Given transmission power $p_k^{(s)}$ and $p_u^{(s)}$, use DDK algorithm to solve problem (P1), obtain the number $U^{(s+1)}$ and deployment $Q^{(s+1)}$ of UAVs, as well as correlation $C^{(s+1)}$;
- Given number $U^{(s+1)}$ and deployment $Q^{(s+1)}$ of UAVs, as well as correlation $C^{(s+1)}$, solve the problem (P2) to obtain the transmission power $p_k^{(s+1)}, p_u^{(s+1)}$ and data transmission rate $R^{(s+1)}$;
- Calculate difference $\lambda^{(0)} = \frac{R^{(s+1)} - R^{(s)}}{R^{(s)}}$;
- Update iteration number $s = s + 1$;

end

Output: Optimal number of UAVs $U^* = U^{(s)}$, optimal UAV 3D deployment $Q^* = Q^{(s)}$, optimal correlation $C^* = C^{(s)}$, optimal transmission power $p_k^* = p_k^{(s+1)}, p_u^* = p_u^{(s+1)}$.

3.4 Complexity analysis

For the CPO algorithm, its complexity is determined by the number of iterations of the alternating optimization, denoted by J_{alt}, and the complexity of solving two sub-problems. The deployment optimization problem (P2) is the first sub-problem, which is solved by the DDK algorithm with the complexity J_D. The second sub-problem is the power optimization problem (P3) with the number of iterations J_P, and a convex problem concerning $(K+U)$ is solved in each iteration. Note that the complexity of convex problems is polynomial, which depends on the number of optimization variables, and the maximum complexity of this polynomial is the fourth power of the number of variables. Therefore, the optimization of the power allocation needs to be calculated $(K+U)^m$ times in each iteration, where $1 \leq m \leq 4$. $J_P(K+U)^m$ is the complexity of power optimization. Therefore, the asymptotic complexity of CPO algorithm can be evaluated as

$$\mathcal{O}(J_{alt}(J_D + J_P(K+U)^m)). \tag{31}$$

4 Simulation analysis

In this section, extensive simulations are conducted to verify the effectiveness of the proposed CPO algorithm. For the purpose of proving the validity of the algorithm, it is compared with two traditional algorithms, namely Random method and the algorithm in [25], as follows:

1. Random method: under the constraint conditions, the number of UAVs is randomly given, and the deployment of UAVs is obtained by using the *k*-means algorithm, as well as the correlation between devices and UAVs. The transmission power of IoRT devices and UAVs is randomly given.
2. Algorithm in [25]: an improved Pattern Search algorithm (PS) is adopted for the deployment optimization of UAVs, the transmission power of IoRT devices and UAVs is the average transmission power.
3. CPO algorithm: the number and deployment of UAVs, the correlation between devices and UAVs, the transmission power of IoRT devices and UAVs are obtained by jointly optimization. Especially, the proposed DDK algorithm is used for deployment optimization. For possible redundancy situations, we propose two optimization algorithms, including the GM-CPO algorithm and the SM-CPO algorithm, which adopts GM-AP and SM-AP, respectively.

In the simulation design, this paper considers an area within a geographical size $800 \times 800m^2$, where 30 IoRT devices are randomly distributed. The simulation parameters set for this experiment are shown in Table 2.

Figure 4 provides a visualization of the coverage achieved through the deployment of multiple UAVs employing various algorithms.. As depicted in Fig. 4a, the use of the *k*-means clustering algorithm does not guarantee complete coverage of devices. Conversely, in Fig. 4b, deploying UAVs with the proposed DDK algorithm, which introduces constraints based on the *k*-means algorithm, effectively compensates for the limitations of the *k*-means approach. This results in the realization of full coverage for terrestrial devices, with additional access policies implemented for redundant devices in overlapping regions. This enhanced flexibility in the deployment scheme ensures its ability to meet diverse demands in practical applications. Overall, the DDK algorithm proves to be

Table 2 System Parameters

Parameter	Value	Parameter	Value
ρ_0, β_0	− 50 dB	$d_{\min}$	100 m
σ^2, δ^2	− 110 dBm	B	1 MHz
$P_k^{\max}$	1 W	$r_u^{\max}$	200 m
$P_u^{\max}$	10 W	θ	60°

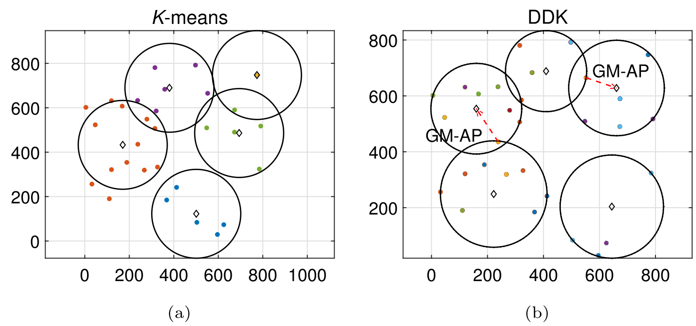

Fig. 4 Comparison of multiple UAVs deployment schemes. **a** Deployment situation under *k*-means algorithm. **b** Deployment situation under the proposed DDK algorithm

a valuable improvement over the *k*-means algorithm, ensuring reliable and comprehensive coverage in multi-UAV deployments.

Figure 5 compares the optimization performance of different algorithms under the same parameter conditions. It can be observed that the random method considers three conditions, that is, the number of UAVs optimized by the CPO algorithm, and two random numbers. Moreover, it is apparent that the proposed CPO algorithm, including the GM-CPO algorithm and the SM-CPO algorithm, exhibits superior optimization performance compared to other algorithms. Furthermore, under the considered system model, due to the optimized variables including the transmission power of devices, the SM-CPO algorithm demonstrates slightly better optimization performance than the GM-CPO algorithm, and subsequent simulation analysis will primarily focus on the proposed SM-CPO algorithm combined with the DDK algorithm.

Figure 6 demonstrates the impact of the maximum transmission power of UAVs uploading data to LEO satellite on the total data transmission rate under different optimization methods. The value of $P_u^{\max}$ is taken uniformly from 37 dBm to 45 dBm for comparison. It can be seen that the proposed SM-CPO algorithm outperforms other traditional algorithms in optimizing data transmission rate in all cases. When the maximum transmission power $P_u^{\max}$ is set to 45 dBm, for data transmission rate, the SM-CPO algorithm achieves a maximum improvement of approximately 240% compared to the random method. Compared with the algorithm presented in [25], the maximum enhancement is about 112%. Furthermore, the total data transmission rate increases with $P_u^{\max}$. This is due to the fact that the increase in transmission power will improve the SNR of UAV-LEO satellite link, subsequently enhancing the SNR from IoRT devices to UAVs and then to LEO satellite. Thus, to further improve

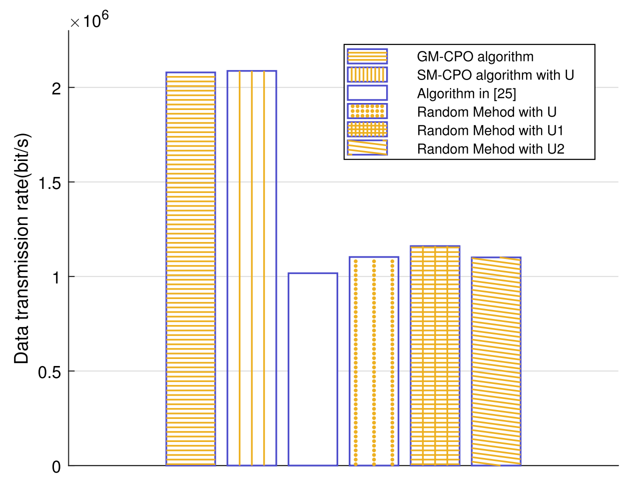

Fig. 5 Comparison of optimization performance of different algorithms

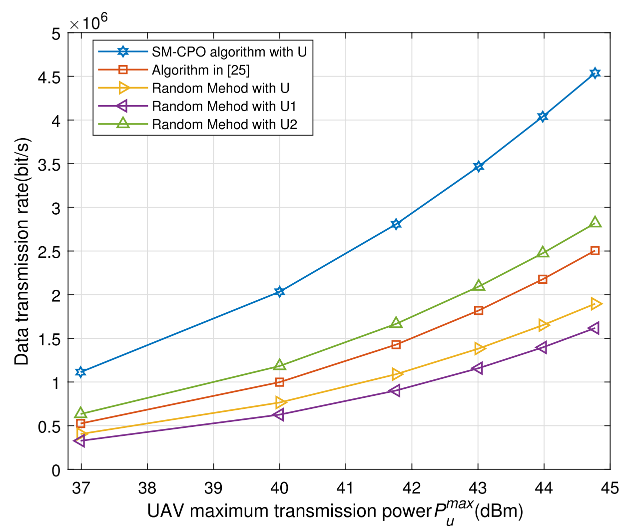

Fig. 6 Total data transmission rate under different maximum transmission power of UAVs.

data transmission rate, it is advisable to appropriately increase the maximum transmission power for uploading data between UAVs and the satellite.

Figure 7 displays the coverage of UAVs under different IoRT device distribution densities. The proposed dynamic deployment optimization strategy for UAVs is compared with two common deployment strategies, namely the k-means algorithm and an improved pattern search algorithm [25]. The results clearly demonstrate that the proposed deployment strategy can achieve full coverage of devices, whereas when deployed using the other two algorithms, there exist situation that some devices cannot be served by UAVs. Consequently, the proposed deployment strategy for UAVs exhibits self-adaptiveness, and can effectively accomplish full coverage of devices, thereby satisfying the communication requirements of IoRT devices in various complicated scenarios.

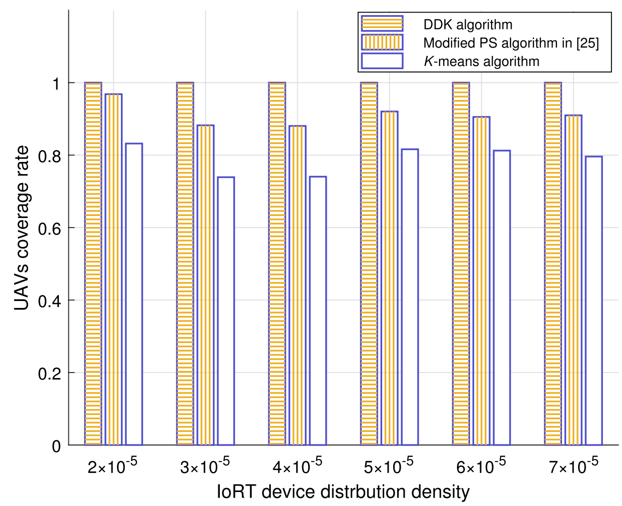

Fig. 7 Influence of different IoRT device distribution density on UAV coverage

Figure 8 demonstrates the effect of different IoRT device distribution densities on the total data transmission rate. It can be observed that the proposed SM-CPO algorithm outperforms other traditional algorithms in optimizing data transmission rate. As the distribution density of IoRT device increases, that is, when the number of devices increases, the total data transmission rate of the uplink will increase accordingly. However, traditional algorithms may encounter difficulties in achieving full coverage of devices, leading to potential instances where the data transmission rate for certain devices is zero. Therefore, the total data transmission rate changes relatively smoothly. The proposed SM-CPO algorithm effectively compensates for this problem, further demonstrating the effectiveness and superiority of the proposed algorithm.

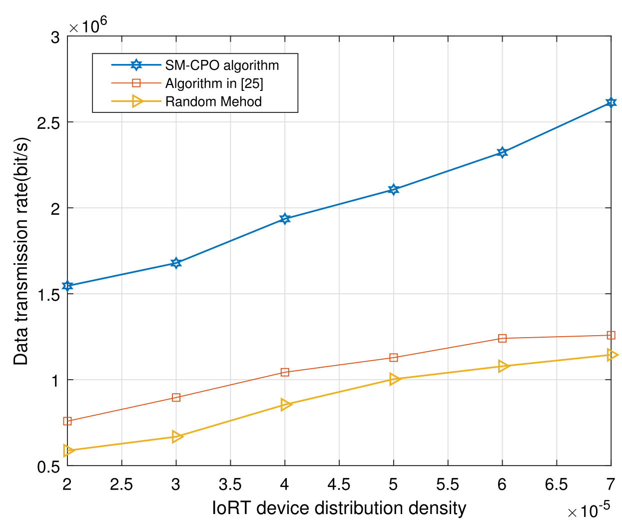

Fig. 8 Influence of different IoRT device distribution density on the total transmission rate

5 Conclusions

This paper investigates the optimization scheme of using multiple UAVs as relays to assist IoRT data transmission within the SATIN framework. In order to maximize data transmission rate, a multi-dimensional optimization algorithm named CPO algorithm is proposed, which jointly optimizes various parameters, including the number and deployment of UAVs, the correlation between UAVs and devices, the transmission power of both devices and UAVs. Especially, to achieve full coverage of large-scale randomly distributed terrestrial devices, a dynamic deployment scheme for multiple UAVs is proposed, namely DDK algorithm, which has strong flexibility in complicated and changeable practical application scenarios. Finally, simulation verification is conducted with the proposed algorithm, and numerical results prove its effectiveness and superiority. Compared to traditional algorithms, our approach yields an impressive up to 240% improvement in data transmission rate.

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Author contributions
All authors contributed to the idea development, study design, theory, result analysis, and article writing. All authors read and approved the final manuscript.

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Availability of data and materials
All data generated or analyzed during this study are included in this published article.

Declarations

Ethics approval and consent to participate
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Consent for publication
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Competing interests
The authors declare no conflict of interest.

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