On-Demanding Information Acquisition in Multi-UAV-Assisted Sensor Network: A Satisfaction-Driven Perspective

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When multiple heterogeneous unmanned aerial vehicles (UAVs) provide service for multiple users in sensor networks, users’ diverse priorities and corresponding priority-related satisfaction are rarely concerned in traditional task assignment algorithms. A priority-driven user satisfaction model is proposed, in which a piecewise function considering soft time window and users’ different priority levels is designed to describe the relationship between user priority and user satisfaction. On this basis, the multi-UAV task assignment problem is formulated as a combinatorial optimization problem with multiple constraints, where the objective is maximizing the priority-weighted satisfaction of users while minimizing the total energy consumption of UAVs. A multipopulation-based cooperation genetic algorithm (MPCGA) by adapting the idea of “exploration-exploitation” into traditional genetic algorithms (GAs) is proposed, which can solve the task assignment problem in polynomial time. Simulation results show that compared with the algorithm without considering users’ priority-based satisfaction, users’ weighted satisfaction can be improved by about 47% based on our algorithm in situations where users’ information acquisition is tight time-window constraints. In comparison, UAVs’ energy consumption only increased by about 6%. Besides, compared with traditional GA, our proposed algorithm can also improve users’ weighted satisfaction by about 5% with almost the same energy consumption of UAVs.

1. Introduction

Nowadays, unmanned aerial vehicles (UAVs) are gaining increasing popularity in various fields [1], such as situation awareness, intelligence reconnaissance, data collection, and relaying. Compared with traditional data collection means, UAVs possess significant advantages such as stronger mobility and flexibility, the ability to realize high-speed data transmission, and no risk of casualties, which makes them more suitable for data collection and transmission within sensor networks in complex environments [2, 3]. As the task execution capability of a single UAV is restricted by its limited flying capacity, battery capacity, reconnaissance capability, etc., it is imperative to use multiple UAVs to carry out cooperative data collection tasks. During this process, efficient task allocation [4–7] is one of the critical factors to improve the task execution efficiency of multiple UAVs effectively. Besides, since task allocation problems and path planning problems in UAV-based data collection are highly coupled, they are usually considered together in practice.

Generally, a data collection task can be abstracted as a process of visiting multiple ground sensors (GSs). When considering multi-UAV-based data collection, a group of GSs and corresponding visiting sequence should be assigned to each UAV through a reasonable task assignment strategy. UAVs need to visit their assigned GSs in sequence, collecting data from the GSs and send it back, directly or indirectly, to users who need it. As a typical COP with multiple constraints, the multi-UAV-based data collection task assignment problem is NP-hard [8] and usually cannot be solved directly to get the optimal solution. Till now, a large amount of studies have focused on this problem and several customized COP method-based problem-solving models, such as cooperative multiple task assignment problem (CMTAP)
to describe user satisfaction. In this paper, we adopt the idea of describing user satisfaction degree as the distance between users' experience and psychological expectation of service quality, which can better reflect the connotation of user satisfaction in our opinions.

Currently, the above ideas of describing user satisfaction have been adopted in wireless communication [35], network management [36] as well as in multi-UAV task assignment [37–39]. As described in [32], user satisfaction (US) is an abstract concept and may be measured differently in different scenarios. When considering user satisfaction degree in the above studies, a satisfaction function related to information transmission rate, information acquisition time, or energy efficiency was defined based on their different optimization objectives. For example, the authors focused on a competitive environment, where different users are trying to meet their different QoS requirements in terms of data rate in a selfish manner [35], and the user satisfaction is then considered a QoS-related concept. On which basis, the game theory is adopted to realize a "satisfaction equilibrium" among users to balance meeting users' expectations and saving energy consumption. In [36], the authors focused on the network management problem, while the metric of user satisfaction is defined as a function of the network response time for serving the decision-making requests, which is used to help realizing an effective load-balancing of the decision-making requests. However, the diverse priorities of users were rarely considered in these studies. Generally, it is a simple but important aim to ensure that the demands of high-priority users should be met first in practice, i.e., users with higher priorities can get as higher satisfaction as possible. To do this, a user-priority-based satisfaction maximization problem related to users' demanding should be considered.

In this paper, we consider a scenario where multiple UAVs provide data collection services for multiple users with different priorities and optimize the task assignment problem by adopting a priority-based user satisfaction-driven strategy. The main contributions are as follows:

Considering users' diverse priorities, a priority-driven user satisfaction model is built to measure users' differentiated satisfaction towards the information obtained. Specifically, a piecewise function considering soft time window and users' priority levels is designed to describe the relationship between user priority and user satisfaction.

A satisfaction-driven multi-UAV cooperative task assignment problem is formulated as a COP, where the problem of maximizing priority-weighted user satisfaction and minimizing UAVs' total energy consumption is considered comprehensively, and weight factors are adapted to realize a trade-off between them. To solve the task assignment problem efficiently, a multipopulation-based cooperation genetic algorithm (MPCGA) by introducing the idea of "exploration-exploitation" into traditional GAs is proposed. Numerical
results demonstrate the effectiveness of MPCGA in realizing an efficient user satisfaction-driven task assignment while minimizing total energy consumption.

2. System Model and Problem Formulation

2.1. System Model. As shown in Figure 1, we consider a multi-UAV-based data collection scenario, including one base station (BS), one relay UAV (UAVr), N data collection UAVs (UAVn), denoted by \( \mathcal{N} = \{1, 2, \ldots, N\} \), M users, denoted by \( \mathcal{M} = \{1, 2, \ldots, M\} \), and K GSs, denoted by \( \mathcal{K} = \{1, 2, \ldots, K\} \). Among them, rotary-wing UAVs that can hover above GSs when executing data collection are used. BS is responsible for receiving information requirements from users, assigning tasks to UAVs, and distributing the collected information obtained by UAVs to the corresponding users. UAVr is responsible for visiting all the GSs in \( \mathcal{K} \) and sending collected information back to BS, where the received data from a UAV is denoted by \( \mathcal{K} \). Among them, rotary-wing UAVs that can hover above GSs. During the data collection process, all UAVs are assumed to take off from BS and remain unchanged during the process of data collection. We assume that there is no direct communication link between each UAV and BS, while the data from a UAV to BS should be relayed through UAVs, which can maintain connection with BS and UAVs during the process of data collection.

In this paper, our goal is to find an optimal task allocation strategy that maximizes users’ satisfaction with the information obtained while minimizing the total energy consumption of the data collection UAVs. The constraints, data collection and transmission process, energy consumption model, user satisfaction model, and optimization objective are described as follows.

2.1.1. Constraints of Target Visiting. During the data collection process, all UAVs are assumed to take off from BS simultaneously (time 0) and return to BS after finishing their tasks, i.e., conducting data collection on the respective task targets in turn and sending the collected data collection on the respective task targets data back to BS. Besides, it is assumed that a UAV can only visit a target, and the UAV can only visit it once. On this basis, the constraints of target visiting can be described by equation (1), where \( |K_n| \) represents the number of elements in \( K_n \).

\[
\begin{align*}
\mathcal{K} &= \cup_{n=1}^{N} K_n, \quad n \in \mathcal{N}, \\
K_{n1} \cap K_{n2} &= \emptyset, \quad n1, n2 \in \mathcal{N} \land n1 \neq n2, \\
\sum_{n \in \mathcal{N}} K_n &= K
\end{align*}
\]

2.1.2. Constraints of Flight Time. The location of the BS is denoted as \((0, 0, H_0)\), where \(H_0\) is the height of BS. The location of target \( k \) is denoted by \( l_k(t) = (x_k(t), y_k(t), H_k(t)) \), and the location of UAV \( i \) is denoted by \( l_i(t) = (x_i(t), y_i(t), H_i(t)) \). Besides, the location of \( n \) is denoted by \( l_n(t) = (x_n(t), y_n(t), H_n(t)) \), where the horizontal coordinate of the UAVs’ initial and final locations is \((0, 0)\). Ignoring the process of take off and landing, UAV \( n \) is supposed to fly at a constant height \( H_n(t) \) during the whole data collection process, and the flight heights of UAVs are supposed to be different from each other to realize collision avoidance. Besides, it is supposed that \( n \) hovers above \( k (k \in K_n) \) when collecting data from \( k \), while flying in a straight line with a constant speed \( V_0 \) in other cases. Denote the time when \( n \) arrives BS after finishing its data collection task as \( T^F_n \), and then \( T^F_n \) can be calculated as follows:

\[
T^F_n = T^i_n + T^h_n = \frac{|\mathcal{D}_n|}{V_0} + \sum_{i=1}^{K_n} \frac{I_{in}}{C_{in}}, \quad n \in \mathcal{N},
\]

where \( T^i_n \) and \( T^h_n \) represent the flight time and hovering time of \( n \), respectively. \( \mathcal{D}_n \) represents the flight trajectory of \( n \), and \( |\mathcal{D}_n| \) represents the Euclidean norm of \( \mathcal{D}_n \). \( I_{in} \) represents the total amount of data that should be retrieved from \( k \), and it is determined by the requirements of all users who need to acquire the information about \( k \). Here, we assume that the difference in users’ information acquisition demands about \( k \) is only reflected in the amount of data collected, and \( I_{in} \) is selected as the maximum amount of data required by the users, which can be described as \( I_{in} = \max \{I_{m,n}, I_{m,n} \} \). Among them, \( m \in \mathcal{M} \). \( I_{m,n} \) represents the amount of data, collected from \( k \), required by \( m \), and \( x_{m,n} \) is an indicator variable, which is used to determine whether \( m \) needs the information about target \( k \). If \( m \) needs the information about target \( k \), then \( x_{m,n} = 1 \); otherwise, \( x_{m,n} = 0 \). Besides, \( C_{in} \) represents the data collection ability of \( n \) regard to \( k \), i.e., the amount of data that can be transmitted from \( k \) to \( n \) per second. In this paper, we assume that the wireless channels between GSs and UAVs are dominated by line-of-sight (LoS) links, and the power gain of the channel between \( k \) and \( n \) is represented by \( h_{in} = B_0 / (H_n(t) - H_k(t))^2 \), where \( B_0 \) represents the power gain at the reference distance \( d_0 = 1 \) m. Then, \( C_{in} \) can be calculated as follows:

\[
C_{in} = B \log_2 \left( 1 + \frac{p_0 h_{in}}{\sigma^2} \right),
\]

where \( p_0 \) represents the transmit power of \( f(k_{in}) \), and \( \sigma^2 \) is the additive white Gaussian noise (AWGN) power at the receiver, and \( B \) represents the available channel bandwidth.

Denote \( T_{n, max} \) as the maximum flight duration of \( UAV_n \); then the constraints of flight time for UAVs can be expressed as follows.

\[
T^F_n \leq T_{n, max}, \quad n \in \mathcal{N}.
\]

Considering that UAV, is the last one to depart from BS and the first one to return to BS after finishing the relay of data collected from the last target, we assume that the endurance of UAV, is sufficient enough during the data collection process as long as equation (4) can be satisfied.
2.1.3. Data Collection and Transmission. Suppose the start and finish time of collecting data from $k^i_n$ is $t_{i,n}^0$ and $t_{i,n}^1$, respectively, then $t_{i,n}^0$ and $t_{i,n}^1$ can be calculated as follows.

$$
\begin{align*}
  t_{i,n}^0 &= t_{i,n}^{0,1} + \frac{\|z_{i,n} - x_{i,n}\|}{V_0}, \\
  t_{i,n}^1 &= t_{i,n}^0 + \frac{\text{Inf}_{i,n}^d}{C_{r,B}^i}.
\end{align*}
$$

(5)

where $i \in [1, |K_n| + 1]$. Here, we use target sequence number 0 and $|K_n| + 1$ to represent BS to simplify the analysis process, e.g., $t_{i,n}^{0,1}$ represents the time when $n$ takes off from BS and $t_{i,n}^{1,0}$ represents the time when $n$ lands at BS. $\|z_{i,n} - x_{i,n}\|$ is the length of flight trajectory segment with $k_{i,n}^0$ and $k_{i,n}^1$ as endpoints. Then, the time that BS receives the information about $f(k^i_n)$, denoted by $t_{B,n}^i$, can be calculated as follows.

$$
\begin{align*}
  t_{B,n}^i &= t_{n}^{i,1} + \frac{I_{r,n}^f}{C_{r,B}^i} + \frac{t_{r,n}^i}{C_{r,B}^i},
\end{align*}
$$

(6)

where $C_{n,r}$ represents the data transmission rate from $n$ to UAV$_r$, and $C_{r,B}$ represents the data transmission rate from UAV$_r$ to the BS. We suppose $C_{n,r}$ and $C_{r,B}$ to be constant during the whole data collection process, which can be guaranteed by reasonable channel bandwidth allocation and channel access strategy. In this paper, an orthogonal frequency division multiple access (OFDMA) strategy similar as described in [40] is adopted, where the total available bandwidth is divided into multiple subcarriers with equal bandwidth. When multiple data collection UAVs need to transmit data to the relay UAV simultaneously, different subcarriers can be allocated to different UAVs, and the communication interference among UAVs is therefore ignored.

In this paper, the communication time between BS and users is not considered. That is, we take the time when BS receives the information about $f(k^i_n)$ as the time when the users, who need the information about $f(k^i_n)$, obtain the required information. Denote the time when $m (m \in \mathcal{M})$ get the information about $f(k^i_n)$ as $t_{m,n}^i$. Then, it can be described as follows.

$$
\begin{align*}
  t_{m,n}^i &= \begin{cases}
    t_{B,n}^i, & x_{m,n}^i = 1, \\
    0, & x_{m,n}^i = 0.
  \end{cases}
\end{align*}
$$

(7)

2.1.4. Energy Consumption Model. Generally, the energy consumption of UAVs during flight can be divided into two parts: motion energy consumption and communication energy consumption, while ignoring the energy consumption during the take off and landing stage. Since the position of UAV$_r$ and BS remain unchanged during the data collection process, the communication energy consumption between them, as well as the motion energy consumption of UAV$_r$, can be viewed as a constant term that is not affected by the task assignment strategies. In this section, we mainly consider the influence of task assignment strategies on the energy consumption of data collection UAVs.

(1) Motion Energy Consumption. During the data collection process, UAVs’ movement state mainly includes two kinds: flying and hovering. The corresponding motion energy consumption is viewed as flight energy consumption and hover energy consumption, which mainly depends on the propulsion power of UAV in the two states. Here, the power consumption (watt) model derived in [27] is adopted, which is described as follows.

$$
\begin{align*}
  P(V) &= P_0 \left( 1 + \frac{3V^2}{U_{\text{tip}}^2} \right) + P_{r,0} + \frac{1}{2} d_p \rho s A V^3, & \text{flight} (V \neq 0), \\
  P_h &= P_0 + P_{r,0}, & \text{hovering} (V = 0),
\end{align*}
$$

(8)

where $P_0 = \delta/8 \rho s A \Omega l^3 R^3$, $P_1 = (1 + l)W^{3/2}/\sqrt{2 \rho A}$, which represents the profile power and induced power of UAV in hovering state, respectively. $\delta$ is airfoil drag coefficient, $W$ is the weight of the UAV (Newton), $\Omega$ is blade angular velocity (radians/second), $R$ is rotor radius (m), $l$ is an incremental correction factor of the induced power, $U_{\text{tip}}$ represents the tip velocity of the suspension blade, $v_0$ represents the average rotor induced velocity during hovering, and $d_p$ and $s$ represent the fuselage resistance ratio and rotor compactness,
respectively, while $\rho$ and $A$ represent air density and rotor disc area, respectively.

For UAV $n$, when it arrives at BS after finishing its data collection tasks, the total motion energy consumption, denoted by $E_n^M$, can be calculated as follows.

$$E_n^M = \int_0^{T_n^e} P(\|V_n(t)\|) \, dt.$$  \hspace{1cm} (9)

Specially, when $n$ is in flying state from $f(k_n^0)$ to $f(k_n^{i+1})$ ($i \in [0, |K_n]|$) with constant speed $V_0$, its propulsion power consumption remains constant, and the energy consumption can be expressed by $P_n(\|V_0\|) \cdot T_n^f(i, i + 1)$, where $T_n^f(i, i + 1)$ represents the flying time spent from $f(k_n^i)$ to $f(k_n^{i+1})$.  When $n$ is in the hovering state while reconnaissance target $f(k_n^i)$, its energy consumption can be expressed by $P_n^h \cdot T_n^h(i)$, where $T_n^h(i)$ represents the hovering time spent over $f(k_n^i)$. On this basis, equation (9) can be reorganized as

$$E_n^M = \sum_{i=0}^{|K_n|} \left[ P_n(\|V_0\|) \cdot T_n^f(i, i + 1) + P_n^h \cdot T_n^h(i) \right]$$  \hspace{1cm} (10)

Combining equation (2) and equation (10), $E_n^M$ can be calculated by

$$E_n^M = P_n(\|V_0\|) \cdot \frac{\|\mathcal{D}\|}{V_0} + P_n^h \cdot \sum_{i=1}^{|K_n|} \frac{I_n}{C_n}.$$  \hspace{1cm} (11)

(2) Communication Energy Consumption. UAV communication-related energy consumption mainly occurs during the process of signal processing, signal radiation, signal reception, etc. Here, we assume that the transmitted power of UAVs remain constant and use equation (12) [29] to calculate the communication energy consumption of transmitting the data about $k_n$ from $n$ to UAV $r$:

$$E_{nr}(k_n^i) = I_n^r(d_{nr}^i(i_{nr}^i))^\alpha \epsilon_{rx},$$  \hspace{1cm} (12)

where $d_{nr}^i(i_{nr}^i)$ represents the communication distance between $n$ and UAV $r$, when $n$ collects data from $k_n^i$ and $\epsilon_{rx}$ represents the energy consumption generated by transmitting 1 bit data by 1 meter.

Based on the above analysis, the total energy consumption of data collection UAVs, denoted by $E_{sum}$, can be calculated by

$$E_{sum} = \sum_{n=1}^N \left[ E_n^M + \sum_{i=1}^{|K_n|} E_{nr}(k_n^i) \right].$$  \hspace{1cm} (13)

2.1.5. User Satisfaction Model. When evaluating the satisfaction of users, several factors, such as information acquisition time and information acquisition quality (quantity, precision, etc.), are usually considered. Here, we suppose the information acquisition quality can be well guaranteed, and the information acquisition time is mainly considered when describing user satisfaction. To quantifying user satisfaction, the concept of soft time window is used. For user $m$, when $x_{m,n}^i = 1$, denote the expected time window for obtaining the required information as $[0, t_{m,n}^i]$, and the acceptable time window for obtaining the information as $[t_{m,n}^i, t_{m,n}^{i+1}]$. When $t_{m,n} \in [0, t_{m,n}^i]$, take the information acquisition satisfaction, denoted by $S_{m,n}^i$, as 1; when $t_{m,n} \in [t_{m,n}^i, t_{m,n}^{i+1}]$, an exponential is designed to calculate the value of $S_{m,n}^i$; when $t_{m,n} \in [t_{m,n}^{i+1}, \infty)$, take $S_{m,n}^i$ as 0. Here, we use time 0 to represent the time when BS receives user’s request, as well as the approximate time when data collection UAVs take off from BS.

Besides, considering different users usually possess different service priorities, their priorities are also considered when describing user satisfaction. Here, we suppose users’ priorities to be known when BS conducts task assignment process, and the priority of $m$ is denoted as $P_m$. Among them, $P_m$ is a positive actual number, and the higher the value of $P_m$, the higher the priority of $m$. The priority-driven user satisfaction model with a soft time window is described as

$$S_{m,n}^i = \left\{\begin{array}{ll}
1, & t_{m,n} \in [0, t_{m,n}^i], \\
A_m \cdot \exp((t_{m,n}^i - t_{m,n})/\epsilon) + B_m, & t_{m,n} \in (t_{m,n}^i, t_{m,n}^{i+1}], \\
0, & \text{other},
\end{array}\right.$$  \hspace{1cm} (14)

where $S_{m,n}^{i,\max}$ represents the maximum satisfaction of $m$ toward the information about target $f(k_n^i)$, $A = (1 - S_{m,n}^{i,\max}) / (\exp((t_{m,n}^i - t_{m,n})/\epsilon) - 1)$, and $B = S_{m,n}^{i,\min} - A$.

As shown in Figure 2, we appoint that the higher the priority of $m$, the smaller the value of the $S_{m,n}^{i,\min}$. In addition, we suppose that the higher the user’s priority, the more time-sensitive their satisfaction is. That is, when $m_1$ and $m_2$ both require the information about $f(k_n^i)$ and their time window of acquiring information is the same, if $t_{m_1,n}^i > t_{m_2,n}^i$, then the satisfaction of high-priority users declines even faster over information acquisition time.

On this basis, a priority-oriented strategy is adopted to determine the value of $S_{m,n}^{i,\min}$, which is described as

$$S_{m,n}^{i,\min} = \frac{\text{Max}[P_j] - P_m + \epsilon}{\text{Max}[P_j] - \text{Min}[P_j] + \epsilon}, \quad j \in [1, M],$$  \hspace{1cm} (15)

where $\epsilon$ is a positive real number used to make sure the formula always makes sense. Besides, it makes users, with different priorities, have different gradients of satisfaction on the information acquisition time. This is helpful to ensure that the satisfaction of high-priority users can be better guaranteed by the algorithm described in Section 2.2. In this paper, we choose $\epsilon$ as $(\text{Max}[P_j] - \text{Min}[P_j])/2$, i.e., the value of the minimum satisfaction of the highest priority users is $S_{m,n}^{i,\max}/3$, and that of the lowest priority users is 1.

Generally, in addition to considering the total satisfaction of users, we also need to ensure that the satisfaction of high-priority users is as high as possible when assigning tasks. To this end, users’ satisfaction is weighted accordingly based on their priorities, and the weighted satisfaction of users, denoted by $S_{m,n}^{w}$, can be described in equation (16). Among them, $\alpha$ is an amplification factor that is bigger than 1.
2.2. Problem Formulation. Our goal is to maximize $S_{\text{sum}}^W$ while minimizing $E_{\text{sum}}$ through practical task assignment, subject to the constraints of target visiting in (1) and the constraints of flight time in (4). Since it is difficult to meet the two objectives of maximizing user satisfaction and minimizing energy consumption at the same time, we introduce two weight factors $\varpi_1$ and $\varpi_2$ to achieve a trade-off between them. Among them, $\varpi_1, \varpi_2 \in [0, 1]$ and $\varpi_1 + \varpi_2 = 1$. On this basis, our optimization objective is formulated as

$$P1: \max_{a \in {\mathcal{A}}} \left( \varpi_1 \frac{S_{\text{sum}}^W}{S_{\text{max}}^W} + \varpi_2 \frac{E_{\text{min}}}{E_{\text{sum}}} \right),$$

s.t. (1), (4),

where $A$ represents the set of task assignment strategies and $a \in {\mathcal{A}}$ represents a feasible solution in $A$. $S_{\text{max}}^W$ represents the maximum user satisfaction that can be achieved if taking user satisfaction maximization as optimization objective only, while $E_{\text{min}}$ represents the minimum energy consumption that can be achieved if taking energy consumption minimization as optimization objective only. In particular, if we take $\varpi_1 = 1$, problem P1 will degenerate into a satisfaction maximization problem, while problem P1 will degenerate into an energy consumption minimization problem if $\varpi_1 = 0$.

Obviously, problem P1 is a nonconvex optimization problem due to the nonconvexity of the objective function, and it is not easy to be solved directly to obtain an optimal solution. In this paper, we propose a multipopulation cooperation-based genetic algorithm (MPCGA), which preserves the advantages of genetic algorithm, i.e., simple, efficient, and fast convergence, and combines the advantages of swarm intelligence, i.e., solid global search-ability and the ability to jump out of locally optimal solutions.

3. Algorithm Description

3.1. Overview of GA. GA is a random search algorithm that simulates the genetic and evolutionary process of organisms, while it is suitable to deal with complex nonlinear optimization problems, such as COP, that are difficult to be solved by traditional search algorithms [41]. In GA, initial solutions are first generated randomly to form an initial population, where a solution is represented as a chromosome (or an individual). Then, the next population is generated through several evolutionary operators, i.e., selection operator, crossover operator, and mutation operator. In which process, a fitness function, which is closely related to the optimization objective, is needed to evaluate the performance of the solutions. After a certain number of iterations, with new populations constantly generated to renew their previous population, the algorithm can converge to the chromosome/individual with the best fitness value, which can be viewed as the optimal or suboptimal solution of the problem.

GA has the advantages of simple structure, high efficiency, fast convergence, etc., but it is easy to fall into local optimal solutions prematurely, which leads to insufficient global search-ability. By adopting the idea of “exploration-exploitation” which is widely used in current swarm
3.2. Description of MPCGA.

As follows.

The MPCGA is proposed and described in detail in the following sections.

Following are the description of some details:

1. Calculate the shortest flight distance from BS to GS $k (k \in \mathcal{K})$, denoted as $d_{ik}$, and that between $k_1$ and $k_2 (k_1, k_2 \in \mathcal{K})$, denoted as $d_{ik_1k_2}$, respectively.
2. Obtaining the mileage that can be saved if visit $k_1$ and $k_2$ one after the other in the same flight path according to saving-mileage formula, i.e., $\Delta d_{ik_1k_2} = d_{ik_1} + d_{ik_2} - d_{ik_1k_2}$.
3. Sort the saving-mileage in descending order.
4. According to the constraints of flight time and energy consumption, as well as the value of saving-mileage, connect each GS sequentially to finally determine the flight routes of data collection UAVs, as well as the number of UAVs used.
5. Calculate $E_{min}$ according to (13).
6. Return $E_{min}$.

Algorithm 1: MPCGA for multi-UAV task assignment.

Input: $\mathcal{N}$, $\mathcal{K}$, $[k_1]$, $l_r$.
Output: $E_{min}$.

1. Calculate $S_{max}$ and $E_{min}$, respectively.
2. Population initialization.
3. for $i = 1$ to $N_p$ do
4. $a_i^0 \leftarrow$ the task strategy $a_{(i,1)}$ represented by the first individual in the $i$-th population.
5. end
6. $a_{opt} \leftarrow \text{Max} \{a_{(i,1)} | i \in [1, N_p]\}$.
7. $l \leftarrow 1$.
8. while $l < \text{Iter}$ do
9. for $j = 1$ to $N_p$ do
10. Calculate $S_{sum,j}$ and $E_{sum,j}$ achieved based on the task strategy $a_{(i,j)}$ that is represented by the $j$-th individual.
11. Calculate the fitness of $a_{(i,j)}$ through $f(a_{(i,j)})$.
12. Evolutionary operation: selection, crossover, and mutation.
13. end
14. Calculate the fitness of each individual in the current population.
15. Update $a_i^l$.
16. end
17. Update $a_{opt}$.
18. $l \leftarrow l + 1$.
19. end
20. $a_{opt} \leftarrow a_{opt}$.
21. return $a_{opt}$.

Algorithm 2: MSA for calculating $E_{min}$.

Input: $\mathcal{N}$, $\mathcal{K}$, $[k_1]$, $l_r$.
Output: $E_{min}$.

1. Calculate the shortest flight distance from BS to GS $k (k \in \mathcal{K})$, denoted as $d_{ik}$, and that between $k_1$ and $k_2 (k_1, k_2 \in \mathcal{K})$, denoted as $d_{ik_1k_2}$, respectively.
2. Obtaining the mileage that can be saved if visit $k_1$ and $k_2$ one after the other in the same flight path according to saving-mileage formula, i.e., $\Delta d_{ik_1k_2} = d_{ik_1} + d_{ik_2} - d_{ik_1k_2}$.
3. Sort the saving-mileage in descending order.
4. According to the constraints of flight time and energy consumption, as well as the value of saving-mileage, connect each GS sequentially to finally determine the flight routes of data collection UAVs, as well as the number of UAVs used.
5. Calculate $E_{min}$ according to (13).
6. Return $E_{min}$.

3.2. Description of MPCGA. In this section, the MPCGA is proposed, and its specific steps are shown in Algorithm 1. Following are the description of some details:

$S_{max}$ is calculated by assuming that all users’ satisfaction toward their desired information is 1, i.e.,

$$S_{max} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{i=1}^{K} f_m \cdot s_{mn}.$$  

Since the difference of UAVs’ total energy consumption under different task allocation strategies is mainly caused by the difference of UAVs’ total flying distance. Here, we use a mileage-saving algorithm (MSA) [44], which is more accurate than GAs, to calculate $E_{min}$ and its specific steps is as showed in Algorithm 2.

$a_i^l$ represents the local optimal feasible solution of the $i$-th population in the $l$-th iteration.

$a_{opt}$ represents the global optimal feasible solutions of the $N_p$ populations till the $l$-th iteration.

$f(\cdot)$ is the fitness function based on $S_{sum}$ and $E_{sum}$, where

$$f(a_{(i,j)}) = \bar{\omega}_1 (S_{sum,j}/S_{max}) + \bar{\omega}_2 (E_{min}/E_{sum,j}).$$

Evolutionary operators: (1) selection operator: when conducting selection operation for the $i$-th population, a proportional roulette selection operator is used within the population. While the $a_i^l$ and $a_{opt}$ can also be selected as a parent with a certain probability that is
of calculating $E_{\text{max}^w}$ and $E_{\text{min}}$; (2) the complexity of multipopulation cooperation based GA. Generally, the complexity of calculating $S_{\text{max}^w}$ is $O(1)$, and the complexity of calculating $E_{\text{min}}$ is $O(K^2)$. Besides, the complexity of multipopulation cooperation-based GA can be viewed as $O(N_pN_o Ite)$. Then, the time complexity of MPCGA can be approximate as $O(N_pN_o Ite + K^2)$, which is polynomial.

### 4. Simulation Results

In this section, the performance of our proposed MPCGA for the multi-UAV task assignment problem is evaluated, while traditional GA with/without user’ satisfaction considered is also simulated for comparison. Among them, the GA with user’ satisfaction considered is denoted as BGA, while the algorithm without considering user satisfaction is denoted as GAWS.

#### 4.1. Parameter Setting

The targets are assumed to be randomly distributed in a $1.5 \text{ km} \times 1 \text{ km}$ rectangular area, while the circular area’s center is $1.75 \text{ km}$ far from BS. Regarding the coordinate of BS as $(0, 0, 25)$, set up a coordinate system with the line between BS and the center of the circular area as the X axis. That is, $x_t^c \in [1000 2500]$ and $y_t^c \in [-500 500]$. Besides, $H_f^c$ is supposed to follow a uniform distribution within $[0 60]$. The default number of targets, users, and available UAVs, is set as 50, 10, and 5, respectively. Other major simulation parameters are as shown in Table 1.

#### 4.2. Performance Evaluation

Figure 3 shows the convergence of MPCGA. It can be seen that, with the increase of the number of populations, the global search ability of the MPCGA will be enhanced to some extent, but when the number of populations is greater than a certain value, e.g., 8, the optimal solution converges to almost the same value, which means that to increase the number of populations too much does not make much sense. Besides, too large several populations will also increase the calculation complexity of the algorithm obviously. To show this more clearly, Table 2 displays the execution time of MPCGA with different population numbers, where $N_p$ is set as 40, and $Ite$ is set as 200. From the simulation results, one can see that the execution time of MPCGA will increase near linearly as the number of population increases, which is in line with the theoretical analysis results in Section 3. And, it indicates that, in the case of a similar convergence rate, a smaller population number is beneficial to reduce the running time of MPCGA.

Table 3 displays the comparative results, i.e., the total energy consumption of UAVs, total weighted user satisfaction, and the max completion time of tasks, of MPCGA, BGA, and GAWS with $\omega_1 = 0.7$ and $\omega_2 = 0.3$. Among them, the situation with loose time window constraints means that most users can obtain their required information within their expected time window when UAVs visit the GSs according to the shortest path. In contrast, the situation with tight time window constraints means that most users cannot obtain their required information within their expected time window when UAVs visit the GSs according to the shortest path. The simulation results show that our proposed algorithm performs best in both situations, i.e., the highest weighted user satisfaction can be achieved at the cost of a small amount of energy consumption. In particular, when in the situation with tight time window constraints, our proposed algorithm can improve the weighted user satisfaction by about 47% compared with GAWS, while the energy consumption only increased by about 6%. Besides, compared with BGA, our proposed algorithm can also improve the weighted user satisfaction by about 5% with almost the same energy consumption.

To better show users’ satisfaction with different priorities, the simulation results of each user’s satisfaction when using different algorithms under the situation with tight time window constraints are shown in Figure 4. Among them, users’ priorities are showed as labels, and the situations where users are with the same/different time-window constraints are shown, respectively. We can see from the simulation results that users with higher priorities usually can obtain higher satisfaction when completing task assignments by using MPCGA than using BGA or GAWS in both situations. For example, user 7 and user 8 can realize the highest satisfaction as they are with the highest priority, which is consistent with our original intention. Although user 7 is more satisfied than user 8 in some cases, while the opposite is true in other cases, considering their equal priority, this is an acceptable task assignment result. In addition, the average weighted user satisfaction of users with different priorities is shown in Figure 5. Sometimes users with higher priorities may achieve higher satisfaction when conducting task assignments by using BGA than MPCGA, e.g., the satisfaction of user 8 in Figure 4(a). However, from the average satisfaction of users with the same priority, MPCGA still performs better than BGA.

Figure 6 shows the weighted user satisfaction as well as total energy consumption of UAVs with different $N$, where $M = 10$ and $K = 50$. One can see that, with the increase of $N$, the weighted user satisfaction will increase correspondingly, while it finally converges since all the users can get their required data within their expected time window as long as $N$ is big enough. For the total energy consumption of UAVs, it will still increase with the increase of $N$ even after the user satisfaction has converged, which means that more data collection UAVs is not always better as it will cause extra energy consumption when $N$ is large, and each UAV is assigned a mission set. On this basis, if we want to meet...
Table 1: Simulation parameters.

| Notation | Physical meaning | Value |
|----------|------------------|-------|
| $V_0$   | Flight speed of UAVs | 20 m/s |
| $[H_{i,j}]$ | Range of UAVs’ flight height | 100~150 m |
| $[I]$   | Range of data quantity collected from one target | 40~80 Mbit |
| $B$     | Communication bandwidth between GSs and UAVs | 2 MHz |
| $C_{m,r}$ | Data transmission rate between $UAV_i$ and $UAV_r$ | 4 Mbps |
| $C_r,B$ | Data transmission rate between $UAV_r$ and the BS | 8 Mbps |
| $T_{\text{max}}$ | Maximum flight duration of $UAV_i$ | 600 s |
| $P_m$   | The priority of user $m$ | 1~5 |
| $\alpha$ | The amplification factor for users’ priority | 2 |
| $\epsilon_{tx}$ | Energy consumption parameter of communication | $10 \text{ pJ/(m bit)}$ |
| $[H_{i,j}]$ | Height range of GSs | 0~60 m |
| $\sigma^2$ | Additive white Gaussian noise (AWGN) power | $-174 \text{ dBm}$ |
| $\delta$ | Airfoil drag coefficient | 0.012 |
| $W$     | Weight of UAV | 20 N |
| $\Omega$ | Blade angular velocity | 300 rad/s |
| $R$     | Rotor radius | 0.4 m |
| $U_{\text{t}}$ | Tip speed of the rotor blade | 120 m/s |
| $v_0$   | Mean rotor induced velocity in hovering | 4.03 |
| $\rho$  | Air density | $1.225 \text{ kg/m}^3$ |
| $A$     | Rotor disc area | 0.503 m$^2$ |
| $d_0$   | Fuselage resistance ratio | 0.6 |
| $s$     | Rotor solidity | 0.05 |
| $p_0$   | Transmit power of GSs | 5 mW |
| $\beta_0$ | Power gain at the reference distance $d_0 = 1 \text{ m}$ | $-50 \text{ dB}$ |

Figure 3: Convergence of MPCGA.

Table 2: Execution time of MPCGA with different population numbers.

| NP  | Execution time (s) |
|-----|---------------------|
| 3   | 6.48                |
| 4   | 8.78                |
| 6   | 12.59               |
| 8   | 17.17               |
| 10  | 20.95               |
| 12  | 25.09               |
users’ needs as much as possible while saving energy consumption, the reasonable number of UAVs that are needed can be determined.

Figure 7 displays the average weighted user satisfaction as well as total energy consumption of UAVs with different $K$, where $N = 5$ and $M = 10$. It can be seen that, with the

| Algorithms  | Energy consumption (J) | Task completion time (S) | Weighted user satisfaction |
|------------|-------------------------|--------------------------|---------------------------|
| MPCGA      |                         |                          |                           |
| Loose time window constraints | $3.21 \cdot 10^5$ | 251                      | 2235.80                   |
| Tight time window constraints  | $4.20 \cdot 10^5$ | 365                      | 1854.92                   |
| BGA        |                         |                          |                           |
| Loose time window constraints | $3.60 \cdot 10^5$ | 271                      | 2112.75                   |
| Tight time window constraints  | $4.26 \cdot 10^5$ | 339                      | 1767.31                   |
| GAWS       |                         |                          |                           |
| Loose time window constraints | $3.12 \cdot 10^5$ | 314                      | 1951.44                   |
| Tight time window constraints  | $3.95 \cdot 10^5$ | 350                      | 1259.36                   |
increase of $K$, the average weighted user satisfaction will decrease while the total energy consumption of UAVs will increase. The main reason is that with the increase of $K$, the UAVs need to visit more GSs, which will cause more flight time and hover time, resulting in more energy consumption. Besides, as it takes longer for users to get the data they need, their satisfaction will decrease correspondingly.

Figure 6 shows the weighted user satisfaction as well as total energy consumption of UAVs with different $I$, where $N = 5$, $M = 10$, and $K = 50$. From the simulation results, one can see that, with the increase of $I$, the average weighted user satisfaction will decrease since the data collection and data transmission time will increase, which results in a long time for users to get their required data. Besides, the total energy consumption of UAVs presents an upward trend as the hover energy consumption, and communication energy consumption of UAVs will increase. It is noted that since the minimization of energy consumption is considered in the objective function, the total energy consumption of UAVs does not always increase with the increase of $I$.

Figure 8 shows the weighted user satisfaction as well as total energy consumption of UAVs is displayed in Figure 9. It can be seen that, with the increase of $M$, although the total user satisfaction will increase, the average satisfaction is about the same, and the total energy consumption of UAVs tends to stabilize. The main reason is that the increase of $M$ may affect the order of UAVs’ visiting GSs, but not the number of GSs visited and the time of data collection and transmission. As a result, the total distance traveled by UAVs will vary, but there will not be significant fluctuations.
5. Conclusion
This paper studied a multi-UAV-based sensor network where multiple UAVs need to collect data from multiple GSs in sequence and transmit the information back to BS through a relay UAV. In the process of task assignment, considering different users’ diverse priorities and corresponding priority-related satisfaction, a priority-driven user satisfaction model was constructed, where a piecewise function considering soft time window and users’ priority levels was designed to describe user satisfaction. A combinatorial optimization problem with multiple constraints was formulated, where the objective is maximizing the priority-weighted satisfaction of users while minimizing the total energy consumption of UAVs. Furthermore, a multi-population-based cooperation genetic algorithm (MPCGA) was proposed by adopting the idea of “exploration-exploitation” into traditional GA. Simulation results showed the convergence and the effectiveness of our proposed algorithm.

In the follow-up work, we will consider the distribution features of GSs and the priority-based fairness problem between users to improve our algorithm’s effectiveness and applicability further.

Data Availability
No data were used to support this study.

Disclosure
Hua Yang and Cuntao Liu are co-first authors.
Conflicts of Interest
The authors declare that they have no conflicts of interest.

Authors’ Contributions
Hua Yang and Cuntao Liu contributed equally to this work.

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