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Collaborative Task Allocation and Optimization Solution for Unmanned Aerial Vehicles in Search and Rescue

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Abstract: Earthquakes pose significant risks to national stability, endangering lives and causing substantial economic damage. This study tackles the urgent need for efficient post-earthquake relief in search and rescue (SAR) scenarios by proposing a multi-UAV cooperative rescue task allocation model. With consideration the unique requirements of post-earthquake rescue missions, the model aims to minimize the number of UAVs deployed, reduce rescue costs, and shorten the duration of rescue operations. We propose an innovative hybrid algorithm combining particle swarm optimization (PSO) and grey wolf optimizer (GWO), called the PSOGWO algorithm, to achieve the objectives of the model. This algorithm is enhanced by various strategies, including interval transformation, nonlinear convergence factor, individual update strategy, and dynamic weighting rules. A practical case study illustrates the use of our model and algorithm in reality and validates its effectiveness by comparing it to PSO and GWO. Moreover, a sensitivity analysis on UAV capacity highlights its impact on the overall rescue time and cost. The research results contribute to the advancement of vehicle-routing problem (VRP) models and algorithms for post-earthquake relief in SAR. Furthermore, it provides optimized relief distribution strategies for rescue decision-makers, thereby improving the efficiency and effectiveness of SAR operations.

Keywords: multi-UAV collaboration; search and rescue; post-earthquake relief; task allocation model; PSOGWO algorithm

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1. Introduction

In recent years, the world has witnessed an increase in the frequency of major natural disasters that pose significant threats to national stability, human safety, and economic well-being. Among these, earthquakes stand out as particularly devastating events due to their sudden onset, extensive reach, severe destructiveness, and the difficulty of defending against them. In addition to the direct effects of these shaking events, earthquakes often trigger secondary disasters such as aftershocks, landslides, and floods that further endanger lives and property. This complex and multifaceted threat underscores the urgent need for innovative and effective disaster response strategies.

In the aftermath of such devastating natural events, SAR missions are of paramount importance in locating and assisting those in dire need. The use of scientific rescue methods, along with advanced SAR equipment, is critical to increasing the efficiency of post-earthquake relief efforts [1]. The first 72 h following an earthquake are often referred to as the "golden rescue time", a period considered critical for maximizing survival rates [2].

Given the harsh conditions and intimidating environments that characterize post-disaster scenarios, conducting rapid rescue operations poses significant challenges, at times even jeopardizing the safety of the rescuers themselves. In addition, these critical moments underscore the urgent need for rapid delivery of medical supplies and first aid equipment to support life-saving interventions.

Traditional SAR strategies that rely on deploying ground personnel to all potential disaster sites are particularly inefficient and time-consuming. This inefficiency is exacerbated in areas with complex terrain and the looming threat of aftershocks, where the pace of search and rescue operations is critically hampered. Enter the advent of UAVs, highly flexible and agile aircraft capable of navigating intricate mountainous landscapes and urban ruins. Their use in disaster areas such as earthquake zones, forest fires, and flooded areas has demonstrated significant advantages over traditional methods by providing broader and more effective coverage.

Despite these advances, the use of UAVs has been largely limited to single-unit operations, which has not realized their full potential [3]. The concept of multi-UAV cooperative operations is emerging as a revolutionary approach that offers enhanced flexibility, increased payload capacity and superior adaptability to environmental conditions [4–6]. These capabilities enable the execution of complex flight missions, significantly increasing overall operational efficiency. In addition, rapid advances in wireless communication technologies now facilitate seamless interaction between multiple UAVs, enabling coordinated efforts to achieve broad mission objectives [7]. This synergy through UAV swarm collaboration represents a burgeoning area of interest within the SAR domain, with UAV pre-detection technology being one of the more mature methodologies in this arena. In light of these considerations [8], our study focuses on utilizing multi-UAV cooperative methods, informed by post-earthquake environmental data collected by UAVs, to assist multiple stationary victims within a constrained search environment. This approach is expected to increase the speed and effectiveness of rescue missions, thereby playing a critical role in mitigating the effects of earthquakes and protecting public health.

The effectiveness of multi-UAV collaboration in SAR operations depends critically on the formulation of an effective rescue task allocation scheme. Such a scheme aims to maximize the utility of limited time and resources by facilitating the execution of as many life-saving missions as possible. In the context of post-earthquake SAR, UAVs are equipped to carry a variety of rescue supplies—including medicine, food, and lighting equipment—enabling them to perform coordinated missions in challenging environments. Developing an optimal scheme for allocating these rescue tasks has significant practical value, particularly in reducing the mortality rate of those trapped by debris and increasing the safety of the rescue teams involved.

Building on the outlined need for advanced post-earthquake SAR methodologies, this study makes three major contributions. First, it addresses the critical issue of multi-UAV collaborative task allocation with a focus on rescue time optimization within post-earthquake SAR missions, a topic of increasing interest in current research. Second, we develop a comprehensive model for multi-UAV collaborative rescue mission planning aimed at post-disaster relief in SAR. This model is designed to effectively allocate available resources and maximize the efficiency of rescue operations. Third, to ensure the derivation of high-quality solutions, we employ a novel approach that combines PSO with the GWO algorithm to solve the proposed model.

This paper is structured to methodically explore the multifaceted aspects of multi-UAV collaborative task allocation for post-earthquake relief in SAR scenarios and is organized as follows. The review of the prevailing literature and presents an overview of models and algorithms that have been developed for multi-UAV collaborative task allocation in disaster relief operations are drawn in Section 2. Section 3 introduces the proposed model for multi-UAV collaborative rescue mission planning, which aims to improve the effectiveness of post-disaster relief efforts. Following this, Section 4 details the development of an innovative hybrid algorithm, the PSOGWO algorithm, specifically designed to address the complexities of the proposed model. Sections 5 and 6 is dedicated to the presentation of results and discussion. Finally, Section 7 concludes the paper by summarizing the key contributions.

2. Literature Review and Related Work

2.1. Models of Multi-UAV Collaborative Task Allocation for Search and Rescue

The multi-UAV collaborative rescue task allocation problem mainly corresponds to UAVs for each task's decision-making, which refers to decision-making based on constraints such as task demand, environmental conditions, UAV performance, carrying load, task objectives, task execution capability, task importance, and so on, by maximizing the benefit and minimizing the cost of executing the tasks as the performance index. The multi-UAV collaborative task allocation problem is essentially one class of combinational optimization problems. When formulating the scheme, not only should the body constraints of the UAVs be considered, but the constraints between the tasks should also be taken into account, so the scheme of multi-UAV collaborative tasking schemes has high requirements.

For post-disaster relief in SAR, a better multi-UAV collaborative rescue task allocation method can effectively allocate the available resources and maximize the rescue efficiency. Multi-UAV collaborative task allocation is that of making a non-deterministic polynomial issue, which is characterized by multi-constrained combinatorial optimization. The followings are the main relevant research work carried out in the field of SAR. Jevtiü used the traveling salesman problem (TSP) to design a shortest path method for UAVs to achieve coordinated coverage of a designated area [9]. Zillies researched a path flow formulation and a column generation algorithm to realize the use of a set of homogeneous UAVs to serve a series of specified target locations that needed to fulfill certain requirements [10]. Bakhshipou viewed the UAV collaborative search and rescue problem as a simpler shortest path problem that does not require a return to the starting point [11]. Senthilkumar proposed buildings an overlap network to find victims and find paths to reach them [12]. Kim and Lodeiro-Santiago considered setting up a securing network connectivity with victims [13,14]. Beck, Choi, Chatziparaschis, and Straub have used several robotic task assignment models and methods, as described in the literature [15–18]. Kurdi used Max-sum for UAV task allocation in SAR, which is also a centralized optimization approach [19].

Based on the above literature, it can be seen that no one has yet applied the VRP model to this kind of problem for multi-UAV collaborative rescue in post-earthquake SAR scenarios. In this paper, by applying and improving the vehicle routing problem with time windows (VRPTW), we establish an effective rescue model by considering the cost of flight distance, cost of fixed turnout, and cost of rewards and penalties in the process of coordinated UAV rescue, and by utilizing the limited time and resources.

2.2. Algorithms of UAV Cooperative Task Allocation in Disaster Relief Operations

Centralized or distributed approaches are often used in the solution of multi-UAV cooperative task allocation problems. Centralized approaches include such methods as ant colony optimization (ACO), genetic algorithm (GA), and particle swarm optimization (PSO). Ding and Abdulsaheb optimized multiple terrestrial robots using ACO to find a specific target location [20,21]. Majeed exploited the TSP using ACO to find the most efficient traversal of the tour [22]. Shima and Ye addressed the problem of multi-tasking for UAVs using GA [23,24]. Hayat and Pishkenari explored GA and differential evolution (DE) to ultimately optimize the routing task mentioned in their paper [25,26]. Some researchers used the PSO algorithm for solving the problem, utilizing the agents in the group to alert the group to the optimal solution, and then the agents would decide to increase the optimal value [27–29]. Centralized collaborative tasking can be centrally controlled, has a simple structure, is globally good, and can obtain better feasible solutions, but is not scalable enough and is computationally intensive. With the evolution of cloud-based internet management systems for UAVs and less computationally intensive algorithms, the centralized algorithm dilemma may be solved in the future when UAVs can communicate with cloud servers via an internet connection and cloud servers can coordinate the allocation of tasks between them.

In terms of decentralized methods to solve UAV task allocation, various distributed methods have been proposed. Kurdi proposed a bio-inspired algorithm for the multi-UAV tasking problem in SAR missions, which is inspired by locust species in nature and the different abilities and behaviors they exhibit during their lifetime [30]. However, the efficiency of this search and rescue method is inconsistent. Oh presented a new market-based decentralized algorithms which is used to assign tasks to multi-UAV with limited communication rang in dynamic environments [31]. The proposed algorithm has good scalability in terms of running time and communication burden. Hassanalian [32] utilized the acquired or prior knowledge of the target location through partially observable Markov decision process (POMDP) can speed up the search, but its computational cost could not be ignored. The advantage of distributed mission decision-making approach is that it reduces the dependence on the ground station center and improves the solving speed, but it increases the dependence on the intelligence level of each UAV and suffers from partial state observability problems.

3. Description of the Problem and Multi-UAV Cooperative Task Allocation Method

3.1. Problem Description

The multi-UAV collaborative rescue task allocation scenario in a disaster-oriented rescue mission is shown in Figure 1, and this paper focuses on the multi-UAV cooperative post-disaster rescue scenario in an earthquake-stricken area with many different rescue locations with different rescue urgency levels. In this scenario, a number of individual UAVs with limited power for flight and limited rescue supplies start from a fixed starting location (i.e., the start point), perform rescue tasks (i.e., drop-off of the rescue supplies) at the rescue target points according to the rescue needs of the different rescue locations, and return to the start point before their own power is depleted. Under the premise of successfully completing the rescue mission, the goals of using the smallest number of UAVs, the shortest total distance traveled by UAVs, and the smallest rescue cost are achieved. While considering the specificity of the rescue mission, the execution of the rescue work must be completed in the specified time window, or else it will be regarded as an ineffective rescue. Therefore, this paper adds a time window constraint, which sets a time period for each rescue location to accept the rescue service, and UAVs must arrive and conduct the rescue work within the range specified in the time window. Due to the complexity of the terrain, the harsh environment, and other factors (such as the presence of walls, debris, or other obstacles), the UAVs to reach the various rescue points in the process must go through a series of intermediate positions, which will be encountered in the natural disasters and threaten their own safety, and after reaching the designated rescue points, the UAVs can release the rescue goods.

The model of this problem makes the following assumptions: Information about the above-mentioned rescue point has been obtained by the start point before the mission begins, including information about the location of the rescue point and the requirements, as well as the time window for the last visiting. In addition, the loading capacity and maximum driving distance of the UAVs are known. In order to clarify the scope of application of this paper, several assumptions are made: (1) the different types of rescue mission targets have different demand requirements; (2) the different rescue urgency levels is distinguished by the order of the rescue time window; (3) for each rescue point, there will be no temporary changes in the demand, the service time window, or the service time; (4) the paths between the two rescue points are unique with fixed distances; (5) the UAVs at the start point are all of the same type and have the same properties; (6) the UAVs all depart from the same start point to participate in the rescue mission and return to the same start point at the end of the mission; (7) the speed at which the UAV flies between the different rescue points is constant; (8) each rescue point is visited by one UAV and only one UAV; (9) when a UAV meets the requirements of the rescue mission for a certain rescue point and still has the power and load capacity, it can continue to provide rescue to the next mission; (10) other factors such as weather, personnel, and mechanical failures are not considered; (11) ignore the charging of the UAVs; that is, the UAVs are fully charged before release.

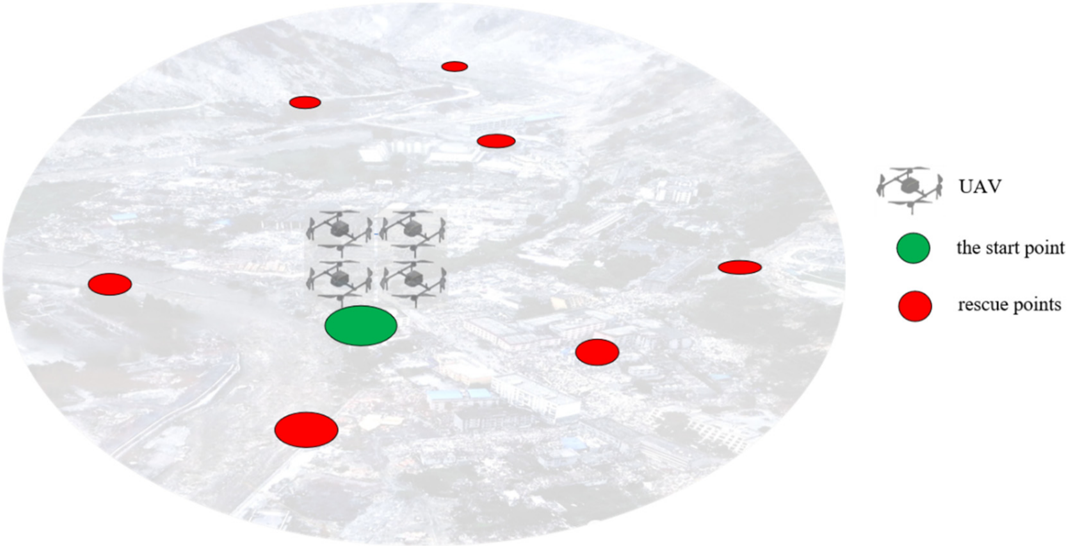

Figure 1. Multi-UAV cooperative rescue scenario for post-earthquake relief in SAR.

In a word, the problem solved in this paper can be characterized as a rescue mission UAV routing problem with time windows (RMURPTW); that is, under the constraints of limited time and load, multiple UAVs cooperate to accomplish the post-earthquake rescue task in the designated area. It is proposed that rescue tasks be allocated to each UAV with the expectation that the number of UAVs performing the tasks will be minimized and the total rescue cost will be minimized.

3.2. Symbols and Decision-Making Variables

In this section, the formulation of RMURPTW is presented. It is given a directed graph $G = (T \cup H, A)$, where T is the rescue target points set (i.e., drop-off of the rescue materials), and H is the UAVs' base (i.e., the start point). The set of arc A is formed by all possible connections between any two vertices in G. U is for a group of homogeneous UAVs. The UAVs in U take off from a fixed starting location, then visit a subset of A, and finally return to the start points. Each UAV is limited by its range capability. As a UAV approaches the rescue destination, it has a certain probability of success in obtaining a profit associated with the target weights. The optimization objective of the RMURPTW is to minimize the expected cost. Table 1 defines the main representations of relevant sets, indices, parameters, and variables of RMURPTW.

Table 1. List of main representations of relevant sets, indices, parameters, and variables of RMURPTW.

Notation	Explanation
G	$G = (V \cup A)$, directed graphdata
T	set of rescue target points, $T = \{1, \ldots, i, \ldots, N\}$
V	set of all vertices, $V = T \cup H$, $H = \{0\}$ represent a base
i, j	index of rescue target points, $i, j \in V$
A	set of arcs, where (i, j) denote the arcs between i, j nodes
d_{ij}	distance between the rescue target points i and j
U	group of homogeneous UAVs, $U = \{1, \ldots, k, \ldots, K\}$
e_i	earliest time window of the rescue target point i
et_i	optimal early time window for the rescue target point i

Table 1. *Cont.*

Notation	Explanation
lt_i	optimal last time window for the rescue target point i
l_i	latest time window of the rescue target point i
s_i	service time of the UAV at the rescue target point i to complete the mission
q_i	demands of the rescue target point i
Q_k	load capacity of UAV k
H_k	the maximum flight distance traveled by UAV k
w_{ik}	starting service time of UAV k on point i
x_{ijk}	decision-making variable. If UAV k travels in link (i, j), $x_{ijk} = 1$, else, $x_{ijk} = 0$
o_k	decision-making variable. 1, if UAV k is being used, 0, otherwise
a_{ik}	the service start time for UAV k at point i
b_{ik}	time for UAV k to arrive at point i
h_{ik}	traveled distance for UAV k after visiting point i
C_1	cost per unit distance traveled for UAV
C_2	fixed sortie costs for UAV
C_3	UAV waiting cost per unit of time
C_4	UAV penalty cost per unit of time

3.3. Effect of Loaded Materials on UAV Flight Time

In the scenario of UAVs coordinated rescue for post-earthquake relief in SAR, the demand for rescue materials at the rescue point requires high timeliness. While UAV capacity has a notable effect on UAV flight time, the obtained UAV collaborative task allocation scheme is not applicable to the actual scenarios if the impact of UAV capacity factor is not taken into account. Therefore, in this work, we adapt a flight time weight function, which is based on the current load of materials. Equation (1) characterizes the flight time weight function of UAV k from point i to point j after finishing rescue task i, where $i \in T$; N_{ik} is the total demand for flight allocation and the upper limit of N_{ik} is Q_k.

$$f_{ijk}(N_{ik}) = \{1 + \frac{Ul - 1}{Q_k}(N_{ik})\}, \forall i \in T, j \in T, k \in U \quad (1)$$

Mikrokopter stated that rough calculations from experiments have shown that the flight time of UAVs decreases linearly as the amount of payload increases [33]. Consequently, in Equation (1), we make the assumption that the flight burden increases linearly with the amount of loaded materials is increased. Figure 2 presents a graphical presentation of the weight function.

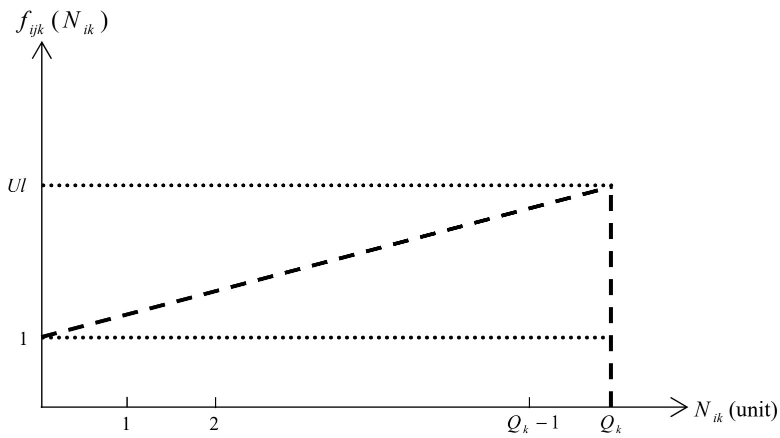

Figure 2. Linear weight function imposed on flight.

3.4. Effect of Service Time on UAV Behaviour

As defined in Section 3.2, the time window for rescue points to be served is $[e_i, l_i]$, and the optimal time window for the rescue points to be served is $[et_i, lt_i]$. If the UAV completes the service within the optimal time window, it is not penalized; if the UAV completes the service outside the optimal time window, the quality of the service decreases and it is penalized to some extent; and if the UAV has not arrived at the rescue point within the latest time window, the victims do not receive the service. Assuming that the UAV is penalized at the rescue point during the rescue process, the penalty cost is as follows:

$$P_{ik} = \begin{cases} C_3 \cdot (t_{ik} - e_i), e_i < t_{ik} < et_i \\ C_4 \cdot (t_{ik} - lt_i), lt_i < t_{ik} < l_i \\ 0, et_i \leq t_{ik} \leq lt_i \end{cases} \tag{2}$$

3.5. Establishment of RMURPTW Model

Based on the above analysis, the multi-UAV collaborative rescue mission planning problem for post-earthquake relief in SAR can be mathematically modeled as follows, with the modeling objective of minimizing the rescue cost.

$$\min(C_1 \sum_{k\in U} \sum_{i\in V} \sum_{j\in T, i\neq j} t_{ijk} x_{ijk} + C_2 \sum_{k\in U} o_k + \sum_{k\in U} \sum_{i\in T} P_{ik}) \tag{3}$$

$$s.t. \qquad \sum_{l\in V, l\neq i} x_{lik} = \sum_{j\in V, i\neq j} x_{ijk}, \forall i \in T, k \in U \tag{4}$$

$$\sum_{i\in V} x_{ijk} = 1, \forall j \in T, k \in U \tag{5}$$

$$\sum_{r\in H, i\in T} x_{rik} \leq 1, \forall k \in U \tag{6}$$

$$t_{ijk} = \frac{d_{ijk}}{v_k}, \forall (i,j) \in A, k \in U \tag{7}$$

$$w_{ik} + s_i + t_{ij} \cdot f_{ijk}(N_{ik}) - w_{jk} \leq (1 - x_{ijk})M, \forall (i,j) \in A, k \in U \tag{8}$$

$$w_{ik} \leq l_i, \forall k \in U, i \in T \tag{9}$$

$$\sum_{i\in T} q_i \cdot x_{ik} \leq Q_k, \forall k \in U \tag{10}$$

$$N_{ik} = \sum_{i\in T} q_i \cdot x_{ik}, \forall k \in U \tag{11}$$

$$x_{ijk} \in \{0,1\}, \forall i \in V, j \in T, i \neq j \tag{12}$$

$$o_k \in \{0,1\}, \forall k \in U \tag{13}$$

$$N_{ik} \text{ is nonnegative integer}, \ \forall i \in T, k \in U \tag{14}$$

The objective function is in Equation (3). The aim of the objective function is to minimize the cost of multi-UAV collaborative rescue and disaster relief, including the UAVs' flight cost, the fixed turnout cost, and the penalty cost. Constraint (4) makes sure that each rescue point will be visited only once. Constraint (5) ensures the balance constraints of entry and exit for each rescue target point. Constraint (6) guarantees that each UAV is used only once. Constraint (7) means the flight time of UAV from point *i* to point *j* is equal to the distance between point *i* and point *j* divided by the flight speed of the UAV. Constraint (8) shows the continuity of the flight time of UAV. Constraint (9) indicates that UAV has to provide service before the latest service time at the rescue point. According to constraint (10). Each UAV can be assigned no more rescue needs than the loadable capacity of the UAV. The total assigned demand required for each UAV per flight is ensured by Constraint (11). The time of flight from position *i* to position *j* is weighted by Equation (1). Constraints (12)–(14) signify the RMURPTW decision variables.

4. Description of the Innovative Hybrid Algorithm

4.1. Particle Swarm Optimization

The PSO algorithm is a prominent population-based optimization algorithm. The behavior of swarms of bees, flocks of birds and other groups of self-governing entities with a social component and a common purpose form the basis of PSO. When the population size is N and the solution space dimension is L, the position of the ith particle is $X_i = [x_{i1}, x_{i2}, \ldots, x_{il}, \ldots, x_{iL}]$, and the velocity of the ith particle is $V_i = [v_{i1}, v_{i2}, \ldots, v_{il}, \ldots, v_{iL}]$, $i = 1, 2, \ldots, N$. Then the updated velocity and position of the ith particle will be:

$$v_{i,j}(t) = wv_{i,j}(t) + c_1 r_1 (p_{best_{i,j}} - x_{i,j}(t)) + c_2 r_2 (g_{best_{i,j}} - x_{i,j}(t)) \tag{15}$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \tag{16}$$

where $p_{best^t_{i,j}}$ represents the particle's personal best position and $g_{best^t_{i,j}}$ represents the population's best position with $j = 1, 2, \ldots, L$; c_1, c_2 are two learning factor; r_1, r_2 are two stochastic values in the range of [0, 1]; w is the inertia weight.

4.2. Grey Wolf Optimizer

The GWO algorithm is a meta-heuristic algorithm inspired by the mechanism of hunting and the hierarchy of leadership of grey wolves in nature [34]. Grey wolves are considered apex predators, which means that they are at the top of the food chain [35,36]. A pack usually consists of 5 to 12 members and possesses a strict social hierarchy. In GWO, the crowd is divided into four different teams, alpha (α), beta (β), delta (δ), and omega (ω), which are used to model the leadership hierarchy. By simulating the processes of tracking, encircling, pursuing, and attacking the prey of wolves, the predatory behavior of grey wolf packs is reproduced, and a set of candidate solutions of the optimization problem is randomly generated in the search space [37].

1. Encircling. Wolves surrounding their prey can be represented as:

$$D = \left| CX_p(t) - X(t) \right| \tag{17}$$

$$X(t+1) = X_p(t) - AD \tag{18}$$

where D is the distance between the prey and the wolves; $X(t)$ and $X_p(t)$ are the grey wolves position vector and the prey position vector, respectively; A and C are the coefficient vectors of the grey wolves; t is the number of current iterations.

$$A = 2a \cdot r_1 - a \tag{19}$$

$$C = 2r_2 \tag{20}$$

where the convergence factor a decreases linearly from 2 to 0 during the iteration; r_1 and r_2 are random variables on [0, 1]; A has a range of $[-2, 2]$, and C is in [0, 2].

2. Pursuing. Wolves α, β, and δ in the pack are closest to the prey, so the distance between the other grey wolves and these three wolves can be determined first, which in turn determines the best direction to attack the prey.

$$D_k = |C_i X_k(t) - X(t)| \tag{21}$$

$$X_i = X_k - A_i D_k \tag{22}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{23}$$

where $k = \alpha$, β, δ, $i = 1, 2, 3$, $X(t+1)$ denotes the position vector of the grey wolf when it evolves to generation $t+1$.

3. Attacking. The last step of the prey behavior is attacking, which is the stage where the wolves need to hunt their prey; i.e., the GWO algorithm obtains the optimal solution.

The attacking is mainly realized by a linear decrease of a, making the positional adjustment coefficient A vary in the interval $[-a, a]$. When $|A| > 1$, the wolves have an increased global search capability that contributes to the global search; when $|A| < 1$, the wolves are pushed to attack the prey.

4.3. Description of the PSOGWO Algorithm

In this paper, we integrate PSO with GWO. The interval transformation is used to realize the conversion of the particle swarm coding space to the solution space of the discrete problem; the PSOGWO algorithm incorporates PSO, which improves the global convergence ability of the algorithm, while retaining GWO individual update mechanism; the algorithm, improved by fusion, avoids the local stagnation and local optimization problems and develops towards the optimized solution of the objective. The following describes the idea in more detail.

4.3.1. Encoding and Decoding

For the GWO algorithm, unsuitable selection of the primary population can result in an inability to converge on the optimal solution or decelerate the convergence rate. In this text, the PSO algorithm is used to carry out the coding and implement the initialization of the α, β, and δ wolves.

Encoding is a bridge connecting the problem with an algorithm, and the way of encoding is different for different problems. How to find a suitable expression to make the particles correspond to the solutions is one of the key problems in implementing the algorithm. Since the RMURPTW problem cannot predict the number of UAVs, we draw on ideas from the literature [38] to construct each particle of the PSO algorithm as a $2L$-dimensional vector X corresponding to the RMURPTW problem with L rescue point missions, and each rescue mission corresponds to two dimensions. For expressive and computational convenience, the 2-dimensional vector X corresponding to each particle is divided into $2L$-dimensional vector: X_v (denoting the UAV number corresponding to each rescue mission) and X_r (denoting the execution order of each rescue mission in the corresponding UAV mission execution).

For example, let the number of rescue missions in the RMURPTW problem be 7 and the number of UAVs be 3. If the position vector corresponding to a particle are given in Table 2. Then the corresponding decoding scheme for this particle are shown in Table 3:

Table 2. Position vector corresponding to a particle.

Rescue Mission No.	1	2	3	4	5	6	7
X_v	1	2	2	2	2	3	3
X_r	1	4	3	1	2	2	1

Table 3. Corresponding decoding scheme for the particle.

UAV No.	Decoding Scheme
1	$0 \to 1 \to 0$
2	$0 \to 4 \to 5 \to 3 \to 2 \to 0$
3	$0 \to 7 \to 6 \to 0$

The velocity vector V of the particle corresponds to X and is also divided into 2 L-dimensional vector, V_v and V_r. The decoding is similar.

The greatest advantage of this representation is that it allows each rescue point to be served by one UAV and restricts the rescue needs of each rescue point to be fulfilled by only one UAV, making the computation of the solution feasibility process much less complicated. Although the dimensionality of the representation is high, the increase in dimensionality does not increase the computational complexity, as the PSO algorithm has an excellent property in multi-dimensional optimization problems [39], as can be seen in the experimental results.

Particle positions will have decimals after updating, and in the task allocation problem, decimals are not allowed in positions. Therefore the updated positions need to be recoded. The process is divided into four steps as follows:

1. Update the position X to X' according to the position update formula and find the minimum value p and maximum value q in X'.
2. Apply an interval transformation to the components in X', transforming $X' \in [p, q]$ to $X'' \in [1, n]$. The interval transformation formula is shown below:

$$c'' = \frac{n-1}{q-p}(c' - p) + 1 \tag{24}$$

3. Rounding the components in X'' makes $X'' \in [1, n]$ become X''', i.e., changing continuous data to discrete data.
4. At this point the components in X''' are all positive integers between $[1, n]$, but it may still not be possible to construct a full permutation of n. Keep only the first of the duplicate numbers in X''' and fill in the rest by the numbers that do not appear to ensure the construction of a complete full permutation.

When the above steps are followed, the information in the original position vector can be used to the maximum extent to ensure the legitimacy of the position coding.

4.3.2. Nonlinear Convergence Factor

The GWO has adaptive regulation of linear convergence factor a and control parameter mechanism. However, the parameter a decreases linearly in the process, which cannot pacify this algorithm's ability to search globally and develop locally, and the GWO has a greater possibility of falling into the local optimization, which is not conducive to dealing with the problem. Therefore, this paper introduces a nonlinear convergence factor, which is formulated as

$$a = a_m \left[1 - \left(\frac{e^{t/t_{\max} - 1}}{e - 1} \right)^k \right] \tag{25}$$

where t is the current number of iterations; $t_{\max}$ is the maximum number of iterations; a_m is the initial value of the convergence factor; $k \in [1, 10]$ is the control factor.

As indicated in Figure 3, the nonlinear convergence factor a decays slowly, so the coefficient vectors A varies in a large range, and GWO has a strong ability to explore the global space, which ensures that GWO fully explores the search space in the beginning of the algorithm; when the algorithm runs to the later period, the rapid decay of A is conducive to the algorithm's ability to explore the local area, which is conducive to the algorithm's search for the optimal solution based on the existing information.

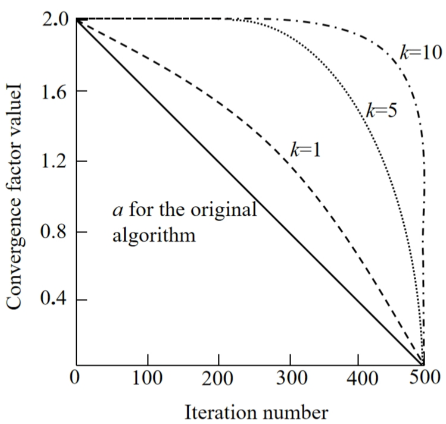

Figure 3. Comparison of nonlinear convergence factors.

4.3.3. Individual Update Strategy

In this paper, the PSO algorithm and the GWO algorithm are integrated. The exploration capability of the PSO algorithm is used to optimize the GWO algorithm. The grey wolf position, which is responsible for finding a globally optimal solution to the problem, is replaced with a particle position that corresponds to the grey wolf position but efficiently pushes the solution to the global optimum. The PSO algorithm leads the wolves to an optimal position. The PSOGWO algorithm has avoided the problem of local stagnation and local optimality and moves towards the optimal solution of the objective.

First, the decision-making individuals α, β, and δ are identified according to the particles' value. Update the population according to Section 4.3.1; then the corresponding rescue sequences are obtained according to the decoding rules in Section 4.3.1; finally, the objective function value of each solution is acquired according to the rescue sequences. Based on above operations, the update of the whole grey wolf population is completed. The speed update is completed according to Equation (15), and the position update equations for grey wolves guided by α, β and δ are listed below:

$$M = x_{i,j}(t) + v_{i,j}(t+1) \cdot \left(\frac{Maxit - it}{Maxit}\right) \tag{26}$$

$$\begin{cases} D_\alpha = |C_1 X_\alpha(t) - M| \\ D_\beta = |C_2 X_\beta(t) - M| \\ D_\delta = |C_3 X_\delta(t) - M| \end{cases} \tag{27}$$

$$\begin{cases} X_1 = X_\alpha(t) - A_1 D_\alpha \\ X_2 = X_\beta(t) - A_2 D_\beta \\ X_3 = X_\delta(t) - A_3 D_\delta \end{cases} \tag{28}$$

where it is the current iteration number of the algorithm; $Maxit$ is the maximum iteration number.

4.3.4. Dynamic Weighting Rules

The position update strategy based on Equation (28) shows that updating the grey wolf positions by the positions of the α, β, and δ wolves does not take into account the exchange of individual grey wolf information. This drawback raises the possibility of the algorithm slipping into the local best. To address this issue and also to maintain the leadership role of the α wolf, a dynamic weighting rule is introduced; see Equations (29)–(32).

$$X(t+1) = s_3 X_1 + s_2 X_2 + s_1 X_3 \tag{29}$$

$$s_1 = \frac{random(0,1)}{2} \tag{30}$$

$$s_2 = \frac{1 - random(0,1)}{2} \tag{31}$$

$$s_3 = 0.5 \tag{32}$$

The dynamic weighting rule promotes the communication between β and δ by keeping the proportion of the head wolf unchanged and introducing random inertia weights for β and δ. Since the α as the leader always plays a role, the result can gradually obtain the optimal value, and β wolf and δ wolf are the subordinate wolves to α; by adopting different coefficients for them, it helps to increase population diversity and reduce the likelihood of the algorithm falling into local optimization.

4.3.5. The PSOGWO Algorithm Flow

Figure 4 shows the flowchart of the PSOGWO algorithm; the main steps are as follows.

Step 1: Determine of initial population size, the maximum number of iterations $Maxit$ and the current number of iterations it.
Step 2: Initialize individuals and groups of particles, initialize α wolves, β wolves, δ wolves.
Step 3: Update the convergence factor a according to Equation (25) and initialize A and C according to Equations (19) and (20), respectively.
Step 4: Calculate the particle position using Equations (26)~(32).
Step 5: Calculating the fitness of all particles, i.e., the rescue cost.
Step 6: Updating individual best, and global best.
Step 7: Update the velocity and position of the ith particle, and then add 1 to the current iteration number.
Step 8: If the current iteration number is lower than $Maxit$, the particles update their positions according to Equations (26)~(32); if the maximum iteration number is attained, the loop is stopped and the optimal position X is output.

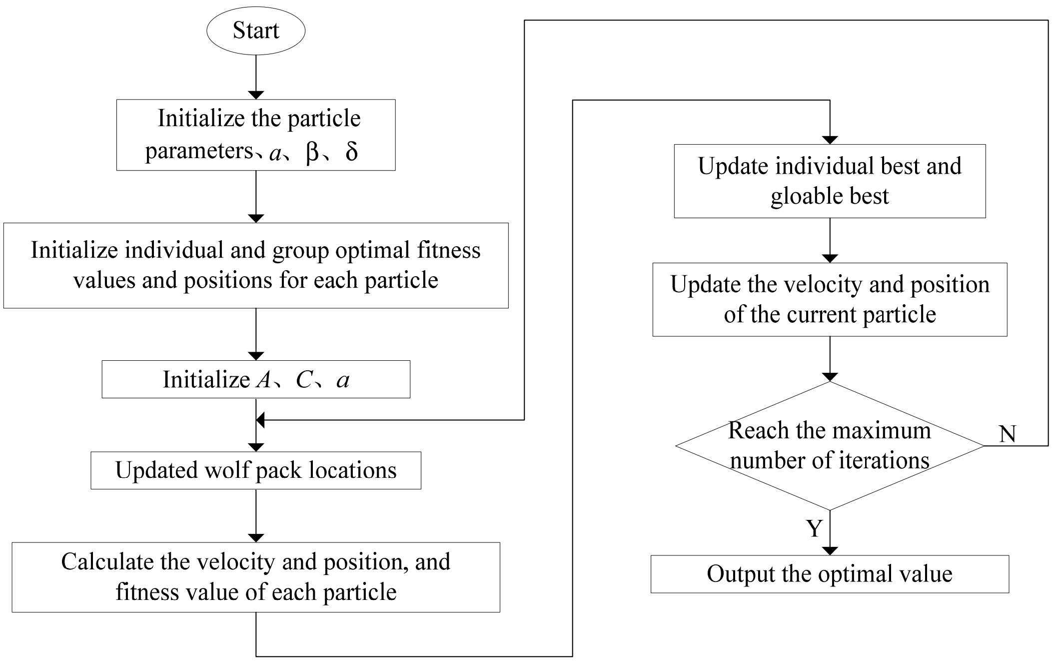

Figure 4. Flowchart of the PSOGWO Algorithm.

5. Results

5.1. Experiments Setup

On the basis of the above modeling study and algorithm design, simulation experiments are conducted on our PC (11th Gen Intel(R) Core(TM) i7-11700 CPU @ 2.50 GHz, 16 GB RAM, NVIDIA GeForce RTX 3090) using Matlab R2021b.

Post-earthquake rescue work in an area of M City is selected as a simulated experimental scenario to validate the performing of the model and algorithm mentioned herein, assuming that in this scenario, it is necessary to provide emergency assistance in the form of rescue materials to a number of stationary victims, which include medical supplies, first-aid equipment, daily necessities, etc., and assuming that the location information of these victims is already known. The example of calculation is shown below: 10 communities are required to be serviced in time windows, which are numbered 1, 2, 3, . . ., 10, and 0 is the UAVs' base center; the rescue needs are quantified according to different rescue needs at each community (i.e., rescue point), as shown in Table 4.

Table 4. Facial mask requirements of the 10 communities.

Number	1	2	3	4	5	6	7	8	9	10
Need/kg	8	6	4.5	2.2	7.5	11	2	1.5	5	7.5

Assume that the flight speed of UAVs is 100 km/h, the load capacity is 20 kg, and the endurance is 0.5 h. For the cost of the UAVs, assume that cost per unit distance traveled per UAV is $5, fixed sortie cost per UAV is $12, waiting cost per unit of time for each UAV is $4, and penalty cost per UAV per unit of time is $6. The location of the rescue distribution center and the victims to be rescued are distributed in the range of 10×10 (unit: km). The specific coordinates of rescue points are shown in Table 5. The distance between any two rescue points can be calculated by the coordinate positions, in km. Assuming that the UAVs carry relief goods at 14:00, the community service time windows are given in Table 6.

Table 5. The specific coordinates of nodes in the network.

Number	0	1	2	3	4	5	6	7	8	9	10
X Coordinate	1.9	0	0.2	1.1	1.6	1.4	1.8	3.5	4.3	2	3.2
Y Coordinate	0.9	0.9	1.4	1.7	0	2.1	1.9	1.6	0.2	2.4	2.9

Table 6. Service time window of each point.

Number	0	1	2	3	4	5	6	7	8	9	10
Start Window	14:00	14:21	14:02	14:04	14:05	14:15	14:11	14:05	14:02	14:05	14:09
End Window	14:30	14:27	14:03	14:05	14:06	14:21	14:14	14:10	14:04	14:07	14:15

5.2. Comparison among Different Algorithm

The GWO, PSO, and PSOGWO algorithms proposed in this paper are used to calculate the example, the maximum iterations of the parameters are set to 200, and the population size is set to 100. The initial value of a_m is 2, the learning factor $c_1 = c_2 = 1.5$, the inertia weight $w = 0.98$. The evolutionary iterative comparison of the three algorithms is illustrated in Figure 5. The number of iterations is in the horizontal coordinate and for the vertical coordinate is the total rescue cost.

Based on Figure 5, it can be seen that the minimum rescue costs obtained by PSOGWO are superior to the PSO algorithm and the GWO algorithm. The optimal objective function is about $67.6052 after 20 iterations.

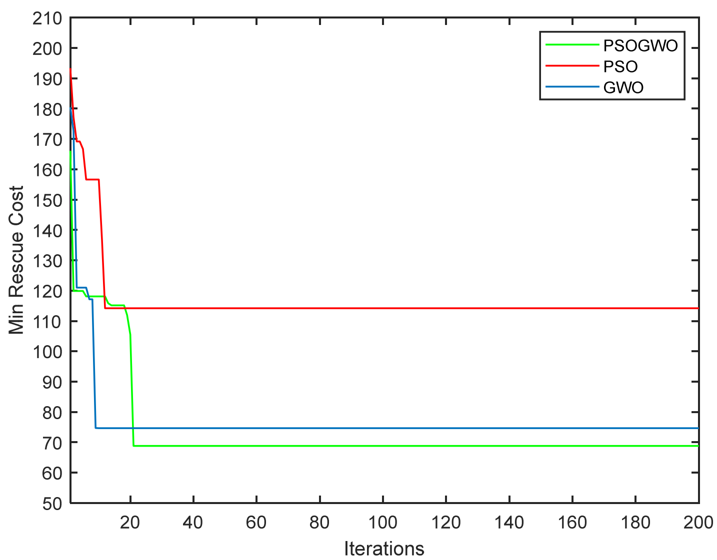

Figure 5. Iterative optimization process of the three algorithms.

5.3. The Optimal Allocation Results

The optimal allocation results of each UAV task obtained by PSOGWO are shown in Table 7; it can be seen that a total of 5 UAVs complete the task allocation of rescue work of 10 communities, while the task allocation plan and flight range of each UAV are provided. The generated routemap for UAVs carrying rescue supplies in M City is depicted in Figure 6. In the whole rescue process, the UAV rescue delivery routes are as follows: UAV1 route: $0 \rightarrow 2 \rightarrow 1 \rightarrow 0$; UAV2 route: $0 \rightarrow 3 \rightarrow 0$; UAV3 route: $0 \rightarrow 4 \rightarrow 6 \rightarrow 0$; UAV4 route: $0 \rightarrow 8 \rightarrow 7 \rightarrow 10 \rightarrow 0$; UAV5 route: $0 \rightarrow 9 \rightarrow 5 \rightarrow 0$. Each rescue route is constrained by the flight range of the UAV and the time window.

Table 7. The calculation results.

UAV	Route	Flight Range/km
UAV1	$0 \rightarrow 2 \rightarrow 1 \rightarrow 0$	2.31
UAV2	$0 \rightarrow 3 \rightarrow 0$	2.26
UAV3	$0 \rightarrow 4 \rightarrow 6 \rightarrow 0$	3.86
UAV4	$0 \rightarrow 8 \rightarrow 7 \rightarrow 10 \rightarrow 0$	7.54
UAV5	$0 \rightarrow 9 \rightarrow 5 \rightarrow 0$	3.47

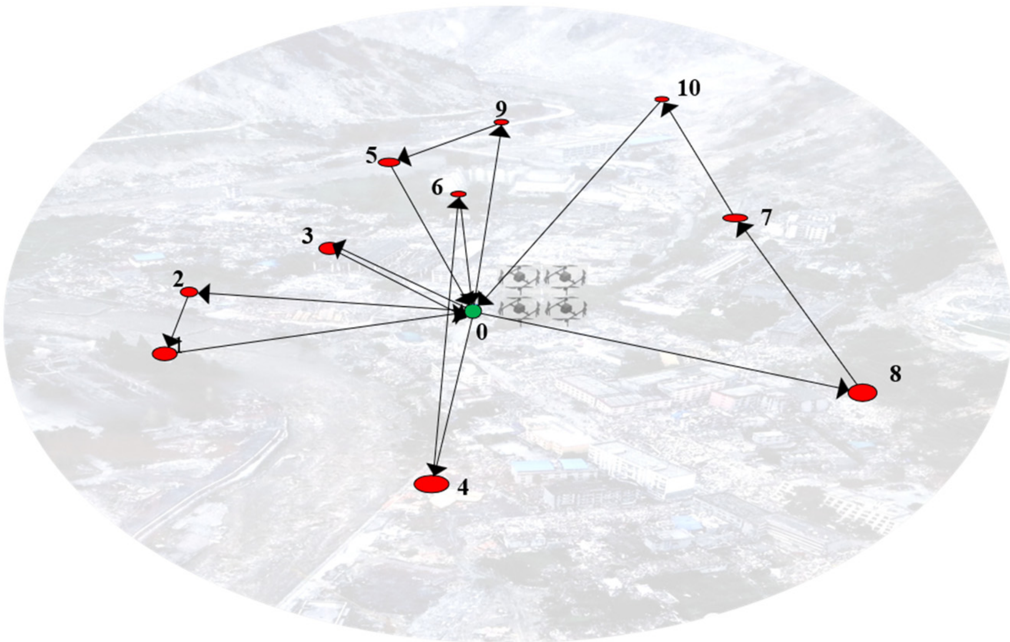

Figure 6. Roadmap for relief medical goods delivered by UAVs in M City.

5.4. Comparison among Multiple UAV

In this section, we analyze the task allocation solutions and corresponding time costs of rescue for UAVs with different load capacities of 20 kg, 30 kg, 40 kg, and 50 kg. The analysis is performed based on a randomized dataset.

A comparison of the simulation results of the multi-UAV cooperative rescue solutions with different load capacities is listed in Table 8.

Table 8. The simulation result comparison of multi-UAVs with different load capacities.

Capacity	N-UAV	Routes	Rescue Time/s	Rescue Cost/$
20	9	0 → 3 → 11 → 17 → 0; 0 → 7 → 12 → 0; 0 → 18 → 14 → 10 → 0; 0 → 13 → 2 → 0; 0 → 4 → 1 → 6 → 0; 0 → 12 → 5 → 0; 0 → 15 → 20 → 0; 0 → 16 → 5 → 8 → 0; 0 → 9 → 19 → 0;	10,500	152
30	7	0 → 10 → 17 → 5 → 14 → 0; 0 → 13 → 2 → 6 → 0; 0 → 10 → 9 → 3 → 0; 0 → 12 → 11 → 20 → 0; 0 → 15 → 8 → 0; 0 → 16 → 19 → 7 → 1 → 0; 0 → 18 → 4 → 0;	9826	246
40	5	0 → 14 → 16 → 9 → 0; 0 → 20 → 15 → 8 → 7 → 4 → 0; 0 → 19 → 11 → 6 → 0; 0 → 18 → 12 → 1 → 2 → 0; 0 → 13 → 17 →10 → 5 → 3 → 0;	8905	380
50	5	0 → 8 → 14 → 15 → 20 → 9 → 1 → 0; 0 → 18 → 16 → 3 → 0; 0 → 15 → 6 → 7 → 4 → 0; 0 → 19 → 12 → 5 → 0; 0 →17 → 10 → 13 → 11 → 2 → 0;	8689	530

6. Discussion

6.1. The Use of Improved VRP Models in SAR

Post-disaster relief in SAR is a growing topic of interest in the current research. In this paper, we have addressed the vital technologies of multi-UAV collaborative task allocation with a focus on rescue time optimization for post-earthquake in SAR. We have developed a comprehensive model for multi-UAV collaborative rescue mission planning—the RMURPTW model designed to provide post-disaster relief in SAR, which is obtained by improving VRP model. This study discusses the feasibility of the RMURPTW model in SAR scenario. By considering UAV flight cost, fixed take-off cost, penalty cost, and time window constraints, the objective function is established to minimize the cost of multi-UAV collaborative rescue. It is verified by simulation that each rescue route in the obtained allocation method satisfies the UAV body endurance constraints and the rescue time window constraints. The results show that the improved VRP model can be used in SAR scenarios and can provide the rescue decision-makers with an optimal rescue plan.

However, the complexity of real-world rescue environments, characterized by frequent secondary disasters, constantly changing environmental and mission information, and the potential for UAV communication interference, provides avenues for further research that could be further considered in subsequent studies. These factors underscore the need to improve the robustness and adaptability of UAV-based SAR operations in post-earthquake contexts.

6.2. The PSOGWO Algorithm for Solving the Improved VRP in SAR

According to Figure 5, PSOGWO has superior search accuracy, plans the optimal solution, and obtains the lowest rescue cost. Meanwhile, compared with the traditional PSO algorithm, PSOGWO can effectively improve the problem of PSO dropping into local optimality in the course of the design process. The initial solution of the PSOGWO algorithm is superior to the PSO algorithm and the GWO algorithm, which proves that the initial population generated by this paper's algorithm is more advantageous. Meanwhile, convergence of the GWO algorithm is the fastest, followed by PSO and PSOGWO. This is mainly because PSOGWO, compared with GWO, needs to use interval transformation to transform the solution space of discrete problems in the initial stage of the algorithm. Therefore, the PSOGWO algorithm can be seen and shown to have some superiority in solving the UAV cooperative task assignment problem in SAR.

6.3. Comparison among Multiple UAV

Table 8 reveals that the rescue cost of coordinated rescue by multiple UAVs with different load capacities is different. We can quite clearly see that a UAV with a 20 kg capacity would spend the longest time to perform the rescue mission. Similarly, the entire program runtime is also decreased significantly. It can be seen that the capacity of UAVs and the rescue time of the multi-UAV have substantial impact on UAV rescue costs.

Accordingly, considering the practical post-earthquake relief work process and the rescue cost situation, selecting UAVs with appropriate loading capacity can effectively reduce not only the cost of time, but also the number of UAVs. This conclusion can provide an optimized rescue distribution strategy for SAR decision makers, so as to improve the efficiency and effectiveness of SAR operations.

Furthermore, for post-earthquake relief in SAR, it provides optimized relief distribution strategies for rescue decision-makers, which can further advance the field of SAR mission planning and execution

7. Conclusions

In this paper, we have focused on addressing the challenges of post-earthquake rescue in SAR scenarios. A multi-UAV collaborative rescue task assignment model for post-earthquake relief in SAR has been developed. This model integrates the different characteristics of post-earthquake disaster events, emphasizing the specificity of rescue tasks and the goals of using the minimum number of UAVs, achieving the lowest rescue cost, and minimizing the rescue time. To address this model, we introduced the PSOGWO algorithm, a novel solution that merges PSO and GWO, incorporating strategies such as interval transformation, a nonlinear convergence factor, individual update strategies, and dynamic weighting rules.

Comparative analyses with the stand-alone PSO and GWO algorithms demonstrate the superior power of the PSOGWO algorithm to circumvent the problem of local optimization that plagues PSO during the planning phase. It exhibits remarkable search accuracy, identifies the optimal solution, and achieves the lowest rescue cost. The simulation analysis also considers the impact of the UAV payload on the rescue time and cost, further validating the effectiveness and feasibility of the algorithm. The rescue strategy proposed herein represents a more sophisticated solution to the complex problem of dispatching relief supplies in post-earthquake SAR scenarios. It provides substantial support to decision makers in devising effective disaster relief strategies. The findings of this study also offer worthwhile insights for future responses to similar disaster events.

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