Task Scheduling for UAV Swarms with Limited Communication Range

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Abstract: With the widespread adoption of unmanned aerial vehicle (UAV) technology, task scheduling for UAV swarms has become a crucial approach to improve operational efficiency. Most existing studies oversimplify the operational process rules of UAVs, making it difficult to accurately characterize the adaptability differences of UAVs to various tasks under practical operational constraints. To address this limitation, this paper proposes a UAV swarm task scheduling problem with limited communication range (UAVS-LCR) and establishes an integer programming model for its formal description. For solving this problem, a multi-neighborhood iterative local search (MNILS) algorithm is designed, which adopts a doubly linked list solution representation method to reduce the computational complexity of basic neighborhood operations. This algorithm generates high-quality initial solutions via a greedy construction strategy, combines insertion search, multi-swap search and the two-opt operator to enable alternating exploration across multiple neighborhoods, and incorporates a simulated annealing mechanism to balance search efficiency and solution diversity. This method can provide an effective solution for various application scenarios including wide-area UAV inspection and heterogeneous UAV collaborative operations. Experimental results on 12 power grid maintenance test instances demonstrate that the MNILS algorithm significantly outperforms the genetic algorithm, the artificial bee colony algorithm, the ant colony optimization algorithm and the variable neighborhood search algorithm in terms of both solution quality and scalability for large-scale problems.

Key words: unmanned aerial vehicle (UAV) swarms; task scheduling; neighborhood structure; iterative local search

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0 Introduction

With the rapid advancement of wireless communication, distributed control, and artificial intelligence algorithms, unmanned aerial vehicle (UAV) swarms, a revolutionary paradigm for collaborative operations, are quickly transitioning from the laboratory to widespread application[1]. Task allocation and path planning, serving as critical components of UAV swarm operations, directly determine the overall operational efficiency and mission completion quality[2]. However, in practical scenarios, UAV swarms face a variety of challenges, including dynamic obstacles[3], complex terrain[4], energy depletion[5], and communication constraints[6], all of which influence their operational effectiveness. These factors render the task allocation and path planning problem exceptionally complex, requiring UAV swarms to accomplish tasks relatively efficiently under multiple constraints.

UAV task allocation involves reasonably assigning a series of tasks to individual UAVs based on factors such as UAV capabilities, positions, task

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requirements, and environmental conditions, with the aim of maximizing overall operational efficiency and optimizing task completion quality. Currently, conventional task allocation algorithms primarily include centralized linear programming methods, distributed market-based mechanisms, and heuristic approaches[7]. Schumacher et al.[8] systematically formalized UAV task allocation problems involving complex collaborative constraints such as timing requirements and task sequences into a solvable centralized mixed integer linear programming (MILP) model. Choi et al.[9] developed a distributed auction algorithm based on task package extension to address the challenges of heterogeneous multi-agent teams in distributed decision-making under complex constraints. Zhong et al.[10] combined the hybrid genetic algorithm based on integer encoding to improve the algorithm solving performance in the UAV collaborative task planning modeling. Gao et al.[11] incorporated robust optimization within the classical MILP framework to handle uncertainties such as fuel consumption, effectively mitigating the impacts of parameter variability.

However, traditional approaches often treat path planning and task allocation as separate optimization problems, failing to adequately account for the coupling between task allocation and route optimization[12]. This can lead to significant deviations between the computed solutions and the actual optimal outcomes. Such discrepancies may be further amplified, ultimately affecting overall mission execution efficiency and resource utilization. Additionally, decoupled optimization methods struggle to effectively respond to unexpected changes during task execution, failing to meet modern multi-UAV requirements for efficiency, real-time responsiveness, and adaptability. In multi-UAV collaborative task scenarios, task allocation and path planning are interdependent and mutually influential, optimizing only one aspect can hardly achieve optimal overall performance[13].

Building on this, Sun et al.[14] developed an integrated architecture for UAV cooperative control by combining the improved A* algorithm with the enhanced particle swarm optimization (PSO), which optimizes task allocation and flight trajectory planning. Su et al.[7] introduced the improved ant colony optimization algorithm to achieve collision-free cooperative operation of multiple UAVs in multi-task environments. Qin et al.[15] combined the improved genetic algorithm with the enhanced PSO, which effectively reduced the overall cost compared to traditional PSO and chaotic immune PSO. Integrating UAV swarm task allocation with path planning can significantly enhance mission execution efficiency, reduce energy consumption, and improve the adaptability and robustness of UAV swarms in co1mplex environments. Meanwhile, owing to their exceptional flexibility and strong terrain adaptability, UAVs have been widely applied in fields such as environmental monitoring[16-18], logistics distribution[19-21], and emergency response[22-24], and are increasingly becoming indispensable tools in disaster relief operations in complex terrains. In environments with relatively complete communication infrastructure, UAVs can operate across entire maps via satellite networks or ad-hoc networks.

However, in complex and large-scale operational environments, UAV swarm scheduling must consider the impact of communication conditions. Wang et al.[25] integrated communication factors, employing an adaptive large neighborhood search to effectively reduce communication service time. Considering the limited transportation capacity under disaster conditions, Du et al.[26] developed a multi-stage dynamic programming mode for material allocation and resource deployment. Zhao et al.[27] developed a spatiotemporal path coordination optimization model for drones and support vehicles, effectively mitigating the interference of external information on communication quality. Sun et al.[28] tackled the challenges of collaboration in dynamic environments by proposing an integrated multi-agent reinforcement learning model to enhance the self-organizing collaborative capabilities of UAV swarms. In large-scale UAV operational environments, especially given the extensive distribution of power lines and complex terrain, communication range limitations pose a significant challenge for UAV swarms during cooperative operations.

Zhong et al.[29] developed a technical approach for an emergency communication system based on 5G and intelligent UAV networking, providing critical support for emergency communication capabilities. Wu et al.[30] utilized the Poisson point process (PPP) combined with distance constraints to model UAV positions, offering a mathematical framework for large-scale UAV deployment. Panowicz et al.[31] employed one UAV as an information hub to exchange data with the ground control station, thereby enabling communication within UAV swarms. Although these methods can, to some extent, alleviate the impact of communication range limitations, they primarily focus on improving communication quality or reducing signal interference, without considering collaborative strategies for UAV swarms under communication distance constraints.

Based on the above research landscape, this paper proposes a UAV swarm task scheduling problem with limited communication range (UAVS-LCR), and the main contributions of this paper are as follows.

(1) For the UAV swarm scheduling problem under limited communication distance, an integer linear programming model is proposed. This model rigorously defines the feasible region for each UAV, significantly enhancing the model's practical applicability.

(2) By incorporating UAV communication range constraints as core limitations, this study effectively improves the scheduling efficiency and reliability of UAVs in complex environments, addressing the issue of over-idealized communication assumptions in existing research.

(3) To tackle the non-deterministic polynomial-hard (NP-hard) problem derived from this model, an efficient heuristic solution algorithm is designed, capable of rapidly generating high-quality and executable solutions for swarm task allocation and route planning.

1 UAVS-LCR

1.1 UAV swarm system

In scenarios such as border control, emergency rescue, or agricultural production, UAVs often undertake tasks such as information collection, inspection, material transportation, and low-altitude operations. However, these environments typically present challenges such as complex terrain and extensive task coverage. Due to limitations in communication range, a single base station is often insufficient to cover the entire operational area. In such cases, a swarm of UAVs must depart from their respective base stations and collaborate to accomplish all tasks. To enable UAV swarms to complete all assigned tasks more rapidly under communication range constraints, we propose a task scheduling problem of UAV swarm with limited communication range.

Consequently, the primary objective of UAV cluster task scheduling is to rationally allocate tasks and determine the operation sequence under multiple physical constraints, aiming to minimize minimal total makespan.

As shown in Fig.1, the UAV swarm needs to depart from several base stations and proceed to various task points. Each task point must be serviced exactly once, with each requiring a dedicated service period from the UAVs. The movement process between two task points consists of three phases, take-off, cruising, and landing. The total time consumption for this process is calculated as

$$t_{ij}=\frac{w_{ij}}{v}+t_{\mathrm{a}}+t_{\mathrm{b}} \tag{1}$$

where t_{ij} represents the time required for a UAV to travel from point i to point j, v the cruising speed of the UAV, and w_{ij} the distance between locations i and j; t_{a} and t_{b} correspond to the time consumed during take-off and landing procedures, respectively.

Furthermore, communication and energy constraints must be taken into account. Each UAV is re-

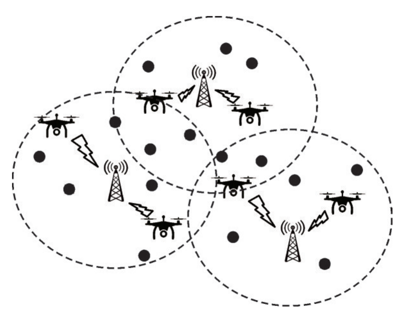

Fig.1 Task distribution of a UAV swarm

stricted to operating within the communication range of its assigned base station and must return before its battery is depleted.

1.2 Problem formulation

The node set is defined as $N=\{1,2,\cdots,n\}$, which contains all task points and base stations. The first l nodes in N represent base station nodes. The operation time of each task point is $D=\{d_1,d_2,\cdots,d_n\}$. The base station coverage set is defined as $L=\{l_i|i\leqslant l\}$, where $l_i=\{j|d_{ij}<R,j>l\}$ represents the task point set within the communication range of base station i, and R the maximum communication distance between the UAVs and the base station. The UAV swarm task scheduling problem can be modeled as a mixed integer programming model

$$f=\sum_k\sum_i\sum_j w_{ij}x_{ijk} \quad \forall k\in V;\forall i,j\in N \tag{2}$$

$$\sum_j x_{ijk}=\sum_l x_{lik} \quad \text{s.t. } \forall i\in N;\ \forall k\in V \tag{3}$$

$$\sum_k\sum_j x_{ijk}=\sum_k\sum_j x_{jik}=1 \quad \forall i\in N \tag{4}$$

$$u_{ik}-u_{jk}+n\times x_{lik}\leqslant n-1 \quad \forall i\neq j\in N;\forall k\in V \tag{5}$$

$$\sum_j x_{ijk}=\sum_j x_{jik}=0 \quad \forall i\in N;\forall j\notin l_k \tag{6}$$

$$\sum_i\sum_j w_{ij}x_{ijk}\leqslant Q_k \quad \forall k\in \mathrm{V} \tag{7}$$

$$x_{ijk}\in\{0,1\} \tag{8}$$

where Eq.(2) represents the objective function aimed at minimizing the total makespan; Eq.(3) ensures that when a UAV enters a task point, it must depart from the same point; Eq.(4) guarantees that each point is serviced exactly once by only one UAV; Eq.(5) eliminates sub-tours in the UAV routes; and Eq.(6) restricts UAVs from operating on task points outside the communication range of their base stations. Note that for autonomous network systems or satellite communications, the communication range can cover the entire map. In such cases, the set l_k may be the total node set. Eq.(7) maintains sufficient energy reserves for UAVs during operations.

Fig.2 illustrates a task scheduling instance involving 16 task points three base stations and four UAVs. In this configuration, each UAV departs from its designated base station and returns to the same base upon completion of all assigned tasks. Within the overlapping communication ranges of base stations, multiple UAVs demonstrate efficient cooperative capabilities.

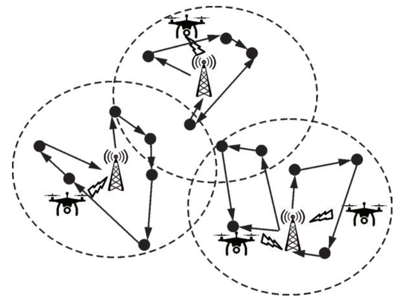

Fig.2 A task scheduling instance for power grid maintenance

2 Multi-bidirectional-Link Representation

The core of the neighborhood search algorithm adopted in this paper relies on insertion, swap, and inversion operators to directly transform solutions, thereby enabling exploration of the solution space. The essence of task scheduling for UAV cluster lies in determining both the allocation of task points and the sequence in which they are serviced. Therefore, the solution can be represented by an m-segment disjoint sequence. Each sequence represents a closed tour for a single UAV. Balancing storage space and computational efficiency, a novel representation for bidirectional links is designed. This representation takes the form of a specialized doubly linked list. Fig.3 shows a sequential bidirectional link. Each task occupies two storage units. The basic storage unit is designated as a node. For the same point, two nodes can be swapped using a twin operation. Owing to the symmetric nature of the UAV task scheduling problem, a given sequence is considered equivalent to its reverse. To leverage this property, next pointers are used to connect point nodes, thereby constructing two linked lists that represent both the given sequence and its reverse. The two nodes of a task point maintain a next pointer that connects the next and the after nodes. Starting from any node of any point within the linked structure, sequential or reverse traversal of the sequence can be achieved by following the next pointers. Switching to the alternate node of the same customer yields the opposite traversal direction.

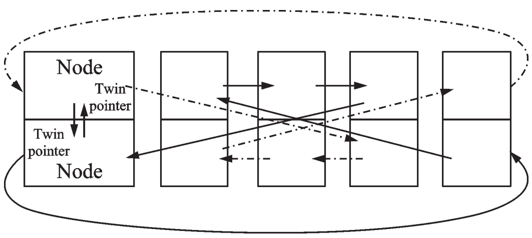

Fig.3 Bidirectional link reversal

A bidirectional link can store a symmetrical circular path with a space complexity of $O(n)$. For a task scheduling problem with m UAVs, one of its solutions can be expressed as m-segment bidirectional links. Similar to a linked list, the swap operation removes the task point from the bidirectional link and then implements it by changing only a fixed number of next pointers. Therefore, their computational complexity is $O(1)$. The inversion of some fragments of a linked list needs to be realized by breaking the pointers of points at the beginning and the end of the fragment, and reversing the pointers of all points in the fragment. The process takes $O(n)$ time. The reverse of the bidirectional link can be achieved by only changing the node pointer of the point at the head and tail of the fragment, as seen in Fig.4.

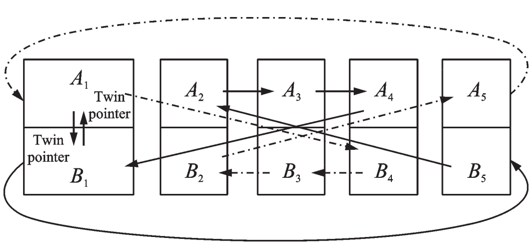

Fig.4 Bidirectional link

The time-consuming process does not increase with the length of the sequence. The bidirectional link mechanism leverages the symmetry of data structures, with its core concept being the creation of two mirror-image storage nodes (node A and node B) for each point. Through a specific pointer linkage method, both forward and reverse sequences of the same path are encoded simultaneously within a single structure. Each node's next pointer strictly points to the corresponding node of the next task point, not arbitrarily, but maintains a fixed mapping: The current node A_1 points to the next node A_2, node B_1 to node B_2, and so on. Two nodes at the same task point are interconnected via twin pointers, enabling instant switching. During traversal, the directionality is determined by the initial node selection rather than pointer orientation. Starting from node A_1, traversal along the next pointer yields the forward sequence A_1—A_2—A_3—A_4—A_5. Conversely, starting from node B_1, traversal produces the identical path B_1—B_2—B_3—B_4—B_5. However, since the chain inherently encodes reverse information, the sequence appears in a reverse order: B_5—B_4—B_3—B_2—B_1. Therefore, when starting from node A_1, the next pointer should normally jump to the next node A_2. But through the twin pointer's instant switching mechanism, it jumps to node B_4, completing the entire storage process sequentially. This bidirectional link representation method not only achieves simultaneous encoding of both forward and reverse paths in structure, but also provides significant convenience at the algorithmic application level. Moreover, the architecture supports efficient insertion and deletion operations. When adjusting a task point in the path, simply modifying the pointer direction of relevant nodes enables rapid updates without reconstructing the entire path.

3 Multi-neighborhood Iterative Local Search

3.1 Overall framework

In order to solve UAVS-LCR, the proposed approach is built upon the iterated local search (ILS) framework, incorporating exploration of three specific neighborhoods, swap, insertion, and reversal. These neighborhoods are designed to perform inter-route swap and insertion operations, along with intra-route inversion operations. Inter-route operators enhance task allocation, while intra-route operators improve the execution order within individual UAV routes. Additionally, a segment mutation mechanism is introduced within the multi-neighborhood ILS (MNILS) to stochastically modify sub-paths of certain UAV, thereby enabling escape from local optima and mitigating premature convergence.

The detailed procedure of the algorithm is illustrated in Fig.5. Initially, MNILS constructs an initial solution using a nearest-neighbor heuristic. Subsequently, three local search operators-insertion, sequential swap, and two-opt are applied iteratively to optimize both task assignment and execution order. If no improvement is achieved by any of these three local search operators, a fragment mutation operator perturbs the current solution, accepting inferior solutions to facilitate escape from local optimal.

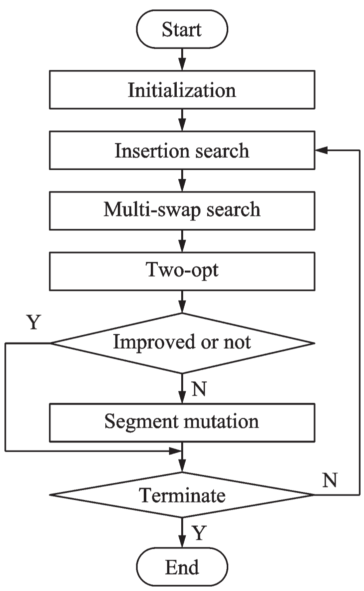

Fig.5 Process of MNILS

3.2 Initialization

We use the greedy nearest neighbor strategy to construct the initial solution of the algorithm. First, we set the base station corresponding to each UAV as the starting point of all UAV paths. Second, we insert all tasks into the current solution step by step in a random order. The specific UAV path and corresponding position for insertion can be calculated as

$$p(j)=\underset{i\in r_k,k\in U(j)}{\operatorname{argmin}}\ w_{ij}+w_{j,i+1}-w_{i,i+1} \tag{9}$$

where $U(j)$ denotes the set of UAVs that can perform task j; and r_k the path of UAV k. $U(j)$ ensures that task j can only be assigned to UAVs within the communication range of their respective base stations. Additionally, during the construction process, we need to verify the battery constraint according to Eq.(7).

3.3 Insertion search

The insertion search employs path inter-node neighborhoods, which are constrained by the communication range and power constraints shown in Eqs.(6, 7). The insertion search immediately attempts to relocate all tasks using a new mechanism. It removes a task from the current solution, finds UAV that satisfy both communication range and power constraints, and calculates insertion costs at all locations along the UAV routes. Once a solution with lower relocation costs is found during traversal, the algorithm immediately replaces the current solution with this improved one. Insertion search will try all possible insertion operation with a position and a task. Therefore, its time complexity is $O(n^2)$.

3.4 Multi-swap search

Algorithm 1 presents the pseudo-code for the multi-swap search. This procedure utilizes a novel swap operator designed to exchange the positions of only two tasks within a solution. A local search employing solely this basic swap operator would be unable to discover the solution depicted in Fig.6(a). This is because swapping only tasks 7 and 5 would yield the inferior solutions shown in Figs.6(b, c), causing the algorithm to naturally reject such a move. To achieve the improved solution in Fig.6(d), the algorithm must first swap tasks 7 and 5, and then subsequently swap customers 5 and 8. To address this limitation, the sequential swap search is proposed.

Algorithm 1 Continues multi-swap search

Input: Current solution S.

(1) For $p\in S$ do

(2) $S'\leftarrow S$; Improved$\leftarrow$False; $f_{\min}\leftarrow\varnothing$;

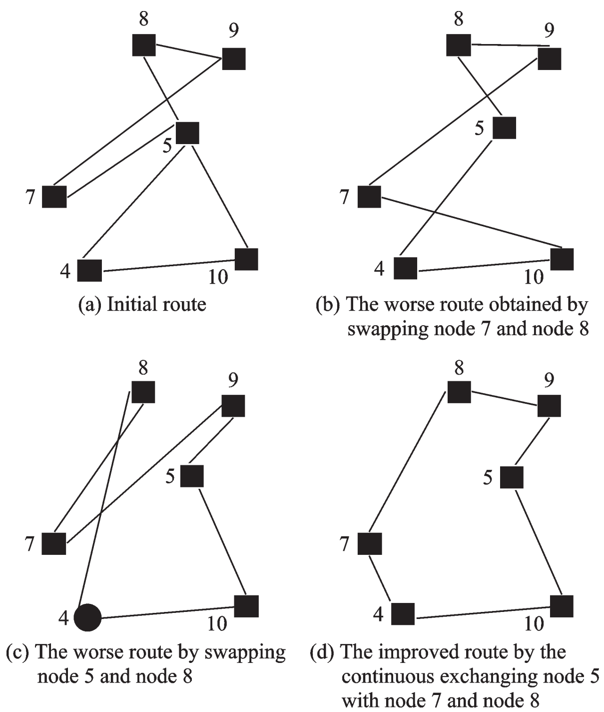

Fig.6 Multi-swap operation

```
    For step=1, 2, 3, 4, 5 do
      Sb←∅;
      For i∈S do
        S'← Swap(S, i, p); // Swap customer i and p. // S' is the solution obtained by swap.
        If f(S')<f(S) then
          S←S';
          Improved←True;
            Break;
        End If
        If f(S')<f_min or f_min=∅ then
          S_tmp←S'; f_min←f(S'); // S_tmp is the best solution in the current layer local search.
        End If
      End For
      If Improved then
        Break;
      End If
      S'← S_tmp;
      if f(S')<f(Sb) or Sb=∅ then
        Sb← S'; // Sb records the best solution during the whole multi step swap search.
      End If
    End For
    Pt←Rand(0, 1);
    If Pr(S, Sb, T)≥Pt then // Pr is the probability to accept the worse solution Sb.
      S←Sb;
    End If
End For
```

The multi-swap search operates by attempting multi-step continuous swap operations for each position in the solution. For a given swap position P, the procedure iterates over all other tasks in the solution, evaluating the change in solution quality resulting from each possible swap. If this step swap improves the current solution, the multi-step operation is terminated. Otherwise, the swap operation with the minimum cost increase is retained and the algorithm proceeds to the next swap operation. This process repeats for up to five sequential steps. If an improved solution is found within these five steps, it is accepted. If no improvement is found, an inferior solution may be accepted with a probability defined by Eq.(10), following a simulated annealing strategy.

$$\Pr(S,S',T)=\mathrm{e}^{(f(S)-f(S'))/T} \tag{10}$$

The number of multi-swap steps for a given position is not fixed. For instance, if an improved solution is found at the third step, the swapping process terminates immediately, resulting in a total of three steps for that sequence. Throughout the search, each candidate swap must be evaluated for feasibility, ensuring that the involved task point can serve the swapped tasks and that all capacity constraints remain satisfied. Specifically, if the task at position p falls outside the communication range of the base station assigned to the UAV currently handling task i, the swap operation will not be executed. In this case, Swap(S, i, p) directly returns the current solution S. The same applies conversely. Additionally, the swap operation checks whether the two UAVs would exceed their total travel distance limits after the exchange. If so, the swap is likewise not performed.

However, if the number of steps is switched, the computational complexity of the algorithm will also increase at the polynomial level. For the efficiency of continuous multi-exchange search, we consider the Euclidean characteristic of customer distribution, introduce k-neighbor candidate sets, limit each layer search only among k-neighbor tasks, and then limit the computational complexity of each layer search to k. The continues multi-swap search aims to find an improved multi-swap operation with a position and a tasks sequence. The elements in the sequence is from the k-neighbor tasks set of the position. There are n positions need to be search. And k tasks should be examined in each swap step. The time complexity of the multi-swap search is $O(nk^5)$.

3.5 Two-opt

Two-opt is a well-known local search algorithm for solving the traveling salesman problem (TSP). It improves solution quality by swapping two edges in the route to achieve fine-grained sequence optimization. In the context of the UAVS-LCR, two-opt serves as a UAV path optimization algorithm, and does not change the task allocation. It always ensures that the communication range constraint remains satisfied. Since two-opt only reduces the total travel distance of UAVs, the energy constraint is likewise never violated. Similar to other operators, two-opt employs an immediate update mechanism. It is important to note that updating the current solution shifts the neighborhood center. Therefore, the search process is reset after each improvement to ensure a comprehensive exploration of the new neighborhood. Two-opt can be seen as a flip search. Its time complexity is $O(n^2)$.

3.6 Fragment mutation

When the algorithm becomes trapped in a local optimum, the fragment mutation module introduces a perturbation. This operator randomly selects a segment from a UAV's route, with a length equal to approximately 20% of the route, and reinserts it into a randomly chosen feasible position elsewhere in the solution while ensuring communication range and power constraints remain satisfied. By disrupting the current solution structure in this way, the mutation enables the search to escape into previously unexplored regions of the solution space.

4 Computational Complexity Analysis

In MNILS, insertion search, swap search, two-opt, and fragment mutation are performed iteratively. Therefore, the complexity of the algorithm is mainly composed of four modules. The search operation has a two-tier loop. In the worst case, that is, the search requires a complete search for all feasible, and its time complexity is $O(n^2)$. The continuous switching search is a five-step continuous switching operation for n positions, and each step of switching needs to search for k neighboring points, so its computational complexity is $O(nk^5)$. Similar to this search, two-opt has a computational complexity of $O(n^2)$. Genetic mutation is to relocate $0.2n$ tasks, and its computational complexity is $O(n)$. In summary, the time complexity of the main loop is $O(2n^2 + 0.2nk^5)$.

5 Experimental Analysis

5.1 Experimental setup

The communication range-constrained UAV scheduling problem and its MNILS solution algorithm have broad applicability. For instance, in wide-area scenarios such as power grid maintenance or disaster relief, the base station communication range R can be derived using the calculation method provided in the appendix. UAV swarms can operate around their respective base stations and collaborate within overlapping communication areas. In scenarios with better communication conditions or narrower coverage areas, the communication range can be set to cover the entire map to adapt accordingly.

Moreover, the concept of communication range defined here is rather broad. In specialized inspection or maintenance contexts, UAVs of different types may have distinct functional responsibilities. Certain tasks may only be performed by one or several specific types of UAVs. In such cases, the base station coverage set can extend beyond communication limitations to describe the operational feasibility of heterogeneous UAVs for given tasks. In other words, if a certain type of UAV is stationed at base j and is capable of performing task i, task i can be assigned to that UAV.

Similarly, in UAV swarm transportation scenarios, different bases may store distinct types of cargo. Different locations may require different goods. The matching relationship between location demands and cargo types can also be described through the base station coverage set L. This problem and its solution provide an effective approach for some application scenarios in the low-altitude economy.

5.2 Verification experiment

Fig.7 presents the UAV swarm routing diagram for instance 1 obtained by MNILS. As observed in Fig.7, all UAVs perform inspection tasks within their respective base station coverage areas, satisfying all constraints defined in UAVS-LCR. Notably, within overlapping regions of adjacent base stations, UAVs demonstrate effective cooperative capabilities. Compared to scheduling methods that strictly enforce non-overlapping operational zones, the proposed approach achieves significantly higher UAV utilization rates. Furthermore, the communication range of the second base station can be covered by the other two. The first and the third UAVs are sufficient to complete all tasks. However, due to energy constraints, all three UAVs are required to operate jointly across the entire map, with no task preemption occurring. We design 12 UAVS-LCR test instances by modifying the Traveling Salesman Problem Library (TSPLIB) datasets. They are listed in Table 1.

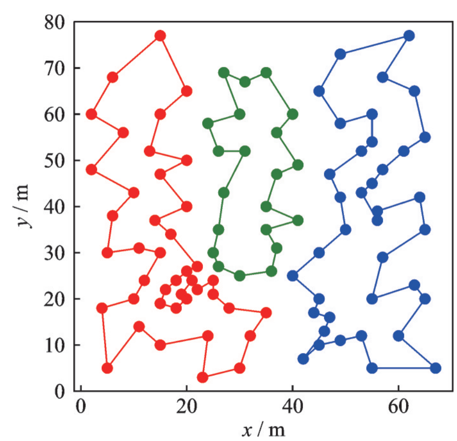

Fig.7 UAV routes of Eil101-3-3 instance

Table 1 UAVS-LCR instances

No.	Instances	Checkpoints	Base station	UAV
1	Eil101-3-3	101	3	3
2	Eil101-3-5	101	3	5
3	Eil101-5-5	101	5	5
4	Eil101-7-9	101	7	9
5	Rat575-3-3	575	3	3
6	Rat575-3-5	575	3	5
7	Rat575-5-5	575	5	5
8	Rat575-7-9	575	7	9
9	Pr1002-3-3	1002	3	3
10	Pr1002-3-5	1002	3	5
11	Pr1002-5-5	1002	5	5
12	Pr1002-7-9	1002	7	9

5.3 Parameter experiment

To achieve the best performance of MNILS, the influence of different parameter settings is investigated. Fig.8 illustrates the convergence behavior of MNILS on the Rat575 instance under varying numbers of swap steps. As shown in Fig.8, increasing the number of swap steps enhances the search capability of the algorithm, leading to a gradual improvement in solution quality. However, an excessive number of swaps increases computational complexity and eventually degrades performance. The algorithm achieves the best balance between computational efficiency and search effectiveness when the number of swap steps is set to 5.

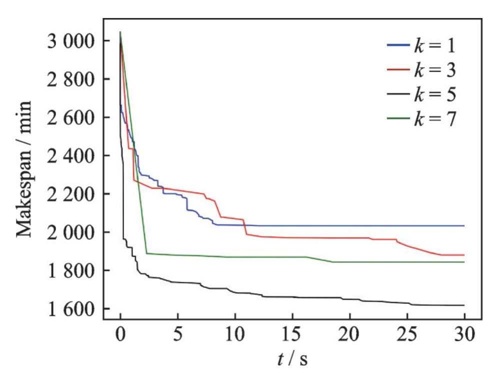

Fig.8 Convergence curves of MNILS with different k values

Furthermore, when the number of swap steps is set to 1, the multi-swap search reduces to a simple swap search algorithm. In this case, the algorithm tends to converge prematurely, often becoming trapped in a local optimum early in the process and failing to escape. These experimental results validate the effectiveness of the proposed multi-swap search strategy.

5.4 Comparative experiments

To evaluate the performance of MNILS, three comparative algorithms, the genetic algorithm (GA), the artificial bee colony (ABC), the ant colony optimization (ACO), and the variable neighborhood search (VNS), are implemented on the same platform. To enhance the performance of the comparative algorithms, an efficient two-opt algorithm is applied to optimize the routes of the best individuals within the three population-based algorithms. VNS adopts the same initialization method with MNILS. All four algorithms are evaluated through ten independent runs on each of the 12 UAVS-LCR instances, with a computational time limit of 1 min/run. Table 2 summarizes the best and average makespan values obtained by each algorithm over the ten runs. As shown in Table 2, the proposed MNILS outperforms all comparative algorithms on ten instances, achieving the best results in both solution quality and consistency. We also conduct the Wilcoxon signed-rank test to verify the conclusion. The p-value is less than 0.05. It means the gaps between algorithms are robust. Z values indicate that MNILS is superior than others. Furthermore, the performance advantage of MNILS become more pronounced as the scale of the instances increased, demonstrating its stronger scalability and robustness in handling larger problem sizes.

Table 2 Comparison results min

Instance	MNILS		ABC		GA		ACO		VNS	
	Min	Avg	Min	Avg	Min	Avg	Min	Avg	Min	Avg
1	115.9	119.3	120.4	121.8	126.5	127.5	116.2	120.3	115.1	118.7
2	120.2	122.9	148.7	158.8	140.9	165.1	121.7	129.6	120.2	123.3
3	136.3	138.4	162.1	173.9	181.4	181.9	135.7	141.1	137.2	140.5
4	167.9	172.0	178.1	182.9	198.1	201.3	172.6	173.2	169.4	171.8
5	1 173.2	1 174.0	1 244.3	1 247.9	1 348.7	1 365.4	1 292.2	1 317.4	1 198.9	1 247.3
6	1 200.3	1 223.9	1 283.7	1 295.6	1 401.2	1 412.6	1 319.6	1 331.9	1 270.6	1 313.7
7	1 256.2	1 260.1	1 386.0	1 406.4	1 546.9	1 552.2	1 379.0	1 402.1	1 322.1	1 352.0
8	1 275.4	1 283.0	1 450.2	1 452.9	1 560.9	1 591.4	1 406.1	1 407.6	1 341.2	1 367.6
9	43 120.5	43 552.1	45 403.8	46 277.4	45 875.8	46 104.9	49 228.8	50 211.8	44 582.5	46 125.5
10	43 819.7	44 042.1	47 210.2	47 484.7	44 803.9	46 790.7	49 117.0	49 941.9	45 207.2	46 771.9
11	45 598.6	46 020.6	48 954.9	49 373.4	48 869.0	50 091.9	51 211.7	51 735.5	46 982.6	48 753.3
12	46 074.5	46 550.0	49 529.9	50 340.6	48 725.7	50 143.3	52 064.6	52 756.8	49 005.1	50 123.7
Z	—	—	−3.059	−3.059	−3.059	−3.059	−2.903	−3.059	−2.845	−2.746
p-value	—	—	2.218×10^{-3}	2.218×10^{-3}	2.218×10^{-3}	2.218×10^{-3}	3.702×10^{-3}	2.218×10^{-3}	4.439×10^{-3}	6.040×10^{-3}

We also compare the convergence performance of MNILS with four benchmark algorithms. Fig.9 shows the convergence curves of these five algorithms. The three population-based algorithms use the same population initialization method, and they consistently underperform the two search-based algorithms throughout the entire iteration cycle. VNS adopts the same initialization method as MNILS, so it can start from the same initial point as MNILS. However, as the iteration proceeds, MNILS dem-

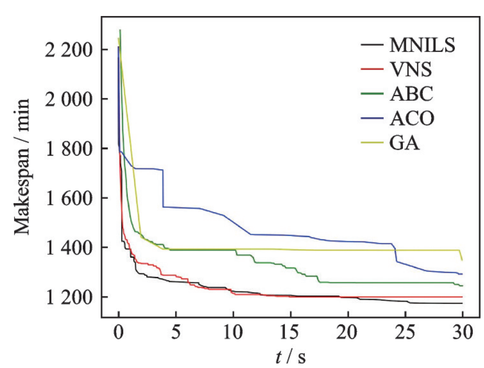

Fig.9 Convergence curves of MNILS and comparative algorithms

onstrates strong search capability and eventually converges to a better local optimum.

6 Conclusions

A novel task scheduling problem for UAV swarm-based power grid maintenance is introduced, which comprehensively considers complex constraints including UAV energy limitations and communication range. To solve the UAVS-LCR problem, an MNILS algorithm is proposed, featuring enhanced exploration capabilities through sequential swap operations. MNILS demonstrates the ability to obtain high-quality solutions for medium and large-scale instances containing up to 1 000 inspection points within 1 min. The proposed problem model and its solution algorithm can be effectively applied to wide-area inspection, maintenance, and transportation scenarios. The communication range constraint can be generalized to describe the executability of tasks by UAV swarms. For UAV swarm scheduling problems under complex communication conditions and in heterogeneous equipment environments, the methodological framework proposed in this study offers an effective solution.

Appendix Communication Range

To ensure the continuous availability of the control link between the UAV and the ground base station, the calculation method of the communication range is elaborated here. When the distance between a UAV and the base station is R, the received signal power is

$$P_r(R)=P_r+G-L(R)-L_{\mathrm{misc}} \tag{A.1}$$

where P_r is the transmission power; G the antenna gain; L_{misc} the miscellaneous line loss, and $L(R)$ the path loss.

The noise power at the receiver is

$$N=-174+10\log B+F \tag{A.2}$$

where 174 dBm/Hz is the thermal noise spectral density at room temperature; B the bandwidth; and F the receiver noise figure. Thus, the communication signal-to-noise ratio (SNR) between the UAV and the base station can be expressed as

$$\mathrm{SNR}(R)=P_r(R)-N \tag{A.3}$$

To guarantee communication quality, we set γ as the minimum SNR threshold. The maximum allowable path loss can then be derived as

$$L(R)<P_r+G-L_{\max}-N-\gamma \tag{A.4}$$

Note that the right side of the inequality is a constant, denoted as $L_{\max}$. In the context of power grid inspection, UAVs typically operate at relatively high altitudes with relatively open inspection paths. Therefore, the air-to-ground link can be modeled on a large scale using free-space propagation as the baseline. This paper adopts the free-space attenuation calculation method provided by ITU-R Recommendation P.525. When frequency is in the unit of MHz and the distance in km

$$L(R)<32.45+20\log f_m+20\log R \tag{A.5}$$

The maximum communication range between the base station and the UAV is

$$R_{\max}=10^{\left(\frac{L_{\max}-32.45-20\log f_m}{20}\right)} \tag{A.6}$$

where f_m is the communication frequency.

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通讯范围受限的无人机集群任务调度问题研究

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摘要:随着无人机技术的广泛应用,无人机集群的任务调度已成为提升作业效率的重要手段。现有研究大多对简化了无人机作业的工艺规则,难以准确刻画实际作业约束下无人机对不同任务的适应性差异。为弥补这一不足,本文提出一种通讯范围受限的无人机集群任务调度问题(Unmanned aerial vehicle swarm task scheduling problem with limited communication range, UAVS-LCR),并建立整数规划模型进行形式化描述。为求解该问题,设计了一种多邻域迭代局部搜索算法(Multi-neighborhood iterative local search, MNILS),采用双向链表解表示方法以降低基本邻域操作的计算复杂度。该算法通过贪婪构造策略生成高质量初始解,结合插入搜索、多交换搜索与2-opt算子实现多邻域交替探索,并引入模拟退火机制平衡搜索效率与多样性。本文所提出的方法能够为各类广域覆盖无人机巡检场景与异构无人机协同作业场景提供了一种有效的解决方案。在12个电力检修测试算例上的实验表明,MNILS算法在解的质量和大规模问题可扩展性上均显著优于遗传算法、人工蜂群算法、蚁群算法及变邻域搜索算法。

关键词:无人机集群;任务调度;邻域结构;迭代局部搜索