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Multi-UAV path planning methodology for dual-task power inspection scenarios based on genetic algorithm

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Abstract: With the continuous expansion of power systems, employing unmanned aerial vehicles (UAVs) for power inspection has become a practical necessity. In this paper, two critical inspection tasks in single-depot, multi-UAV scenarios are investigated: target point inspection and transmission line inspection. For the target point inspection problem, a mathematical model incorporating maximum flight distance constraints is established, and an improved genetic algorithm that integrates the 2-opt operator and an adaptive mutation rate mechanism is proposed. Experimental results demonstrate that the improved algorithm achieves superior solution quality and convergence stability. For the transmission line inspection problem, an optimisation model is developed to minimise the total flight distance. An adaptive genetic algorithm (AGA) is proposed to solve this model. Comparative experiments on maps of different scales verify that AGA significantly reduces the total flight distance and optimises the number of dispatched UAVs compared to the classical adaptive genetic algorithm.

Keywords: unmanned aerial vehicles; UAVs; target point inspection; transmission line inspection; genetic algorithm; GA.

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Biographical notes: Haitao Li graduated from Nanjing Institute of Technology in China with a Bachelor's degree and has been working at the State Grid Changzhou Power Supply Company for over 20 years. He is passionate about research in the field of drone-based power inspection, encompassing the study and application of image recognition for power components as well as drone-based laser radar imaging technology. Currently, he holds the position of a Senior Engineer, responsible for power transmission and equipment management and maintenance. He has applied for over ten projects in the power industry and achieved a transformation of results worth up to millions of RMB.

Chao Che graduated from China Nanjing University Jinling College with a Bachelor's degree and has accumulated more than five years of professional experience at State Grid Changzhou Power Supply Company. He currently serves as a Project Manager, where he is mainly responsible for the application, completion, and acceptance of projects related to drone-based power inspection technology. In this role, he has gained solid experience in project coordination, technical management, and process implementation. With a strong professional foundation and practical industry expertise, he has contributed to the advancement of innovative inspection methods in the power sector. At present, he holds the title of Junior Engineer.

Chenyang Duan graduated from a reputable university with a Bachelor's degree in Engineering and has developed a solid foundation in power systems and related technologies. After joining a power supply company, he has accumulated several years of hands-on experience in technical operations and project execution. He is currently engaged in the research and application of intelligent inspection technologies, including the integration of digital tools and modern equipment into daily maintenance work. In his role, he participates in project planning, on-site implementation, and performance evaluation, demonstrating strong analytical and problem-solving abilities. With a diligent work ethic and continuous learning mindset, he has steadily improved his professional competence and contributed to enhancing efficiency and safety in power system operations.

Xin Zhang graduated with a Bachelor's in an engineering-related field and has built strong expertise in UAV applications within the power industry. Since joining a power supply company, he has been actively involved in drone-based power line inspection, focusing on precise flight operations in complex environments. He is proficient in route planning, autonomous flight control, and real-time data acquisition, ensuring efficient and safe inspection of transmission and distribution lines. He has extensive experience in handling various terrain and weather conditions, demonstrating excellent operational stability and risk awareness. His work significantly improves inspection efficiency, reduces manual workload, and enhances the accuracy of fault detection.

Li Sun graduated from Southeast University with a Bachelor's degree in 2012, obtained a PhD from Tsinghua University in 2016, visited Cornell University in 2017, and worked at Southeast University in 2017. He mainly engages in research on modelling, simulation, control, and system software and hardware integration of typical and renewable energy systems such as fuel cells, electrolytic cells, integrated energy systems, and heat pump air conditioning. Accumulatively published over 70 SCI papers, more than ten Chinese core papers, and authorised over 30 invention patents. He hosted four National Natural Science Foundation and Youth Fund projects, participated in 15 achievement transformation and key research and development projects, with a cumulative achievement transformation of millions of RMB.

1 Introduction

With the continuous growth in electricity demand, ensuring the stability of power systems has become increasingly critical. Power inspection plays a vital role in maintaining the stability of power systems (Zhang et al., 2025a). Traditional power inspection methods mainly rely on manual inspection. However, in urban areas with densely interlaced transmission lines or in mountainous regions with complex terrain, manual inspection is often inefficient, costly, and poses significant safety risks (Qin et al., 2018). The advancement of unmanned aerial vehicle (UAV) technology has created new opportunities for power inspection. Compared to traditional manual methods, UAVs offer advantages including compact size, high mobility, and reduced costs. The deployment of UAVs in power inspection can not only significantly enhance efficiency and reduce error rates but also minimise the potential risks inspectors face when exposed to high-voltage equipment, thereby safeguarding their lives (Chung et al., 2020). Additionally, embedding algorithms in UAVs to enable intelligent inspection has become a popular research focus. By analysing inspection data, the safety of the power system can be further ensured (Liu et al., 2024). UAVs have already been widely adopted in various inspection scenarios, particularly in the power sector. A notable example is the large-scale pilot program in Guizhou Province, China, where multi-rotor UAV swarms were deployed to comprehensively inspect UHV transmission lines in mountainous areas. Similarly, Xcel Energy in the USA has greatly improved inspection efficiency across its grid infrastructure in Colorado and Minnesota by utilising proprietary autonomous UAV systems (Liu et al., 2019).

UAV power inspection tasks can be broadly classified into two categories: target point inspection and transmission line inspection. Target point inspection tasks primarily focus on examining the status of tower components, such as damage to lightning protection facilities, deformation of discharge hammers, and breakage in insulator strings (Wang et al., 2020). In contrast, transmission line inspection tasks assess whether there are safety risks within the transmission line corridor (Wang et al., 2024). These two types of inspections represent a ‘point-to-line’ relationship and are inseparable. In practice, target point inspection provides precise diagnostics for the operational condition of individual equipment, while transmission line inspection evaluates the overall safety status of the entire line. Conducting regular inspections of these two types of targets is crucial for ensuring the stable operation of the power system, reducing fault-related losses, extending equipment lifespan, and preventing secondary disasters (Zhao et al., 2023).

In the model of target point inspection tasks, the tower components requiring inspection are treated as target points. The objective is to assign these target points to each dispatched UAV and determine the optimal visiting sequence (Han et al., 2025). Essentially, the target point inspection problem can be formulated as a multiple traveling salesman problem (MTSP). In MTSP, n nodes are distributed among k salesmen, each of whom departs from a starting point, visits a subset of nodes, and ends at a designated endpoint, with the goal of minimising the total travel distance of all salesmen (Liu et al., 2025). To improve the applicability of the target point inspection model in specific scenarios, several studies have proposed extensions to the basic framework (Liu et al., 2024; Li et al., 2024b; Chen et al., 2025; He et al., 2025). Li et al. (2024b) incorporated multi-wind-field conditions into UAV inspection planning, refining the flight cost to account for distance, time, and wind field variation. Liu et al. (2024) introduced a

risk-level assessment mechanism and time window constraints, aiming to maximise the average utility of UAV inspections. Chen et al. (2025) integrated a charging mechanism into multi-depot, multi-UAV inspection, enabling UAVs to dynamically schedule charging stops during task execution. He et al. (2025) developed a bi-objective optimisation model for large-scale multi-UAV inspection, aiming to minimise both the total flight distance of all UAVs and the maximum flight distance of any single UAV.

Due to the complexity of the target point inspection problem, heuristic algorithms are predominantly used for its solution, including genetic algorithm (GA) (Chen et al., 2025), ant colony optimisation (ACO) (Sheng, 2024), and particle swarm optimisation (PSO) (Yan et al. (2023)). Sheng (2024) enhanced ACO by introducing Tent chaotic mapping for initial pheromone distribution and implementing adaptive adjustment of the evaporation coefficient, thereby enabling efficient multi-UAV inspection in agricultural applications. Yan et al. (2023) developed a hybrid PSOHAC algorithm, which combines ACO for local refinement and PSO for global optimisation, to plan optimal UAV inspection paths in forest fire scenarios. Beyond the standalone use of heuristic algorithms, integrating them with deep learning algorithms has become a common approach to solving target point inspection problems. Zhang et al. (2025b) combined a heuristic algorithm with a deep reinforcement learning algorithm to propose a robust inspection solution for offshore wind farms. Among various heuristic algorithms, GA is widely used in combinatorial optimisation problems because of its high flexibility and global search capability (Ye et al., 2020). To enhance algorithm performance, numerous improvements to GA have been proposed in existing studies, which can be broadly categorised into global strategies and local strategies. Wu et al. (2021) integrated simulated annealing into GA's secondary selection process, leveraging its suboptimal solution acceptance mechanism to enhance population diversity and global search capability. Bai et al. (2018) developed a hybrid multi-population GA that incorporates multi-offspring strategies and cross-mating mechanisms to address multi-vehicle task allocation problems. For heterogeneous UAV cooperative area mapping, Li et al. (2024a) proposed a dual-chromosome encoded GA with a conflict resolution mechanism, and experiments demonstrated that this encoding method significantly enhances GA's performance. The above studies focus on global strategies, which expand the search range and maintain population diversity, but may increase computational cost and slow convergence. Conversely, Bai et al. (2025) addressed multi-UAV electronic product delivery by designing a novel crossover operator and introducing multiple local search strategies to strengthen GA's local exploration capability. Chen et al. (2025) addressed multi-depot multi-UAV tower allocation using fuzzy grouping strategies and incorporated tabu search as a local search mechanism for GA. These studies primarily employ local improvement strategies, which improve computational efficiency and local optimisation precision but may lead to entrapment in local optima. Based on the above analysis, relying solely on either global or local improvement strategies has inherent limitations. Therefore, this paper combines the advantages of both approaches and proposes an improved GA in Section 3.1, which can effectively enhance algorithmic performance.

Most existing studies on UAV power inspection have focused exclusively on target point inspection while neglecting transmission line inspection. Indeed, incorporating transmission lines into power inspection programs is imperative. The goal of transmission line inspection is to enable multiple UAVs to traverse transmission lines in the shortest time with a balanced plan through reasonable path planning. This essentially constitutes a path coverage problem, which existing studies typically model as units represented by

graph structures (Cabreira et al., 2019). For example, the path coverage problem can be transformed into the vehicle routing problem (VRP) to cover graph nodes and into the Chinese postman problem (CPP) or the rural postman problem (RPP) to cover graph edges. Several studies have extended models of edge covering problems, especially the transmission line inspection problem (Matlekovic and Schneider Kamp, 2023; Campbell et al., 2021; Luo et al., 2019). Matlekovic and Schneider Kamp (2023) introduced a multi-weight model with the objective of minimising the maximum UAV flight distance, differentiating inspection costs from no-load flight costs to achieve weighted optimisation. Campbell et al. (2021) addressed the length-constrained RPP, classifying transmission lines into mandatory edges and non-mandatory edges. Their approach requires UAVs to traverse mandatory edges exactly once while allowing repeated traversal of non-mandatory edges. Luo et al. (2019) proposed a bi-level arc routing problem model for urban road inspection using vehicles and UAVs, which allows the same UAV to perform multiple flights. In this paper, the transmission line inspection problem is modelled as a multiple Chinese postmen problem (MCPM). Given a connected graph comprising multiple transmission lines, the objective is to determine the shortest set of closed paths that enable multiple UAVs to traverse each edge at least once. However, the prevailing mathematical models in the above studies typically employ goal-point-based path planning variables (such as x_i, j, k , indicating whether the UAV k travels from i to j), which limits their ability to incorporate complex constraints. This paper introduces a hybrid approach combining this type of decision variable with route-indexed edge assignment variables (such as y_e, k , indicating whether edge e is assigned to UAV k). The former constructs the Eulerian circuit, while the latter captures the edge assignment scheme. This clear functional division not only enables the model to accommodate complex constraints, but also ensures seamless integration of the assignment variables with the proposed solution algorithm, thereby facilitating the design of a well-structured solution.

Since the transmission line inspection problem is NP-Hard, existing studies predominantly employ exact algorithms or heuristic approaches for small-scale instances. Altin and Sipahioglu (2024) tackled the arc routing problem for UAVs with multiple service requirements using a simulated annealing algorithm. Xie et al. (2024) proposed a two-phase heuristic algorithm for the RPP: the first phase simplifies complex route networks, and the second phase solves the simplified RPP using an integer programming model. Campbell et al. (2021) developed a heuristic algorithm with a multi-level segmentation mechanism for transmission lines, which iteratively splits promising segments and eliminates unused splitting points to minimise no-load travel costs. Ahr and Reinelt (2006) used Tabu search to solve the MCPM, aiming to minimise the maximum individual cost. Experimental results showed a 10-20% average improvement in optimal solutions compared to alternative heuristics. Matlekovic and Schneider Kamp (2023) utilised the OR-Tools solver for the multi-weight MCPM, and comparative experiments demonstrated its superior performance over other solvers. However, real-world applications often involve large-scale power grid networks, while the above studies primarily validated their approaches on small-scale maps and did not consider potential algorithmic failure risks in extensive networks. To address these limitations, this paper proposes an adaptive genetic algorithm (AGA) in Section 3.2 for the transmission line inspection problem. Building upon the classical GA, the proposed AGA incorporates an adaptive parameter strategy and employs a dedicated chromosome encoding scheme based on the edge assignment variables in our model. Furthermore, the experimental

evaluation comprehensively compares the proposed AGA with the classical GA across maps of varying types and scales.

Based on the analysis presented above, existing studies on these two types of inspection problems have certain limitations, which are effectively addressed herein. The main contributions of this paper are summarised as follows:

- An improved GA is proposed for solving the target point inspection problem. The main enhancements are: a. incorporating a 2-opt operation after mutation to refine offspring paths, thereby enhancing local search capability; b. introducing an adaptive mutation rate mechanism to prevent entrapment in local optima and accelerate convergence. The effectiveness of the proposed algorithm is validated on maps with varying numbers of target points and through comparisons with three other algorithms on different test sets, demonstrating its superior performance, solution quality, and convergence stability.
- The transmission line inspection model introduces edge assignment variables to ensure that each edge in the graph is assigned to appropriate UAVs for inspection, while allowing multiple traversals if necessary. This approach ensures that all UAV routes form connected paths starting and ending at the depot, and prevents unnecessary detours through optimised edge allocation. Moreover, these edge assignment variables are effectively integrated with the proposed solution algorithm via a specially designed chromosome encoding scheme.
- An AGA is employed to solve the transmission line inspection problem, featuring two key innovations: a. dynamic adaptation of crossover and mutation rates based on population diversity and iteration progress; b. a dedicated chromosome encoding scheme derived from edge assignment variables, combined with greedy strategy decoding. Experimental results demonstrate that the proposed AGA outperforms the classical GA across various map types and scales, confirming its improved solution quality and operational efficiency.

The structure of the remaining parts of this paper is as follows. Section 2 establishes mathematical models for two types of inspection problems. Section 3 introduces algorithms to solve these two types of inspection problems. Section 4 presents experimental analyses, including effectiveness validation and comparative analysis. Finally, Section 5 concludes the paper and proposes future research directions.

2 Problems modelling

This section presents the modelling of the target point inspection problem and the transmission line inspection problem. Section 2.1 describes these two categories of problems, Section 2.2 establishes the mathematical model for target point inspection, and Section 2.3 develops the mathematical model for transmission line inspection.

2.1 Problem description

A single-depot, multi-UAV power inspection scenario is considered, in which the inspection tasks are categorised into two types: target point inspection and transmission line inspection. For the target point inspection problem, the assignment of target points to

multiple UAVs operating from a single depot is investigated. Given a set of UAVs $K = \{1, 2, \dots, m\}$ and a set of target points $V = \{1, 2, \dots, n-1\}$, each dispatched UAV k is required to execute a closed route that starts and ends at the depot d , covering its assigned subset of target points while complying with the maximum allowed flight distance constraint, each target point $i \in V$ must be visited exactly once by a single UAV, ensuring complete coverage. The objective is to optimally allocate target points to UAVs and determine their visiting sequences so that the total flight distance of all UAVs is minimised.

For the transmission line inspection problem, the objective is to minimise the total flight distance of all UAVs. The problem is defined on an undirected graph $G = (V, E)$, where V represents the set of target points and E denotes the set of transmission lines. Upon receiving an inspection request, transmission lines are allocated to each dispatched UAV, with the requirement that each UAV's flight path forms a closed loop that starts and ends at the depot d . To ensure the continuity of the UAV path and maintain the feasibility of the solution, UAVs are allowed to traverse a transmission line multiple time.

2.2 Target point inspection model

To construct mathematical models for the two types of inspection tasks, the descriptions of the symbols involved are presented in Table 1.

The multi-UAV target point inspection model is formulated as follows.

$$\min \sum_{i \in d \cup V} \sum_{j \in d \cup V} \sum_{k \in K} x_{ij}^k r_{ij} \quad (1)$$

subject to

$$\sum_{j \in V} x_{dj}^k = \sum_{i \in V} x_{id}^k = z_k, \forall k \in K \quad (2)$$

$$\sum_{j \in d \cup V} x_{ji}^k = \sum_{j \in d \cup V} x_{ij}^k, \forall i \in V, k \in K \quad (3)$$

$$\sum_{j \in d \cup V} \sum_{k \in K} x_{i,j}^k = 1, \forall i \in V \quad (4)$$

$$u_i^k - u_j^k + nx_{ij}^k \leq n-1, \forall i, j \in V, k \in K \quad (5)$$

$$\sum_{i \in d \cup V} \sum_{j \in d \cup V} x_{ij}^k r_{ij} \leq r_{\max}, \forall k \in K \quad (6)$$

$$x_{ij}^k \in \{0, 1\}, \forall i, j \in d \cup V, k \in K \quad (7)$$

$$u_i^k \in \{1, 2, \dots, n\}, \forall i \in V, k \in K \quad (8)$$

Objective (1) aims to minimise the total flight distance of all UAVs. Equation (2) ensures that each dispatched UAV departs from the depot and returns to it upon completing its mission. Equation (3) guarantees that for each UAV, the number of arrivals at any target point equals the number of departures. Equation (4) specifies that each target point is visited exactly once by a single UAV. Equation (5) eliminates subtours in UAV routes.

Equation (6) restricts the flight distance of each UAV to not exceed the maximum allowed flight distance. Equations (7) and (8) define the variable domains.

Table 1 Descriptions of symbols in the two inspection models

Type	Symbol	Definition	Unit
Variable	$x_{i,j}^k$	Binary variable: 1 if UAV k flies from node i to node j , 0 otherwise	-
	y_e^k	Binary variable: 1 if transmission line e is assigned to UAV k , 0 otherwise	-
	l_k	Flight distance of UAV k	km
	u_i^k	Sequence index of target points i visited by UAV k	-
	z_k	Binary variable: 1 if UAV k is dispatched for inspection, 0 otherwise	-
Parameter	$r_{i,j}$	Distance of path (i, j)	km
	r_{max}	Maximum flight distance per UAV	km
	n	Total number of nodes	-
	m	Total number of UAVs	-
	C	Maximum number of edges assigned to a single UAV	-
Index	d	Depot	-
	V	Set of target points	-
	K	Set of UAVs	-
	E	Set of transmission lines	-

2.3 Transmission line inspection model

The mathematical model for the transmission line inspection problem is formulated as follows.

$$\min \sum_{k \in K} l_k \quad (9)$$

subject to

$$\sum_{k \in K} y_e^k \geq 1, \forall e \in E \quad (10)$$

$$z_k \geq \frac{1}{|E|} \sum_{(i,j) \in E} y_e^k, \forall k \in K \quad (11)$$

$$\sum_{j \in V} x_{ji}^k = \sum_{i \in V} x_{id}^k = z_k, \forall k \in K \quad (12)$$

$$\sum_{j \in d \cup V} x_{ji}^k = \sum_{j \in d \cup V} x_{ij}^k, \forall i \in V, k \in K \quad (13)$$

$$x_{ij}^k + x_{ji}^k \geq y_e^k, \forall e = (i, j) \in E, k \in K \quad (14)$$

$$\sum_{e \in E} y_e^k \leq Cz_k, \forall k \in K \quad (15)$$

$$x_{ij}^k, y_e^k, z_k \in \{0,1\}, \forall k \in K \quad (16)$$

Objective (9) aims to minimise the total flight distance of all UAVs. Equation (10) ensures that each transmission line is assigned to at least one UAV. Equation (11) guarantees that only dispatched UAVs are allocated transmission lines. Equations (12) and (13) collectively ensure that the trajectory of each dispatched UAV forms a closed loop that starts and ends at the depot. Equation (14) requires that any transmission line assigned to a UAV must be physically traversed, thereby preventing the allocation of transmission lines without actual coverage. Equation (15) ensures that the number of transmission lines assigned to each UAV does not exceed the maximum allowed. Equation (16) specifies the domains of the variables.

3 Algorithm design

This section delineates the algorithmic frameworks for the two categories of inspection tasks. Section 3.1 introduces an improved genetic algorithm (IGA) for the target point inspection problem presenting its workflow along with two specialised refinement strategies. Section 3.2 presents the workflow of the AGA for the transmission line inspection problem and describes the greedy algorithm used for chromosome decoding.

3.1 Target point inspection algorithm

The multi-UAV target point inspection problem is classified as an NP-hard problem. In high-dimensional environments, its computational complexity increases exponentially with the number of target points. Exact algorithms often fail to efficiently obtain optimal solutions in practical scenarios due to their prohibitive computation time. As a type of heuristic algorithm, GA emulates the process of natural selection and population evolution, demonstrating superior capability in exploring near-optimal solutions within complex solution spaces.

3.1.1 IGA workflow

The classic genetic algorithm (CGA), a widely employed metaheuristic for optimisation problems, inherently exhibits several well-documented limitations in practical application. These constraining factors, notably including high solution path tortuosity, susceptibility to entrapment in local optima, and relatively slow convergence rates, significantly constrain its efficacy in solving complex optimisation problems, impacting both computational efficiency and final solution quality. Such deficiencies can potentially yield solutions deviating from the global optimum while incurring unnecessary computational resource expenditure and temporal costs. To systematically address these recognised challenges and enhance the algorithm's overall performance, key refinements were introduced to the CGA framework. This was achieved through the strategic incorporation of the 2-optoperator and the integration of an intelligent adaptive mutation rate mechanism. The algorithmic workflow is outlined as follows.

Figure 1 Procedure of the proposed improved genetic algorithm.**Algorithm 1** Improved Genetic Algorithm**Input:** Number of UAVs K , number of target points $|V|$, population size N , maximum iteration count t_{max} **Output:** Optimal solution X^*

```

1:  $P_0 \leftarrow \text{InitializePopulation}(N, |V|, K)$  // Hybrid initialization
2:  $t \leftarrow 0$ 
3:  $F_{best} \leftarrow -\infty$  // Store the fitness of the optimal solution
4:  $X^* \leftarrow \emptyset$  // Store the optimal solution
5: while  $t < t_{max}$  do
6:    $F \leftarrow \emptyset$ 
7:    $P_m^t \leftarrow P_m^{base} \left( 1 + \beta \left( 1 - \frac{t}{t_{max}} \right) \right)$  // Adaptive mutation rate
8:   for individual in  $P_t$  do
9:      $F_{current} \leftarrow \text{Fitness}(\text{individual})$ 
10:     $F \leftarrow F \cup F_{current}$ 
11:    if  $F_{current} > F_{best}$  then
12:       $F_{best} \leftarrow F_{current}$ 
13:       $X^* \leftarrow \text{individual}$ 
14:    end if
15:  end for
16:   $P_{t+1} \leftarrow \text{EliteSelection}(P_t, F, e)$  // Preserve elite individuals
17:   $P_{selected} \leftarrow \text{TournamentSelection}(P_t, F, N)$ 
18:  while  $|P_{t+1}| \leq N$  do
19:     $P_a, P_b \leftarrow \text{RandomSelect}(P_{selected}, 2)$ 
20:     $P_{child} \leftarrow \text{Crossover}(P_a, P_b)$ 
21:     $P_{child} \leftarrow \text{Mutation}(P_{child})$ 
22:     $P_{child} \leftarrow \text{TwoOption}(P_{child})$ 
23:     $P_{t+1} \leftarrow P_{t+1} \cup P_{child}$ 
24:     $|P_{t+1}| \leftarrow |P_{t+1}| + 1$ 
25:  end while
26:   $t \leftarrow t + 1$ 
27: end while
28:  $X^* = \text{TwoOption}(X^*)$ 
29: return  $X^*$ 

```

- 1 Initialisation: after configuring the relevant parameters, a hybrid initialisation strategy combining greedy initialisation, K-Means clustering initialisation, and random initialisation is proposed to generate a diverse and high-quality initial population.
- 2 Parameter update and fitness calculation: at the beginning of each iteration, the mutation rate is first updated, followed by fitness calculation. The fitness function serves as a critical metric for evaluating individual quality, with higher fitness values corresponding to superior solutions. The fitness function is defined as:

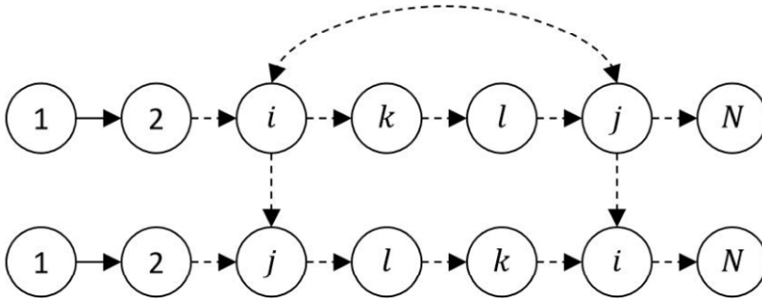
$$F = \frac{1}{\sum_{i \in d \cup V} \sum_{j \in d \cup V} \sum_{k \in K} x_{ij}^k r_{ij} + \sum_k \max \left(0, \alpha \left(\sum_{i \in d \cup V} \sum_{j \in d \cup V} x_{ij}^k r_{ij} - r_{\max} \right) \right) + \varepsilon} \quad (17)$$

where $\sum_k \max \left(0, \alpha \left(\sum_{i \in d \cup V} \sum_{j \in d \cup V} x_{ij}^k r_{ij} - r_{\max} \right) \right)$ represents a penalty term for UAVs

violating maximum distance constraints, denotes the total flight distance of all dispatched UAVs, and ϵ is a minimal constant to prevent division by zero. After the fitness calculation and ranking, the optimal solution is updated. Furthermore, ϵ elite individuals are preserved and directly added to the subsequent generation's population.

- 3 Selection operation: a tournament selection strategy is employed. In each iteration, a fixed number of individuals are sampled from the population, and the individual with the highest fitness is added to the mating pool.
- 4 Crossover operation: the path inheritance crossover operator is employed. Each UAV path in the offspring is randomly selected from one of the two parents. During selection, duplicate nodes are eliminated and unassigned nodes are subsequently inserted randomly into paths.
- 5 Mutation operation: four mutation operators are designed:
 - a Swap – randomly exchange two target points between different paths
 - b Move – relocate a point from one path to another
 - c Inversion – reverse a randomly selected subsequence within a path
 - d Path reconstruction. – delete a path and reassign its target points to other paths.
- 6 2-opt operation: individuals generated through crossover and mutation are further improved by applying the 2-opt operator with a certain probability.
- 7 Output: the iterative execution of Steps 2–6 continues until the termination criteria are satisfied. The optimal solution, further refined by the 2-opt operator, is then output as the final solution.

Figure 2 Principle illustration of the 2-opt operator



3.1.2 2-opt operator

The 2-opt operator, a local search method, effectively resolves path crossing issues and reduces route tortuosity (Feng et al., 2024). In IGA, it is employed to enhance the algorithm's local search capability. The fundamental principle of the 2-opt operator is as follows: it iteratively examines pairs of non-adjacent points along a UAV's path, reverses the segment between these two points, calculates the objective function values of the solution before and after the reversal, and retains the superior path. The principle of the 2-opt operator is illustrated in Figure 2, which depicts the reversal of the segment

between target points i and j . By continuously reversing segments, the 2-opt operator finds the optimal path for each UAV under the current target point allocation.

3.1.3 Adaptive mutation rate

To mitigate the tendency of CGA to converge to local optima, IGA adopts an adaptive mutation rate instead of a fixed rate. The computational formulation is given in (18):

$$P_m^t = P_m^{base} \left(1 + \beta \left(1 - \frac{t}{t_{max}} \right) \right) \quad (18)$$

where P_m^t denotes the current mutation rate at iteration t , P_m^{base} represents the basic mutation rate, signifies the expansion factor, and t_{max} indicates the maximum number of iterations. By adaptively adjusting the mutation rate, the algorithm maintains high population diversity in the early stages and gradually focuses on fine-grained search near high-quality solutions in the later stages.

Furthermore, a stagnation escape mechanism is implemented through (19):

$$P_m^{t+1} = \min((1 + \gamma)P_m^t, 0.5) \quad (19)$$

when algorithmic stagnation persists for more than 100 generations, the mutation rate increases by $(\gamma \times 100)$ % per iteration, capped at 0.5. This mechanism effectively mitigates premature convergence to local optima.

3.2 Transmission line inspection algorithm

The multi-UAV transmission line inspection problem also exhibits NP-hard characteristics, with its solution space growing exponentially as the problem scale increases. For small-scale instances, exact algorithms are capable of obtaining theoretically optimal solutions. However, when addressing the large-scale scenarios commonly encountered in practical applications, exact algorithms face significant computational challenges. To overcome these limitations, the AGA is employed to solve the transmission line inspection problem.

3.2.1 AGA workflow

AGA introduces a parameter self-adaptation mechanism based on CA. By dynamically adjusting the crossover and mutation rates, it effectively achieves a balance between exploration and exploitation, which can accelerate convergence and facilitate escape from local optima. The algorithmic workflow is as follows:

- 1 Initialisation: random initialisation is employed to generate the initial population and con-figure relevant algorithmic parameters.
- 2 Fitness calculation: equation (20) presents the fitness function designed for AGA in this paper, where l_k denotes the flight distance of UAV k .

$$F = \sum_{k \in K} l_k \quad (20)$$

Figure 3 Procedure of the proposed adaptive genetic algorithm**Algorithm 2** Adaptive Genetic Algorithm**Input:** Number of UAVs K , number of transmission lines $|E|$, population size N , maximum generations $t_{\max}$ **Output:** Optimal solution X^*

```

1:  $P_0 \leftarrow \text{InitializePopulation}(N, |E|, K)$  // Random initialization
2:  $t \leftarrow 0$ 
3: while  $t < t_{\max}$  do
4:    $F \leftarrow \emptyset$ 
5:    $P_c^t \leftarrow \text{Update}(P_c^{t-1})$  // Update crossover rate
6:    $P_m^t \leftarrow \text{Update}(P_m^{t-1})$  // Update mutation rate
7:   for individual in  $P_t$  do
8:      $F_{\text{current}} \leftarrow \text{Fitness}(\text{individual})$ 
9:      $F \leftarrow F \cup F_{\text{current}}$ 
10:  end for
11:   $P_{t+1} \leftarrow \emptyset$ 
12:   $P_{\text{selected}} \leftarrow \text{TournamentSelection}(P_t, F, N)$ 
13:  while  $|P_{t+1}| \leq N$  do
14:     $P_a, P_b \leftarrow \text{RandomSelect}(P_{\text{selected}}, 2)$ 
15:     $P_{\text{child}} \leftarrow \text{Crossover}(P_a, P_b)$ 
16:     $P_{\text{child}} \leftarrow \text{Mutation}(P_{\text{child}})$ 
17:     $P_{t+1} \leftarrow P_{t+1} \cup P_{\text{child}}$ 
18:     $|P_{t+1}| \leftarrow |P_{t+1}| + 1$ 
19:  end while
20:   $t \leftarrow t + 1$ 
21: end while
22: return  $X^*$ 

```

- 3 Adaptive crossover and mutation rates: the crossover rate P_c , and mutation rate P_m are adaptively adjusted based on population diversity and iteration progress, respectively. Their formulations are defined as:

$$P_c^t = \begin{cases} \max(P_c^{\min}, \theta_1 P_c^{t-1}), & \text{if } \text{diversity} < \text{div}_{\text{low}} \\ \min(P_c^{\max}, \theta_2 P_c^{t-1}), & \text{if } \text{diversity} > \text{div}_{\text{high}} \\ P_m^{t-1}, & \text{if } \text{div}_{\text{low}} \leq \text{diversity} \leq \text{div}_{\text{high}} \end{cases} \quad (21)$$

$$\text{diversity} = \frac{\sigma(F)}{F_{\text{ave}} - F_{\text{best}} + \varepsilon} \quad (22)$$

$$P_m^t = \begin{cases} \min(P_m^{\max}, \beta_1 P_m^{t-1}), & \text{if } \text{progress} < \text{pro}_{\text{low}} \\ \max(P_m^{\min}, \beta_2 P_m^{t-1}), & \text{if } \text{progress} > \text{pro}_{\text{high}} \\ P_m^{t-1}, & \text{if } \text{pro}_{\text{low}} \leq \text{progress} \leq \text{pro}_{\text{high}} \end{cases} \quad (23)$$

$$\text{progress} = \frac{t}{t_{\max}} \quad (24)$$

In equation (21), $\theta_1 < 1$ and $\theta_2 > 1$ denote the reduction and expansion factors for the adaptive crossover rate, where diversity represents population diversity, and div_{low} and div_{high} are the lower and upper bounds of population diversity. In equation (23), $\beta_1 > 1$ and $\beta_2 < 1$ represent the expansion and reduction factors for the adaptive

mutation rate, where progress indicates iteration progress, and pro_{low} and pro_{high} are the lower and upper bounds of iteration progress.

- 4 Selection operation: the selection operation employs a binary tournament strategy, in which high-quality individuals are selected based on fitness values, while those with lower fitness are added to the mating pool. Crossover and mutation operations: a two-point crossover strategy is employed, where two crossover points are randomly selected to facilitate the exchange of genetic segments between parental chromosomes.
- 5 Mutation operation stochastically resets gene values at a low probability, thereby preserving population diversity while exploring novel regions of the solution space.
- 6 Output: Steps 2–5 are iteratively executed until the termination criteria are satisfied, after which the optimal solution is output.

3.2.2 Encoding and decoding

An integer encoding scheme based on edge assignment is adopted, in which the chromosome structure is defined as an integer vector with dimensionality equal to the number of transmission lines E . As illustrated in Figure 4, the integer value at the genetic locus E , indicates that transmission line E_k is assigned to UAV d .

Figure 4 Chromosome encoding schematic (see online version for colours)

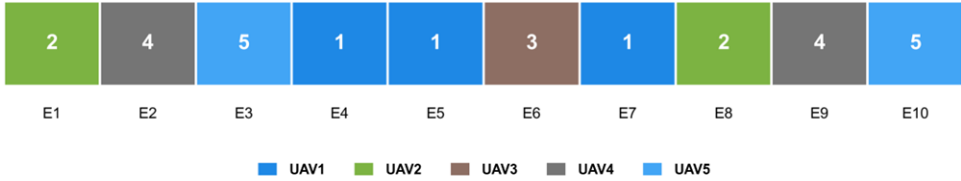


Figure 5 Structure of the greedy algorithm

Algorithm 3 Greedy Algorithm

Input: Assigned edges E_k , depot d , distance matrix D

Output: Path P_k , distance d_k

- 1: $P_k \leftarrow [d]$ // Initialize path with depot
 - 2: $current \leftarrow d$
 - 3: $unvisited \leftarrow E_k$
 - 4: **while** $unvisited \neq \emptyset$ **do**
 - 5: $e^* \leftarrow \underset{e \in unvisited}{\operatorname{argmin}} \min(D[current, u_e], D[current, v_e])$
 - 6: $p^* \leftarrow \underset{p \in \{u_{e^*}, v_{e^*}\}}{\operatorname{argmin}} D[current, p]$
 - 7: $q^* \leftarrow \{u_{e^*}, v_{e^*}\} \setminus \{p^*\}$
 - 8: $P_k \leftarrow P_k \oplus \text{ShortestPath}(current, p^*)$ // Add shortest path
 - 9: $P_k \leftarrow P_k \oplus [q^*]$ // Traverse edge e^*
 - 10: $current \leftarrow q^*$
 - 11: $unvisited \leftarrow unvisited \setminus \{e^*\}$
 - 12: **end while**
 - 13: $P_k \leftarrow P_k \oplus \text{ShortestPath}(current, d)$ // Return to depot
 - 14: $d_k \leftarrow \text{CalculatePathDistance}(P_k)$
 - 15: **return** P_k, d_k
-

During the optimisation process of AGA, each solution must be decoded to interpret the information carried by its chromosome. A greedy algorithm is employed for decoding: first, the transmission lines are sorted, and then these transmission lines are connected in sequence to form a closed path that starts from the depot, traverses all assigned edges, and finally returns to the depot. The pseudocode of the greedy algorithm used for chromosome decoding is presented as follows.

4 Experiments and analysis

4.1 Target point inspection experiments

In this section, effectiveness validation and comparative analysis of IGA are conducted, the settings of relevant parameters are presented in Table 2.

4.1.1 Effectiveness validation

To validate the effectiveness of IGA, both the Gurobi solver and IGA are applied to various maps with target point quantities ranging from 15 to 25. The Gurobi solver is used to obtain the exact optimal solutions for the target point inspection problem, The effectiveness of IGA is verified by comparing its results with those obtained from Gurobi. The comparative results are presented in Table 3.

Table 2 Parameter settings for experiments of IGA

<i>Object</i>	<i>Parameter</i>	<i>Value</i>
UAV	Number of UAVs in depot	3
	Maximum flight distance per UAV	300 km
IGA	Population size	100
	Maximum iterations	600
	Number of preserved elite solutions	5
	Crossover rate	0.9
	Basic mutation rate	0.2
	Amplification factor of mutation rate	4
	Proportion of mutation rate increase	0.1

As shown in Table 3, IGA produces solutions identical to those of Gurobi, thereby confirming the effectiveness of IGA. Furthermore, as the number of target points increases, the runtime of Gurobi rises dramatically, whereas the runtime of IGA increases much more slowly, eventually surpassing Gurobi in performance.

4.1.2 Comparative analysis

The performance of IGA is evaluated on six datasets selected from TSPLIB: eil22, eil30, eil33eil51, eil76, and eil101. The experimental results are systematically compared with those obtained from three classical heuristic algorithms: CGA, ACO, and artificial bee colony (ABC) algorithm. Table 4 summarises the performance metrics of all four algorithms over 30 independent runs for each dataset, while Figure 6 and Figure 7

illustrates their convergence characteristics and the results of all algorithms on the ei151 dataset.

Table 3 Comparison results of Gurobi and IGA

<i>Number of target points</i>	<i>Best optimal solution</i>		<i>Runtime (s)</i>		<i>Gap (%)</i>
	<i>Gurobi</i>	<i>IGA</i>	<i>Gurobi</i>	<i>IGA</i>	
15	431.81	431.81	7.15	22.42	0.00
16	457.57	457.57	2.11	24.59	0.00
17	445.54	445.54	3.10	25.07	0.00
18	519.88	519.88	6.49	24.59	0.00
19	414.46	414.46	5.81	25.48	0.00
20	439.92	439.92	10.01	29.16	0.00
21	479.15	479.15	16.85	29.98	0.00
22	445.30	445.30	67.02	29.25	0.00
23	418.69	418.69	102.21	34.99	0.00
24	448.14	448.14	114.58	40.15	0.00
25	515.76	515.76	303.38	66.48	0.00

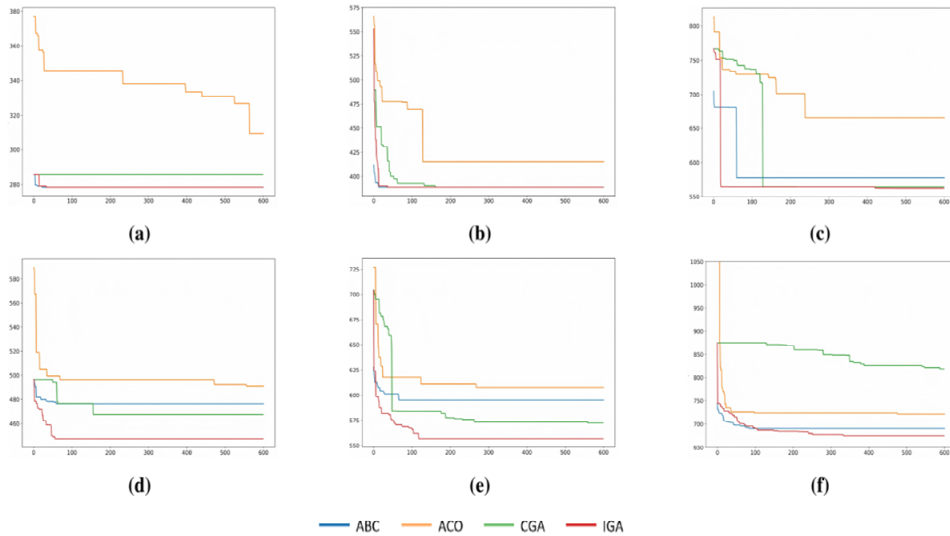
Table 4 Comparison results of four algorithms

<i>Dataset</i>	<i>Metric</i>	<i>CGA</i>	<i>ACO</i>	<i>ABC</i>	<i>IGA</i>
ei122	Best optimal solution	285.49	309.36	278.44	278.44
	Average optimal solution	285.49	330.52	279.02	282.15
	Average runtime(s)	3.43	7.16	3.51	6.71
ei130	Best optimal solution	389.09	415.59	389.09	389.09
	Average optimal solution	470.53	450.18	389.09	389.19
	Average runtime(s)	15.30	22.85	21.75	22.89
ei133	Best optimal solution	564.40	666.05	577.19	562.50
	Average optimal solution	695.58	704.46	665.03	598.00
	Average runtime(s)	14.26	22.67	14.38	14.87
ei151	Best optimal solution	461.56	493.18	472.26	444.57
	Average optimal solution	481.18	508.90	477.59	461.35
	Average runtime(s)	28.05	53.81	40.48	42.75
ei176	Best optimal solution	572.09	607.66	594.86	556.82
	Average optimal solution	598.58	625.96	598.05	563.76
	Average runtime(s)	54.50	108.06	66.25	72.46
ei1101	Best optimal solution	819.67	722.34	690.73	675.31
	Average optimal solution	852.07	764.74	695.14	712.91
	Average runtime(s)	129.53	186.12	123.03	142.11

CGA explores feasible solutions through crossover and mutation operations but lacks local search mechanisms and adaptive mutation probability adjustment. ACO incorporates positive feedback based on pheromones to enhance the probability of selecting high-quality paths (He et al., 2025). ABC proposed by Karaboga and Basturk

(2007), mimics the intelligent division of labour in honeybee colonies through a phased cooperative search mechanism.

Figure 6 Comparison of convergence curves of four algorithms, (a) Eil22, (b) Eil30, (c) Eil33, (d) Eil51, (e) Eil76, (f) Eil101 (see online version for colours)

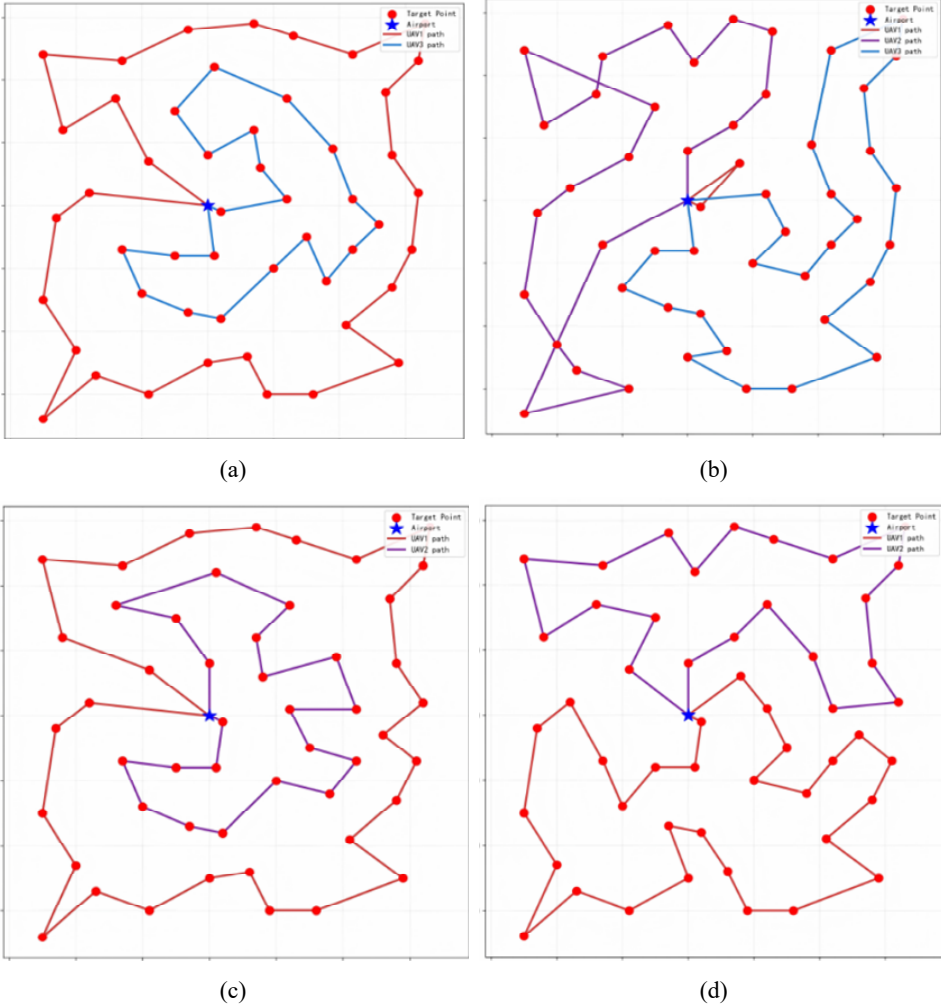


As shown in Table 4, the best optimal solutions obtained by CGA and ACO are consistently inferior to those of IGA among the three algorithms used for comparison. Although ABC achieves the same optimal solutions as IGA on the eil22 and eil30 datasets, its performance gradually worsens than that of IGA as the problem scale increases. Therefore, in general, IGA demonstrates the strongest optimisation capacity among the four algorithms, with its best optimal solution quality improving by an average of 4.70%, 9.18%, and 2.82% compared to the CGA, ACO and ABC respectively. Furthermore, a comparison of the average optimal solutions shows that most of the average optimal solutions obtained by IGA are not inferior to those of the other algorithms in all other cases, demonstrating the stability of the optimisation capacity of IGA.

The convergence curves in Figure 6 show that both ACO and CGA exhibit significant oscillations due to their limited ability to escape local optima. ABC exhibits a relatively smooth convergence curve; however, it is prone to being trapped in local optima. In contrast, IGA not only maintains moderate initial convergence across all datasets, but also preserves robust global search capability, demonstrating better convergence stability.

Figure 7 displays the optimal paths identified by all algorithms. While CGA, ACO, and ABC exhibit uneven distribution of UAV path lengths, IGA achieves a reasonable allocation of target points. Additionally, ACO utilises three UAVs, whereas the remaining algorithms only deploy two. As shown in Table 4, ACO demonstrates the poorest performance among all algorithms, indicating that employing more UAVs does not necessarily lead to better results.

Figure 7 The results of four algorithms on the eil51 dataset, (a) result of CGA, (b) result of ACO, (c) result of ABC, (d) result of IGA (see online version for colours)



4.2 Transmission line inspection experiments

In this section, a comparative analysis of CGA and AGA is performed, relevant parameters are shown in Table 5.

To compare the performance of CGA and AGA, two types of maps are designed for the experiments. The first type uses regular maps with incrementally added target points to enable a performance comparison of the two algorithms, effectively eliminating the uncertainties inherent in random maps and allowing for a preliminary evaluation of algorithm performance. The second type uses irregular maps, which simulate the physical connection structure of power grids in reality, Through Delaunay triangulation, the depot and target points are treated as a set of planar points to generate triangular grid

connections. Similarly, on the irregular maps, the performance of the two algorithms is evaluated by continuously increasing the number of target points.

Table 5 Parameter settings for experiments of AGA

<i>Object</i>	<i>Parameter</i>	<i>Value</i>
UAV	Number of UAVs in depot	8
	Maximum number of edges assigned to a single UAV	25
AGA	Population size	5 times the number of edges
	Maximum iterations	500
	Crossover rate	0.9
	Mutation rate	0.1
	Distribution index	3

Table 6 Comparison results of CGA and AGA on regular maps

<i>Number of target points</i>	<i>Optimal solution</i>		<i>Gap (%)</i>	<i>Runtime(s)</i>		<i>Number of dispatched UAVs</i>	
	<i>CGA</i>	<i>AGA</i>		<i>CGA</i>	<i>AGA</i>	<i>CGA</i>	<i>AGA</i>
10	578.12	578.12	0.00	12.51	14.81	4	3
11	630.46	630.46	0.00	14.86	17.68	4	4
12	684.00	639.52	6.50	17.87	19.98	5	3
13	738.46	692.82	6.18	20.12	24.46	4	2
14	747.03	700.38	6.24	23.42	26.68	6	3
15	779.39	754.44	3.20	25.08	30.96	5	3
16	760.93	760.93	0.00	28.59	34.06	4	2
17	815.62	815.62	0.00	32.09	38.36	7	4
18	862.99	821.31	4.83	37.11	42.64	6	3
19	935.77	876.52	6.33	40.41	47.64	6	4
20	956.67	881.58	7.85	44.70	51.58	6	4
21	1,017.70	937.22	7.91	49.72	56.97	7	5
22	1,035.94	941.78	9.09	51.60	61.76	5	3
23	1,079.48	997.78	7.57	59.45	69.31	6	5
24	1,033.26	1,001.94	3.03	59.55	74.86	6	3
25	1,080.80	1,058.24	2.09	63.64	81.04	7	5
26	1,148.84	1,062.06	7.55	76.03	89.20	7	4
27	1,146.49	1,118.62	2.43	73.89	108.48	7	4
28	1,289.64	1,122.15	12.99	89.32	125.41	7	6
29	1,224.36	1,178.95	3.71	88.62	140.45	7	3
30	1,257.49	1,182.23	5.98	97.91	142.52	7	6
40	1,614.26	1,567.19	2.92	173.52	232.90	7	6
50	1,970.93	1,888.05	4.21	377.10	420.33	7	6

4.2.1 Regular map testing

The results presented in Table 6 show the optimal solutions, runtime and the number of dispatched UAVs for both algorithms on regular maps with the number of target points ranging from 10 to 30. Additionally, two large regular maps with 40 and 50 target points are tested to validating algorithm performance in high-dimensional scenarios, A comparison of the optimal solutions indicates that AGA achieves better results than CGA on some maps. However, due to the simple structure of regular maps, where the number of polygon sides increases with the number of target points while the depot remains at the centre, in some cases, the optimal solutions of AGA and CGA are identical. In addition, a comparison of the number of UAVs scheduled by CGA and AGA demonstrates that AGA is capable of planning longer fight paths for UAVs while satisfying all constraints, thus requiring fewer UAVs than CGA. Figures 7 and 8 present the results of both algorithms on a regular map with 13 target points. [Figures 7(a) and 8(a)] show the flight paths of all UAVs, while the remaining subfigures illustrate the fight paths of individual UAVs. As can be seen from the figures, AGA not only achieves a better optimal solution than CGA, but also requires fewer UAVs.

Figure 7 The results of AGA on a regular map with 13 target points, (a) complete flight paths, (b) flight path of UAV1, (c) flight path of UAV4 (see online version for colours)

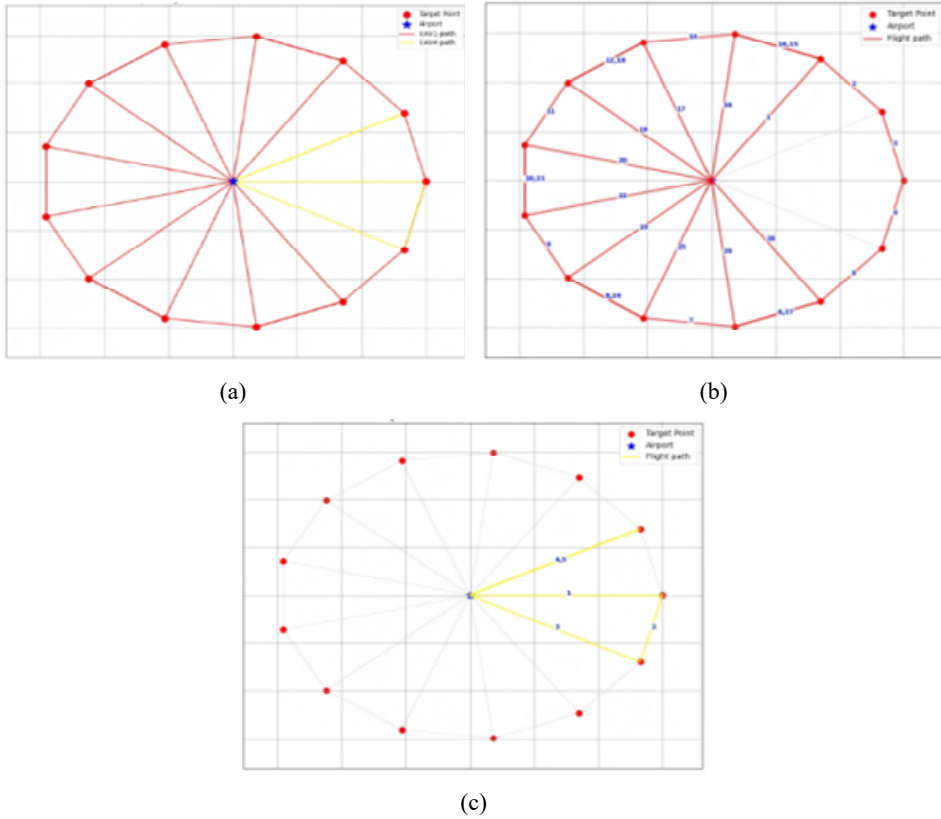
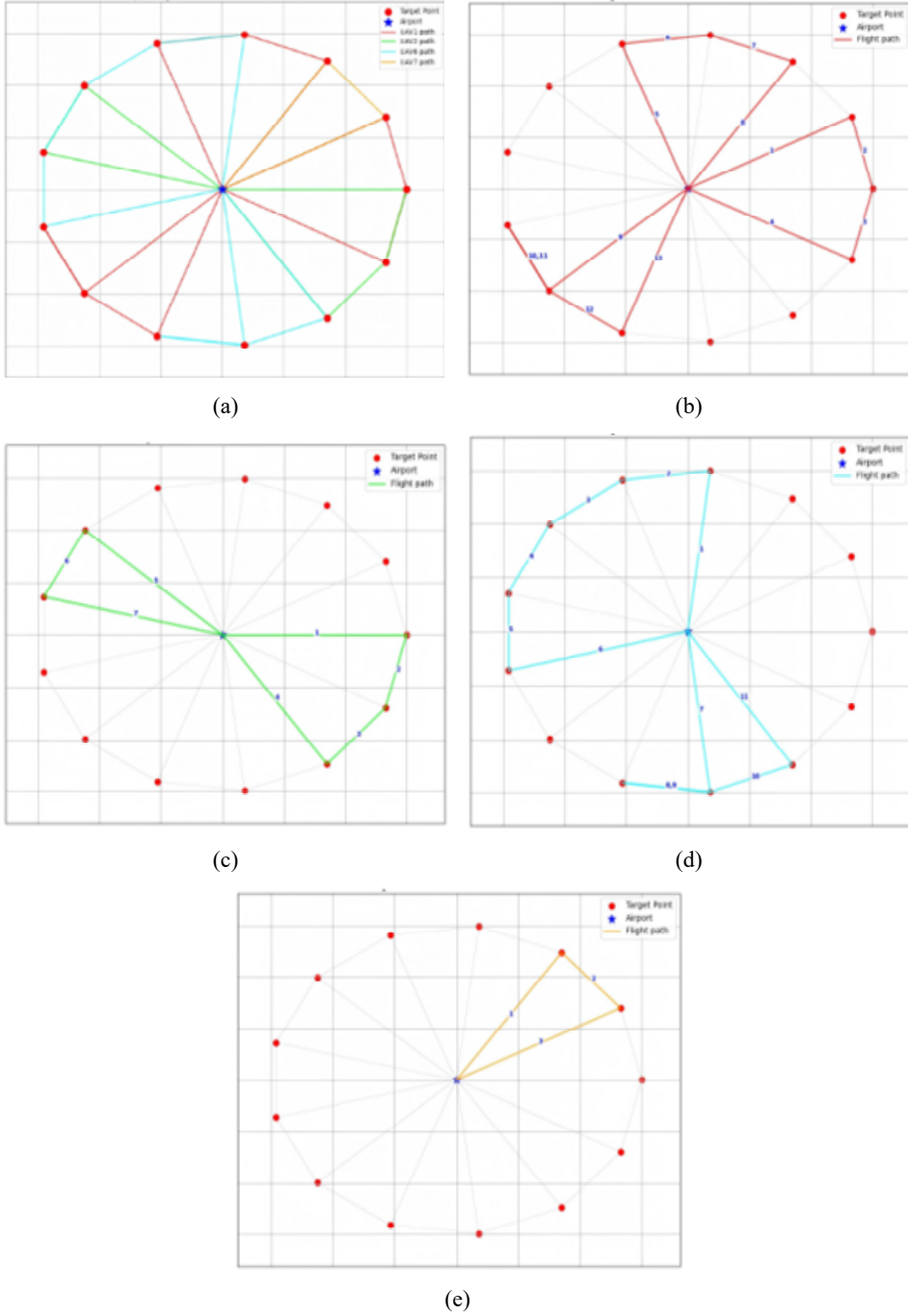


Figure 8 The results of CGA on an irregular map with 10 target points, (a) complete flight paths, (b) flight path of UAV1, (c) flight path of UAV2, (d) flight path of UAV6, (e) flight path of UAV7 (see online version for colours)



4.2.2 Irregular map testing

Table 7 presents the relevant metrics of both algorithms on irregular maps with the number of target points ranging from 10 to 30 and 40, 50. In scenarios with more irregular layouts and complex structures, AGA demonstrates a more pronounced optimisation capability for flight distance compared to CGA. AGA achieves better optimal solutions than CGA on all maps. In addition, similar to the results on regular maps, AGA consistently requires fewer UAVs. Figures 9 and 10 present the results of both algorithms on an irregular map with 10 target points. As shown in the figures, AGA outperforms CGA in terms of both the optimal solution and the number of UAVs required.

Table 7 Comparison results of CGA and AGA on irregular maps

<i>Number of target points</i>	<i>Optimal solution</i>		<i>Gap (%)</i>	<i>Runtime(s)</i>		<i>Number of dispatched UAVs</i>	
	<i>CGA</i>	<i>AGA</i>		<i>CGA</i>	<i>AGA</i>	<i>CGA</i>	<i>AGA</i>
10	1,103.90	1,049.30	5.20	17.86	19.79	4	3
11	1,153.04	1,081.95	6.57	22.13	24.15	4	2
12	1,301.81	1,135.72	14.62	25.62	30.63	5	2
13	1,348.46	1,186.37	13.66	31.64	34.39	6	3
14	1,414.26	1,267.74	11.56	36.24	41.53	5	3
15	1,363.38	1,316.95	3.53	42.49	47.56	4	3
16	1,519.04	1,337.56	13.57	47.42	54.20	5	3
17	1,607.35	1,473.86	9.06	52.17	58.87	3	2
18	1,644.53	1,468.50	11.98	56.12	65.31	6	3
19	1,841.25	1,527.05	20.58	67.08	70.65	6	3
20	1,797.27	1,547.08	16.17	72.31	83.67	7	3
21	1,898.17	1,736.16	9.33	79.89	91.03	6	5
22	1,872.03	1,652.54	13.28	86.44	97.22	6	4
23	1,858.93	1,669.21	11.37	95.19	112.42	7	4
24	1,918.03	1,720.81	11.46	102.83	127.34	7	4
25	2,128.59	1,851.44	14.97	119.47	144.51	6	4
26	2,275.52	1,937.87	17.43	128.71	161.34	7	4
27	2,203.31	1,965.16	12.12	149.75	192.20	7	4
28	2,327.87	1,985.07	17.27	158.34	183.61	7	4
29	2,110.38	1,957.16	7.83	159.98	216.49	6	4
30	2,218.99	1,938.39	14.47	187.98	236.88	7	4
40	2,729.06	2,537.13	7.03%	302.64	344.93	7	6
50	3,166.50	2,969.74	6.21%	547.05	682.48	7	7

Figure 9 The results of CGA on an irregular map with 10 target points, (a) complete flight paths, (b) flight path of UAV1, (c) flight path of UAV3, (d) flight path of UAV4, (e) flight path of UAV5 (see online version for colours)

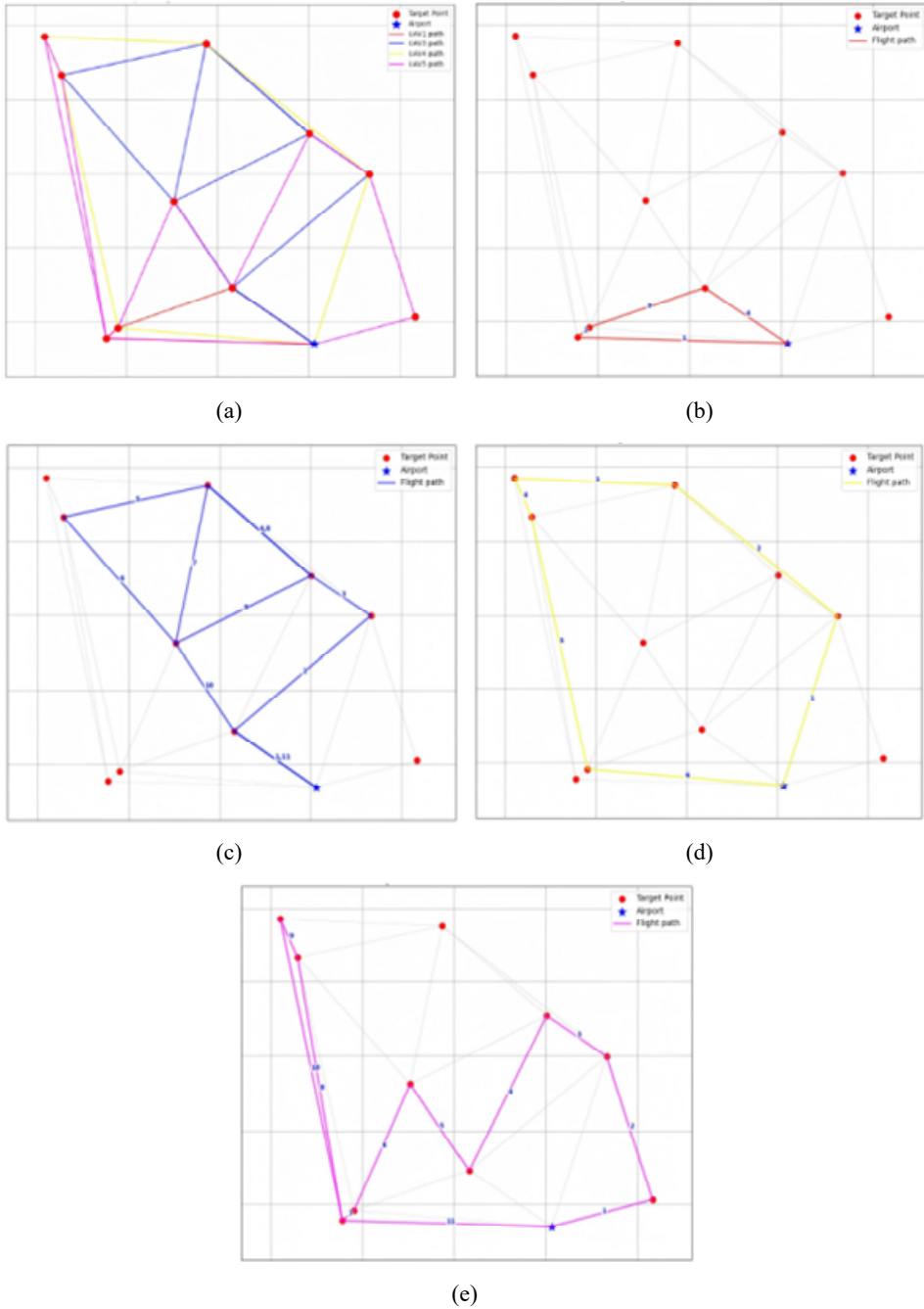
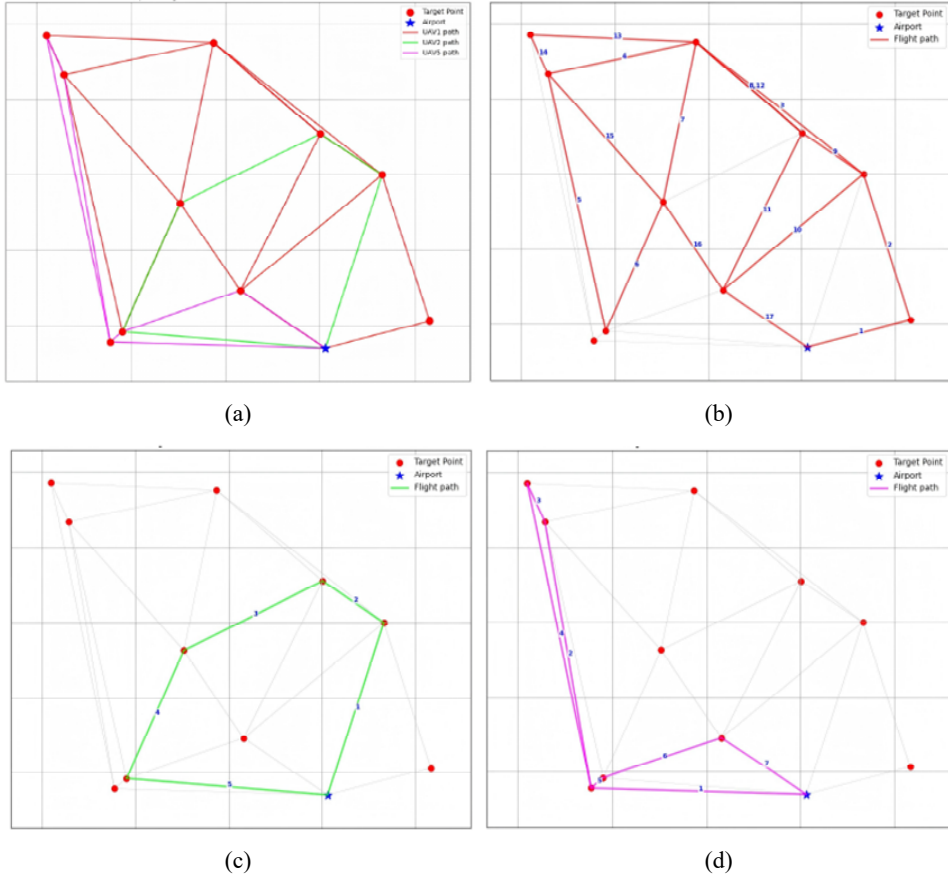


Figure 10 The results of AGA on an irregular map with 10 target points, (a) complete flight paths, (b) flight path of UAV1, (c) flight path of UAV2, (d) flight path of UAV5 (see online version for colours)



In the target point inspection problem, IGA achieves optimal or co-optimal solutions in the tested datasets compared to other algorithms, demonstrating performance as outstanding as AGA in the edge inspection problem. Regarding runtime, however, the average solution time of IGA is not the longest – it delivers both speed and quality in certain datasets. In contrast, AVGA consistently sacrifices some additional computational time to obtain superior solutions, though this extra time remains within acceptable limits. Therefore, when evaluating performance based on both solution quality and computational efficiency, both IGA and AGA outperform other algorithms, with IGA exhibiting an advantage in solution time.

5 Conclusions

In this paper, both the target point inspection problem and the transmission line inspection problem are modelled and addressed in a single-depot, multi-UAV scenario. For the target point inspection, an innovative mathematical model is developed that

allows UAVs to be idle, and an IGA is proposed, incorporating the 2-opt operator and an adaptive mutation rate mechanism. Experimental validation demonstrates the effectiveness of the proposed algorithm through comparative analysis with the Gurobi solver on small-scale maps, while comparisons with three classical heuristic algorithms across multiple test sets confirm its superior performance. For the transmission line inspection, edge assignment variables are introduced to establish a mathematical model aimed at minimising the total flight distance of all UAVs while allowing multiple traversals of the same edge. Furthermore, a chromosome encoding scheme based on edge assignment is designed, and comparative testing is conducted between the classical genetic algorithm and the proposed AGA across two distinct types of grid maps. The experimental results conclusively demonstrate the superior performance of the AGA.

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Declarations

All authors declare that they have no conflicts of interest.

References

- Ahr, D. and Reinelt, G. (2006) 'A Tabu search algorithm for the min-max k-Chinese postman problem', *Computers and Operations Research*, Vol. 33, No. 12, pp.3403–3422.
- Altin, I. and Sipahioglu, A. (2024) 'Drone arc routing problems and metaheuristic solution approach', *Drones*, Vol. 8, No. 8, p.373.
- Bai, X.S., Jiang, H.Y., Li, C., Ullah, I., Al Dabel, M.M., Bashir, A.K., Wu, Z.Z. and Sam, S. (2025) 'Efficient hybrid multi-population genetic algorithm for multi-UAV task assignment in consumer electronics applications', *IEEE Transactions on Consumer Electronics*, Vol. 71, No. 2, pp.2395–2406.
- Bai, X.S., Yan, W.S., Ge, S.S. and Cao, M. (2018) 'An integrated multi-population genetic algorithm for multi-vehicle task assignment in a drift field', *Information Sciences*, Vol. 453, pp.227–238.
- Cabreira, T.M., Brisolara, L.B. and Paulo Jr., R.F. (2019) 'Survey on coverage path planning with unmanned aerial vehicles', *Drones*, Vol. 3, No. 1, p.4.
- Campbell, J.F., Corberán, Á., Plana, I., Sanchis, J.M. and Segura, P. (2021) 'Solving the length constrained K-drones rural postman problem', *European Journal of Operational Research*, Vol. 292, No. 1, pp.60–72.
- Chen, X.L., Jia, Y.H., Liao, X.C. and Chen, W.N. (2025) 'A fuzzy grouping-based memetic algorithm for multi-depot multi-UAV power pole inspection', *Applied Soft Computing*, Vol. 168, p.112472.
- Chung, H.M., Maharjan, S., Zhang, Y., Eliassen, F. and Strunz, K. (2020) 'Placement and routing optimization for automated inspection with unmanned aerial vehicles: a study in offshore wind farm', *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 5, pp.3032–3043.

- Feng, T.P., Li, J.M., Jiang, H., Yang, S.X., Wang, P.X., Teng, Y.X., Chen, S.Y., Fu, Q. and Luo, B.J. (2024) 'The optimal global path planning of mobile robot based on improved hybrid adaptive genetic algorithm in different tasks and complex road environments', *IEEE Access*, Vol. 12, pp.18400–18415.
- Han, L.H., Ding, J.Z., Liu, S.T. and Meng, M. (2025) 'The path planning problem of robotic delivery in multi-floor hotel environments', *Sensors*, Vol. 25, No. 6, p.1783.
- He, C., Ouyang, H.B., Huang, W.Q., Li, S., Zhang, C.L., Ding, W.P. and Zhan, Z.H. (2025a) 'An adaptive heuristic algorithm with a collaborative search framework for multi-UAV inspection planning', *Applied Soft Computing*, Vol. 174, p.112969.
- He, N.H., Zhang, D. and Bettayeb, B. (2025b) 'A hybrid approach using ant colony optimisation for integrated scheduling of production and transportation tasks within flexible manufacturing systems', *Computers and Operations Research*, Vol. 180, p.107059.
- Karaboga, D. and Basturk, B. (2007) 'A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm', *Journal of Global Optimization*, Vol. 39, No. 3, pp.459–471.
- Li, J.X., Yang, X.R., Yang, Y.J. and Liu, X.L. (2024a) 'Cooperative mapping task assignment of heterogeneous multi-UAV using an improved genetic algorithm', *Knowledge-Based Systems*, Vol. 296, p.111830.
- Li, K., Yan, X.X. and Han, Y. (2024b) 'Multi-mechanism swarm optimization for multi-UAV task assignment and path planning in transmission line inspection under multi-wind field', *Applied Soft Computing*, Vol. 150, p.111033.
- Liu, K., Liu, M., Tang, M. and Zhang, C. (2024) 'Power inspection UAV task assignment matrix reversal genetic algorithm', *Cognitive Robotics*, Vol. 4, pp.245–258.
- Liu, S., Liu, D. and Le, M.L. (2025) 'Multi-UAV delivery path optimization based on fuzzy C-means clustering algorithm based on annealing genetic algorithm and improved hop field neural network', *World Electric Vehicle Journal*, Vol. 16, No. 3, p.157.
- Liu, Z.Y., Zhao, X.D., Qi, H.C., Li, Y.F., Zhang, G.B. and Zhang, T. (2019) 'Prospect of power inspection using UAV technology', in *Proceedings of the 2019 7th International Conference on Geoinformatics in Sustainable Ecosystem and Society*, November, pp.151–159.
- Luo, H., Zhang, P., Wang, J.J., Wang, G.Q. and Meng, F.H. (2019) 'Traffic patrolling routing problem with drones in an urban road system', *Sensors*, Vol. 19, No. 23, p.5164.
- Matlekovic, L. and Schneider Kamp, P. (2023) 'Constraint programming approach to coverage-path planning for autonomous multi-UAV infrastructure inspection', *Drones*, Vol. 7, No. 9, p.563.
- Qin, X., Wu, G., Lei, J., Fan, F. and Ye, X. (2018) 'Detecting inspection objects of power line from cable inspection robot LiDAR data', *Sensors*, Vol. 18, No. 4, p.1284.
- Sheng, L. (2024) 'Multi-uav task allocation and path planning method for agricultural patrol scene', *INMATEH – Agricultural Engineering*, Vol. 74, No. 3, pp.582–591.
- Wang, J., Wang, G.Q., Hu, X.X., Luo, H. and Xu, H.Q. (2020) 'Cooperative transmission tower inspection with a vehicle and a UAV in urban areas', *Energies*, Vol. 13, No. 2, p.326.
- Wang, W., Shen, Z. and Zhou, Z. (2024) 'A novel vision and radar-based line tracking assistance system for drone transmission line inspection', *Remote Sensing*, Vol. 16, No. 2, p.355.
- Wu, X.L., Yin, Y.N., Xu, L., Wu, X.J., Meng, F.H. and Zhen, R. (2021) 'Multi-UAV task allocation based on improved genetic algorithm', *IEEE Access*, Vol. 9, pp.100369–100379.
- Xie, A.L., Miyagawa, K., Wu, W. and Yagiura, M. (2024) 'A heuristic algorithm for the drone rural postman problem', *Journal of Industrial and Management Optimization*, Vol. 20, No. 5, pp.1951–1966.
- Yan, X.H., Chen, R.W. and Jiang, Z.H. (2023) 'UAV cluster mission planning strategy for area coverage tasks', *Sensors*, Vol. 23, No. 22, p.122.

- Ye, F., Chen, J., Tian, Y. and Jiang, T. (2020) ‘Cooperative task assignment of a heterogeneous multi-UAV system using an adaptive genetic algorithm’, *Electronics*, Vol. 9, No. 4, p.687.
- Zhang, B.Y., Zhu, M.J., Li, H.B., Zou, H.L. and Wang, X.Y. (2025a) ‘Power inspection robot dog inspection line planning and autonomous navigation strategy’, *International Arab Journal of Information Technology*, Vol. 22, No. 3, pp.490–504.
- Zhang, X.Y., Yu, H., Zheng, X. et al. (2025b) ‘Hybrid deep reinforcement learning for UAV inspection in large-scale wind farms: deployment and routing optimization’, *IEEE Transactions on Industrial Informatics*, Vol. 21, No. 11, pp.9011–9021.
- Zhao, B., Wu, C.D., Zhao, X., Sun, R.H. and Jiang, Y. (2023) ‘Research on hybrid navigation algorithm and multi-objective cooperative planning method for electric inspection robot’, *Energy Reports*, Vol. 9, pp.805–813.