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Safety inspection path of unmanned aerial vehicle

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Abstract

Unmanned aerial vehicle (UAV) safety inspection is a developing technology that offers the benefits of high efficiency, low cost, and freedom from dangerous areas and unique situations. An urgent fundamental issue in the deployment of UAV in factories is how to successfully strike a balance between the effectiveness and cost of UAV safety inspection. In view of this, we build a route planning model for UAV inspection. And then, by using the path planning of UAV safety inspection as the research object, based on the two important evaluation indicators of cost and efficiency, we exploit fuzzy time window and adaptive genetic algorithms to design the solution algorithm. Finally, a case verifies the applicability and logic of the proposed model. The results show that the proposed path optimization model with fuzzy time window can reasonably pass all inspection points under balanced conditions, and the hybrid genetic algorithm has good optimization ability.

Keywords: Unmanned aerial vehicle, path planning, fuzzy time window, genetic algorithm.

1 Introduction

Unmanned aerial vehicle (UAV) safety inspection has been widely employed in electric power detection [20], environmental detection [16], urban planning [15], agriculture and forestry safety detection [1], and other industries in recent years as a safe and effective new technology. For multidimensional, real-time monitoring and early warning, UAV safety inspection combines aviation, electronics, communication, flight control, computer image recognition, and many other high-tech, with sensors, cameras, and other sensing equipment [4, 12, 27]. This ensures the safety of industrial production personnel and property. UAVs are unrestricted inspectors of dangerous areas and special scenes, flying at low altitudes and fast speeds. Compared with the traditional factory safety inspection, the UAV can have a bird's eye view of the equipment and personnel in the monitoring area when flying, which is conducive to collecting on-site data and mastering the on-site situation faster. The cost is relatively modest compared to the price of building maintenance and surveillance systems used for UAV safety assessment. The use of UAVs for safety inspection in the factory environment significantly raises the level of intelligence in factory operation, maintenance, and emergency response, and provides a solid guarantee for the factory's security. The need to raise the factory as a whole's intelligence level is crucial.

The path planning of UAVs is one of the key technologies to ensure the safe operation of UAVs. The safety of UAVs in the execution of tasks may also meet the requirements of factory safety inspection and ensure the comprehensive and effective operation of company operations. An ideal path is designed using these elements to accomplish the safety inspection task. The path planning of UAV considers a variety of aspects like energy consumption cost, flying area, and arrival time. In order to raise the intelligent level of factory safety inspection, lower business production costs, and increase business economic benefits. This led to the construction of a path planning model for UAV safety inspection taking into account a fuzzy time window, the integration of three algorithms, and the calculation of a hybrid genetic algorithm to efficiently solve the model.

What's left is as follows: The pertinent study results are discussed in Section 2. We design and build a manufacturing UAV safety inspection path model taking time window into consideration in Section 3. A hybrid genetic algorithm-

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based path algorithm that takes time window into account is designed. Using numerical example analysis and simulation solution, it is demonstrated in Section 4 that this algorithm can efficiently lower the cost of UAV safety inspection in factories and enhance the efficiency of UAV safety inspection. The conclusion is presented in section 5.

2 Literature review

With the rapid development of industrial capabilities, safety inspection is increasingly valued by enterprises. UAV safety inspection, a new technology, has benefits like great efficiency and is not constrained by dangerous areas and distinctive scenes [24]. Its process requires targeted research on such issues as cost, efficiency and coverage [5]. According to a search of literature review, the current research largely focuses on the Vehicle Routing Problem with Time Window (VRPTW), which is related to UAV path planning, and the problem's solution method.

2.1 UAV path planning problem

The ability to efficiently and efficiently define a feasible path is a key study area in UAV technology. Path planning is a requirement for UAV operations. For the issue of obstacle occlusion perception in UAV reconnaissance, Zhang and Huang [28] proposed an asymptotically optimal waypoint generating technique, taking into account the dynamic coverage of the target region. In order to detect targets and build communication relay chains quickly, Yanmaz [25] proposed a hybrid path planning technique for UAV teams employed for search and rescue missions that makes use of joint optimized search UAVs and optimized relay UAVs through decoupling. The weight of the target and the UAV's performance constraints are taken into account when Li, Xiong, and She [14] handle the minimal time maximum coverage problem of many UAVs in scanning coverage in path planning, which not only affects the mission time but also the coverage rate. UAV path planning in 3D dynamic environments has proven to be a difficult NP problem that requires collision avoidance while deciding the best feasible trajectory in dynamic environments. Chowdhury and De [5] proposed a new approach based on the Reverse Glowworm Swarm Optimization algorithm that takes into account cost minimization and optimal path. Cui, Wang, and Yang et al. [6] used a chaotic initialization and co-evolutionary algorithm to solve a two-point path planning problem for UAVs in complex forest environments that took into account all important UAV performance and environmental factors with the goal of information freshness. Alpdemir [2] addresses the problem that path planning for tactical unmanned aerial vehicles under enemy radar tracking threats is different from that for UAV in confined or urban environments by combining the utility of core RL algorithms and machine learning solutions to improve the performance of learning agents and proposes a RL-based based solution. Li and Liu [13] used VTOL UAV as a research object to consider the impact of urban buildings on UAV operations at different flight heights and plan accessible UAV operation paths in urban areas with minimal energy consumption. Xu, Xu, and Ying [23] created a threat model based on the complex adversarial environment of UAVs, built a multi-constrained objective optimization model under time and space constraints, and solved the optimization model using an improved grey wolf optimizer algorithm. Wang, Pan, and Yang et al. [21] Path planning for UAVs in the UAV route planning problem is transformed into an optimization problem that satisfies the UAV feasible path requirements and path safety constraints by proposing an improved Mayfly algorithm for path discovery at the lowest overall cost when determining the optimal flight path to reach the target location. Yang and Huang [24] addresses the problem of current UAV path planning. To establish an intelligent planning model for UAV clusters, the algorithm is based on a multi-objective optimization algorithm.

2.2 UAV path planning solving algorithm

As UAV path optimization problems become more complex, the ability of the solution algorithm to converge, optimality of the solution, and computational speed become more important. Zhang, Xia, and Li et al. [31] proposed a multi-modal cooperative multi-objective particle swarm optimization algorithm to solve a multi-UAV collaborative path planning problem in a multi-constrained complex environment in order to find the optimal path while also handling constraints. Zhang, Xia, and Zhang et al. [30] proposed an improved collaborative algorithm of Fireworks Algorithm and Particle Swarm Optimization for UAV global path planning, which was well applied in obtaining high-quality solutions and handling constraints. Han, Qu, and Tong et al. [10] addressed the UAV path planning problem in complex indoor environments, attempting to construct a set of grid-optimized UAV indoor path planning algorithms, namely GO-IAM, GO-APP, and GO-LBPP algorithms, which combine airspace modeling and path planning in 3D indoor environments. Xu, Li, and Zhang [22] proposed a flight path planning method for UAV forest fire monitoring based on the forest fire risk map by considering the forest fire risk level using the Ring Self-Organizing Mapping algorithm to plan the corresponding flight paths for UAV forest fire monitoring. Aslan and Erkin [3] extend the IP algorithm to a multipopulational domain supported by migration modes by considering optimization objectives regarding enemy threats and operating system fuel consumption, and propose a new multiIP algorithm as a UAV path planner. Phung and Ha [18] proposed a spherical vector-based PSO algorithm for the path planning problem of UAVs in complex environments with multiple threats, considering various requirements and constraints related to UAVs and their flight paths, and establishing an objective function. Shen, Zhu, and Kang et al. [19] proposed a spherical vector-based PSO algorithm for evolutionary algorithm path planner for UAVs in the presence of obstacles, where the path is easily violated during the evolutionary process, the path planning is constructed as a multi-objective optimization problem with constraints in a 3D terrain scene. Ge, Li, and Han et al. [9] UAVs are widely used in oilfield inspections; we define the cost function for finding the optimal path while keeping in mind that the oilfield is a complex three-dimensional space, and we propose a PIOFOA algorithm to solve the 3D path planning problem for UAVs used in oilfield inspection in dynamic environments. Zhao, Yan, and Hu et al. [32] considered UAV autonomous exploration and path planning capabilities in unknown environments, combined boundary-based exploration and sample-based exploration algorithms in unknown spaces to achieve fast and safe autonomous exploration, and proposed a fast exploration random tree algorithm combining adaptive weights and dynamic step size. Yu, Li, and Zhou [26] addressed the problem of UAV situational awareness capability in disaster rescue, and proposed an adaptive selection variance constrained differential evolutionary algorithm to optimize UAV path planning and select the best path for disaster rescue, considering the three constraints of UAV height, UAV angle, and limited UAV slope.

2.3 Path optimization problems considering time windows

The vehicle path problem with time windows is similar to the UAV safety inspection path planning problem with fuzzy time windows. For this purpose, Demir, Özmen, and Esnaf et al. [7] proposed a forbidden search heuristic algorithm for VRPTW, which effectively solves the time window problem. R.J. Kuo et al. addressed the truck logistics transportation problem with UAV participation. Fernández, Lalla-Ruiz, and Gómez et al. [8] proposed an optimisation model for transportation fuel consumption and environmental factors that takes into account both hard and soft time windows, and incorporate the optimisation model into a greedy stochastic adaptive search process, allowing the model to provide better solutions with less computational effort. Öztop, Kizilay, and Çil [17] addressed the problem of high value cargo transportation arising in the field with constructs MILP and CP models to efficiently solve the periodic vehicle path problem (PVRP) with time windows and time diffusion constraints, considering customers with different vehicles and specific periodic demands. Zhang, Li and Yang et al. [29] proposed a hybrid multi-objective combined timing-based evolutionary algorithm that minimizes the total number of vehicles while reducing time wasted due to vehicles arriving early in the delivery process. Hoogeboom, Dullaert and Lai et al. [11] proposed an exact algorithm for the multi-time-window vehicle path problem that allows customers to consider minimizing the duration of any given route by evaluating the neighbourhood operations during the local search to accurately calculate the route duration.

According to the above discussion and analysis, current research is primarily focused on the problem orientation of UAV path planning, solution algorithms, and related VRPTW problems. However, there are two problems in research: (1) There are few researches on safety UAV inspection in factories, most of which focus on power detection and environmental detection; (2) Existing studies on UAVs lack the evaluation and optimization of path planning for safe inspection. To address these issues, a hybrid genetic algorithm combining the 3D A* algorithm, the NCC algorithm, and the adaptive genetic algorithm is proposed, and countermeasures are proposed by combining several case studies.

3 Basic model

Currently, the development of inspection paths for UAV in factory safety inspections is usually based on human-related experience, which is too subjective and makes ensuring the quality and cost of safety inspections difficult. For factory enterprises, a safety inspection path planning method that takes into account various factors such as the UAV's energy cost, flight area, and arrival time is required. To address this issue, we build a path planning model with fuzzy time windows to balance the cost and efficiency of UAV safety inspections while keeping the UAV inspection process on time, and we design hybrid algorithms to solve the model effectively.

A plant has 20 safety inspection points that must be inspected at a specific time and location for time-sensitive safety items. As a result, the plant safety department must arrive within the time frame of the safety inspection to complete the inspection items. Because the safety inspection items must be inspected at a specific time, the drones cannot arrive early at the inspection points; otherwise, the safety inspection may be incorrect, resulting in injuries to the personnel involved or damage to the equipment; thus, balancing the cost and efficiency of the inspection while taking into account the timely arrival of the drones is an urgent issue, as illustrated in Figure 1.

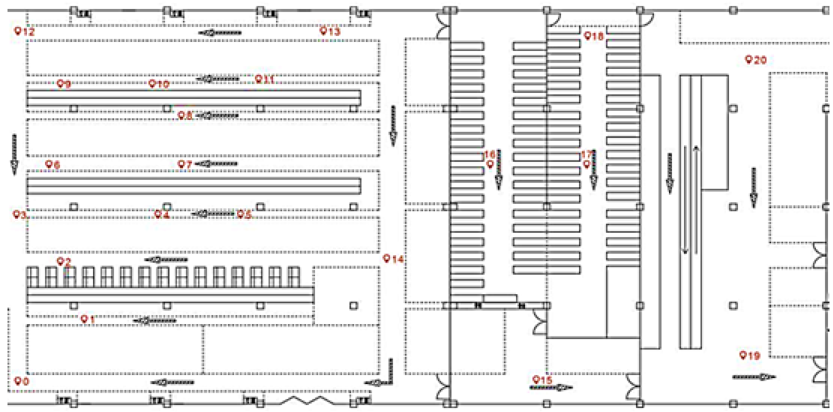

Figure 1: Schematic diagram of sample plant plan

3.1 Influencing factors analysis for UAV safety inspection

This paper studies the problem of using UAV for safety inspection in factories, so the inspection path, inspection time and inspection environment of UAV must be considered and analyzed. The following are the factors affecting the safety inspection of drones:

(1) The number of safety inspection nodes;
(2) The length of the path between the security center and the inspection point and the two inspection points;
(3) How fast the UAV flies;
(4) Unit energy consumption cost of UAV;
(5) Safety inspection time;
(6) The length of inspection time of the safety inspection point;
(7) The number of safety inspection drones;
(8) The fixed use cost of the UAV;
(9) Changes in the surrounding environment of safety inspection.

Since UAV is used for safety inspection of factories, it is especially necessary to consider the impact of obstacles and no-fly zones in three-dimensional space. In addition, when safety inspection is conducted, it is necessary to consider the constraints of inspection time on UAV. If it is earlier than or later than the inspection time, inspection will lose value, and in serious cases, additional safety accidents will be caused, resulting in significant economic losses.

3.2 Model assumptions

The route planning of the safety inspection must be considered before the plant safety inspection begins. We consider the personnel, equipment, and so on involved in security production to be safety inspection nodes, and the safety inspection path planning is to sort the safety inspection nodes and find the line with the lowest safety inspection cost. Some assumptions are given below based on the above analysis of influencing factors and target planning:

(1)Suppose that there exists a factory, which has safety inspection of the starting point and the end point of the drone from the starting point of the safety inspection, according to the specified sequence to complete the safety inspection of personnel, equipment, and then land at the end point, the starting point and the end point are the same, let $C = \{S, D_1, D_2 ... D_{n-1}, S\}$, $A = \{(i, j)|i, j \in C, i \neq j\}$ represents the set of nodes and the set of edges, respectively, where S is the start and end point, $D_1, D_2 ... D_{n-1}$ are intermediate path nodes.

(2) Due to the limited number of UAVs available for use in security centers, it is necessary to plan the use of UAVs carefully to ensure the effectiveness and efficiency of monitoring, patrol, and rescue tasks. As a result, the number of drones that can be used by security centers must be limited and managed. For the convenience of description, let T_f represents the number of drones available for the security center.

(3) When studying the performance of UAVs in security center applications, we must place some constraints on their capabilities. We specifically assume that the UAV's flight cruising ability is certain, which means that we ignore flight trajectory smoothness in flight dynamics and performance constraints such as maximum flight altitude and maximum turning angle. This will allow us to focus more on the UAV's basic flight capability and performance, laying the

groundwork for subsequent model development and analysis. For convenience of description, let α, δ and s represents as the flight cruise time, flight hovering time and flight speed of the UAV, respectively.

(4) Certain assumptions and constraints on the time of the UAV is required in the security center's UAV patrol task. We assume, specifically, that no one has the time to leave the security center and return to the security center after the inspection. This is due to the fact that scheduling UAV patrol tasks has a significant impact on the quality and efficiency of task completion. For convenience of description, let t_{ks} and t_{ke} represents the departure time of UAV from security center and the end time of UAV return to security center, respectively.

(5) To better plan the flight path and task assignment of the UAV while controlling the cost and efficiency of the task, the energy consumption of UAVs must be considered in the security center's UAV patrol mission. To simplify the problem, we assume that all UAVs are the same model, have the same unit energy consumption, and their energy consumption increases linearly with flight distance. For convenience of description, let C_d and C_h represent the cost of energy consumption per unit distance of UAV and UAV hovering in energy costs, respectively.

(6) In the security center's UAV patrol task, we must consider the priority of each security patrol point, because different security patrol points may correspond to different levels of security risk. At the same time, we must consider the safety inspection node's inspection time window and maximum tolerance inspection time window. Specifically, let $[s_i, e_i], [S_i, E_i]$ represents the inspection time window of the safety inspection node and the maximum tolerance inspection time window of the safety inspection node, respectively.

(7) In the security center's UAV patrol mission, we assume that each security patrol point can only be visited once. This means that each inspection point can only be patrolled at a specific time during the task, and the drone must patrol each safety inspection point in turn based on reasonable path planning. In order to describe the patrol path of UAV, let x_{ijk} represents the UAV(k) from the path of the node i to node j is selected.

(8) In order to reduce the extra cost, create a more reasonable safety inspection task plan. Given that the time window is known, we can specify a start and an end time for each safety inspection point. If the drone does not complete the inspection within the specified time frame, we must consider the additional penalty cost. Specifically, let θ_1 and θ_2 represents the penalty cost of the safety inspection node earlier than the designated patrol time window and the penalty cost of the safety inspection node i later than the designated patrol time window, respectively.

In order to better understand the model and increase its clarity, the variables and definitions involved in the construction of the model are summarized in Table 1.

3.3 Establishment of factory environment model

The important use of UAV for safety inspection is that it can fly at different altitudes for safety inspection. However, two-dimensional space cannot represent altitude information, resulting in incorrect UAV path planning decisions. As a result, a three-dimensional raster map was chosen to model the factory environment, and a ROS three-dimensional raster map model was created, as shown in Figure 2.

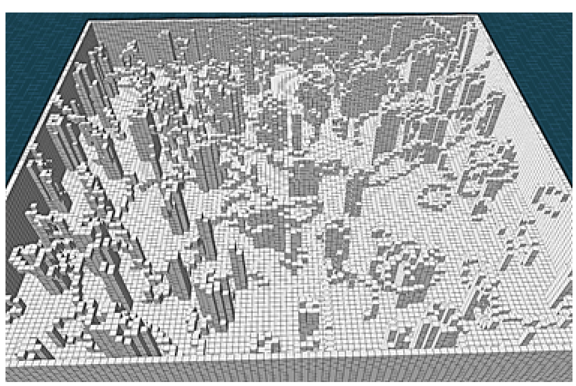

Figure 2: ROS Three-dimensional raster map

The UAV's movement direction in the raster map is multi-directional, but it cannot cross obstacles. As shown in Figure 3, the movement direction of the UAV set in the two-dimensional raster map is multi-directional.

Table 1: Symbol description

Variable	Definition
$C = \{S, D_1, D_2 \ldots D_{n-1}, S\}$	The set of nodes
$A = \{(i,j) \vert i, j \in C, i \neq j\}$	The set of edges
S	The start and end point
$D_1, D_2 \ldots D_{n-1}$	Intermediate path nodes
T_f	The number of drones available for the security center
α	The flight cruise time of the UAV
δ	The flight hovering time of the UAV
s	The flight speed of the UAV
t_{ks}	The departure time of UAV from security center
t_{ke}	The end time of UAV return to security center
C_d	The cost of energy consumption per unit distance of UAV
C_h	UAV hovering in energy costs
$[s_i, e_i]$	The inspection time window of the safety inspection node
$[S_i, E_i]$	The maximum tolerance inspection time window of the safety inspection node
x_{ijk}	The path selection for the kth UAV from node i to node j
θ_1	The penalty cost of the safety inspection node i earlier than the designated patrol time window
θ_2	The penalty cost of the safety inspection node i later than the designated patrol time window

3.4 Time window and penalty function construction

The factory safety inspection task fits the fuzzy time window application scenario. It can accept the requirement of being earlier or later than the time window, but not earlier or later than the maximum tolerance time window. Assume that the safety inspection time window specified by the factory security management center is $[s_i, e_i]$. If node i is entered within the specified time window, no penalty cost of time window will be generated. However, due to personnel or equipment, the UAV may arrive at the detection point early or late, resulting in a penalty cost of time window. We set S_i as the earliest acceptable safety inspection time at inspection point, and E_i as the latest acceptable safety inspection time at inspection point i . It is assumed that in the time range of $[S_i, s_i]$ and $[E_i, e_i]$, the penalty cost for violating the time window will linearly decrease and increase with time. If the UAV conducts safety inspection outside $[S_i, E_i]$ hours, the penalty cost for violating the time window becomes infinite P . Factory penalty cost function for violation of inspection time window, as shown in Figure 4.

The penalty cost function for violating the time window is expressed as

$$C_4 = \begin{cases} P, t_{ki} < S_i, t_{ki} > E_i \\ \theta_1(s_i - t_{ki}), S_i < t_{ki} < s_i \\ \theta_2(t_{ki} - e_i), e_i < t_{ki} < E_i \\ 0, s_i < t_{ki} < e_i \end{cases}$$

3.5 Model construction

The costs associated with UAV safety inspection include the cost of using the UAV, the cost of flight energy consumption, the time cost of safety inspection, and the satisfaction penalty cost of the safety inspection node. The path planning

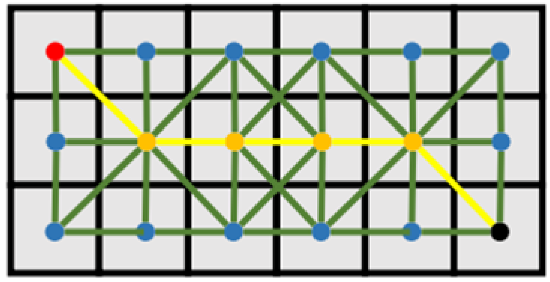

Figure 3: ROS Three-dimensional raster map

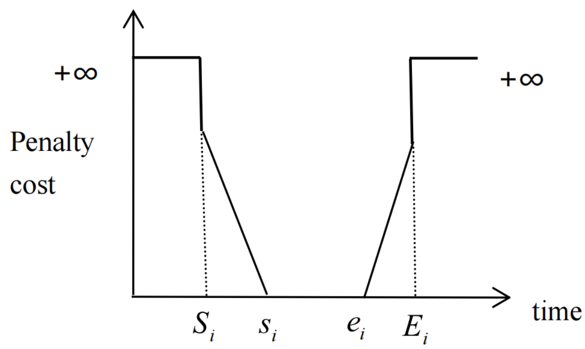

Figure 4: Schematic diagram of penalty cost function for violation of inspection time window

model of using UAV for safety inspection in factories is built with the minimum and sum of these four costs as the target.

3.5.1 Cost variable analysis

(1) Fixed cost of UAV safety inspection

Fixed cost refers to the comprehensive cost such as cost, depreciation cost, maintenance cost and labor cost when the UAV is inspected from the starting point. In our company, the fixed cost of each UAV is C_e, so the total fixed cost is:

$$C_1 = \sum_{k=1}^{n} C_e Z_k. \tag{1}$$

Where Z_k is 0-1 variable, if the UAV is used, then $Z_k = 1$, otherwise $Z_k = 0$.

(2) UAV flight cost

Flight cost refers to the cost of UAV during flight, mainly the energy consumption cost of UAV, which is expressed by d_{ij}. For example, formula (2) represents the flight cost of UAV, while formula (3) represents the cost of UAV hovering during safety inspection.

$$C_2 = \sum_{k=1}^{m} \sum_{j=0}^{n} \sum_{i=0}^{n} C_d d_{ij} x_{ijk}, \tag{2}$$

$$C_3 = \sum_{k=1}^{m} \sum_{i=0}^{n} C_h S_{ik} T_i. \tag{3}$$

3.5.2 Construction of UAV safety inspection path cost model considering fuzzy time window

By analyzing the four costs of the objective function through the above related costs: the fixed cost of UAV safety inspection, the flight cost of UAV safety inspection, the hovering cost of UAV safety inspection, and the satisfaction penalty cost of UAV safety inspection, the objective function of the path optimization model of UAV safety inspection considering fuzzy time window is as follows:

$$\begin{aligned} &\min C = C_1 + C_2 + C_3 + C_4 \\ &= \sum_{k=1}^{n} C_e Z_k + \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{i=0}^{n} C_d d_{ij} b_{ijk} + \sum_{k=1}^{m}\sum_{i=0}^{n} C_h S_{ik} T_i + \begin{cases} P, t_{ki} < S_i,\ t_{ki} > E_i \\ \theta_1(s_i - t_{ki}),\ S_i < t_{ki} < s_i \\ \theta_2(t_{ki} - e_i),\ e_i < t_{ki} < E_i \\ 0, s_i < t_{ki} < e_i \end{cases} \end{aligned} \tag{4}$$

For the equation (4), its constraints satisfy $\sum_{k=1}^{m} S_{ik} = 1$, which indicates that only one UAV performs security check on node i in the same period. Where, C_4 stands for the penalty cost of satisfaction of UAV safety inspection, which satisfy as follows:

$$C_4 = \begin{cases} P, t_{ki} < S_i,\ t_{ki} > E_i \\ \theta_1(s_i - t_{ki}),\ S_i < t_{ki} < s_i \\ \theta_2(t_{ki} - e_i),\ e_i < t_{ki} < E_i \\ 0, s_i < t_{ki} < e_i \end{cases} \tag{5}$$

In an inspection task, the UAV at any node can only be inspected for safety once, and then the formula (6) and formula (7) can be obtained as follows, respectively.

$$\sum_{i=0}^{n} x_{ijk} = S_{jk}, \forall j, k, \tag{6}$$

$$\sum_{j=0}^{n} x_{ijk} = S_{ik}, \forall i, k. \tag{7}$$

For the time window requirements of safety inspection, we can determine as follows:

$$S_i \le t_{ik} \le E_i. \tag{8}$$

For the value constraints of variables, representing x_{ijk}, Z_k both of which are 0-1 variables, we can obtain as follows, respectively.

$$Z_k(1 - Z_k) = 0, k = 1, 2..., m. \tag{9}$$

$$\mathrm{x}_{ijk}\left(1 - \mathrm{x}_{ijk}\right) = 0, i, j = 0, 1, \ldots n, k = 1, 2 \ldots, m. \tag{10}$$

3.6 Algorithm design

The UAV safety inspection path planning problem with a fuzzy time window is similar to the vehicle routing problem with a time window. VRPTW is an NP-hard problem. When solving large-scale combinatorial optimization NP-hard problems, accurate algorithms typically struggle to obtain a better solution, whereas intelligent optimization algorithms can provide a satisfactory solution in a short time. Due to differences in actual use, the path planning of UAV safety inspection differs from that of VRPTW. As a result, the intelligent optimization algorithm cannot be directly applied to the path planning of UAV safety inspection, and it must be adjusted and adapted. To tackle the previously mentioned issues, we proposed using a genetic algorithm to solve the safe path planning problem model of an unmanned aerial vehicle while considering a fuzzy time window. Meanwhile, the genetic algorithm was improved based on the model's specific characteristics, and a hybrid genetic algorithm was designed to solve the model.

3.6.1 Algorithm step

Step 1: Establish a three-dimensional raster map and label it with the coordinates of the security center and each inspection point.

Step 2: The A* algorithm is used to compute the distance matrix between the pairwise inspection points, which is one of the fitness function's important parameters.

Step 3: Set the weighted parameters of the NCC algorithm and generate the genetic algorithm's initial feasible solution.

Step 4: Use the adaptive algorithm to solve the fitness function, determine the best inspection cost, and design the UAV inspection strategy.

3.6.2 A* (A Star) Algorithm

The A* (A Star) algorithm is a global heuristic graph search algorithm with a simple principle and predictable planning results. It is widely used in a variety of engineering practices. Based on the Dijkstra algorithm, it introduces heuristic information into the search process via the greedy strategy, so that the search path tends to the optimal path, which can be shown in Figure 5.

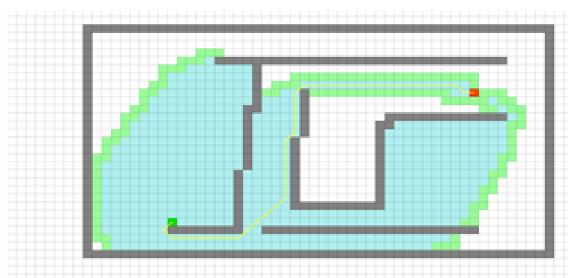

Figure 5: A* algorithm

According to Figure 5, the shortest distance between two points cannot be solved using Euclidean distance due to potential obstacles or other constraints in the environment when traveling from green to red points. The cost function of A* algorithm is:

$$f(n) = g(n) + h(n). \tag{11}$$

Where, $f(n), g(n), h(n)$ stands for the path cost function from the starting point to the inspection node n, the path cost from the current node n to the starting point, and the heuristic cost function representing the estimation function from the inspection node to the current position of the UAV, respectively.

And, the selection of cost function $h(n)$ determines the quality of the path obtained by A* algorithm to some extent. As a result, the A* algorithm is used to find the shortest distance between safety inspection centers, inspection points, and inspection points in a three-dimensional raster map, and the distance matrix obtained between all points is used in path planning, which is required for model construction.

3.6.3 Genetic algorithm

The genetic algorithm can be used to solve the optimal solution of the UAV path planning problem, but its local search ability is limited, which is dependent on the initial population selection. We investigate the safety inspection path problem of a UAV while keeping the time window in mind. The violation of the time window requirement by the inspection time is an important index as well as a parameter affecting the fitness function. As a result, generating the initial feasible solution of the genetic algorithm and improving the quality of the feasible solution are beneficial to the genetic algorithm's convergence rate and obtaining better calculation results.

3.6.4 Nearest Neighbor Algorithm with Minimum Cost (NNC algorithm)

The NCC algorithm generates the genetic algorithm's initial feasible solution and improves the quality of the feasible solution through a local search operation.

The specific steps of NCC algorithm are as follows:

Step 1: Select one of the available safety inspection drones to begin from the security center based on the departure time.

Step 2: Choose the uninspected node closest to the last safety node visited. Insert this node into the current path if it meets the model's constraints.

Step 3: Repeat Step 2. The calculation is completed when all nodes are accessed.

On the basis of those facts, we can obtain the distance between two safety inspection nodes as follows:

$$c_{ij} = \delta_1 t_{ij} + \delta_2 T_{ij} + \delta_3 E_j. \tag{12}$$

Where, c_{ij} is the distance between safety inspection nodes; t_{ij} is the flight time between safety inspection nodes; T_{ij} is the closeness of the time window between safety inspection nodes; E_j is the urgency of the time window for safety inspection nodes; $\delta_1, \delta_2, \delta_3$ is the weighting coefficient, and it has to satisfy condition $\delta_1 + \delta_2 + \delta_3 = 1$.

T_{ij} s given by equation (13):

$$T_{ij} = s_j - (s_i + \Delta_i). \tag{13}$$

Where, s_i expresses the start time of safety inspection nodes and Δ_i is the total inspection time of a secure inspection node.

E_j is given by equation (14):

$$E_j = e_j - (s_i + \Delta_i + t_{ij}). \tag{14}$$

Where, e_j stands for the latest service time of the secure inspection node.

In the above formulas (12) to (14), "distance" between nodes is the weighted sum of the travel time between secure inspection nodes, the degree of similarity of the time window, and the urgency of the time window of the next secure inspection node. The difference between the Start Inspection Time of the current secure inspection node and the Finish Inspection Time of the previous node is indicated by Time Window Similarity. A secure inspection node's Time Window Urgency indicates the difference between the latest inspection time and the start inspection time. By using the above algorithm, we can obtain the initial feasible solution of the genetic algorithm improves the genetic algorithm's convergence rate and yields better results.

3.6.5 Adaptive genetic algorithm

Although the traditional genetic algorithm has advantages such as strong global search ability, wide application range, continuous learning, and so on, it is easy to demonstrate its lack of local search ability when dealing with complex practical problems, which leads to the phenomenon of premature convergence, and the solution is therefore not optimal. The selection of crossover probability p_c and mutation probability p_m is very important to the performance of genetic algorithm.

The rate of new individuals will be faster if the crossover probability of p_c is larger, but if the crossover probability of p_c is too large, the possibility of destroying the genetic pattern will be greater. Otherwise, the search process will become slow. For the mutation probability of p_m, the genetic algorithm becomes a random search algorithm if p_m is too large. Otherwise, it is not conducive to produce new individuals. Therefore, it is generally necessary to conduct repeated experiments for different problems to determine crossover probability p_c and mutation probability p_m. In fact, determining the optimal value to adapt to various problems is difficult. As a result, rather than taking fixed values, we focus on improving the setting of crossover probability p_c and mutation probability p_m, and use adaptive strategies to make the crossover and mutation probability values change with the average fitness of individuals.

It is assumed that f_{max} is the maximum individual fitness value in the population, f_{avg} is the fitness value of the average individual in the population, and f' is the larger fitness of the two individuals when the crossover is selected. Then the cross probability p_c and mutation probability p_m can be improved adaptively by the following formula (15) among $p_{c1} = 0.9, p_{c2} = 0.6, p_{m1} = 0.5, p_{m2} = 0.1$.

$$\begin{aligned} p_c &= \begin{cases} p_{c1} - \frac{(p_{c1} - p_{c2})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ p_{c1}, & f' < f_{avg} \end{cases} \\ p_m &= \begin{cases} p_{m1} - \frac{(p_{m1} - p_{m2})(f' - f_{avg})}{f_{\max} - f_{avg}}, & f' \geq f_{avg} \\ p_{m1}, & f' < f_{avg} \end{cases} \end{aligned} \tag{15}$$

The improved adaptive genetic algorithm increases the probability of generating new individuals and the population's diversity, increasing the algorithm's random search and causing the algorithm to exit the local optimal solution.

3.6.6 Hybrid genetic algorithm

To solve the path planning problem of UAV safety inspection with a time window, we combined A*, NNC, and IAGA algorithms. The specific steps of hybrid genetic algorithm are as follows:

Step 1: Establish a three-dimensional raster map that includes the coordinates of the security center and each inspection point.

Step 2: The A* algorithm is used to compute the distance matrix between the pairwise inspection points, which is one of the fitness function's important parameters.

Step 3: The NCC algorithm generates the initial feasible solution of genetic algorithm.

Step 4: The IAGA algorithm increases the likelihood of new individuals being born, improves population diversity, and departs from the local optimal solution.

4 Case analysis

A large intelligent manufacturing factory is a large and medium-sized automation equipment production base, the intelligent manufacturing factory prior to the safety inspection side of the model mainly relies on traditional manual inspection and fixed position camera, but due to the update of production equipment and process line, the security of people and equipment production, put forward higher security requirements, the old way of security and security cannot satisfy the requirements. The use of unmanned aerial vehicles (UAVs) to replace a portion of security personnel for inspection can significantly improve the reliability and convenience of safety inspections, ensuring inspection results file, backtrack, and efficient management.

4.1 Case survey data

A three-dimensional raster map is used to model the model, which is based on historical data of safety inspections in a factory workshop. The relevant information of security center and safety inspection node is shown in Table 2.

Table 2: Information table of factory safety inspection node

Serial number	Coordinate (x,y,z)	Agreed time window(s)	Maximum tolerance inspection time window(s)	Safety inspection time(s)
0	5,5,0			
1	80,78,0	[707,848]	[667,888]	60
2	12,17,2	[143,252]	[103,292]	40
3	55,45,2	[527,587]	[487,624]	40
4	90,20,1	[678,801]	[638,841]	40
5	65,70,1	[34,209]	[0,249]	40
6	58,30,2	[415,514]	[415,514]	40
7	20,50,1	[331,410]	[291,450]	40
8	10,43,1	[404,481]	[364,521]	40
9	55,60,1	[400,497]	[360,537]	40
10	30,60,2	[577,637]	[537,672]	40
11	20,65,1	[206,325]	[166,365]	40
12	50,35,1	[228,345]	[188,385]	40
13	30,25,1	[690,827]	[650,867]	40
14	15,10,1	[32,243]	[0,283]	40
15	30,5,1	[175,300]	[135,340]	40
16	25,20,1	[272,373]	[272,373]	40
17	5,30,4	[733,870]	[693,910]	40
18	20,40,1	[377,434]	[337,474]	40
19	15,60,2	[269,378]	[229,418]	40
20	45,65,1	[571,666]	[531,706]	40

In the simulation process, the target points are distributed on the three-dimensional raster map with the size of 100*100*50(m), The fixed number of the position of the security center is 0 and the coordinate is (5,5,0), and the number of each safety inspection site is 1,2,3...,20. The three-dimensional coordinate distribution is shown in the table above. The number of available UAV in the safety inspection center is 5.

Using the three-dimensional A* algorithm and the UAV safety inspection path optimization model with the time window, we first obtained the distance d_{ij} from the security center to each inspection point and between each inspection point. According to the above information table, you can obtain the inspection time of each safety inspection node T_i , inspection time window $[s_i, e_i]$, and maximum tolerance inspection time window $[S_i, E_i]$. And then, we can obtain performance and cost simulation parameters of UAV, which are shown in Table 3.

Table 3: Some parameter values

Description	Symbol	Numerical value
Average velocity	s	0.8m/s
Maximum cruising time	α	45 minutes (2700s)
Maximum hover time	δ	60 minutes (3600s)
UAV flight battery	m	2000 yuan
Battery charging and discharging times of UAV	β	400 times
Single use cost of UAV	C_e	100yuan/set
Unit energy consumption cost of UAV flight	C_d	$m/\beta/\alpha \approx 0.002$ yuan/m
Unit energy consumption cost of UAV hovering	C_h	$m/\beta/\delta \approx 0.001$ yuan/m
penalties cost earlier than the time window	θ_1	0.167yuan/s
Penalty costs for drones late in the time window	θ_2	16.7yuan/s

4.2 Model solving

Because the distance between safety inspection nodes is the most important factor affecting UAV fitness and the most important cost affecting the objective function, this study believes that the weighting coefficient is the highest and δ_1 is set as 0.6. The second consideration is the close proximity of time windows between safety inspection nodes. If there are multiple points in the corresponding time window that need to be inspected at the same time, we may need to exclude multiple UAVs for support in order to meet the demand. The weighted coefficient of δ_2 is set as 0.3. Finally, we set the weighted coefficient of δ_3 to 0.1.

4.2.1 Parameter setting of adaptive genetic algorithm

The relevant parameter Settings of adaptive genetic algorithm are shown in Table 4.

Table 4: Parameter Settings of adaptive genetic algorithm

Genetic algorithm parameter	Definition	Numerical value
NIND	population size	300
Max Gen	maximum number of iterations	200
p_c	crossover probability	Equation (7) is solved
p_m	mutation probability	Equation (7) is solved
GGAP	generation gap	0.9

4.2.2 Simulation results and comparison

To facilitate comparison, the algorithm is programmed using the standard genetic algorithm rather than the NCC algorithm. The solution in the preceding example is the best of the ten running results, and then we can the solution results based on the three algorithms, which are shown in Table 5.

Based on hybrid genetic algorithm, we can obtain the convergence chart, which is shown in Figure 6. The simulation results show that the algorithm begins to converge after the 20th iteration.

Table 5: Results of the three algorithms

Algorithm	Convergence iteration times	Number of UAV	Total flight distance	Inspection cost	Number of path constraint violations	Inspection strategy
A* + NCC algorithm + Adaptive genetic algorithm	20	3	745.6.28	302.3	0	safety inspection route 1: 0→2→16→6→3→4→13→0; safety inspection route 2: 0→14→5→11→19→7→18→8→10→17→0; safety inspection route 3: 0→15→12→9→20→1→0
A* + Adaptive genetic algorithm	36	3	760.7	302.3	0	safety inspection route 1: 0→14→5→12→9→6→4→13→0; safety inspection route 2: 0→15→16→7→18→8→3→1→0; safety inspection route 3: 0→2→19→11→10→20→17→0
A* + standard genetic algorithm	60	3	806.12	302.19	0	Safety inspection route1: 0→14→5→12→16→18→9→20→13→0; Safety inspection route 2: 0→2→11→19→10→17→0; Safety inspection route 3: 0→15→7→8→6→3→4→1→0

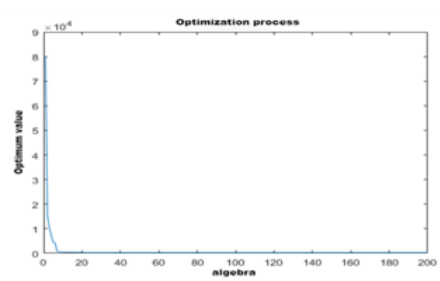

Figure 6: Iterative diagram of adaptive genetic algorithm

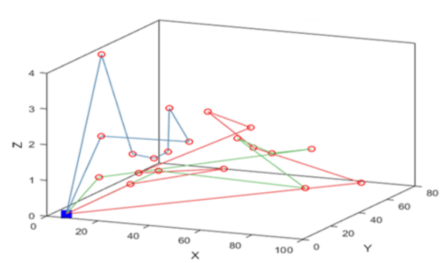

Figure 7: Optimal inspection route map for UAV safety inspection

The simulation experiment results, as shown in Figure 7. It can be seen that the hybrid genetic algorithm proposed by us can solve the path planning problem of UAV safety inspection with time window, and the results are better than the basic genetic algorithm using NCC algorithm, and even better than the basic genetic algorithm:

(1) Instead of directly using Euclidean distance, we propose using the A* algorithm to find the shortest distance

between the security center and each safety inspection node. Increasing the accuracy and consistency of the data source with the actual use of drones.

(2) The NCC algorithm is used to provide the first viable solution of the genetic algorithm. The quality of viable solutions is increasing. It has the potential to improve execution efficiency and results. The speed is increased by about 60% when compared to the basic genetic algorithm.

(3) To avoid falling into local optimality and achieve fast convergence, an adaptive genetic algorithm is used.

4.3 Parameter setting and sensitivity analysis

Sensitivity analysis on UAV speed, UAV unit energy consumption cost, UAV time window penalty cost, and safety inspection time was performed to explain the degree of influence of UAV flight and performance parameters on the path planning scheme of safety inspection, in order to achieve more reasonable and effective safety inspection suggestions for different factories and manufacturing centers.

4.3.1 Impact of UAV flight speed on safety inspection path cost

By using the UAV's flight speed of 0.8m/s, the cost model can be solved. In practice, the speed of the UAV changes at any time depending on the flight conditions. By solving the problem of UAV speeds of 0.5m/s, 0.8m/s, 2m/s, and 3m/s ten times, we can obtain the impact results, which are shown in Table 6.

Table 6: The impact of UAV flight speed on the solution results of cost model

Flight speed / Consequence	0.5m/s	0.8m/s	1.5m/s	3m/s
Inspection cost (yuan)	402.4	302.3	202.1	202.1
Flying distance (m)	784.9	745.6	648.4	688.1
UAV(set)	4	3	2	2

As can be seen from Table 6: When the flight speed is 0.5m/s, the inspection cost is the highest, which is 402.4 yuan. This is mainly due to the increased inspection time of low-speed flying, which increases hover cost and total flight time. At the same time, the total flying distance in this case is the longest, at 784.9 meters. This is because low-speed flying results in more path coverage, increased flying distance, and more UAVs are needed to cover the same inspection area.

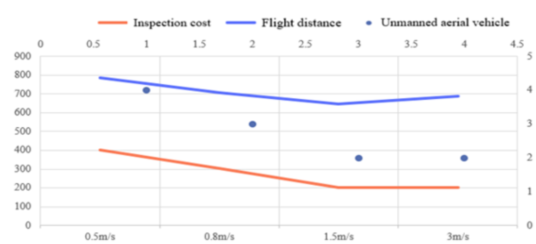

Figure 8: The impact of UAV flight speed on the solution results of cost model

From Figure 8, we can determine the chart that how the flight speed of a UAV affects the total cost of safety inspection, flight distance, and the number of UAVs. The cost of safety inspection decreases as flight speed increases, and the number of UAVs decreases as flight speed increases. As previously stated, the fixed cost of UAV is 100 yuan/sortie, so the reduced cost is the fixed cost of UAV. This indicates that increased UAV speed can more efficiently meet the time window requirements for safety inspection; on the other hand, slower UAV flight speed will make meeting the time window for safety inspection more difficult, resulting in a higher penalty cost. When the cost exceeds the fixed operating cost of the UAV, the number of UAV flights must be increased.

The flight speed of the UAV may not always meet the requirements of the lowest cost due to the specific environmental restrictions of the factory and the flight dynamics requirements of the UAV. As a result, the most appropriate flight speed should be chosen to meet the cost requirements based on the specific factory environment and the UAV's own limitations. Then, in the analysis of this paper, 1.5m/s speed is the most appropriate. This not only reduces the inspection cost, but also ensures the stability and inspection efficiency of the UAV.

4.3.2 Influence of UAV unit energy consumption cost on safety inspection path cost

The cost of UAV unit energy consumption will also have an impact on the total cost of safety inspection, resulting in a deviation from the planned path. On the basis of the default, the unit energy consumption cost of UAV will be reduced by 50%, increased by 100%, and increased by 200%. UAV's standard unit energy consumption cost is 0.002 yuan/meter. The hover's unit energy consumption cost is 0.001 yuan/s, and its average value is taken after 10 times of solving. The outcomes are shown in the Table 7.

Table 7: The impact of UAV flight speed on the solution results of cost model

Consequence \ Ratio of unit energy consumption to default energy consumption	-50%	0%	100%	200%
Inspection cost (yuan)	301.1	302.3	304.4	306.9
Flying distance (m)	730.8	706.2	701.8	732.1
UAV(set)	3	3	3	3

As can be seen from Table 7, the lowest inspection cost is 301.1 yuan when the unit energy consumption is reduced by 50%. This suggests that the reduction in energy consumption can effectively reduce inspection costs, although not by much. The influence of energy consumption on flight distance is not significant. Although there were some variations, such as 730.8 meters for a 50 percent reduction in unit energy consumption and 732.1 meters for a 100 percent increase, the overall variation was small.

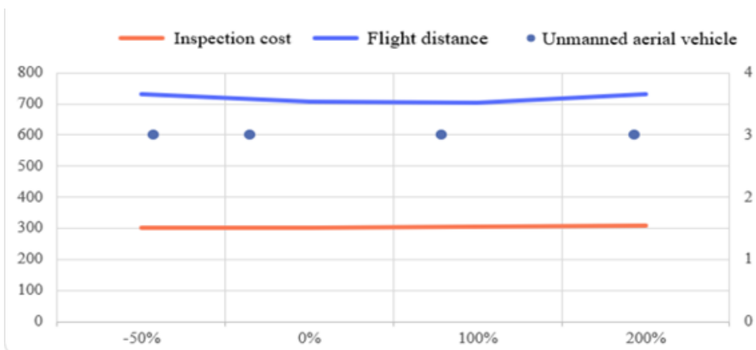

Figure 9: The influence of UAV unit energy consumption on the solution results

As can be seen from Figure 9, the increase or decrease of unit energy consumption has a very small impact on inspection cost and flying distance. Moreover, under different unit energy consumption conditions, the number of UAVs remains unchanged, indicating that changes in unit energy consumption will not significantly affect the quantity demand of UAVs, further indicating that even if the factory or enterprise uses a slightly lower price, the UAVs with a slightly higher unit energy consumption will not significantly increase the cost of safety inspection. Therefore, choosing a more cost-effective UAV can make it easier for factories to import UAV for safety inspection. However, in large-scale applications, the cumulative energy savings will bring significant economic benefits to a certain extent.

4.3.3 Influence of penalty cost of time window on cost of safety inspection path

The model is built with a penalty cost of 0.167 yuan/s before the time window and 16.7 yuan/s after the time window in mind. The penalty cost of the time window is now reduced by 50%, increased by 100%, and increased by 200%, and solved in three cases based on the default. After ten times of solving, the average value is obtained. The outcomes are shown in the Table 8.

As can be seen from Table 8, when the time window penalty cost is reduced by 50% and increased by 200%, the inspection cost is 302.2 yuan, indicating that the reduction of penalty cost has limited impact on the overall inspection cost. When the penalty cost was reduced by 50 percent, the flight distance was 730.8 meters, while when the penalty cost was increased by 100 percent, the flight distance was 723.4 meters, and the change was also smaller. Under different penalty costs, the number of UAVs remained the same, at 3.

Table 8: The impact of UAV flight speed on the solution results of cost model

Consequence \ Ratio of penalty to default penalty cost	-50%	0%	100%	200%
Inspection cost (yuan)	302.2	302.3	302.3	302.2
Flying distance (m)	730.8	706.2	723.4	722.1
UAV(set)	3	3	3	3

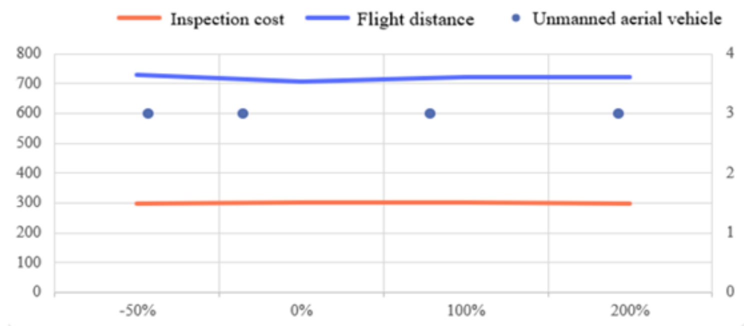

Figure 10: The effect of time window penalty cost on the solution results

As can be seen from Figure 10, in this case, the penalty cost of time window has very little impact on the inspection cost, flying distance, and the number of UAVs. Although the impact of time window penalty costs on inspection costs is small, strict time window management is still crucial in highly demanding safety inspection scenarios. We also attempted to raise the penalty cost of the time window to a very high level, resulting in an increase of about 100 yuan in total inspection cost, indicating that when the penalty cost rises, unmanned aerial vehicle inspection should be added to avoid the penalty cost of the time window rising. This penalty cost factor must be determined separately based on the specific industry or scenario requirements.

4.3.4 Impact of safety inspection time on safety inspection path cost

Because safety inspection times vary, we set the inspection time to 30 seconds, 40 seconds (default inspection time), 55 seconds, and 60 seconds for 10 times of solution and take the average value. The outcomes are listed in the Table 9.

Table 9: The influence of safety inspection time on the solution results of the cost model

Consequence \ Inspection time	30s	40s	55s	60s
Inspection cost (yuan)	301.9	302.3	402.6	402.6
Flying distance (m)	670.34	706.2	733.9	720.02
UAV(set)	3	3	4	4

According to the results, we can determine the impact of safety inspection time on the solution result of the cost model. As can be seen from Table 9, when the inspection time is 30 seconds, the inspection cost is the lowest, which is 301.9 yuan. A shorter inspection time can effectively reduce the total cost. The inspection time has little effect on the flying distance. Although the flying distance varies slightly under different inspection times, the overall change is not large, such as 670.34 meters at 30 seconds and 720.02 meters at 60 seconds. For short inspection periods (30 seconds and 40 seconds), the number of UAVs remained at 3. However, when the inspection time was extended to 55 seconds and 60 seconds, the number of UAVs increased to four.

According to the results, we can determine the influence of safety inspection time on the solution results of the cost model, which is shown in Figure 11. According to the data in the chart 11, increasing the time for safety inspection will result in an increase in total inspection cost, flight distance, and the number of UAVs. When the safety inspection time increases, the number of UAV sorties should be increased to meet the inspection time window requirements. Reduced inspection time, on the other hand, will not necessarily reduce cost due to the time window limitation. As a result,

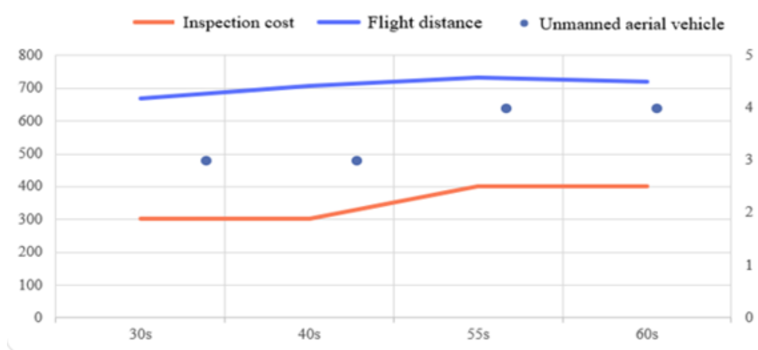

Figure 11: The influence of safety inspection time on the solution results

selecting the appropriate inspection time within a certain range can not only ensure the safety inspection time, but also control the cost of UAV path planning.

4.3.5 Summary of sensitivity parameters

The following results can be obtained based on the above sensitivity analysis of UAV speed, UAV unit energy consumption cost, UAV time window penalty cost, and safety inspection time:

(1) The cost of safety inspection is heavily influenced by UAV speed and safety inspection time. Choosing the appropriate UAV speed and inspection time based on the specific environment of the factory and the flight dynamics requirements of the UAV can reduce the total cost of safety inspection.

(2) UAV unit energy consumption has a negligible impact on current inspection costs. Using a lower-cost UAV with a higher unit energy consumption will not significantly increase the cost of safety inspections. Choosing a low-cost UAV can make it easier for factories and businesses to take the initiative to import security drones.

(3) The penalty cost of the UAV time window has no effect on the total cost of inspection in specific scenarios, but it should be noted that some factories have strict inspection timeliness requirements. As a result, in this scenario, the UAV's planned route must be reset, and the inspection cost will rise.

In addition to this, while the improved hybrid genetic algorithm proposed in this paper performs well in optimizing the safety inspection path for UAV, we also recognize the challenges it may face in dealing with large-scale problems. Specifically, as the number of safety inspection node increases, so does the computational burden of the algorithm, because genetic algorithms need to evaluate a large number of possible paths in each iteration, and this evaluation can become time-consuming in large-scale problems. Therefore, for large-scale problems, further optimization is needed. In future studies, more efficient path evaluation methods can be explored to improve the computability of the algorithm, and more advanced optimization strategies, such as multi-objective optimization, can be introduced to improve the scalability of the model.

5 Conclusions

In this paper, we construct an optimization model for UAV safety inspection path considering fuzzy time window, and propose a hybrid genetic algorithm to solve the model. Some conclusions from the analysis and discussion are as follows:

(1) In the process of UAV safety inspection, the path optimization model with fuzzy time window effectively balances the profit and loss between cost and efficiency, so that the UAV can reasonably pass all inspection points under balanced conditions.

(2) The hybrid algorithm overcomes the problem that the traditional path planning algorithm's minimum path value does not conform to the actual constraints, and it avoids the shortcomings of the genetic algorithm, which is prone to local optimal and premature convergence. The simulation results show that the hybrid genetic algorithm has good optimization ability and can effectively reduce the number of UAVs used and the cost of safety inspection while meeting the safety inspection requirements.

(3) Optimization suggestions for UAV safety inspection are provided based on sensitivity analysis of UAV flight speed, unit energy consumption cost of UAV, penalty cost of UAV time window, and safety inspection time of UAV.

In this paper, the problem of using multiple UAVs for safety inspection path planning in factories is studied, which enriches the research on path optimization of UAVs in safety inspection to a certain extent, but there are some limitations and deficiencies in the research process. First of all, the cruise capability of the UAV considered in this paper is determined, and the trajectory smoothing problem in the flight of the UAV and the performance constraints such as the maximum flight altitude and maximum turning Angle are not considered. Secondly, this paper assumes that each UAV safety inspection is a static global path planning, and the environment is carried out under known conditions. However, in practical applications, external factors such as weather conditions and unexpected outages may have an important impact on the effect of the model, so it is necessary to study the dynamic path planning of UAVs under local environmental changes. Finally, the factory enterprises considered in this paper have a single security center when conducting safety inspection, and the unmanned aerial vehicles for safety inspection are also of the same type. Moreover, the factory enterprises may have too scattered inspection points due to the large production area and storage area in reality, and there will be multiple security centers and the use of multiple types of inspection unmanned aerial vehicles. In the future research, we should try to meet more complex conditions in the actual situation and be more in line with reality.

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Data Availability

The data used to support the findings of this study will be considered by the corresponding author.

Conflict of interest statement

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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