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The Programming Model of Air-Ground Cooperative Patrol Between Multi-UAV and Police Car

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ABSTRACT This paper investigates a patrol problem based on air-ground cooperation between multiple UAVs and police vehicles. Facing the uncertainty of patrol environment and patrol resources, the model guarantees the deterrence and emergency response capability of the patrol mission by optimizing the allocation strategy of patrol points and patrol routes. Relying on genetic algorithms, we encode patrol points and UAV launch/recovery points together to enhance the local search ability and convergence of the algorithm. Based on the real case of the D police station in Beijing, we explore the interactions among patrol elements and the impact on patrol tasks in different patrol environments. The results show that the Patrol missions formulated by Air-Ground Cooperative Patrol Optimization Model can be used to develop patrol tasks with better environmental adaptability. By analyzing the relationship between multiple groups of patrol elements, controlling the number of UAVs in future missions can improve the security of the area. And raise the ratio of hovering time in medium-risk areas to low-risk areas can improve the efficiency of patrols.

INDEX TERMS Air-ground cooperative, patrol elements, genetic algorithm, crime deterrence, emergency response.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have been widely used in military, agriculture, transportation, communication, security and other fields because of their small size, high mobility/flexibility and low cost [1]. In recent years, with the expansion of using low-energy rotary-wing UAVs with airborne cameras and voice equipment, police work has gradually become an important field of UAV application [2]. The addition of UAVs in the police force helps with problems existing in police departments at this stage, such as insufficient police, low-tech police equipment, and weak synergy of multiple polices.[1] According to the UAV use survey report released by the Center for the Study of the Dragon at Bard College in 2018, at least 910 state and local public security agencies in the United States have purchased drones, two-thirds of which are used by law enforcement agencies [3]. In China, the earliest involvement of drones in policing activities can be traced back to the 2008 Beijing Olympics, in which the Beijing and Qingdao police took the lead in acquiring several sets of UAV systems for patrols in large-scale events. From 2017 to 2018, Guangzhou Tianhe police UAVs carried out more than 570 security tasks and conducted more than 8355 UAV inspections [4]. During the COVID-19 pandemic, the cooperation of UAV use and police vehicles can better carry out noncontact law enforcement patrol and monitoring work, and the model has been adopted in many countries around the world [5].

The routing strategies of UAVs are quite different in different application backgrounds, such as cargo transportation [6], disaster rescue [7] and patrol [8], and the challenges faced by their routing problems are different. Police patrols are the

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[1]The representative models of police drones are ewz-s8, aee f100, a8-h and others. These drones are lightweight, easy to hover and capable of carrying police equipment.

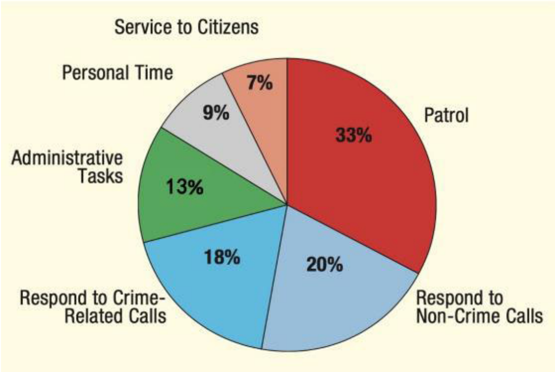

FIGURE 1. Percentage of patrol time by activity.

foundation of public security management and community policing, as shown in Fig. 1 [9], and they take up the most time in policing. Police patrols are often conducted around ''hot areas of crime'' because ''hot spots'' can point out the possible risks for the police in the future. Many scholars have also found that increased police presence in hotspots reduces crimes and disorderly conduct [10]. Additionally, police patrols play an important role in public service by responding to incidents and deterring and preventing crimes [11]. By assigning limited police presence to more critical areas, patrols can be made more efficient and crime prevention can be enhanced. The patrol problem for air-ground cooperation involves the drones and police vehicles' patrol line, and the achievement of patrol objectives——the deterrence of crime and the response of emergencies. In the following, we provide an overview of the air-ground cooperation elements and UAV patrols.

A. OVERVIEW OF AIR-GROUND COOPERATION

The air-ground cooperation concept was first proposed and widely adopted by the U.S. military, which is initiative, sensitivity, deep and coordinated [12]. It is important for the police work of key target protection, three-dimensional space confrontation, mid-low altitude patrol and other tasks. The problem of air-ground cooperation belongs to the research of ''two-level routing,'' and many scholars focus on the ''last mile'' of logistics [13]. They consider UAVs as an extension of vehicles and optimize UAV delivery by considering factors such as delivery paths, radar detection and terrain conditions [14]. A number of articles on two-echelon routing problems have been published in recent years, they are deformed on the vehicle routing problem (VRP) by continuously enriching the relationship between route and location [15]. Since the performance of drones differs from that of cars, researchers tend to use physical tracking, obstacle avoidance and surveillance coverage as UAV flight objectives [16]. Li *et al.* [17] demonstrated the impact of UAV turning on the completion of cruise missions in terms of route length, duration and energy and then carried out a path planning design targeting the least number of turns for a UAV. With the development of UAV technology, most police drones are multi-rotor drones at present, which have low takeoff and landing environment requirements and are more flexible in hovering and turning. New technologies allow UAVs to adapt to patrol work as well as resupply work, and some scholars have optimized patrol lines for public safety and emergency work in terms of patrol coverage capabilities [18], [19].

To realize the remote application of multiple UAVs, assistance with delivery vehicles is the most straightforward option [20]. The vehicle and UAVs perform tasks at the same time, where the vehicle is defined as a moveable intermediate depot to release/recycle UAVs and serve other sets of customers. The selection of this point is also part of the line optimization, but considering the efficient use of police resources, we will select a suitable release/recovery point in the patrol target area. With the depth of research, multi-UAV systems are the trend of future application; at the same time, flight stability, effectiveness, endurance and mission management will be more challenging [21]. When the patrol mission is formulated, most scholars use a regional subdivision approach to simplify the problem [22]. However, with multiple UAVs involved in patrol missions, the distribution of individual patrol points and the interaction between UAVs are still issues we need to focus on. The establishment of an air-ground cooperative strategy is more complex in terms of patrol target allocation and route planning issues that closely match the actual situation [23].

B. POLICE PATROLS INVOLVING UAVs

Effective scheduling of drone patrols maximizes the chances of apprehending criminals [24]. The increasing use of drones in policing [25] has also increased the complexity of the problem, and the first thing to consider is where to release and retrieve the drone. By setting the release/recovery points, distance and time constraints, the problem is expressed as mixed integer programming and solved by a heuristic algorithm [26], [27]. In practice, this technology has been carried out by large e-commerce companies such as Amazon and Jingdong. However, through the detailed review of drone-truck combined operations by Chung *et al.* [28], future research needs to focus on the uncertainty of the task environment, especially the robustness and dynamics of the task design. This is what drones and police vehicles need to consider when performing patrol duties.

In addition, patrolling missions involving UAVs are different from logistics dispatch [29] and communication [30] systems; they focus on the environmental worthiness and confrontation strategies against potential perpetrators. According to environmental criminology theory, crimes are based on the intersection of criminals, targets, and the lack of supervisors in the same space and time [31], as shown in Fig. 2. The significance of police patrols is to compensate for the lack of supervision to curb criminals, a visible police presence can increase the public's certainty of punishment, and a frequent police presence enhances potential criminals' perceptions of risk in the local area [32]. The current patrol approach is

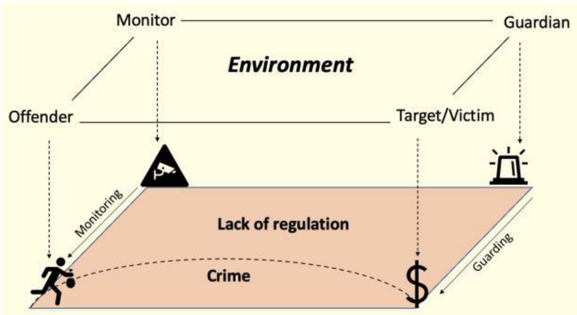

FIGURE 2. The occurrence of crime in environmental criminology.

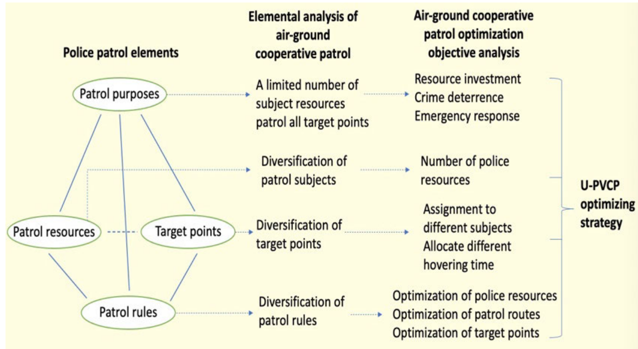

FIGURE 3. Research-oriented chart of air-ground cooperative patrol.

divided into ‘‘hotspot patrolling’’ and ‘‘random patrolling,’’ the latter of which greatly increases the unpredictability of police operations, but more empirical studies [33], [34] have proven the effectiveness of ‘‘hotspot patrolling’’ in reducing crime. The successful operation of air-ground cooperative patrolling to cover ‘‘hotspots’’ requires a detailed routing strategy—specifically, defined and targeted patrol routes. The intensity and location of crime affect the spatial allocation of police, and a uniform standard for patrolling would be a waste of police resources. Here, we consider the difference in patrol resources—patrol time commitment—under different risks. However, focusing on hot spots alone is not sufficient either, as they omit the peculiarities and challenges of police daily patrols. In the process of patrolling, police officers are faced with various possible emergencies and need to send the nearest patrol officer to deal with the incident in time [35]. On the other hand, to reduce crime, patrols need to focus on patrol targets with a high risk of crime, including offender deterrence [36] and emergency disposal [37]. When the number of patrol subjects and patrol hours change, the crime deterrence and emergency response of the jurisdiction will also be affected. Therefore, by adjusting the hovering time at different patrol points, more robust and resilient patrol planning can be explored to better meet the requirements of police patrols.

In this work, we breakdown the patrol task into different constituent elements based on the characteristics and challenges of actual police patrols (Figure 3). After that, we establish the connection between the patrol tasks and each individual patrol element. We build a relational model with a multisubject task balance, police resource input, crime deterrence and emergency response capabilities. Traditional patrol problems are categorized as TSP problems, and their algorithms mostly focus on the behavior-based algorithm (BBA) and the optimization method, e.g., genetic algorithm (GA) and particle swarm optimization (PSO) [38]. By sorting out the problems of air-ground cooperative patrols, we contribute an efficient algorithm called the UAV-Police Vehicle Cooperative Patrol Algorithm (U-PVCPA). This algorithm can solve the data flow clustering efficiency problem effectively. In the solution process, the patrol routes, deterrence capability and emergency response capability are optimized as a whole. The algorithm relies on the vehicle speed in different environments and the hovering time for different crime risk points to simulate the impact of changes between different patrol elements on the overall optimization of the patrol.

This paper is organized as follows. In section 2, we analyze and deconstruct the air-ground cooperative patrol mission and sort out the relationship between each patrol element. In section 3, the air-ground cooperative patrol planning model and UAV-Police Vehicle Cooperative Patrol Algorithm are proposed. In section 4, the model and algorithm are validated using the real precinct environment of the D police station to discuss the influence relationships among patrol elements in different patrol environments and to develop an optimal patrol plan for a limited number of patrol subjects with different hovering times. Finally, in section 5, we summarize prospects of the study.

II. ANALYSIS AND DECONSTRUCTION OF THE AIR-GROUND COOPERATIVE PATROL MISSION

A. AIR-GROUND COOPERATIVE PATROL MISSIONS

UAV and police vehicle collaboration points in patrol missions are not the same as logistics or ship-based aircraft operations. According to the definition and mission planning of modern police patrols by Gaines and Kappeler [39], a complete air-ground cooperative patrol mission includes four elements, as shown in Fig. 3, including developing mission objectives, patrol resources, target points and specific plans in a logical sequence of mission conduct; these four elements are interdependent and supportive. We need to consider all the elements and the impact between them when setting patrol missions.

1) Compared to the ‘‘multi traveler problem,’’ the key point of air-ground patrols is ‘‘cooperation.’’ The speed and routes of police vehicles determine the number of target points they can patrol, which affects the number of UAVs, the assignment of mission points, and the candidates for UAV launch/recycle points. Meanwhile, the duration of the UAV constrains the distance of the police car, and the police car driving routes need to be adjusted to the distribution of drone patrol target locations to ensure that the loss of each drone is balanced.

2) At present, patrol issues focus on a single scenario frequently. However, the reality of the patrol environment

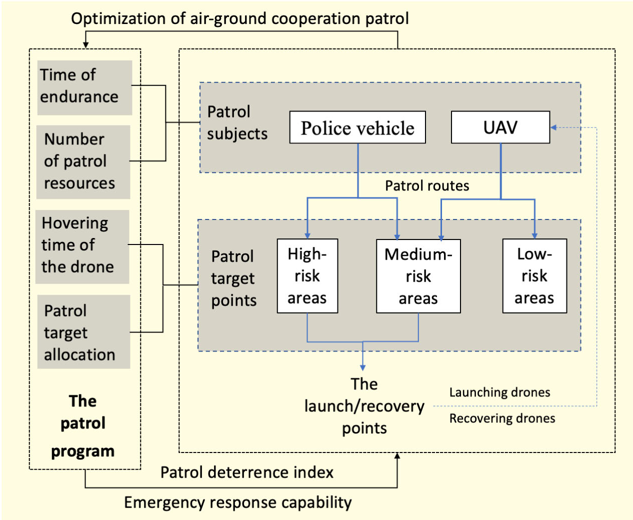

FIGURE 4. Flow chart of air-ground cooperative patrol mission.

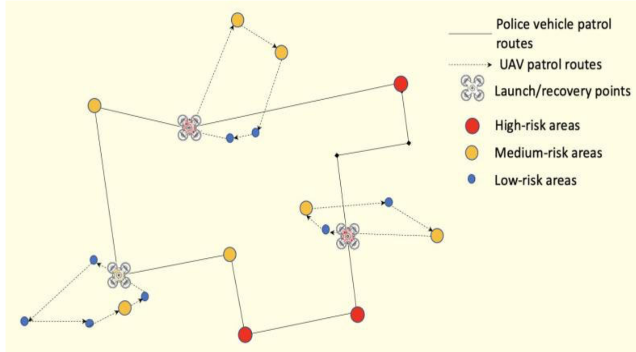

FIGURE 5. Mimic diagrams of air-ground cooperative patrol routes.

is more complex when the police vehicle and UAVs work together on missions. Faced with a large number and variety of patrol target points, changes in the objective environment will have a greater impact on the investment of patrol resources, patrol route planning and patrol point allocation. In this regard, we compare the relationship between patrol elements at different vehicle speeds in the various environments to simulate the impact of different environments on overall patrol planning.

3) Patrol is a police activity aimed at the suppression of crime in the jurisdiction, including controlling responses to emergency situations and threat deterrence to potential offenders [39], [40]. A successful patrol mission ensures the deterrence of criminal activities in the precinct, rapid disposal of emergencies and protects that subsequent patrol missions are conducted properly. Therefore, the objectives of the patrol mission can be summarized as the ability to deal with emergencies and crime deterrence in the jurisdiction.

B. PROBLEM FORMULATION

Based on the description of the air-ground cooperative patrol problem, this paper will examine the patrol mission as a whole. Based on the allocation of target points in the police patrol area, the linkage between the patrol elements is analyzed. A multivariate relationship model was established between the patrol subject, target point, patrol deterrence, and emergency response capability, as shown in Fig. 4. The specific assumptions used in the model are as follows:

1) CLASSIFICATION AND CATEGORIZATION OF PATROL TARGET POINTS

To carry out patrol work accurately, the police divided the precincts into different levels of risk control, identified key areas and set patrol targets based on the crime rate. Police patrols are targeted on the basis of the above work to patrol key areas [40]. Each patrol target area is divided into three categories: high-risk areas, medium-risk areas and low-risk areas. These crime risk points constitute the patrol target set for patrol missions. Since police vehicles have a stronger ability to dispose of and deter criminals compared to drones, we put areas with higher risk levels on police car patrol.

2) SETTING OF UAV LAUNCH/RECOVERY LOCATION

After completing the patrol of the assigned target point within the endurance time, the UAV goes to the landing site and waits for the recovery of the police vehicle, and this patrol constitutes a loop. We disregard the time consumption of the police vehicle to launch the UAV and retrieve it. The launch/recovery points shall be selected among the target points for police vehicle patrols to increase the police visibility in medium- to high-risk areas. In this way, we can ensure the efficiency of air-ground patrols and improve the security level of the district.

3) DISTRIBUTION OF PATROL STATUS AND PATROL SUBJECTS

According to environmental criminology theory [41], areas with high crime rates are patrolled by police officers with police cars, assuming that the police cars have enough fuel storage to complete the patrol tasks. Areas of low crime risk are patrolled by UAVs of the same type, all of which are fully charged before the mission. Some medium-risk targets are handed over to police vehicles for patrols, provided that they can safely launch and recover the drone, as shown in Fig. 5. To make patrol missions more targeted, UAVs differ in their time invested in patrolling low- and medium-risk points. Here, we set the patrol stop time to 0.1 h and 0.2 h for medium-risk areas and 0.01 h, 0.03 h, and 0.05 h for low-risk points. The number of UAVs carried by police vehicles is not capped, the number of drones carried by one police vehicle can meet the patrol of all points of one mission, and all subjects are patrolled at a constant speed.

4) SETTING OF PATROL MISSION TARGET

Historically, visibility was believed to repress crime, and patrol strategies were developed in an attempt to better

TABLE 1. Model symbols and definitions.

symbol definition
O: patrol targeting set
O^C: set of police car patrol points
O^U: set of UAV patrol points
O^H: set of high-risk areas
O^M: set of medium-risk areas
O^L: set of low-risk areas
T: maximum drone endurance
P: set of launch/recovery points
d_{ij}^c: distance from target i to target j for police car C_c patrol
d_{ij}^u: distance from target i to target j for UAV U_u patrol
t^M: hovering time of the drone at point O^M
t^L: hovering time of the drone at point O^L
V_C: police car speed
V_U: UAV speed
S_U: fixed cost of one drone
s_U: cost of attrition per hour of drone flight
S_C: fixed cost of one police vehicle
s_C: cost of fuel consumption per kilometer for police car
U: set of UAV, U=1，2，⋯, u
C: set of police car, C=1，2，⋯, c

respond to service calls, deter crime, or apprehend criminals once crimes have occurred [42]. A police force with good emergency response capabilities can deter crime in a timely manner and achieve a deterrent to other potential crimes. Crime deterrence and emergency response capabilities complement each other. The deterrent effect of patrols is reflected in the visibility of police vehicles and UAVs at key target points. The emergency response capacity of the patrol is mainly reflected in the efficiency of the nearby patrol police force to dispose of the incident after the occurrence of an emergency, as well as the patrol stability of the whole task. The increase in the number of UAVs can prolong the patrol time and improve the police visibility and disposal efficiency, but it also increases police expenditures. To better reflect the relationship between them, we set the number of UAVs to 3, 5, and 7.

C. NOTATION AND TERMINOLOGY

According to the description and assumptions of the real problem, the air-ground cooperative patrol task involves the number of patrol subjects, the allocation of target points, the planning of patrol routes, the determination of the launch/recovery points and the allocation of UAV hovering time in different risk level patrol points. The model notation is defined as shown in Table 1.

$$C_{x_{ij}}^c = \begin{cases} 1 & \text{Police car } C_c \text{ arrives at patrol site } o_j \text{ from } o_i \\ 0 & \text{Otherwise} \end{cases}$$

$$C_{y_i}^c = \begin{cases} 1 & \text{Police car } C_c \text{ arrived at patrol place } o_i \\ 0 & \text{Otherwise} \end{cases}$$

$$U_{x_{ij}}^u = \begin{cases} 1 & \text{UAV } U_u \text{ arrives at patrol site } o_j \text{ from } o_i \\ 0 & \text{Otherwise} \end{cases}$$

$$U_{y_i}^u = \begin{cases} 1 & \text{UAV } U_u \text{ arrived at patrol place } o_i \\ 0 & \text{Otherwise} \end{cases}$$

$$U_{z_i}^u = \begin{cases} 1 & \text{UAV } U_u \text{ released and recovered at point } o_i \\ 0 & \text{Otherwise} \end{cases}$$

$$n_u = \begin{cases} 1 & UAV\ U_u\ (u \in U)\ was\ sent\ to\ patrol \\ 0 & \text{Otherwise} \end{cases}$$

$$n_c = \begin{cases} 1 & Police\ car\ C_c\ (c \in C)\ was\ sent\ to\ patrol \\ 0 & \text{Otherwise} \end{cases}$$

It should be noted that $O = O^H \cup O^M \cup O^L = O^C \cup O^U$ and $O = \{o_i, i = 1, 2, \ldots, o\}$, o is the total number of patrol areas. $O^M = O_C^M \cup O_U^M$, O_C^M, and O_C^M are the medium-risk areas for police vehicle patrols, and O_U^M are the medium-risk areas for UAV patrols.

Maximum drone endurance $T \gg t^M > t^L > 0$.

$$O^C = O^H \cup O_C^M = \left\{o_i^C \mid i = 1, 2, \cdots, o^C\right\};$$
$$P = \{P_m \mid m = 1, 2, \ldots, p\}, \quad P \subseteq O^H \cup O_C^M;$$
$$O^U = O^L \cup O_U^M = \left\{o_i^U \mid i = 1, 2, \cdots, o^U\right\}$$

In reality, UAVs are faster than police cars, and the flight time of the UAV between patrol points is much less than the hovering time at the target point. To make the problem closer to the real situation, we set each UAV to perform the task with flying time between points as $(1-\alpha)\,T$, where α is the influence factor of the objective environment, 0.6≤ α ≤0.8.

III. AIR-GROUND COOPERATIVE PATROL OPTIMIZATION MODEL AND ALGORITHM

The vehicle UAV collaboration problem can be referred to as the two-echelon location and routing problem (2E-LRP), but the air-ground optimization cannot be decomposed into two subproblems to be solved separately [15]. We need to analyze the relationship between multiple subjects and multiple task objectives and consider the sustainable use of each patrol subject from the perspective of police resource optimization.

A. OBJECTIVE FUNCTIONS AND CONSTRAINTS

When setting the patrol tasks, the police officer sets the goal of optimizing the minimum investment of police resources and balancing the tasks of each patrol unit while ensuring crime deterrence and emergency response capability in the precinct. The crime deterrence index and emergency response capability are important indicators of precinct security, and they are set as constraints of the air-ground cooperative optimization model.

1) OBJECTIVE FUNCTION

$$\begin{aligned} f_1 = min \sum\nolimits_{c\in C} (S_C \times n_C) + \sum\nolimits_{u\in U} (S_U \times n_U) \\ + \sum\nolimits_{c\in C} \sum\nolimits_{i,j\in O^C} \left(s_C \times d_{ij}^c \times C_{x_{ij}}^c\right) \\ + \sum\nolimits_{c\in C} \sum\nolimits_{i,j\in O^C} \left(s_U \times d_{ij}^c \times C_{x_{ij}}^c \Big/ V_C\right) \end{aligned} \quad (1)$$

$$f_2 = min\alpha\sqrt{\sum_{i\in O^U}\left[{}^{t_U}\!/_{n_u} - \left(O_U^M + O^L\right)\times U_{z_i}^u\right]^2 \Big/ n_u} \tag{2}$$

$$f_3 = min\sqrt{\sum_{i,j\in O^C}\left({}^{d_C}\!/_{n_c} - d_{ij}^c \times U_{x_{ij}^c}\right)^2 \Big/ n_c} \tag{3}$$

Objective function (1) consists of four components, which are minimizing the assignment cost of police vehicles, the patrol cost of police vehicles, the assignment cost of UAVs and the patrol cost of UAVs; objective function (2) represents minimizing the distribution difference of each UAV task; objective function (3) represents minimizing the distribution difference of each police vehicle task.

2) CONSTRAINT CONDITION

$$\sum_{i,j\in O^C}\left(d_{ij}^c \times C_{x_{ij}}^c\right) \le 1/2V_C T \tag{4}$$

$$\sum_{i\in O^M}\left(t^M \times U_{y_i}{}^u\right) + \sum_{j\in O^L}\left(t^L \times U_{y_j}{}^u\right) \le \alpha T, \quad \forall u \in U \tag{5}$$

$$\sum_{i=1}^{o^C} C_{x_{ij}}^c = C_{y_j}^c, \quad \forall j \in O^C \tag{6}$$

$$\sum_{j=1}^{o^C} C_{x_{ij}}^c = C_{y_i}^c, \quad \forall i \in O^C \tag{7}$$

$$\sum_{i=1}^{P\cup O^U} U_{x_{ij}}^u = U_{y_j}^u, \quad \forall j \in O^U \tag{8}$$

$$\sum_{j=1}^{P\cup O^U} U_{x_{ij}}^u = U_{y_i}^u, \quad \forall i \in O^U \tag{9}$$

$$\sum_{c\in C} C_{y_i}^c = 1, \quad \forall i \in O^C \tag{10}$$

$$\sum_{u\in U} U_{y_i}^u = 1, \quad \forall i \in O^U \tag{11}$$

$$\sum_{j\in O^C, a\neq j} C_{x_{aj}} = 1,; \quad \sum_{i\in O^C, i\neq a} C_{x_{ia}} = 1, \ c \in C \tag{12}$$

$$\sum_{j\in O^U} U_{x_{pj}}^u = 1, \quad \sum_{i\in O^U} U_{x_{ip}}^u = 1, \ p \in P, \ u \in U \tag{13}$$

$$\sum_{i\in P} U_{z_i}^u = 1 \tag{14}$$

$$\sum_{i,j\in O^C} C_{x_{ij}}^c \le \left|O^C\right| - 1, \quad 2 \le \left|O^C\right| \le o^C \tag{15}$$

Condition (4) indicates the constraint of the UAV endurance on the patrol distance of a single police vehicle; condition (5) indicates the constraint of the UAV endurance on the UAV patrol time invested; condition (6) indicates that the patrol location on the police car patrol line is directly accessible from only one of the remaining patrol locations; condition (7) indicates that each patrol location on the police car patrol line reaches only one of the remaining patrol locations; condition (8) indicates that each patrol location on the UAV patrol line is directly accessible from only one of the remaining patrol locations; condition (9) indicates that each patrol location on the UAV patrol line reaches only one of the remaining patrol locations; condition (10) indicates that each point can only be patrolled once by a police car; the condition; constraint (11) indicates that each point can only be patrolled once by one UAV; constraint (12) ensures that the police car still returns to point a after starting patrol from point a (point a is set as a police station); constraint (13) ensures that the UAV returns to the launch/recovery point after taking off from that point; constraint (14) specifies that only one UAV is released at each launch/recovery point; constraint (15) indicates that the police car patrol route can only form a closed loop containing all patrol points.

3) PATROL TARGET CONSTRAINT

a: PATROL DETERRENCE INDEX

As we discuss above, visibility has been a major element in police crime control strategies and practices. As medium- to high-risk areas of UAV launch/recovery points, they are the basis for quantifying patrol deterrence. The hovering time of the drone can objectively reflect the police visibility of key locations in the precinct. Considering the deterrence of patrol points as energy diffusion, the patrol deterrence index is positively correlated with the dispersion of P points and the hovering time.

The average hovering time at point P is assumed to be $\bar{t} = \alpha Tu - t^M \times o_U^M - t^L \times o^L \big/_u$; S is the global dispersion of P points, which can be expressed by the proportion of P points to OC and the distribution of each P point: $S = {}^u\big/\left(maxd_{ij} - mind_{ij}\right) o^C$, $\forall i, j \in P, P \ge 3$. The deterrence index for air-ground cooperation is $\beta\bar{t}S = \beta\frac{\alpha Tu - t^M \times o_U^M - t^L \times o^L}{(maxd_{ij} - mind_{ij})o^C}$, where the number of patrol points is a known initial value. Therefore, the patrol mission deterrence index curvilinear equation can be expressed as $\Phi = u\big/maxd_{ij} - mind_{ij}$. When the UAV launch/recovery points have been established, the trend of the patrol deterrence index is $\frac{\gamma u}{t^M + t^L}$.

b: EMERGENCY RESPONSE CAPABILITY

In case of an emergency during the patrol, the available police resources need to be deployed to the scene of the incident as soon as possible, and the remaining patrol points are patrolled by other drones. To avoid excessive changes or termination of patrol tasks, the patrol plan tries to make minimal changes to the overall UAV patrol line while ensuring that all patrol points are patrolled by UAVs under emergency conditions. For this study, we refer to the supply chain flexibility problem, the min-max strategy, which reassigns the largest number of tasks to the UAV closest to the contingency.

Let t_u be the patrol time of drones u, $t_u = \sum_{i\in O_U^M, j\in O^L} U_{y_i}^u \times t^M + U_{y_j}^u \times t^L, \forall u \in U$, and $t_{max} = maxt_u$, which is indicated as the longest patrol time among the patrol drones, $t_{max} \le \alpha T$. The emergency response capacity of the patrol mission is set to $\Omega = \sum_{u\in U}\frac{\alpha T - t_u}{n_U \times t_{max}}$. From the above equation, we can see that $\Omega \in [0, +\infty)$, and the emergency response capability is positively correlated with the ability of patrol missions to respond to emergencies.

B. UAV-POLICE VEHICLE COOPERATIVE PATROL ALGORITHM

The air-ground cooperative patrol needs to arrange the routes of police vehicles and UAVs, which involves the site selection of UAV launch/recovery points and vehicle path planning. Both of them are NP-hard combination optimization problems, and most problems are solved by heuristic algorithms [43]. Currently, genetic algorithms have been proven to be an effective algorithm for solving combinatorial optimization problems. For this study, the ''target constraint'' does not affect the data convergence time but rather the flexibility of the patrol task in different environments. Because the patrol environment is complicated and variable and policing has certain subjective decision-making attributes, they are difficult to represent by a particular constraint. The UAV-police car collaboration problem requires multiobjective patrol point calculation. When planning a police car patrol route, the overall search for UAV launch/recovery points and patrol points needs to be carried out step by step, with continuous iterative optimization until the results converge, which is consistent with the solution logic of the genetic algorithm. In this paper, an alternative iteration algorithm based on genetic ideas is proposed to efficiently solve the problem.

1) PATROL POINT ALLOCATION FOR DRONES AND POLICE VEHICLES

The patrol task is influenced by the patrol environment, and the change in environment directly affects the speed of the vehicle and then affects the vehicle patrol routes and the allocation of UAV patrol points. When the patrol road is clear, police cars can cover more patrol points with higher speed, and the air-ground cooperative patrol will become more complicated. Besides, we screened the medium-risk points and handed them over to police car patrols (Fig. 6). When the existence of $o_i^M \in O_C^M$ causes $\Delta d_{ij}^c \times s_C \leq \left|-\Delta d_{ij}^u\right| \times s_U + |-\Delta U| \times S_U$, this point is set as a car patrol point. There are three patrol point allocation optimizations as follows:

Scenario 1 changes the attribution of O^M points by increasing the travel distance, thus affecting the number of UAV patrol missions, as shown in Figure 7.

Scenario 2 changes the choice of P points by increasing the travel distance, which affects the number of drones, as shown in Figure 8.

Scenario 3 changes the attribution of O^M points and the selection of p points at the same time by increasing the travel distance, which affects the number of patrol missions of UAVs and the number of UAVs demanded, as shown in Figure 9.

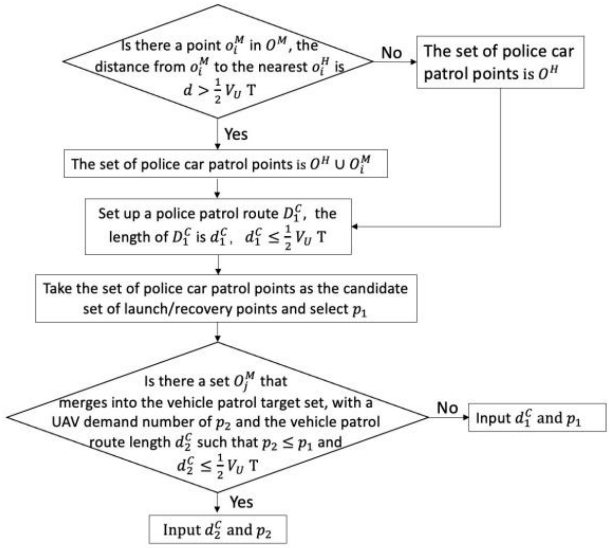

FIGURE 6. Logic diagram of patrol points and patrol routes.

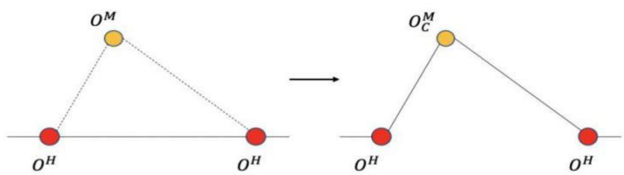

FIGURE 7. Change of single mid-risk points to police vehicle paths.

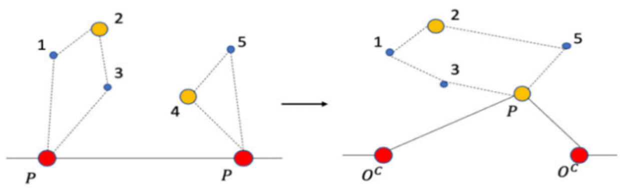

FIGURE 8. Change of single launch/recovery point to police vehicle paths.

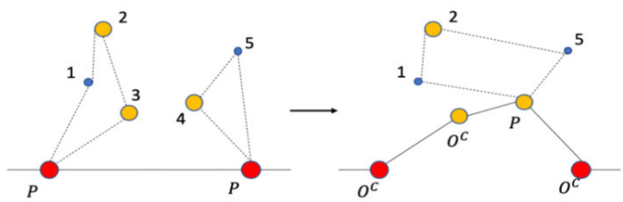

FIGURE 9. Change of multiple mid-risk points to police vehicle paths.

2) HEURISTIC ALGORITHM

Due to the linkage and interactive relationship between the subjects of the air-ground cooperation, when a superior individual emerges in the genes of the offspring, the influence of the optimal genes of the previous generation is added in the transmission as a new ''parent.'' By improving the algorithm in this way (Fig. 10), it ensures the convergence of

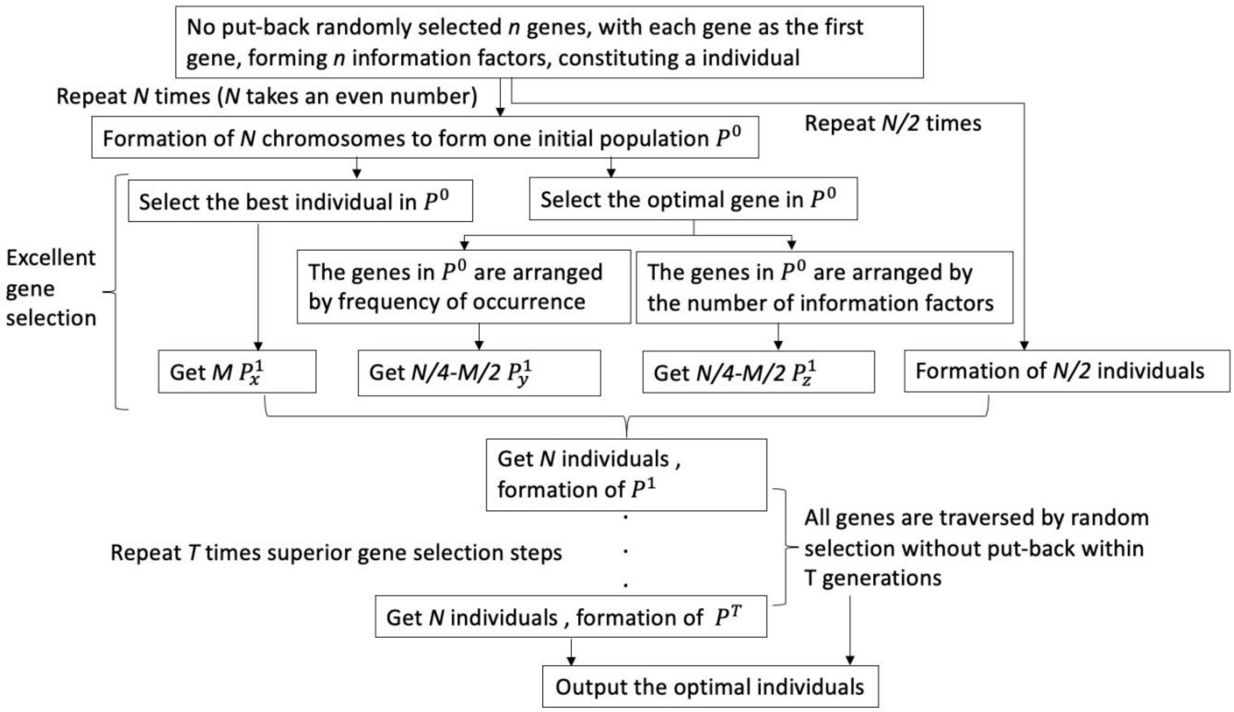

FIGURE 10. Genetic manipulation logic diagram.

the new generation optimal solution while taking into account the influence of the police vehicle patrol points and the launch/recovery points on the optimization of the UAV patrol routes. To better describe the influence of "cooperative" in the algorithm, we construct the interconnection of UAV patrol points, UAV launch/recovery points and police vehicle routes during the iteration of the operation. The article introduces the concept of information-carrying factor and constructs a three-level genetic operation of gene, information factor and chromosome. This algorithm selects high-frequency genes and optimal genes in the parent generation, iterates the gene transmission direction of the new generation together with the optimal individuals of the parent, and then screens the new generation of individuals. Compared with simulated annealing, neighborhood search, and particle swarm algorithms, the improved genetic algorithm is more convergent, and the offspring individuals are more robust. The air-ground cooperative patrol optimization model algorithm is described in Table 2.

IV. CASE STUDY OF THE D'S CONSTABLE WICK IN BEIJING

A. CASE PRESENTATION AND DATA PREPROCESSING

In this study, a police station precinct in city Beijing was selected as the research object, with a total area of 17 square kilometers, involving 165 units and covering a population of nearly 250,000. The average number of daily alerts in this jurisdiction is more than 50, and there are more semi-closed communities with high population density. The speed of police vehicles is as low as 35 km/h during peak hours and up to 45 km/h when the roads are open. In this special security environment and complex road situation, to ensure the patrol of risk points and the handling of emergencies in the district, patrol tasks need to have a certain degree of flexibility and reliability. Based on the distribution of crime hotspots in the jurisdiction, combined with environmental criminology theory, 5 high-risk patrol targets, 9 medium-risk patrol targets and 11 low-risk patrol targets were simulated on the map by criminologists and front-line officers (Figure 11). The star in the picture shows the location of the police station, which is the place of origin for the police vehicles.

Police jurisdictions are based on street distribution, population density, location of key units and police force configuration. In reality, there is no cross-regional patrol task, so the scope of patrol objects in this paper is controlled within a police precinct, and only one police car is dispatched in a single task.

B. EXPERIMENTAL RESULTS AND OPTIMIZATION SCHEME

To study the impact of different patrol situations on patrol task formulation, according to the congestion of the road at different times, we set the police car speed to three stages: $V_C^1 = 35\text{km/h}$, $V_C^2 = 40\text{km/h}$ and $V_C^3 = 45\text{km/h}$. As vehicle speed increases, the number of vehicle patrol points will increase, which will slow down the pressure on the UAV patrol points, but the vehicle patrol distance will be increased. Figures 12-20 represent the calculation results of the patrol deterrence index and emergency response capability as t^M

TABLE 2. Air-ground cooperative patrol optimization model algorithm.

AGPO(C, U, T, V, Φ, B) // H is the number of high-risk points; M is the number of medium−risk points; L is the number of low−risk points; C is the number of police car patrol points; U is the number of UAV patrol points; V is the police car patrol speed; Φ is the police deterrence index; B is the emergency disposal regulation.

// Initialize coordinate information
init POINIS_HIGH_H []
init POINIS_MIDDLE_M []
init POINIS_LOW_L []
// Traverse the path of all coordinate points under the restriction
POINTS_$Path$ []
  for i = 1 **to** POINTS_ $Path$.lengh
   if $distence_{f_1} < (\alpha T * V/2)$ // If there is no police car that travels a distance greater than the actual distance traveled in time $\alpha T/2$, it is valid
    POINTS_ $Path[i]$.verified
  else POINTS_ $Path[i]$.remove
// traverse the clustering samples of medium to high risk points under all confirmed paths
UAV_CLUSTERS[] = cluster(UAV_NUMBER)
UAV_MAX_TIME = O_MAX(UAV_CLUSTERS[])
for $[i]$=1 **to** POINTS_ $Path$.lengh
  if O(POINTS_ $Path[i]$) > UAV_MAX_TIME // If the time for one lap of the police car under this route is greater than the maximum flight time of each cluster point set for UAV patrol, the judgment is valid
  POINTS_ $Path[i]$.verified
else POINTS_ $Path[i]$.remove
// Considering the patrol subject sustainability cluster adjustment
init POINTS_ $Path[i]$
for $f_2 f_3[i]$=1 **to** POINTS_ $Path$.Dissimilar// the degree of discrepancy of the multi-subject patrol paths
  UAV_MIN_TIME.Dissimilar=f_2(UAV_CLUSTERS[])
  CAR_MIN_PATH.Dissimilar=f_3(CAR_CLUSTERS[])
POINTS_$f_2 f_3[i]$
// Calculate the minimum path of GA
$U\_f_2 Path$[] = GA(UAV_CLUSTERS[])
RERUN(params)
// Find the result of M L V under different cases of arithmetic
init M
init L
init V
RERUN(params)
// Calculating the deterrence Index
init Distence_ max$UPath$[]//Maximum distance between adjacent takeoff and landing points of UAVs
init Distence_ $constantinUPath$[]//Minimum distance between UAV landing and takeoff points

TABLE 2. ***(Continued.)*** **Air-ground cooperative patrol optimization model algorithm.**

if $\max UPath[]-minUPath[]=\ U_Path.constant$

$\quad$ $\text{POINTS\_}\Phi = U/\mathrm{M_TIME}[\quad]-L_TIME[]$

else $\text{POINTS}_\Phi = U/\max UPath[\quad]-minUPath[]$

// Calculate emergency response capabilities

$[U\_Path, Location]$=Disposal（r，B，U_Path）// Solving for new drone reassignment locations after the emergency

U_NPath=Reallocate（U，$Location$，U_Path）// Reallocation of UAV patrol points using a min-max strategy

$\Omega=$ Evaluate(U_NPath)

Output C，U，Φ，Ω，$distence_{f_1f_2f_3}$

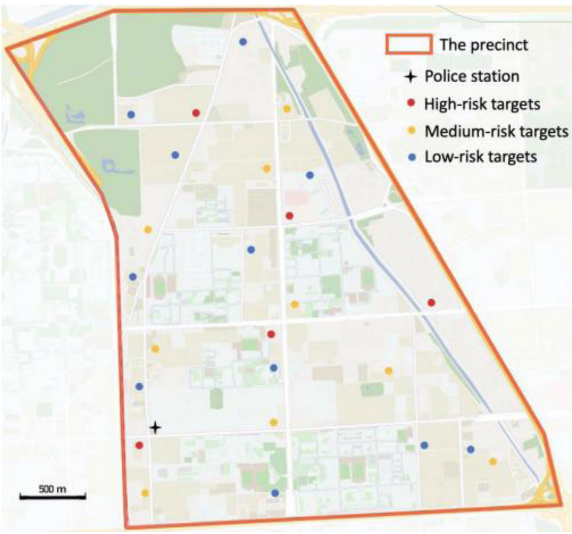

FIGURE 11. **Patrol targets distribution map.**

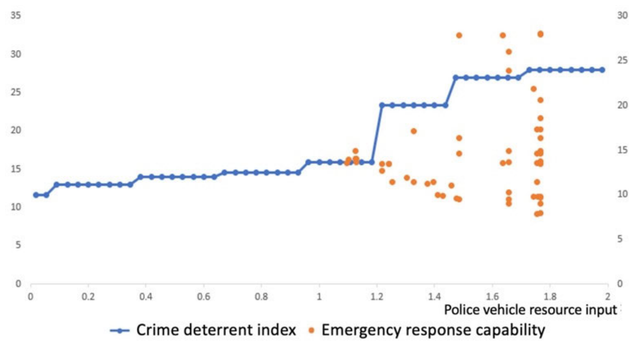

FIGURE 12. **Variation relationship between each patrol element when the police vehicle speed is 35 km/h.**

and t^L change at different vehicle speeds and in different numbers of UAVs. Due to the limitation of the UAV flight range, the task requires at least 3 UAVs to patrol an area.

As seen from the above figures, when police vehicles are traveling at higher speeds, there is a significant increase in the deterrence index as police resources are invested and then

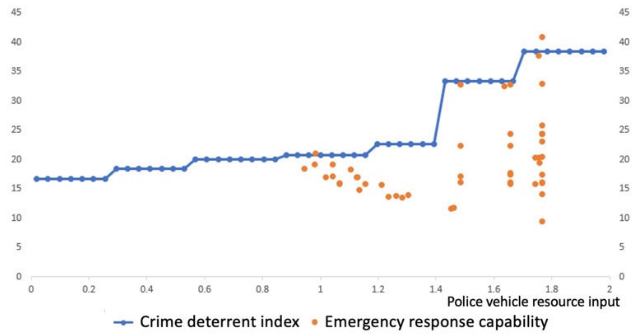

FIGURE 13. **Variation relationship between each patrol element when the police vehicle speed is 35 km/h.**

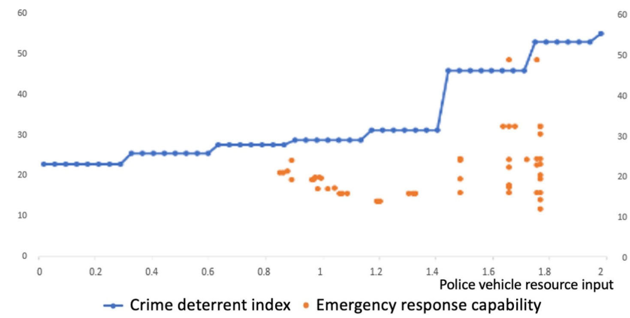

FIGURE 14. **Variation relationship between each patrol element when the police vehicle speed is 35 km/h.**

level off. As the number of UAVs increases, it delays the overall trend of increasing the deterrence index. When the number of UAVs is constant, the increase in vehicle speed has an overall increase in the deterrence index. Compared to the trend in the patrol deterrence index, emergency response capabilities show a trend of high at the ends and low in the middle in all graphs. With the increase in police resources, emergency response capability is increasingly influenced by the hovering time. The increase in drones has an overall improvement in emergency response capability.

For the air-ground cooperative patrol tasks in this jurisdiction, the following patrol plan is developed to ensure

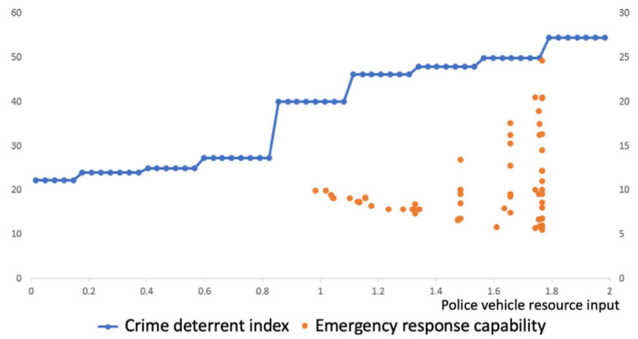

FIGURE 15. Variation relationship between each patrol element when the police vehicle speed is 40 km/h.

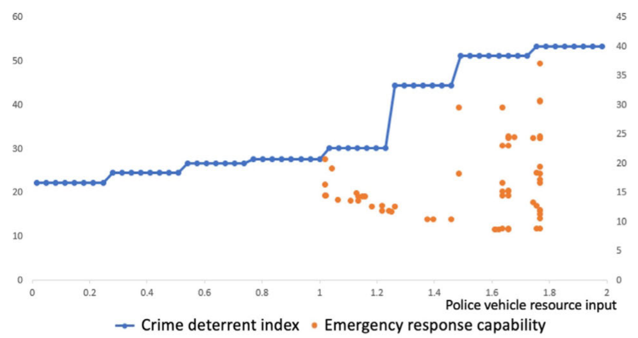

FIGURE 16. Variation relationship between each patrol element when the police vehicle speed is 40 km/h.

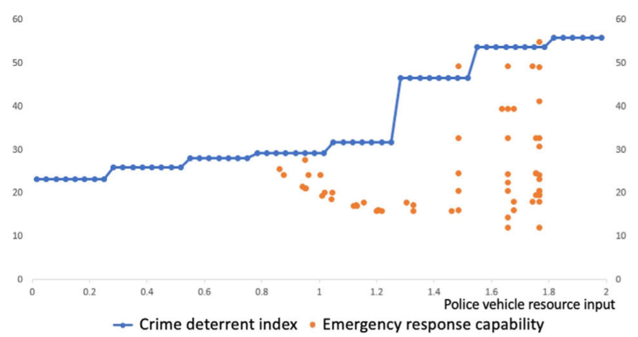

FIGURE 17. Variation relationship between each patrol element when the police vehicle speed is 40 km/h.

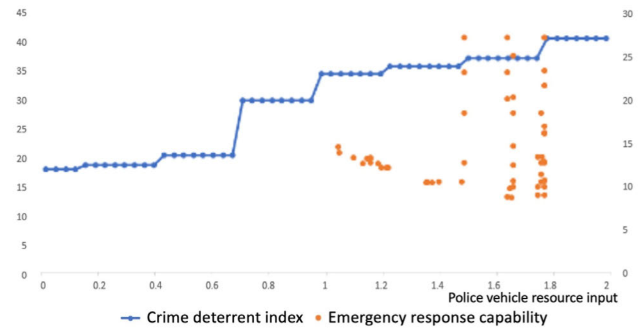

FIGURE 18. Variation relationship between each patrol element when the police vehicle speed is 45 km/h.

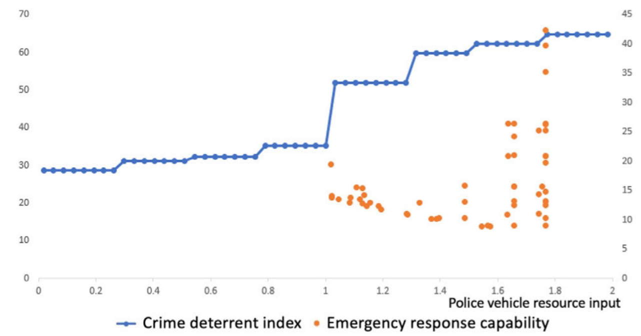

FIGURE 19. Variation relationship between each patrol element when the police vehicle speed is 45 km/h.

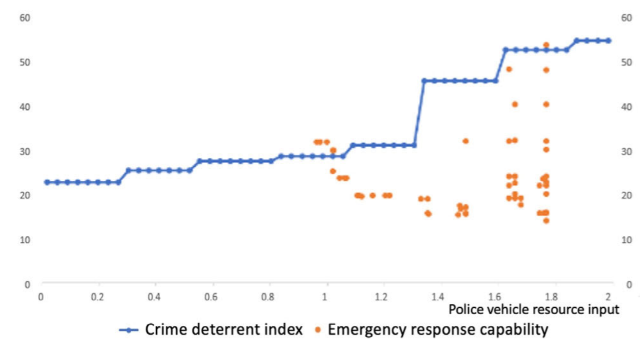

FIGURE 20. Variation relationship between each patrol element when the police vehicle speed is 45 km/h.

robustness in the allocation of police resources, considering the limited police patrol resources.

1) When the road is congested, the police car is slow, with a moderate ratio of t^M to t^L, which can ensure a strong deterrent strength at each patrol point with a small number of drones, and the emergency response capability falls short.

2) When the road is clear, the police car is fast, the investment of patrol resources has a greater impact on the deterrent index and emergency response capability, and the patrol task can increase the hovering time of medium- and low-risk points to make the deterrent strength and emergency response capability optimal under the limited investment. The patrol program is shown in Table 3.

3) When police resources are limited, police vehicles need to patrol at lower speed and shorten the hovering time of medium- and low-risk points to ensure a higher deterrent index and emergency response capability.

4) When police resources are sufficient, the number of drones can meet the disposal requirements of all emergencies in the jurisdiction, and patrol tasks can reduce the ratio of t^M to t^L while increasing the speed of police vehicles to improve patrol efficiency.

C. ANALYSIS OF THE RELATIONSHIP BETWEEN PATROL ELEMENTS

1) ANALYSIS OF THE RELATIONSHIP BETWEEN THE PATROL ENVIRONMENT AND POLICE RESOURCE INPUT

The patrol environment directly determines the speed of the police vehicle and constrains the choice of the police vehicle patrol points, which in turn affects the UAV patrol points

TABLE 3. Air-ground cooperative patrol program (1–2).

Patrol mission parameter	Low speed	High speed
The number of drones	4	5
t^M	0.1 h	0.2 h
t^L	0.01 h	0.05 h
Crime deterrent index	41.23	49.08
Emergency response capability	36.36	24
The number of UAV patrol points	12	11
Launch/ recovery points	6,13,12,5	6,5,14,11,2
The number of police vehicle patrol points	13	14
Police vehicle patrol routes	0,6,11,13,10,9,4, 3,12,2,5,8,7,1,0	0,1,6,5,9,3,4,14, 13,11,2,12,8,10,7,0

TABLE 4. Air-ground cooperative patrol program (3–4).

Patrol mission parameter	Limited resources	Sufficient resources
The number of drones	3	8
t^M	0.1 h	0.1 h
t^L	0.01 h	0.03 h
Crime deterrent index	41.08	49.46
Emergency response capability	27.27	61.54
The number of UAV patrol points	12	12
Launch/ recovery points	11,9,5	1,11,3,14,12,2,5,7
The number of police vehicle patrol points	13	13
Police vehicle patrol routes	0,6,10,13,3,4,14, 11,1,7,2,9,5,8,0	0,1,11,13, 3,4,14, 12,2,10,8,9,5,7,0

and patrol route selection, which are related to the input of police resources. Without regard to the range of the police vehicle, different cruising speeds determine the lower limit of the patrol distance of the police vehicle, but as the speed of the vehicle increases, the length of the patrol distance will increase. The number of drones on the patrol determines the lower limit of police vehicle resources. When the constraint on the number of police vehicles in a single jurisdiction is not considered, a larger number of police vehicles are available for patrol duties, leading to a reduction in UAV participation, so that more medium-risk point tasks will be assigned to police vehicles. When UAV resources are plentiful, the pressure on vehicle patrols decreases significantly.

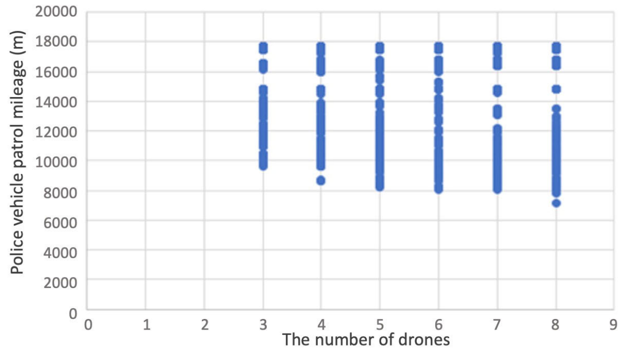

FIGURE 21. Diagrams of the relationship between patrol environment and police resource input.

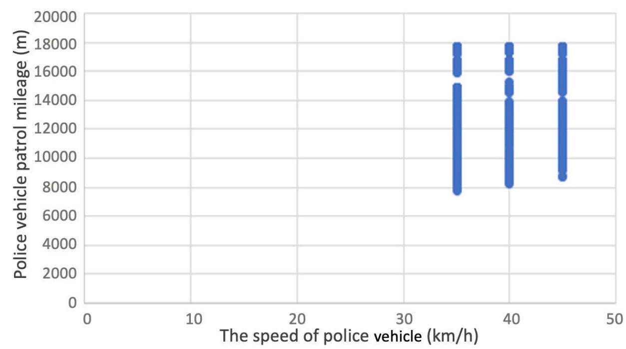

FIGURE 22. Diagrams of the relationship between patrol environment and police resource input.

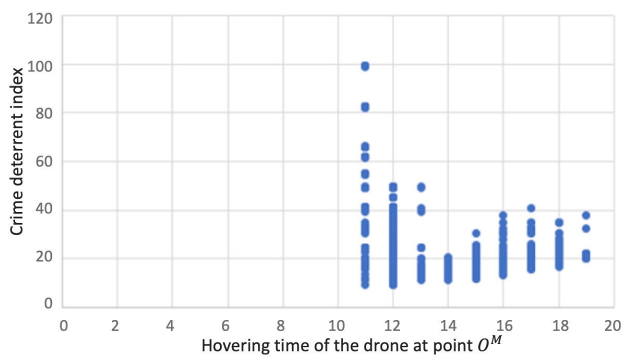

FIGURE 23. Diagrams of the relationship between drone load and crime deterrence index.

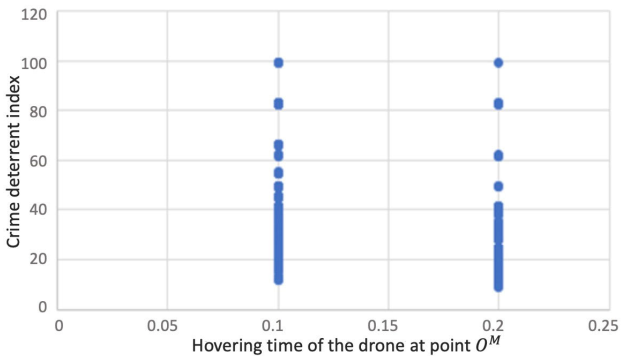

FIGURE 24. Diagrams of the relationship between drone task load and crime deterrence index.

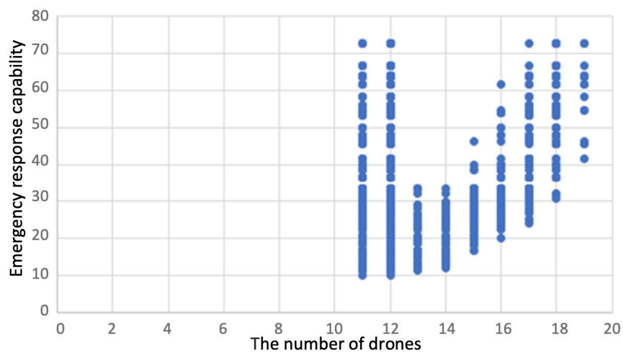

FIGURE 25. Diagrams of the relationship between drone task load and emergency response capability.

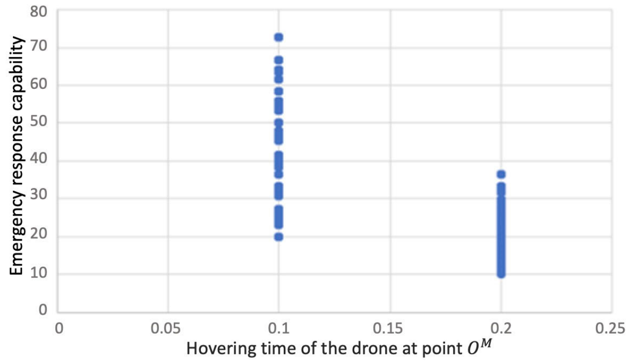

FIGURE 26. Diagrams of the relationship between drone task load and emergency response capability.

2) ANALYSIS OF THE RELATIONSHIP BETWEEN DRONE TASK LOAD AND CRIME DETERRENCE INDEX

As the patrol volume of UAVs increases, the overall trend of crime deterrence by air-ground cooperative patrols decreases first and then increases slightly, with an overall trend in the shape of a "U". The reduction in drone patrol points indirectly leads to an increase in hovering times, and as drone patrol points increase, hovering time will decrease, so a smaller allocation of UAV patrol points can maintain a higher deterrent index. However, if the police resources of the jurisdiction are limited, to ensure a higher crime deterrent index, it is necessary to increase the number of drone patrol tasks. In addition, devoting too much hovering time will lead to a decrease in the average level of deterrence. Therefore, to ensure crime deterrence, the number of drone patrol points should be controlled while increasing the ratio of A to B and reducing the hovering time for the medium- and low-risk points.

3) ANALYSIS OF THE RELATIONSHIP BETWEEN DRONE TASK LOAD AND EMERGENCY RESPONSE CAPABILITY

Similar to the crime deterrence-UAV patrol point relationship chart, with the increase in UAV tasks, the overall emergency response capability first declined and then gradually increased in a "U" shape. To achieve the highest emergency response capability, it is required that the hovering time at medium-risk points is much longer than that at low-risk points, and more UAVs are required to participate in the mission. However, crime deterrence will decrease as the number of UAV patrol points increases while maintaining a high level of emergency response capability. The analysis shows that increasing the hovering times in key areas, especially in the high-risk areas at the launch/recovery points, is the key to determining crime deterrence, while too many hovering times in low-risk areas contribute less to the deterrence index but cause a waste of resources. However, by excessively increasing the total hovering times in the medium-risk points for UAVs, the emergency response capability will decrease, and there is no relationship with the number of UAVs.

V. CONCLUSION

With the development of artificial intelligence, cloud computing, the Internet of Things and other technologies, indirect contact between people or between people and objects is gradually coming into realization. "Contactless" services have been widely used in intelligent logistics, intelligent retail, intelligent security and other fields. The global outbreak of COVID-19 has accelerated the application of "contactless" technology. As a "contactless" convenient aircraft that can carry a variety of instruments, UAVs play an important role in anti-terrorism resource dispatch, criminal investigation and police patrols. In the first half of 2020, the Shenzhen police dispatched more than 1800 sorties of police UAVs [44], which effectively reduced the work pressure and work risk of police officers.

Patrol task optimization is a key task in policing, and the addition of UAVs makes the patrol task arrangements more challenging. This paper takes the resource input and task allocation of police vehicles and UAVs as the patrol task optimization objectives, takes the patrol deterrence index and emergency response capability as the target constraints, discusses the patrol task plan of a police station in Beijing under different patrol situations, and innovatively refines the elements of the patrol task. Furthermore, the interrelationships between the elements and the objectives are identified through the analysis of actual cases to provide the decision makers in different situations with a Pareto task plan for air-ground cooperation cooperative patrol.

Resource dispatching under emergencies such as terrorist attacks and major epidemics has been the focus of scholars [45], but there are few researches on the siting, scheduling and air-ground cooperation of patrol subjects. Police organizations, while undertaking daily patrol tasks, also need to deal with emergencies, victim relief and temporary duty, future research will coordinate the police resource dispatch system that combines human-vehicle-machine to optimize public management resources.

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