A Patrol Platform Based on Unmanned Aerial Vehicle for Urban Safety and Intelligent Social Governance

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***Abstract*—Urban patrols can detect emergencies in a timely manner and collect information, which helps to improve the quality of services in the city and enhance the comfort of residents. This study proposes the use of IoT-based drones for urban patrol tasks, aiming to explore the potential applications of drones in smart city governance. The main technical challenge in the process of urban patrols by drones is how to plan a flight path for them. Therefore, this article first designs a smart patrol system based on drones and Internet of Things (IoT). Meanwhile, as information collection is an important aspect of urban patrol tasks, a mathematical model with the goal of maximizing information collection has been established to provide cost-effective patrol services. On this basis, in order to improve the accuracy of crow search algorithm (CSA), differential crow search strategy and variable flight step size are designed. In addition, the Levy flight strategy is introduced into the traditional CSA algorithm, and an improved crow search algorithm (ICSA) is proposed. Finally, a corresponding simulation environment was established based on the actual urban scene and compared with other algorithms. The numerical results indicate that compared with the other three swarm intelligence algorithms, the algorithm designed in this paper has more superiority.**

***Keywords*—Patrol drones; trajectory planning; smart city governance; crow search algorithm; swarm intelligence algorithm**

I. Introduction

With the development of cutting-edge technologies in the field of artificial intelligence such as the Internet of Things (IoT), digital twins (DT), and swarm intelligence, a foundation has been provided for the implementation of smart cities. Smart social/cities governance (also known as smart social/cities management), as an important application scenario of smart cities, is a potential goal for urban managers and related researchers [2]. As an advanced intelligent robot, unmanned aerial vehicles (UAVs) can provide many reliable services for smart city scenarios, helping to achieve smart city goals at low cost and low energy consumption [3]. In addition to using drones [1] to provide reliable communication services for smart city scenarios in [4], drones can be used to comprehensively monitor urban facilities, transportation, and the environment. For example, in [5], drones are used to monitor roads in cities, while in [6], drones are used to monitor the environment of cities. Another potential application of drones in smart city scenarios is patrol missions [7]-[8]. During the patrol process, drones are equipped with various sensors and cameras, which can collect relevant data of the city and provide timely feedback to the management department, providing decision-making support for urban managers, thereby improving the quality of the urban environment and the quality of life of residents.

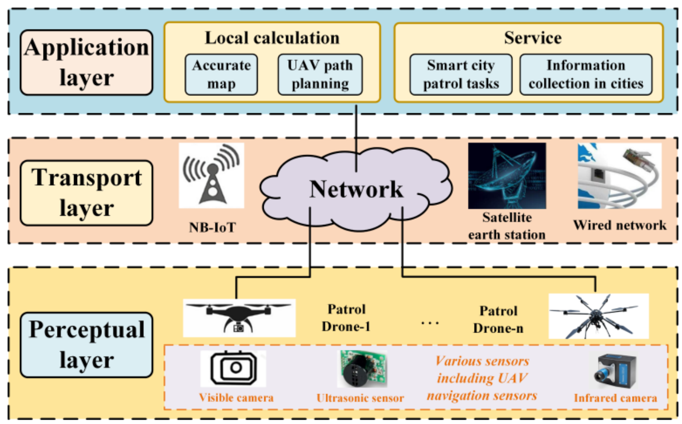

Fig. 1. IoT-based UAV patrol framework.

When deployed in the real world, drones typically require the use of technologies such as IoT to interact with the human world. Therefore, Fig. 1 shows the IoT based unmanned aerial vehicle patrol framework designed by this study. Within this framework, before conducting patrols, the trajectory planner needs to first plan a global trajectory for the drone based on the patrol range, the three-dimensional environment, and geometric model of the UAV. However, in [9], a trajectory planning model for drones in two-dimensional space was developed with the goal of minimizing the length of the drone's trajectory, without considering the pitch angle constraint of the drone. In [10], a trajectory planning model for unmanned aerial vehicles in a three-dimensional mountainous environment was established, but it did not take into account the requirements of patrol tasks for information collection. The above mathematical models are not applicable to the problem of drone patrol trajectory planning in urban market environments. Therefore, this study pays special attention to the trajectory planning problem of patrol drones, establishes an accurate mathematical model for patrol drones in smart city scenarios, and designs an improved swarm intelligence algorithm based

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on CSA algorithm. The main contributions of this study are summarized as follows:

- This study introduces IoT and DT into smart city patrol scenarios, designs an IoT based UAV patrol framework, and describes the working mechanism of the DT based UAV patrol platform, aiming to embed the drone city patrol platform into smart city scenes.

- Based on the operational mechanism of the digital twin patrol platform, a geometric model of patrol drones and a multi-objective mathematical model of urban patrol tasks were established, and a digital twin drone for urban patrol tasks was constructed.

- Based on the DE algorithm and CSA algorithm, corresponding improvement strategies were designed, and a novel differential evolution-based crow search algorithm (DE-CSA) was designed to improve the performance of the patrol drone trajectory planner.

- Six test functions were used to test the GWO, GA, CSA, and DE-CSA algorithms. From the two indicators of mean and standard deviation, the DE-CSA algorithm performed the best; Furthermore, based on real urban scenarios, relevant computational experiments were conducted, and the data results showed that compared with GWO, GA, and CSA algorithms, the DE-CSA algorithm has higher convergence accuracy.

The remaining parts of this study are arranged as follows. In Section II, research related to patrol drones is reviewed; Section III establishes a mathematical model for UAV used for smart city patrol task; In Section IV, an improved CSA algorithm is designed; Section V presents the simulation experiment results. Finally, the full text is summarized in Section VI.

II. Literature Review

When using drones to perform patrol tasks in smart city scenarios, it mainly includes two parts. The first part is to allocate drones based on all patrol areas, ensuring that each area can be covered. This is the previous stage of patrol drone trajectory planning [7]. The other step is to plan a flight trajectory for the patrol drone based on the three-dimensional environment of the area it needs to patrol, which needs to meet the goals of collision free and patrol tasks. Therefore, this article reviews relevant research from three aspects: urban patrols, drone trajectory planning, and the application of swarm intelligence algorithms in drone trajectory planning. The aim is to summarize and summarize the goals of urban patrols, mathematical models of drones, and trajectory planning algorithms.

A. *The Application of UAV in Urban Patrol*

As previously mentioned, relevant researchers have explored the application of drones in smart city communication [4], road or environmental monitoring [5]-[6], disaster management [11], and distribution [12]. It should be pointed out that when using drones to detect roads and environments, the main objective of mathematical models is to collect or organize information [13]. For example, in [14], drones were used to collect environmental information at the dock, and the mathematical model required drones to fly over all detection nodes and use the shortest flight distance. In [15], UAVs were used to patrol transmission lines in a city with the goal of maximizing the coverage of the patrol area. Reference [16], on the other hand, uses ground vehicles in conjunction with UAVs to patrol roads, and similar to [14], the mathematical model requires the UAVs to fly over all patrol nodes. In [17], a drone scheduling model for scenic spot patrols was established, which aims to minimize the flight length of drones while minimizing the number of drones, similar to the drone scheduling problem in [7]. From the above research, it can be concluded that the main goal of UAVs during patrol missions is to collect ground information to the maximum extent possible. However, so far, no research has been conducted on community patrol tasks. In addition, the above research on drone patrols cannot be extended to three-dimensional space.

B. *A Mathematical Model for UAV Trajectory Planning*

Specifically, the establishment of a mathematical model for inspection drones can be divided into two parts: geometric modeling and problem modeling, based on the working mechanism of the digital twin patrol platform. The geometric model is mainly based on the physical performance and flight environment of drones, including obstacle modeling, drone dynamics modeling, and route constraints [18]. The problem model is an objective function composed of one or several objectives, including the shortest path, minimum energy consumption, or minimum flight time [19]. Geometric modeling includes three parts: mathematical model construction of drones, environmental perception, and map construction. In order to plan safe and effective trajectories, drones need to perceive the environment and construct maps, mainly using advanced sensor technology and data fusion technology [20]. Due to the development of digital twin cities, high-precision three-dimensional maps of cities have been established. Therefore, this study focuses on the construction of mathematical models for drones.

The author in [21] studied the trajectory planning problem of ground drones in a two-dimensional environment, which aimed to plan a set of trajectories for a drone cluster. However, the geometric model of the ground drones established did not consider all the physical performance of the drones. In addition, the problem model established in [21] only focuses on the shortest trajectory and cannot be applied to patrol tasks based on drones. The author in [22] proposed a trajectory planning method in three-dimensional space, but it sets the Z-coordinate of the drone trajectory point as a fixed value, which is essentially still trajectory planning in two-dimensional space. The established mathematical model still does not consider the pitch angle constraint of the drone. In addition, it only focuses on the single target of the shortest trajectory. In [23], a trajectory planning scheme for UAV in two-dimensional space was proposed, and the established problem model also aimed to minimize the trajectory. The author in [24] focuses on UAV-based power grid inspection tasks. Similar to [15], there are fewer obstacles during the process of patrolling the power grid, and the mathematical model established is also not applicable to urban patrol tasks. Therefore, it is necessary to establish a mathematical model that simultaneously focuses on information collection and trajectory length.

C. A Swarm Intelligence Algorithm-Based Trajectory Planner

The algorithms used for UAV trajectory planners can be specifically divided into three categories based on their functions: static obstacle avoidance algorithms, dynamic trajectory planning algorithms, and global trajectory planning algorithms [25]. During flight, UAVs may encounter various obstacles such as buildings and trees. How to effectively avoid these static obstacles is an important issue in drone trajectory planning [26]. In addition, in practical applications, UAVs may also encounter dynamic obstacles during flight, such as birds or pedestrians, which requires drones to be able to plan new trajectories in real time to cope with environmental changes [27]. In addition, the global trajectory planning algorithm for drones is to plan a trajectory from the starting point to the endpoint based on the global map using the algorithm [28]. This article focuses on the global trajectory planning algorithm considering static obstacles.

The global trajectory planning algorithm is the core of the drone trajectory planner, and common trajectory planning algorithms include graph search-based algorithms, optimization-based algorithms, sampling-based algorithms, etc. [29]. A trajectory planning model based on graph search: This model discretizes the environmental space into a series of nodes and uses graph search algorithms (such as A * algorithm, Dijkstra algorithm, etc.) to find the optimal path between these nodes. This model is simple and easy to implement, but it has lower computational efficiency when dealing with complex environments or high-dimensional spaces [30]. The sampling-based trajectory planning model randomly samples in the environmental space, constructs paths between sampling points, and finally optimizes the path to obtain the optimal trajectory. This model can handle complex environments and has high computational efficiency, but it cannot guarantee finding the global optimal solution [10]. The learning-based trajectory planning model learns trajectory planning strategies through machine learning methods. This model can handle complex environments and high-dimensional spaces, and can continuously improve trajectory planning strategies through learning, but it requires a large amount of training data and computational resources [31].

Unlike the above three methods, the trajectory planning model based on swarm intelligence transforms the trajectory planning problem into an optimization problem, and obtains the optimal trajectory by solving the optimization problem [32]. When solving optimization problems, swarm intelligence algorithms can not only consider multiple objectives but also find the optimal solution in large-scale complex problems. Representative algorithms include genetic algorithm (GA) [33] and grey wolf optimizer (GWO) [34]. Therefore, at present, more and more swarm intelligence algorithms are being applied to UAV trajectory planning problems. In [35], an improved differential evolution (DE) algorithm was designed and applied to the mathematical model of unmanned aerial vehicle trajectory planning, aiming to improve the convergence accuracy of the DE algorithm. Similarly, an improved DE algorithm in [36] was used for the deployment of multiple drones and achieved good results. This is because the differential strategy in the DE algorithm can help the DE algorithm escape from local optima.

The GWO algorithm has also been applied in the field of drone trajectory planning. In [37], a reinforcement learning strategy based GWO algorithm was designed and applied to drone trajectory planning problems. In [38], the GWO algorithm is applied to the trajectory planning problem for transmission line inspection tasks. The above two studies have successfully applied the GWO algorithm to the trajectory planning problem of unmanned aerial vehicles. Reference [39] proposed an improved GA algorithm and applied it to the target coverage problem. The performance of GA algorithm and Particle Swarm Optimization (PSO) algorithm in solving trajectory planning problems was compared in [27], and experimental results showed that GA algorithm has more potential compared to PSO algorithm. In addition, as a novel swarm intelligence algorithm, there is currently no research testing the performance of CSA in solving unmanned aerial vehicle trajectory planning problems. Therefore, this article improves the CSA algorithm and successfully applies the improved CSA algorithm (ICSA, also known as DE-CSA) to the trajectory planning problem of unmanned aerial vehicles.

III. MODEL

A. Problem Definition

Before establishing the model, we first describe the patrol problem in smart cities. This study uses quadcopter drones to patrol communities within cities, aiming to detect emergencies (such as accidental injuries) and ensure the safety of community residents, while providing timely information. According to [13]-[16], UAVs have two main targets during patrol: maximizing information collection and minimizing the length of flight trajectories. Before flying, the trajectory planner for patrolling UAVs needs to determine the optimal patrol trajectory based on camera constraints. In addition, the trajectory of UAV needs to meet physical performance constraints such as the maximum rotation angle, maximum tilt angle, and maximum flight distance of the drone.

According to the smart city framework established based on digital twin (DT) technology in, this study describes the working mechanism of the DT-based smart patrol platform, as shown in Fig. 2. In the operation process of the DT-based intelligent patrol platform, a large number of sensors need to be used to collect information, and the collected information needs to be collected, classified, and organized. Furthermore, based on the requirements of smart city patrol tasks and the physical performance of patrol drones, a corresponding digital twin model is established. Finally, design experiments and simulation simulations are conducted to feedback the trajectory of patrol drones to the real world. In this study, the data perception, data modeling (geometric model and problem model), and data simulation of DT-based patrol platforms in smart cities were demonstrated. Intended to further explain the operating mechanism of the smart patrol platform, and also to further demonstrate the application of advanced artificial intelligence technologies such as swarm intelligence algorithms in the smart patrol platform.

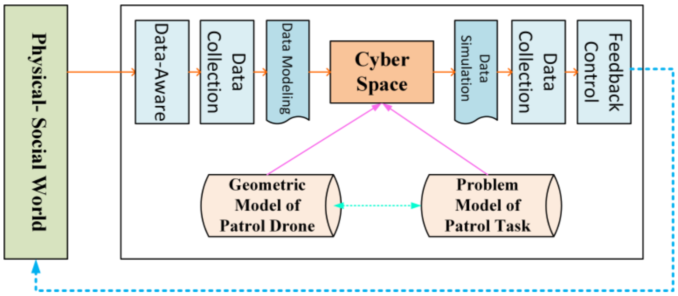


Fig. 2. The working mechanism of smart patrol platform based on digital twins.

B. Data-Aware

In order to plan a safe and effective trajectory, the smart patrol platform based on drones needs to perceive the environment and build maps, mainly using advanced sensor technology and data fusion technology. Fig. 3 shows a map of digital twins in the context of a smart city.

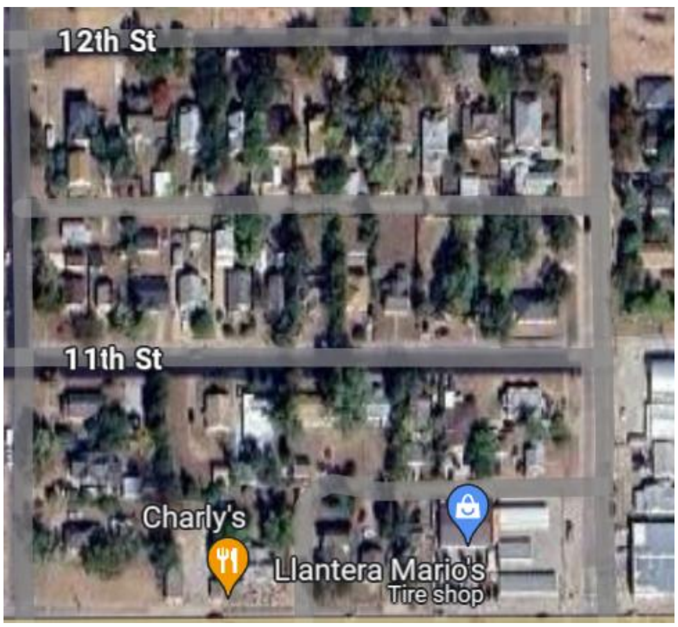


Fig. 3. The map of smart cities.

C. Mathematical Model

1) Geometric model: Geometric modeling includes the establishment of a drone flight space map model, the establishment of a drone mathematical model, and the establishment of an airborne camera model, as shown below:

$$C_b = \left[x_{cb1}, x_{cb2}, y_{cb1}, y_{cb2}, z_{cb1}, z_{cb2}\right] \tag{1}$$

Eq. (1) shows the establishment of building maps in smart cities, where $\forall b \in B$ represents the set of obstacles in the map.

$$Q_a = \left[x_{qa}, y_{qa} z_{qa}\right] \tag{2}$$

Eq. (2) is the coordinates that make up urban road grid $a \in A$.

$$l_k / T_k \le v_{\max} \tag{3}$$

$$\sum_{k \in K} T_k \le T_{\max} \tag{4}$$

$$l_k = \sqrt{\left(x_{k+1} - x_k\right)^2 + \left(y_{k+1} - y_k\right)^2 + \left(z_{k+1} - z_k\right)^2} \tag{5}$$

Eq. (3)-(5) together constitutes the digital twin model of unmanned aerial vehicles. Eq. (3) is the maximum flight speed constraint of the drone, where $v_{\max}$ is the maximum flight speed of the drone; l_k is the distance from the drone's track point k to the drone's track point $k+1$; T_k is the flight time of the drone from the waypoint to the drone's waypoint. Eq. (4) is the battery capacity constraint of the drone, and $T_{\max}$ is the maximum flight time of the drone.

$$\sqrt{\left(x_{qa} - x_k\right)^2 + \left(y_{qa} - y_k\right)^2 + \left(x_{qa} - z_k\right)^2} \le L_{\max} \tag{6}$$

Eq. (6) forms a digital twin model for airborne cameras, and constrains the maximum shooting distance of the camera, where $L_{\max}$ is the maximum shooting distance of the camera.

2) Problem modeling: When drones patrol in a smart city environment, they aim to complete patrols of all areas with the shortest possible cost. According to [35]-[39], the cost of drone trajectory planning includes two types: time cost and path length cost. Therefore, this article selects path length cost as one of the objectives in the multi-objective function. In order to reduce the difficulty of solving the problem, the goal of maximizing the collection of information in the patrol area is established as the corresponding penalty function. When there is a road grid that is not patrolled, the value of the penalty function will increase, otherwise the value of the penalty function will decrease. The modeling of the problem is as follows.

$$\min f = \sum_{k \in K} l_k \times \left(N_{B\max} - \sum E_b\right) \tag{7}$$

$$E_b \in \{0,1\} \tag{8}$$

Eq. (7) is the objective function of the problem, where $\left(N_{B\max} - \sum E_b\right)$ is the penalty function and $N_{B\max}$ is the number of grids that make up the road. As shown in Eq. (8), E_b is a 0-1 variable. When the camera can capture the road grid $\forall b \in B$, $E_b = 1$; Otherwise, $E_b = 0$.

IV. Algorithm Design

A. Algorithm Introduction

The origin of swarm intelligence technology originated from Reynolds' research on the Bodies project, and after continuous evolution and development, swarm intelligence algorithms including GWO, GA, and CSA have emerged [33]-[34]. The swarm intelligence algorithm is a cluster of algorithms based on group behavior and intelligence, which simulates the interaction and cooperation between individuals in a group to achieve the ability to solve problems collaboratively. These algorithms draw inspiration from collaborative behaviors in biological populations, such as bird colonies, ant colonies, fish colonies, etc., and achieve the overall intelligence of the population through information exchange, interaction, and division of labor among individuals. This technology has shown excellent performance in solving the large-scale multi-objective problem. Therefore it is widely used in unmanned aerial vehicle trajectory planning.

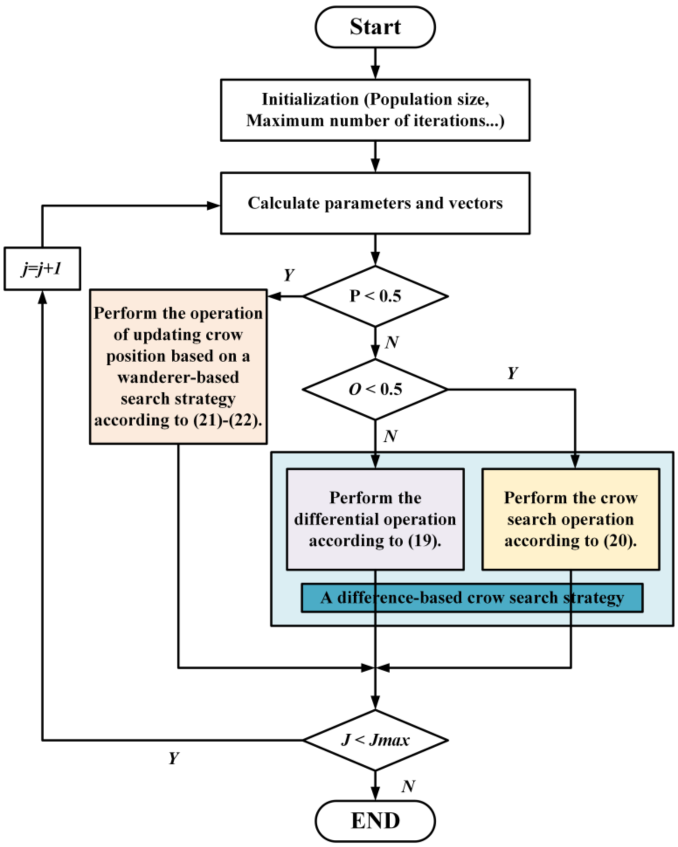


Fig. 4. The flowchart of the DE-CSA algorithm.

The CSA algorithm is a novel swarm intelligence algorithm proposed in 2016, which mimics the hidden food, tracking, and deceptive behavior among crow individuals in a crow population. It performs global search by perceiving probability and flight distance. The CSA algorithm has the advantages of simple search strategy and fewer parameters. In addition, CSA algorithm is a global search algorithm that can find the optimal solution throughout the entire search space. At the same time, CSA algorithm has high search efficiency and can find better solutions in a short time. Although CSA algorithm can perform global optimization, it is determined by perceptual probability. Therefore, when the parameter selection is not appropriate, CSA may fall into local optima and cannot find the global optimal solution. At the same time, this also leads to CSA being unable to optimize in local space, resulting in low convergence accuracy.

B. DE-CSA Algorithm

Due to the concise search method of CSA, it is easy to fall into local optima and other problems when solving large-scale and complex problems. However, differential evolution (DE) algorithms optimize problems through mutation, crossover, and selection operations [14]-[15]. Therefore, it is possible to combine the DE algorithm and CSA algorithm to design a DE based CSA algorithm (DE-CSA) for solving the trajectory planning problem of patrol drones. In the DE-CSA algorithm developed in this study, a flight step size that changes with the number of iterations, a difference-based crow search strategy, and a wanderer-based search strategy were designed to improve the convergence accuracy of the CSA algorithm. Fig. 4 illustrates the flowchart of the DE-CSA algorithm, which (also known as the ICSA algorithm) has the following specific steps.

1) Initialize the location of the crow population: To change the default, adjust the template as follows. Initialize population size $R\max$. Use traditional trajectory planning methods to plan the several trajectories of UAV, making them equal to the population size. Each track represents a crow individual $Track(r,j)$. Initialize the maximum number of iterations $J\max$. Initialize the differential scaling factor F. Initialize crow population position GC.

The definition of the crow individual $Track(r,j)$ is shown in Eq. (9).

$$Track(r,j)=\left\{T(r,j)_1, T(r,j)_2, \cdots, T(r,j)_D\right\} \tag{9}$$

where r represents the r-th individual, and j represents the j-th iteration process, D represents the individual's dimension.

The definition of the crow population position GC is shown in Eq. (10).

$$GC=\left\{Track(1), Track(2), \cdots, Track(R\max)\right\}^{\mathrm{T}} \tag{10}$$

where

$$Track(r)=Track(r,j).$$

2) Population assessment: Evaluate the objective function values of each crow of individual in the crow population and find the optimal solution to the optimization problem according to Eq. (11). The specific process of this step is shown in Algorithm 1. Among them, f_{best} is the optimal fitness function value in the crow population. $Track_{best}$ is the best crow individual in the population.

Algorithm 1

For r=1 to R_{max} do
    Fitness = f (track(r,j))
    if Fitness<f_{best} Then
        f_{best} = Fitness
        $Track_{best}$ = track(r,j)
End for

$$m(r,j)=\begin{cases} Track(r,j), if\ f\left(Track(r,j)\right)\leq f\left(Track(r,j-1)\right) \\ m(r,j-1), Otherwise \end{cases} \tag{11}$$

The definition of the MC is shown in Eq. (12).

$$MC=\left\{m(1,j),m(2,j),\cdots,m(R\max,j)\right\}^{\mathrm{T}} \tag{12}$$

where MC is the memory matrix of the crow population.

3) Calculate search step size: Calculate the flight step size *flyo* of individual crows according to Eq. (13).

$$flyo=2.5-\left(\frac{j}{J\max}\right)^{1/2} \tag{13}$$

4) A difference-based crow search strategy: Randomly generate a random number P in the [0,1] interval, and if $P\geq 0.5$, generate a random number O in the [0,1] interval, and perform a differential crow search operation based on Eq. (14)-(15).

If $O\geq 0.5$, perform differential operation according to Eq. (14).

$$T(r,j+1)_d=T(r1,j)_d+F\times\left(T(r2,j)_d-T(r3,j)_d\right) \tag{14}$$

where $T(r1,j)_d$, $T(r2,j)_d$,and $T(r3,j)_d$ are the *d-th* dimension of randomly selected individuals.

If $O<0.5$, perform crow search operation according to equation (15).

$$T(r,j+1)_d=T(r,j)_d+Rand\times flyo\left(m(best,j)_d-T(r,j)_d\right) \tag{15}$$

where $Rand$ is a random number in the [0,1] interval. $m(best,j)_d$ is the *d-th* dimension of the individual with the best fitness function value in matrix MC .

5) A wanderer-based search strategy: If $P<0.5$, perform a wanderer-based search operation based on Eq. (16)-(17).

$$T(r,j+1)_d=T(r,j)_d+Rand\times flyo\times a \tag{16}$$

$$a=Rand(\sqrt{D+1}) \tag{17}$$

6) Reevaluate the population: Reevaluate the population based on Algorithm 1.

7) Output result: Calculate and determine whether the maximum number of iterations has been reached. If so, end the iteration and output the result; Otherwise, return to 3) Calculate search step size.

V. Presentation of Experimental Results

In order to further demonstrate the performance of the DE-CSA algorithm designed in this study, the performance of the algorithm was demonstrated from two aspects. Firstly, according to [33], this study tested the DE-CSA algorithm using six test functions. In addition, this study established a corresponding simulation environment based on the map shown in Fig. 3 and used the DE-CSA algorithm to plan the trajectory of patrol drones. All the above simulation experiments were conducted on the MATLAB 2022a platform.

A. Benchmark Functions

This study used unimodal test functions (F05-F07) and multimodal test functions (F08-F10) to test the developed algorithm. Among them, F05 is called the Rosenbrock function, also known as the Valley or Banana function, with its global minimum located in a narrow parabolic valley. However, although the valley is easy to find, it is difficult to converge to the minimum. F07 is a multidimensional unimodal flat-bottomed function with random interference, and the algorithm is prone to getting stuck in local optima during operation. F08-F10 are both multimodal test functions. Among them, F09 is the Rastigin function, which has many local minima and is highly multimodal. In the two-dimensional form, the characteristic of the function image of F10 is that the external region is very flat and there is a large hole in the center. This function can also easily trap optimization algorithms into local optima. Therefore, the above test functions can test not only the local search ability of the algorithm, but also the global search ability of the algorithm.

TABLE I. Test Functions

Functions	Expressions of Functions	Domian	Optimal
F05	$F_{05}(x)=100\times\sum_i[(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	[-30,30]	0
F06	$F_{06}(x)=\sum_i[(x_i+0.5)^2]$	[-100,100]	0
F07	$F_{07}(x)=\sum_i[i\times x_i^4+Random[0,1)]$	[-1.28,1.28]	0
F08	$F_{08}=\sum_i[-x_i\sin(\sqrt{\lvert x_i\rvert})]$	[-500,500]	-837.966
F09	$F_{09}(x)=\sum_i[x_i^2-10\times cos(2\pi x_i)+10]$	[-5.12,5.12]	10
F10	$F_{10}(x)=-20exp(-0.2\sqrt{((1/n)\sum_i x_i^2)})-exp(1/ncox(2\pi x_i))+20+e$	[-32,32]	0

TABLE II. THE GRAPH OF THE TEST FUNCTION AND THE ITERATION CURVES OF THE FOUR ALGORITHMS ($R\max$ =30)

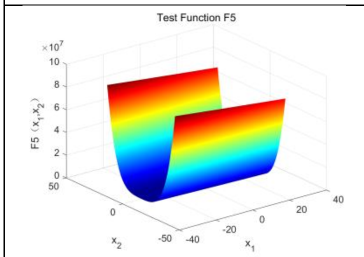
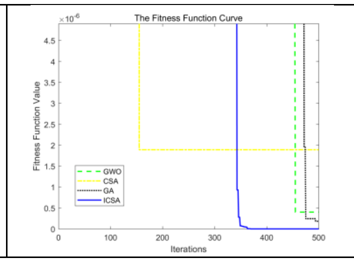
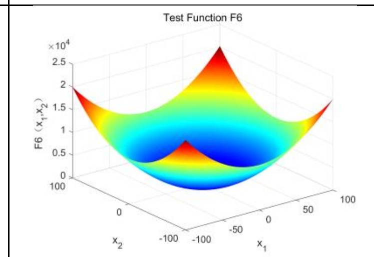
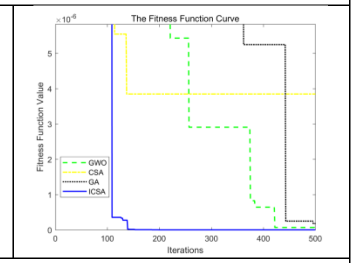
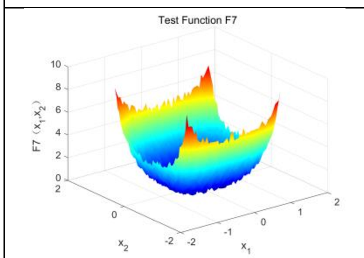
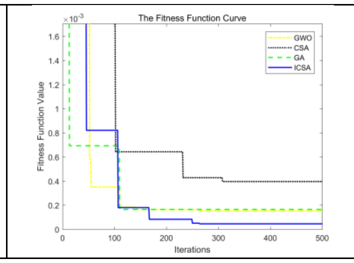
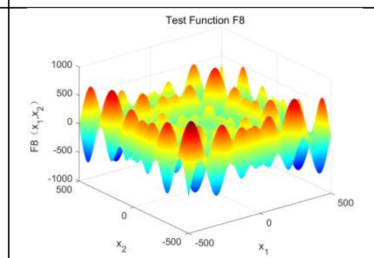
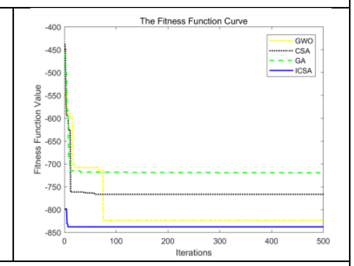
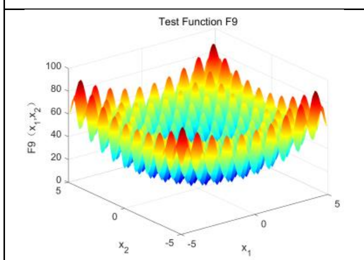
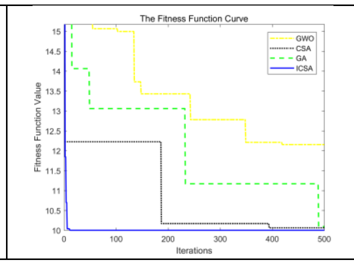
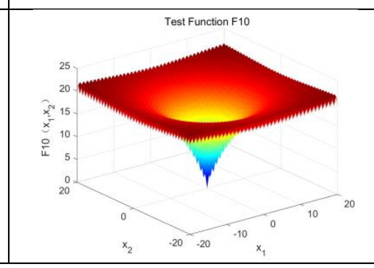
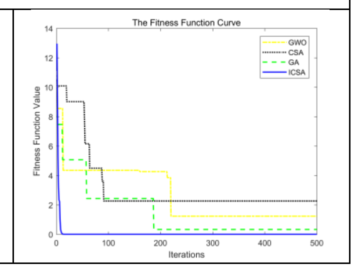
F05		F06	
			
F07		**F08**	
			
F09		**F10**	
			

TABLE III. THE FITNESS FUNCTION VALUES OF THE TEST FUNCTION FOR FOUR ALGORITHMS RUNNING 30 TIMES ($R\max$ =30)

Functions	**F05**		**F06**		**F07**		**F08**		**F09**		**F10**	
Algorithms	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
GWO	1.9E-06	5.1E-07	1.7E-07	2.4E-08	1.6E-04	2.2E-05	-823.430	09.62	12.15	1.61	0.614	0.041
CSA	1.8E-07	1.5E-08	6.4E-09	1.9E-10	3.9E-04	6.3E-05	-719.527	16.02	10.19	0.94	0.471	0.106
GA	4.0E-07	3.6E-08	3.8E-06	1.8E-07	1.6E-04	5.2E-05	-766.749	92.47	10.16	0.56	0.959	0.797
DE-CSA	**5.6E-17**	**0.6E-18**	**00E+00**	**00E+00**	**4.6E-15**	**2.5E-16**	**-837.965**	**00E+00**	**10.00**	**00E+00**	**8.1E-16**	**1.6E-17**

The CSA, GA, GWO, and DE-CSA algorithms were run 30 times in each test function. Table I shows the mathematical formulas, variable ranges, and minimum values of the six test functions F05-F10. Table II shows the convergence curves of the fitness functions during the running process of CSA, GA, GWO, and DE-CSA algorithms using each test function as the fitness function. Table III presents the operational results of CSA, GA, GWO, and DE-CSA methods.

B. Trajectory Planning Results

On this basis, in order to verify the effectiveness of the smart patrol platform designed in this study, a corresponding simulation environment was established based on the map shown in Fig. 3 and the DE-CSA algorithm was used to plan the trajectory of the patrol drone. Fig. 5 shows the patrol trajectory planned by the DE-CSA algorithm for unmanned aerial vehicles. Fig. 6, and Fig. 7, respectively shows the optimal fitness function curves, and average fitness function curves of the four algorithms during 30 runs.

As shown in Fig. 6, during the 30 runs of GWO, GA, CSA, and DE-CSA algorithms, the optimal fitness function value of DE-CSA is 5180.07, while the optimal fitness function values of GWO, GA, and CSA algorithms are 5641.16, 5624.49, and 5781.13, respectively. As shown in Fig. 7, during 30 runs of GWO, GA, CSA, and DE-CSA algorithms, the average fitness function value of DE-CSA is 5179.53, while the average fitness function values of GWO, GA, and CSA algorithms are 5674.75, 5691.29, and 5727.05, respectively. Therefore, it can be concluded that the optimal fitness function, worst fitness function, and average fitness function solved by the DE-CSA algorithm have the best results in 30 runs, fully proving the effectiveness of the smart patrol platform.

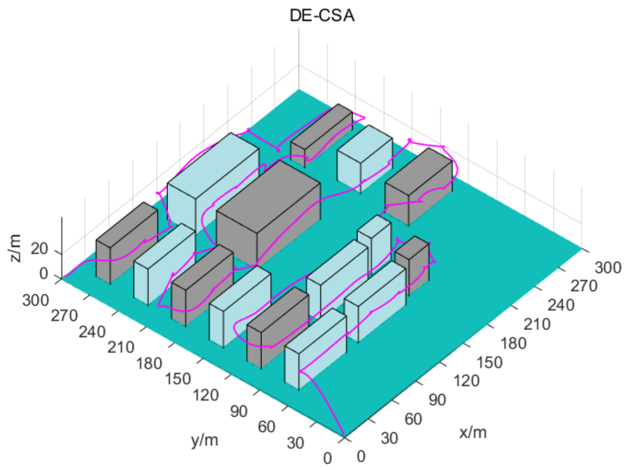


Fig. 5. The trajectory planning results of the DE-CSA.

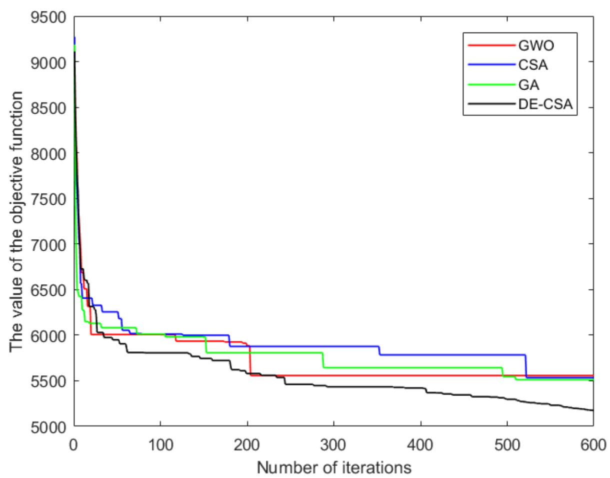


Fig. 6. The optimal fitness function curves of the four algorithms.

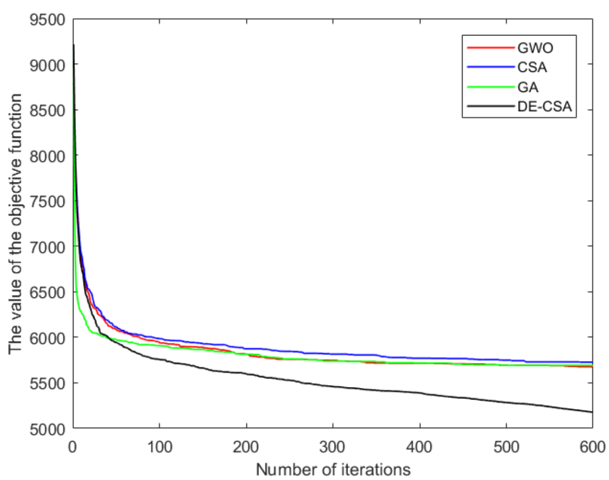


Fig. 7. The average fitness function curves of the four algorithms.

VI. CONCLUSIONS

This study constructed a smart patrol platform for smart cities and developed an improved CSA algorithm. This study expands the application of drones in smart cities, aiming to improve the service quality of cities. The effectiveness of the platform and algorithm was demonstrated through the use of six test functions and a simulation experiment in a real scenario. The simulation results show that the DE-CSA algorithm can achieve the best results in all six test functions, whether it is the mean and standard deviation. In the experiment of drone trajectory planning, the optimal, and average values of the DE-CSA algorithm were better than the other three algorithms in 30 runs of GWO, GA, CSA, and DE-CSA algorithms. In the future research process, the focus will be on the trajectory planning problem of patrol drones in dynamic environments.

REFERENCES

[1] S. Kumaran, V. A. Raj, S. J, and V. R. M. Raman, “IoT-based rescurSearch and Rescue Drone for Precision Firefighting and Disaster Management,” International Journal of Advanced Computer Science and Applications, vol. 14, no. 11, 2023, doi: 10.14569/IJACSA.2023.0141145.

[2] L. Bundgaard and S. Borrás, “City-wide scale-up of smart city pilot projects: Governance conditions,” Technological Forecasting & Social Change, vol. 172, pp. 121014, 2021, doi: 10.1016/j.techfore.2021.121014.

[3] N. Mohamed, J. Al-Jaroodi, I. Jawhar, A. Idries, and F. Mohammed, “Unmanned aerial vehicles applications in future smart cities,” Technological Forecasting & Social Change, vol. 153, pp. 119293, 2020, doi: 10.1016/j.techfore.2018.05.004.

[4] W. Tang, H. Zhang, and Y. He, “Tractable Modelling and Performance Analysis of UAV Networks With 3D Blockage Effects,” IEEE wireless communications letters, vol. 9, no. 12, pp. 2064–2067, 2020, doi: 10.1109/LWC.2020.3012554.

[5] F. Outay, H. A. Mengash, and M. Adnan, “Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges,” Transportation Research. Part A, Policy and Practice, vol. 141, pp. 116–129, 2020, doi: 10.1016/j.tra.2020.09.018.

[6] S.-I. Park and J.-S. Um, “Differentiating carbon sinks versus sources on a university campus using synergistic UAV NIR and visible signatures,” Environmental Monitoring and Assessment, vol. 190, no. 11, pp. 652–12, 2018, doi: 10.1007/s10661-018-7003-x.

[7] S. Rajan, K. Sundar, and N. Gautam, “Routing Problem for Unmanned Aerial Vehicle Patrolling Missions - A Progressive Hedging Algorithm,” Computers & Operations Research, vol. 142, pp. 105702, 2022, doi: 10.1016/j.cor.2022.105702.

[8] Y. Wang, Y. Yue, M. Shan, L. He, and D. Wang, “Formation Reconstruction and Trajectory Replanning for Multi-UAV Patrol,” IEEE/ASME Transactions on Mechatronics, vol. 26, no. 2, pp. 719–729, 2021, doi: 10.1109/TMECH.2021.3056099.

[9] J. I. Vasquez-Gomez, M. Marciano-Melchor, L. Valentin, and J. C. Herrera-Lozada, “Coverage Path Planning for 2D Convex Regions,” Journal of Intelligent & Robotic Systems, vol. 97, no. 1, pp. 81–94, 2020, doi: 10.1007/s10846-019-01024-y.

[10] H. Liu, Y. Sun, N. Pan, Q. Chen, X. Guo, D. Pan, "Multi-UAV Cooperative Task Planning for Border Patrol based on Hierarchical Optimization" Journal of Imaging Science and Technology, vol.65, pp. 040402-1- 040402-8, 2021. doi: 10.2352/J.ImagingSci.Technol.2021.65.4.040402.

[11] J. Fernandez Galarreta, N. Kerle, and M. Gerke, “UAV-based urban structural damage assessment using object-based image analysis and semantic reasoning,” Natural Hazards and Earth System Sciences, vol. 15, no. 6, pp. 1087–1101, 2015, doi: 10.5194/nhess-15-1087-2015.

[12] H. Liu, Y.P. Tsang, C.K.M. Lee, “A cyber-physical social system for autonomous drone trajectory planning in last-mile superchilling delivery,” Transportation Research Part C: Emerging Technologies, vol. 158, pp. 104448, 2024, doi: 10.1016/J.TRC.2023.104448.

[13] Y. Zhou, T. Rui, Y. Li, and X. Zuo, “A UAV patrol system using panoramic stitching and object detection,” Computers & Electrical

Engineering, vol. 80, pp. 106473, 2019, doi: 10.1016/j.compeleceng.2019.106473.

[14] L. Shen et al., “Synergistic path planning for ship-deployed multiple UAVs to monitor vessel pollution in ports,” Transportation Research. Part D, Transport and Environment, vol. 110, pp. 103415, 2022, doi: 10.1016/J.TRD.2022.103415.

[15] Z. Li, H. Wu, Q. Wang, W. Wang, S. Suzuki, and A. Namiki, “Small UAV Urban Overhead Ground Wire Autonomous Correction Inspection System Based on Radar and RGB Camera,” IEEE Sensors Journal, vol. 24, no. 5, pp. 5593-5608, 2023, doi: 10.1109/JSEN.2023.3317076.

[16] B. Xu, K. Zhao, Q. Luo, G. Wu, and W. Pedrycz, “A GV-drone arc routing approach for urban traffic patrol by coordinating a ground vehicle and multiple drones,” Swarm and Evolutionary Computation, vol. 77, pp. 101246, 2023, doi:10.1016/J.SWEVO.2023.101246.

[17] Y. D. Ko and B. D. Song, “Application of UAVs for tourism security and safety,” Asia Pacific journal of marketing and logistics, vol. 33, no.8, pp.1829–1843, 2021, doi: 10.1108/APJML-07-2020-0476.

[18] M. Popović et al., “An informative path planning framework for UAV-based terrain monitoring,” Autonomous Robots, vol. 44, no. 6, pp. 889–911, 2020, doi: 10.1007/s10514-020-09903-2.

[19] M. Samir, S. Sharafeddine, C. M. Assi, T. M. Nguyen, and A. Ghrayeb, “UAV Trajectory Planning for Data Collection from Time-Constrained IoT Devices,” IEEE transactions on wireless communications, vol. 19, no. 1, pp. 34–46, 2020, doi: 10.1109/TWC.2019.2940447.

[20] T. Zhou, S. M. Hasheminasab, and A. Habib, “Tightly-coupled camera/LiDAR integration for point cloud generation from GNSS/INS-assisted UAV mapping systems,” ISPRS journal of photogrammetry and remote sensing, vol. 180, pp. 336–356, 2021, doi: 10.1016/J.ISPRJPRS.2021.08.020.

[21] C. Ramirez-Atencia, V. Rodriguez-Fernandez, and D. Camacho, “A revision on multi-criteria decision making methods for multi-UAV mission planning support,” Expert systems with applications, vol. 160, pp. 113708, 2020, doi: 10.1016/j.eswa.2020.113708.

[22] H. M. Jayaweera and S. Hanoun, “A Dynamic Artificial Potential Field (D-APF) UAV Path Planning Technique for Following Ground Moving Targets,” IEEE access, vol. 8, pp. 192760–192776, 2020, doi:10.1109/ACCESS.2020.3032929.

[23] R. Radmanesh, M. Kumar, D. French, and D. Casbeer, “Towards a PDE-based large-scale decentralized solution for path planning of UAVs in shared airspace,” Aerospace science and technology, vol. 105, pp. 105965, 2020, doi: 10.1016/j.ast.2020.105965.

[24] H. Liu et al., "Study on UAV Parallel Planning System for Transmission Line Project Acceptance Under the Background of Industry 5.0," IEEE Transactions on Industrial Informatics, vol. 18, no. 8, pp. 5537-5546, 2022, doi: 10.1109/TII.2023.3142723.

[25] T. Musil, M. Petrlík and M. Saska, "SphereMap: Dynamic Multi-Layer Graph Structure for Rapid Safety-Aware UAV Planning," IEEE Robotics and Automation Letters, vol. 7, no. 4, pp. 11007-11014, 2022, doi: 10.1109/LRA.2023.3195194.

[26] T. Bruggemann, "Automated Feature-Driven Flight Planning for Airborne Inspection of Large Linear Infrastructure Assets," IEEE Transactions on Automation Science and Engineering, vol. 19, no. 2, pp. 804-817, 2022, doi: 10.1109/TASE.2021.3062154.

[27] J. Rückin, F. Magistri, C. Stachniss and M. Popović, "An Informative Path Planning Framework for Active Learning in UAV-Based Semantic Mapping," IEEE Transactions on Robotics, vol. 39, no. 6, pp. 4279-4296, 2023, doi: 10.1109/TRO.2023.3313811.

[28] S. Papaioannou, P. Kolios, T. Theocharides, C. G. Panayiotou and M. M. Polycarpou, "Integrated Guidance and Gimbal Control for Coverage Planning With Visibility Constraints," IEEE Transactions on Aerospace and Electronic Systems, vol. 59, no. 2, pp. 1276-1291, 2023, doi: 10.1109/TAES.2022.3199196.

[29] H. V. Nguyen, H. Rezatofighi, B. -N. Vo and D. C. Ranasinghe, "Online UAV Path Planning for Joint Detection and Tracking of Multiple Radio-Tagged Objects," IEEE Transactions on Signal Processing, vol. 67, no. 20, pp. 5365-5379, 2019, doi: 10.1109/TSP.2019.2939076.

[30] N. Bashir, S. Boudjit and G. Dauphin, "A Connectivity Aware Path Planning for a Fleet of UAVs in an Urban Environment," IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 10, pp. 10537-10552, 2023, doi: 10.1109/TITS.2023.3280995.

[31] N. Bono Rossello, R. F. Carpio, A. Gasparri and E. Garone, "Information-Driven Path Planning for UAV With Limited Autonomy in Large-Scale Field Monitoring," IEEE Transactions on Automation Science and Engineering, vol. 19, no. 3, pp. 2450-2460, 2022, doi: 10.1109/TASE.2021.3085365.

[32] Y. Wu, K. H. Low and C. Lv, "Cooperative Path Planning for Heterogeneous Unmanned Vehicles in a Search-and-Track Mission Aiming at an Underwater Target," IEEE Transactions on Vehicular Technology, vol. 69, no. 6, pp. 6782-6787, 2020, doi: 10.1109/TVT.2020.2991983.

[33] Qiuhua Pan, “Adaptive Gray Wolf Optimization Algorithm based on Gompertz Inertia Weight Strategy” International Journal of Advanced Computer Science and Applications(IJACSA), vol. 14, no. 11, 2023, doi: 1014569/IJCSA.2023.0141120.

[34] Shereen Alfayoumi, Neamat Eltazi and Amal Elgammal, “AI-Driven Optimization Approach Based on Genetic Algorithm in Mass Customization Supplying and Manufacturing” International Journal of Advanced Computer Science and Applications(IJACSA), vol. 14, no. 11, 2023, doi: 10.14569/IJACSA.2023.01411106.

[35] Y. Yu et al., "Distributed Multi-Agent Target Tracking: A Nash-Combined Adaptive Differential Evolution Method for UAV Systems," IEEE Transactions on Vehicular Technology, vol. 70, no. 8, pp. 8122-8133, 2021, doi: 10.1109/TVT.2021.3091575.

[36] H. Liu, Q. Chen, N. Pan, Y. Sun, Y. An and D. Pan, "UAV Stocktaking Task-Planning for Industrial Warehouses Based on the Improved Hybrid Differential Evolution Algorithm," IEEE Transactions on Industrial Informatics, vol. 18, no. 1, pp. 582-591, 2022, doi: 10.1109/TII.2021.3054172.

[37] C. Qu, W. Gai, M. Zhong, and J. Zhang, “A novel reinforcement learning based grey wolf optimizer algorithm for unmanned aerial vehicles (UAVs) path planning,” Applied soft computing, vol. 89, pp. 106099, 2020, doi: 10.1016/j.asoc.2020.106099.

[38] J.-X. Lv et al., “A new hybrid algorithm based on golden eagle optimizer and grey wolf optimizer for 3D path planning of multiple UAVs in power inspection,” Neural computing & applications, vol. 34, no. 14, pp. 11911–11936, 2022, doi: 10.1007/s00521-022-07080-0.

[39] Y. V. Pehlivanoglu and P. Pehlivanoglu, “An enhanced genetic algorithm for path planning of autonomous UAV in target coverage problems,” Applied soft computing, vol. 112, pp. 107796, 2021, doi: 10.1016/j.asoc.2021.107796.